Analysis of the Pollutant Emissions from Vehicles and their Impact on the Environment and Public Health

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ABSTRACT

In growing motorized towns such as Tirana, urban air pollution poses a substantial issue. This study examines the most detrimental pollutants road vehicles produce and their effects on environment quality and human health. We employ a mixed-methods approach that integrates field data from technical vehicle inspections, official datasets from national transport authorities, and statistical modeling, to assess the relationship between emission parameters and vehicle characteristics such as fuel type, age, mileage, and brand. Our research demonstrates that vehicle age and technological sophistication substantially affect emission levels, with Euro 0-3 vehicles responsible for most pollutants. The study underscores the necessity for fleet renewal programs, enhanced pollution monitoring, and incentives for using low-emission vehicles, as crucial to alleviating environment and health impacts.

Keywords-vehicle pollution; environmental impact; public health; Tirana

I. INTRODUCTION

Air pollution caused by motor movement is a significant environmental concern in urban areas. The extensive utilization of internal combustion engine vehicles substantially contributes to the release of detrimental pollutants, such as nitrogen oxides (NO_x), carbon monoxide (CO), volatile organic compounds (VOCs), sulfur dioxide (SO_2), and particulate matter ($PM_{2.5}$, PM_{10}), many of which are associated with respiratory ailments, cardiovascular disorders, and premature deaths [1]. As of 2022, transportation is responsible for over 3.53 billion metric tons of CO_2 emissions from vehicles and vans worldwide [2]. These emissions impact atmospheric conditions and diminish soil and water quality.

In developing economies nations, especially in the Western Balkans, metropolitan areas present increasing issues of air pollution attributable to the antiquated transportation infrastructure, inadequate regulatory enforcement, and obsolete vehicle fleets. Tirana, the capital of Albania, exemplifies these themes. The metropolis accommodates about one-third of the nation's population and has witnessed a persistent rise in private vehicle ownership since the 1990s [3]. In 2024, diesel vehicles constituted over 70% of the fleet, averaging 17 years in age, with over 60% categorized as Euro 0 to Euro 3, recognized for their subpar emission performance [4, 5]. Notwithstanding recent initiatives by the Municipality of Tirana to advocate for electric taxis and buses, emissions from antiquated vehicles significantly jeopardize air quality and public health. From the reviewed literature, we find a considerable number of studies on vehicle exhaust emissions and their relations to factors such as vehicle age, kilometers travelled, manufacturing technology, driving conditions and maintenance. In their study on vehicle pollution in Israel, authors in [6] found a strong correlation between vehicle age (for the age group of over 12 years) and carbon monoxide (CO) and hydrocarbons (HC) emissions. Through COPERT (Computer Program to Calculate Emissions from Road Transport), authors in [7] empirically modeled the variability of CO, HC, and NO_x emissions and real-world measurements, according to age group and Euro standard and confirmed that the oldest vehicles of the Greek fleet still dominate urban pollution, while technological improvements compensate for some age-related degradation. With PEMS (Portable Emissions Measurement System) testing in Europe, authors in [8] found that NO_x and PN emissions often exceed the RDE (Real-Driving Emissions) test limits on the road in extreme temperatures, altitudes and accelerations, especially for Euro 6 diesel vehicles. Likewise, cold starts and high dynamic driving result in peak emissions. Authors in [9] demonstrated that calculating the "vehicle ageing activity decline" improves inventory accuracy by up to 20%.

Comparative analysis of chassis dynamometer and PEMS studies across countries revealed that emission increases are not linear with age. The largest jumps are observed after ~5-10 years and that aging has a more severe impact on fuel emissions during cold start [9]. Thus, high emitters appear due to after-treatment malfunctions or poor maintenance. Authors in [10] examined two diesel vehicles (Lancia and Citroen) and their findings highlighted high particulate emissions in urban driving and suggested that vehicle age and maintenance have strong impacts on real-world emissions.

Although European and global research has made considerable progress in modeling vehicle emissions with machine learning and spatial-temporal data [11, 12], studies within the Albanian setting are still disjointed. Recent works predominantly emphasize energy policy or environmental sustainability, frequently lacking empirical evidence and technological evaluations [13].

Furthermore, there are limited research endeavors to associate tangible vehicle attributes–such as fuel type, mileage–with particular pollutant metrics like "lambda" deviation, CO concentration, or "opacity". The lack of comprehensive, data-driven analysis obstructs the formulation of evidence-based mitigation solutions.

This study fills the gap by integrating quantitative emission data from technical vehicle inspections with national transport statistics and analytical modeling. The study aims to: (1) identify the most detrimental pollutants released by vehicles in Tirana and (2) examine the impact of vehicle-specific parameters, including fuel type, age, and mileage, on emission intensity. The study independently examines petrol and diesel vehicles to determine which technical criteria accurately predict pollution emissions. The objective is to give policymakers a more precise comprehension of pollution sources inside Tirana's transport sector, enabling focused interventions to enhance air quality and public health results.

II. MATERIALS AND METHODS

This research utilizes a mixed-method approach, combining quantitative and qualitative data to evaluate vehicle emissions and determine principal factors contributing to urban air pollution in Tirana. The analysis is based on empirical data from several official and field sources, followed by a comprehensive statistical evaluation.

A. Data Sources

This research employed three primary sources:

- The General Directorate of Road Transport Services (DPSHTRR) has made available open-access datasets concerning the national vehicle fleet, encompassing registration trends, vehicle categories by Euro standard, and fuel types from 2019 to 2024 [5].
- The Institute of Statistics (INSTAT) provided demographic and urban growth information essential for contextualizing transport-related pollution trends [14].
- Field measurements were collected during standard technical vehicle inspections performed at many inspection centers in Tirana [13]. The measurements encompassed direct assessments of "lambda", CO and HC emissions, and "opacity" for a selection of petrol and diesel vehicles, categorized by year of manufacturing and mileage.
- Also, two focus group talks with specialists from DPSHTRR and the Faculty of Information Technology at Aleksandër Moisiu University enhanced the data collection process, seeking to augment the study with qualitative insights and institutional viewpoints.

Checking of petrol and diesel fuel vehicles was carried out according to the block schemes shown in Figures 1-2.

About 70% of the total vehicles are diesel vehicles. There has been a significant increase in the number of vehicles using diesel, which pollute the air more than other vehicle types, during the period from 2019 to 2024. Figure 3 shows the percentage composition of the main types of used fuel of the vehicle fleet. Throughout the entire period 2019-2024, vehicles using diesel, petrol, and petrol + gas, constitute about 99% of the total fleet. The ratio of the vehicles using diesel to the total has not changed significantly.

The total number of vehicles has increased by about 238.428 from 2019 to 2024 (24%). This increase was mainly contributed by diesel vehicles, which increased by about 173.516 from 2019 to 2024. The rest of the increase belongs to petrol and gas vehicles, which increased by about 33.169, and petrol vehicles, which increased by about 22.781 for the same period [5].

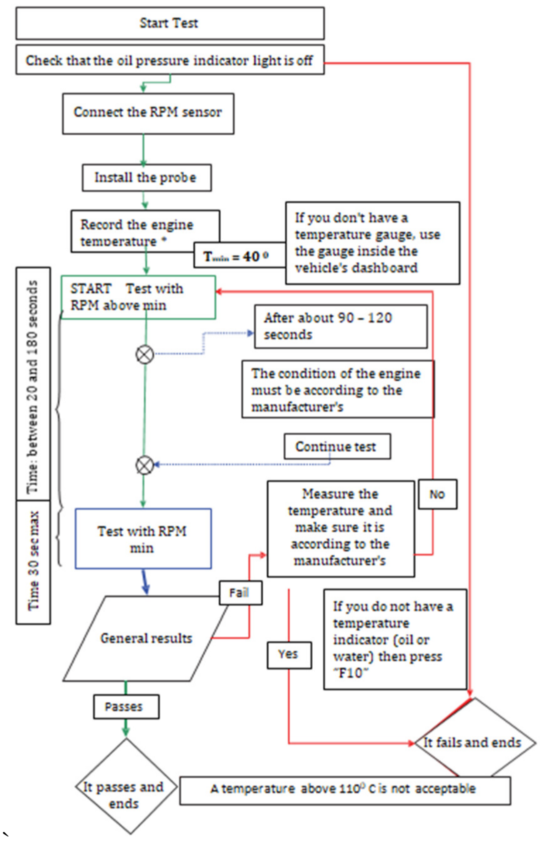

Fig. 1. Block-scheme of petrol vehicle testing.

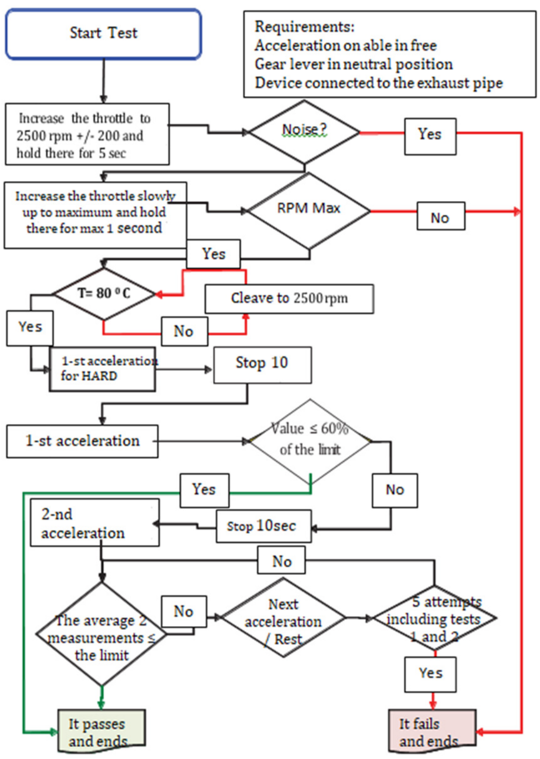

Fig. 2. Block-scheme of diesel vehicle testing.

TABLE I. NUMBER OF VEHICLES BY FUEL TYPE (2020-2024)

Number of vehicles by year					
Fuel	2020	2021	2022	2023	2024
Diesel	396,790	436,756	470,930	513,760	539,986
Petrol	98,380	102,432	107,010	114,050	119,784
Petrol + Gas	43,022	51,776	57,569	64,401	68,799
Petrol + Electric	552	901	1,236	1,736	2,448
Electric	362	624	1,245	2,891	4,029
Gas	219	339	396	563	771
Diesel + Electric	95	246		740	907
Diesel + Electric + Hybrid	3	35	180	460	621
Petrol + Gas + Electric	69	93	119	166	199
Petrol + Electric + Hybrid	3	63	228	501	663
	539,495	593,265	638,913	699,268	738,207

The data is taken from vehicles technical inspection agencies

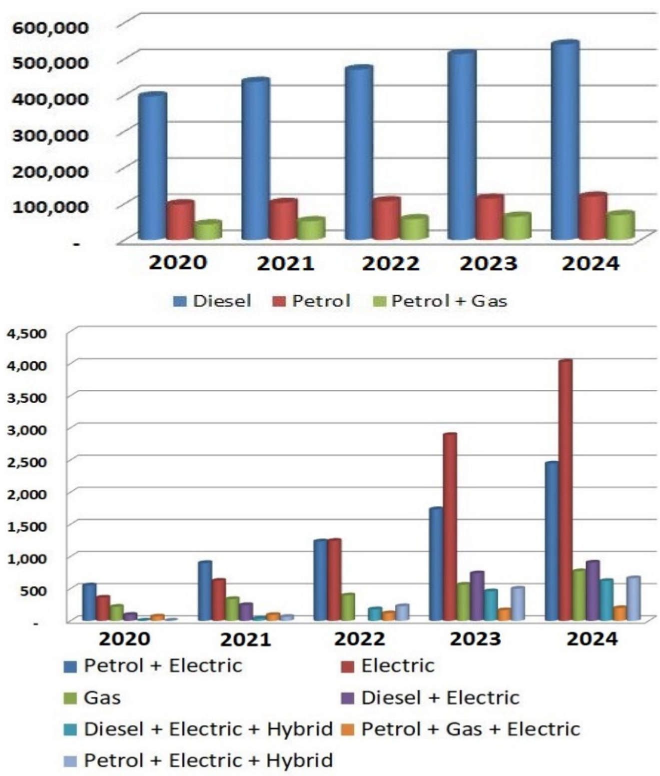

Fig. 3. Number of vehicles by type of fuel from 2020 to 2024.

B. *Analytical Approach*

The analytical framework aims to investigate the relationship between emission indicators and vehicle-specific characteristics using statistical methods, including linear regression, correlation analysis, ANOVA, and residual diagnostics. Due to inherent disparities in combustion systems and emission characteristics, distinct models were created for petrol and diesel-powered vehicles. The investigation concentrated on the "lambda" coefficient, CO (%), and HC (ppm) for petrol vehicles assessed at both low and high engine revolutions. The "opacity" coefficient served as the principal emission metric for diesel vehicles. Each pollutant variable was modeled as a function of the following independent variables:

- Kilometers driven: a continuous variable representing vehicle utilization.
- Year of production: an indicator of technological progress and adherence to European standards.
- Group (coded identifier): a categorical variable utilized to analyze emission trends associated with production.
- Fuel categories: diesel, petrol, as classified in the DPSHTRR registration.

The data were analyzed via Microsoft Excel and Python. Regression diagnostics encompassed the assessment of R^2, adjusted R^2, t-statistics, p-values, and F-statistics to evaluate model fit and the importance of predictors. Boxplots, scatter plots, and correlation matrices were utilized for visualization, while residual plots were created to assess linearity, homoscedasticity, and possible outliers [11].

- R^2: The coefficient of determination shows the proportion of the variance in the dependent variable that is predictable from the independent variable(s). It determines the explanatory power of the model.
- Adjusted R^2: is an indicator that penalizes the addition of determinants unrelated to the model.
- $p-value$: The attained level of significance, critical probability measures the probability of cases where the actual result is associated with values that are larger than the observed.
- F: The Fischer test for comparing two sample variances is used to indicate the significance of the relationship between the dependent variable and the independent variables.
- t: Student's t variable measures the statistical significance of individual characteristics of the independent variable in explaining changes in its value (the dependent variable).
- The "lambda" variance in petrol vehicles was analyzed across vehicle groups and production years to identify discrepancies from the ideal combustion ratio. "Opacity" distributions for diesel vehicles were examined by vehicle group, incorporating kilometers traveled and year of production, using both single and multivariate regressions.

This comprehensive methodology offers both exploratory and causal insights into the factors influencing vehicle emissions, facilitating more precise and effective environmental policies in Tirana and abroad.

C. Petrol-Powered Vehicles

To forecast the pollutant metrics (HC and CO) of petrol vehicles, we employed linear regression. Considering the above mentioned independent variables We also evaluated the values for "high" and "low" speed for each pollutant. Consequently, the dependent variable (target) for each model comprises the pollutant's name and the velocity condition (e.g. "lambda_high"). Initially, we handled categorical variables, followed by a linear regression model. The dataset was partitioned into training and testing subsets. The model has been trained, and the R^2 measure was utilized to assess performance.

To quantify the association between numerical variables, we employ the Pearson correlation coefficient as defined by:

$$r = \frac{\sum(X_i-\bar{X})\cdot(Y_i-\bar{Y})}{\sqrt{\sum(X_i-\bar{X})^2}\cdot\sqrt{\sum(Y_i-\bar{Y})^2}} \quad (2)$$

where X_i, Y_i are individual values of variables X and Y, while $\bar{X}$, $\bar{Y}$ are their averages, and r indicates the strength and direction of the bond.

To compare the "lambda" values by vehicle group, we used the boxplot graph to show the distribution.

D. Diesel-Powered Vehicles

We examined the data considering two variables (year of manufacturing and kilometers traveled) in diesel vehicles by assessing the distribution of the "opacity" coefficient for each variable, creating scatter plots, calculating statistical metrics for their interrelations, and ultimately testing for statistical dependencies between the "opacity" coefficient and these variables. We first calculated each group's average "opacity" and dispersion coefficient to determine which vehicle groups produce the highest pollution levels.

We employed linear regression or trend analysis to examine the variation of "opacity" in the year of production.

$$y = m \cdot x + b \quad (3)$$

where y is the opacity value, x is the year of manufacturing, m is the slope (trend), and b is the interception with the y axis. If m is negative, "opacity" diminishes over time (more recent vehicles emit less pollution).

To examine the correlation between mileage and "opacity", we employed the correlation coefficient, as delineated in (2), where X_i represents the kilometers traveled by vehicle i, Y_i denotes the "opacity" of the vehicle I, and r indicates the strength and direction of the relationship.

A statistical model (linear regression) was developed to investigate further the influence of numerical variables, including the year of manufacturing and the kilometers driven, on "opacity":

$$Y = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \ldots + \beta_n \cdot X_n + \varepsilon \quad (4)$$

where Y represents the dependent variable ("opacity"), X_1 and X_2 denote the independent variables (year of production and kilometers traveled by the vehicle), β_0 signifies the intercept (the value of Y when all X_1 are zero, and β_i are regression coefficients indicating the influence of each component X_i on Y, while ε represents the error term.

The model was constructed using the Ordinary Least Squares (OLS) technique, which minimizes the aggregate of the residuals' squares.

$$\sum\left(Y_i - \hat{Y}_i\right)^2 \quad (5)$$

where Y_i is the current value and $\hat{Y}_i$ is the predicted value by the model.

III. RESULTS

A. *Petrol-Powered Vehicles*

The emission performance of petrol vehicles was assessed using three primary parameters: the "lambda" coefficient (λ), CO, and HC. The "lambda" coefficient indicates the air-fuel mixture during combustion and is essential for enhancing engine efficiency and reducing emissions. Values beyond the normal range (0.97–1.03) generally signify inadequate combustion conditions, resulting in heightened pollutant emissions.

Regression analysis revealed a statistically significant correlation between "lambda" deviation and CO and HC. Higher "lambda" values (lean mixtures) were correlated with increased HC emissions, whereas lower "lambda" values (rich mixtures) were linked to increased CO emissions. These findings align with previous emission behavior models [15] presented, wherein "lambda" variations directly influenced pollutant intensity.

Figure 4 illustrates the tendency for older petrol vehicles to exhibit greater deviation in "lambda", correlating with elevated CO emissions. This supports the hypothesis that engine management systems influence emission performance.

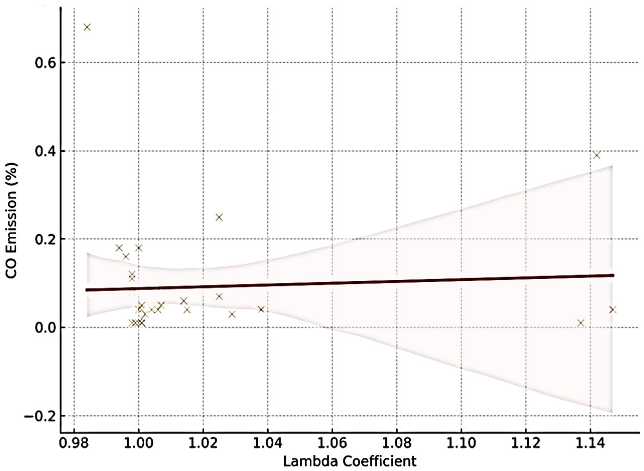

Fig. 4. Correlation between "lambda" coefficient and CO emissions (%), segmented by year manufactured vehicle.

Table II encapsulates the statistical results of the linear regression models for CO and HC, utilizing "lambda" as the predictor variable. Regarding the R^2 values, for CO, the model explains 42% of the variance, while for HC, it explains 38%. These are moderate fits. The Adjusted R^2 is slightly lower, as expected (corrects for the number of variables). It still shows that the model has some explanatory power. The p-value is less than 0.01, so the overall regression model is statistically significant for both CO and HC. Although the regression model explains a moderate portion of the variance in CO and HC levels (R^2 = 0.42 and 0.38 respectively), the individual coefficients for the intercept and "lambda" variable are not statistically significant ($p > 0.7$). This suggests that while the model overall is significant ($p < 0.01$), "lambda" may not be a strong independent predictor in this model. This proves that, although reliable, pre-existing data from standardized technical inspections, lack critical explanatory variables such as engine condition, service records, driving behavior, and fuel quality - elements known to significantly affect emissions.

TABLE II. STATISTICS FOR PETROL VEHICLE EMISSIONS

	Coef.	Std. Err.	t
Const.	-0.11404	0.57697	-0.19765
Lambda	0.20151	0.56693	0.35544
		Confidence Intervals	
	p > |t|	[0.025	0.975]
Const.	0.84457	-1.28929	1.06121
Lambda	0.72459	-0.95329	1.35631
Parameter	**R^2**	**Adjusted R^2**	**p-value**
CO	0.42	0.40	< 0.01
HC	0.38	0.35	< 0.01

The age of the vehicle also had a considerable impact. Models produced before 2005 demonstrated an increased frequency of "lambda" deviation, with R^2 = 0.42 and $p < 0.01$, indicating a correlation between the year of production and CO emissions. Mileage exhibited a weak link with "lambda" (R^2 = 0.18), suggesting that age and fuel system maintenance are more significant than usage alone. This indicates that although nonlinear models have theoretical benefits, their performance may be suboptimal given current data constraints, especially with a restricted dataset and few characteristics.

A Random Forest Regression was trained using the same variables (year, miles, and "lambda") to evaluate the efficacy of machine learning techniques in predicting CO emissions. The model produced an R^2= -0.59 and a root mean square error (RMSE) of 0.07, signifying inferior performance compared to a baseline model that forecasts the mean CO value.

B. *Diesel Vehicles*

"Opacity" is the principal emission indicator in diesel-powered vehicles. It quantifies the concentration of particulate matter (soot) released during combustion. "Opacity" levels vary considerably among vehicle groups and model years. Figure 5 illustrates the mean "opacity" values categorized by production year. Vehicles manufactured before 2005 typically had elevated values. Figure 5 confirms a downward trend in "opacity" levels for more recent production years, implying improvements in diesel particulate filtering and combustion efficiency. Notably, vehicles produced after 2010 exhibit substantially lower average "opacity".

Table III presents the coefficients from the multiple linear regression model where "opacity" is predicted by the year of manufacturing and the kilometers traveled. The correlation between the year of production and the opacity is -0.077, with a p-value of 0.34, indicating a very weak and not statistically significant relationship. The model coefficients are:

- Intercept (const.): 212.08. This is the predicted value of "opacity" when year and mileage are zero (not very meaningful in practice).

- Year of production: -0.1039. A one-year increase in production reduces "opacity" by 0.1039 on average, being a significant factor (p-value = 0.038).

The considered model statistics are:

- R-squared: 0.064. Only 6.4% of the variance in "opacity" is explained by year of production and kilometers, indicating that these factors have limited impact on pollution.
- Model p-value: 0.00645. The model is statistically significant, but with a weak effect.

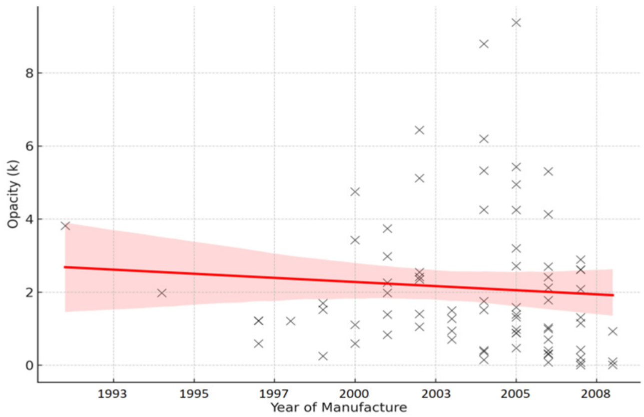

Fig. 5. Average "opacity" levels (k-value) by vehicle production year for diesel engines.

TABLE III. LINEAR MULTIPLE REGRESSION RESULTS FOR "OPACITY" IN DIESEL VEHICLES BY YEAR OF PRODUCTION AND KILOMETERS TRAVELED

	Coef.	**Std. Err.**	**t**
Const.	212.0777	142.5704	1.48753
Year	-0.10385	0.07099	-1.46293
Km	-7.45E-06	3.46E-06	-2.15363
		Confidence Intervals	
	p > ltl	[0.025	0.975]
Const.	0.141067	-71.9371	496.0925
Year	0.147664	-0.24527	0.037566
Km	0.034483	-1.43E-05	-5.59E-07
Predictor	**R^2**	**Adjusted R^2**	**p-value**
Year	0.47	0.45	< 0.001
Km	0.23	0.20	< 0.05
Brand (categorical ANOVA)	—	—	< 0.001

The one-way ANOVA revealed significant differences in "opacity" among vehicle groups ($p < 0.001$), corroborating earlier findings [11], which indicated vehicle group variations in diesel emissions. The correlation between "opacity" and kilometers was weaker ($R^2 = 0.23$), but vehicle age proved to be a more robust predictor ($R^2 = 0.47$, $p < 0.001$).

To investigate more sophisticated modeling techniques, a gradient-boosting regression was employed to estimate diesel "opacity" levels based on the year of production and mileage. Nevertheless, the model exhibited subpar performance, with $R^2 = -0.70$ and RMSE = 2.04, indicating a deficiency in predicting capability. This result may be ascribed to unobserved confounding variables, such as maintenance history, driving behaviors, or fuel quality, which are absent from the current dataset.

C. Statistical Modeling and Cluster Interpretation

A multiple linear regression model was developed to estimate CO emissions based on vehicle year, mileage, and vehicle group. The model produced a value $R^2 = 0.572$, signifying moderate to strong explanatory capability for these key factors. This illustrates the viability of employing constrained but organized inspection data to forecast pollution dynamics in actual vehicle fleets. A k-means cluster analysis was conducted to discern various emission behavior profiles among petrol vehicles. Three clusters were discerned, utilizing CO, HC, and "lambda" as input variables, each embodying a distinct emission profile. These categories can be classified as low, moderate, and high emitters. The capacity to categorize vehicles into emission-risk classifications based on inspection criteria offers a chance for more nuanced and focused policy enforcement.

D. Summary of Statistical Interpretation

The comprehensive regression diagnostics indicated a satisfactory model fit characterized by homoscedastic residuals and a limited number of outliers. Boxplots and correlation matrices (not presented here) corroborated the observed trends. These findings confirm previous research highlighting the significant influence of obsolete vehicle technologies on urban air pollution [3]. The linear regression results indicate a substantial correlation between vehicle age, Euro emission standards, and "opacity". The findings demonstrate that vehicle age and group are significant determinants of pollution levels in Tirana. "Lambda" petrol engine deviations and diesel vehicles elevated "opacity" indicate systematic maintenance deficiencies and technological obsolescence, necessitating regulatory intervention. K-means clustering analysis was conducted to investigate emission heterogeneity, yielding three unique vehicle types based on pollutant intensity. The value $k = 3$ was chosen empirically to guarantee a distinct difference among the vehicle groups while preserving interpretability. This decision facilitated the categorization a vehicle into low, moderate, and high-emission profiles according to CO, HC, and "lambda" values. The visual evaluation (Figure 6) validated the suitability of this segmentation. The k-means algorithm seeks to reduce intra-cluster variance by allocating data points to the closest cluster centroid [13]. This clustering facilitates the identification of high-risk vehicles that disproportionately contribute to urban air pollution. The classification facilitates targeted policy interventions, including improved inspection processes or vehicle replacement programs, customized for the identified emission-risk categories.

Figure 6 illustrates the results of the k-means clustering analysis performed on petrol vehicles, specifically examining their emission patterns for CO, HC, and λ. The three resultant clusters signify discrete kinds of emitters:

- Cluster 1: Low emitters - vehicles demonstrating optimal "lambda" values and minimum CO and HC emissions, generally newer models with superior combustion regulations.

- Cluster 2: Moderate emitters, vehicles exhibiting emissions within allowable limits, however displaying indications of "lambda" deviation or incomplete combustion.
- Cluster 3: High emitters - defined by markedly increased CO and HC emissions, coupled with "lambda" values deviating from the optimal range, frequently linked to older models or insufficient maintenance.

Table IV summarizes the mean and standard deviation values for each emission parameter, grouped by Euro standard and vehicle group. Key insights include consistently higher CO in Euro 0–2 petrol vehicles (Figure 4(a)) and elevated "opacity" in older diesel models (Figure 4(b)). It should be noted that this dataset has 29 entries for petrol vehicles (including complete CO, HC, and Lambda values) and 27 entries for diesel vehicles (containing entire Opacity measurements). The values denote the mean and standard deviation for each emission parameter, categorized by Euro standard and vehicle group, derived from DPSHTRR technical inspection data (2019–2024).

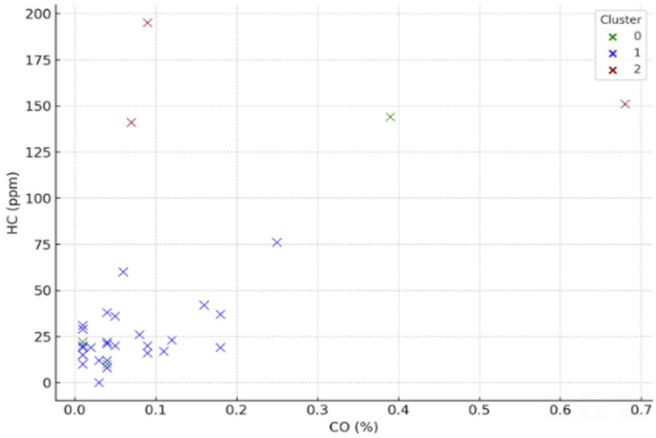

Fig. 6. Cluster analysis of petrol vehicles based on CO, HC, and "lambda" emissions. The plot illustrates three distinct groups with similar emission characteristics, helping identify clusters of high-polluting versus low-polluting vehicles.

TABLE IV. SUMMARY STATISTICS FOR POLLUTANT INDICATORS (CO, HC, "LAMBDA", "OPACITY") BY EURO STANDARD AND VEHICLE GROUP

No	Euro	Petrol – Coded Vehicle Group	CO Mean	CO Std.	HC Mean	HC Std.	Lambda Mean	Lambda Std.
1	Euro 0	Vehicle H	0.56	–	221	–	–	–
2	Euro 1	Vehicle H	0.09	–	195	–	1.009	–
3	Euro 2	Vehicle C	0.03	–	12	–	1.002	–
4	Euro 2	Vehicle D	0.12	–	23	–	0.998	–
5	Euro 2	Vehicle E	0.25	–	76	–	1.025	–
6	Euro 2	Vehicle N	0.05	–	20	–	1.001	–
7	Euro 2	Vehicle Q	0.267	0.359	71.667	68.966	0.999	0.016
8	Euro 2	Vehicle R	0.04	–	8	–	1	–
9	Euro 3	Vehicle A	0.04	–	8	–	1.004	–
10	Euro 3	Vehicle E	0.05	–	36	–	1.007	–
11	Euro 3	Vehicle F	0.047	0.032	76.667	57.83	1.013	0.013
12	Euro 3	Vehicle I	0.04	–	21	–	1.038	–
13	Euro 3	Vehicle H	0.01	–	15	–	1.001	–
14	Euro 3	Vehicle J	0.02	–	19	–	1.001	–
15	Euro 3	Vehicle K	0.18	–	19	–	1	–
16	Euro 3	Vehicle L	0.18	–	37	–	0.994	–
17	Euro 3	Vehicle Q	0.09	–	20	–	1.007	–
18	Euro 3	Vehicle R	0.01	–	22	–	1.137	–
19	Euro 4	Vehicle B	0.03	–	0	–	1.029	–
20	Euro 4	Vehicle F	0.01	–	15	–	1.001	–
21	Euro 4	Vehicle J	0.04	–	22	–	1.001	–
22	Euro 4	Vehicle K	0.09	–	16	–	0.998	–
23	Euro 4	Vehicle M	0.01	–	31	–	0.998	–
24	Euro 4	Vehicle N	0.11	–	17	–	0.998	–
25	Euro 4	Vehicle O	0.39	–	144	–	1.142	–
26	Euro 4	Vehicle Q	0.1	0.085	26	22.627	1.071	0.107
27	Euro 5	Vehicle G	0.04	–	12	–	1.006	–
28	Euro 5	Vehicle P	0.01	0	15	7.071	1	0.001
29	Euro 5	Vehicle Q	0.01	–	19	–	0.999	–

No	Euro	Diesel – Coded Vehicle Group	Opacity Mean	Opacity Std.
1	Euro 0	Vehicle H	2.9	1.301
2	Euro 1	Vehicle H	0.59	–
3	Euro 1	Vehicle Q	1.187	0.501
4	Euro 2	Vehicle D	2.745	1.617
5	Euro 2	Vehicle F	2.967	2.966
6	Euro 2	Vehicle H	2.62	1.841
7	Euro 2	Vehicle T	3.395	3.967

8	Euro 2	Vehicle U	2.35	–
9	Euro 2	Vehicle Q	2.068	1.946
10	Euro 2	Vehicle R	0.15	–
11	Euro 3	Vehicle B	0.1	–
12	Euro 3	Vehicle D	3.837	1.145
13	Euro 3	Vehicle E	1.59	–
14	Euro 3	Vehicle F	2.265	0.899
15	Euro 3	Vehicle S	0.61	0.468
16	Euro 3	Vehicle H	1.814	2.006
17	Euro 3	Vehicle U	5.43	–
18	Euro 3	Vehicle M	0.3	–
19	Euro 3	Vehicle P	1.167	0.581
20	Euro 3	Vehicle Q	2.203	2.832
21	Euro 3	Vehicle R	0	–

The entries refer to the groupings (brands) of the vehicles under review

TABLE V. SUMMARY BY EURO STANDARD AND VEHICLE GROUP

No.	Euro	Petrol – Coded Vehicle Group	No. Brand
1	3	Vehicle A	1
2	4	Vehicle B	1
3	2	Vehicle C	1
4	2	Vehicle D	1
5	2	Vehicle E	1
6	3	Vehicle E	1
7	3	Vehicle F	3
8	4	Vehicle F	1
9	5	Vehicle G	1
10	0	Vehicle H	1
11	1	Vehicle H	1
12	3	Vehicle H	1
13	3	Vehicle I	1
14	3	Vehicle J	2
15	3	Vehicle K	1
16	4	Vehicle K	1
17	3	Vehicle L	1
18	4	Vehicle M	1
19	2	Vehicle N	1
20	4	Vehicle N	1
21	4	Vehicle O	1
22	5	Vehicle P	2
23	6	Vehicle P	1
24	2	Vehicle Q	2
25	3	Vehicle Q	1
26	4	Vehicle Q	3
27	5	Vehicle Q	1
28	2	Vehicle R	1
29	3	Vehicle R	1

No.	Euro	Diesel – Coded Vehicle Group	No. Brand
1	4	Vehicle B	1
2	2	Vehicle D	2
3	3	Vehicle D	4
4	4	Vehicle D	2
5	3	Vehicle E	1
6	2	Vehicle F	2
7	3	Vehicle F	6
8	4	Vehicle F	4
9	3	Vehicle S	1
10	4	Vehicle S	1
11	0	Vehicle H	3
12	1	Vehicle H	1
13	2	Vehicle H	10
14	3	Vehicle H	4
15	2	Vehicle T	1
16	4	Vehicle T	2
17	2	Vehicle U	1
18	3	Vehicle U	1
19	3	Vehicle M	1
20	3	Vehicle P	3
21	4	Vehicle P	5
22	1	Vehicle Q	2
23	2	Vehicle Q	4
24	3	Vehicle Q	7
25	4	Vehicle Q	7
26	2	Vehicle R	1
27	3	Vehicle R	1

The entries refer to the groupings (brands) of the vehicles under review

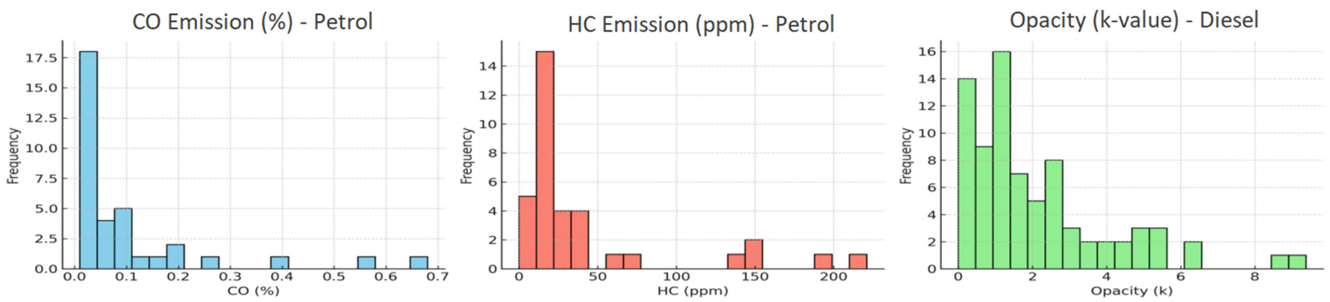

Fig. 7. Distribution of pollutant levels: CO and HC (petrol vehicles) and "Opacity" (diesel vehicles). The histograms show the frequency of emission values across the tested fleet, highlighting concentrations and outliers among high-polluting vehicles

The analysis of the consolidated inspection data indicates a persistent trend of elevated pollutant emissions in older Euro categories (0-2) for both petrol and diesel vehicles. Petrol vehicles in the Euro 0–2 categories, demonstrate increased mean values of CO and HC, indicative of old-fashioned engine designs, inefficient combustion systems, and inadequate maintenance. Lambda deviations in certain vehicle groups indicate poor air-fuel ratios, leading to incomplete combustion and heightened pollutant emissions.

Diesel vehicles in the Euro 0–2 categories exhibit notably elevated opacity values, identified as primary contributors to particle emissions. The noticeable reduction in emission levels in the Euro 4 and 5 categories confirms the efficacy of technological innovations and more stringent standards. Sustainable Urban Streets (SUS) should be developed to ensure a balance between social, economic, and environmental considerations in road design [16]. From a policy point of view, these findings highlight the necessity for focused fleet renewal initiatives that prioritize the replacement of Euro 0–2 vehicles, implement differentiated pricing based on CO_2 and particle emissions, provide incentives for electric and hybrid vehicles, and enhance inspection standards. These initiatives could expedite the shift to a cleaner fleet and produce substantial environmental and public health advantages.

The histograms in Figure 7 further substantiate the existence of emission outliers, especially within diesel vehicles. The distorted distributions underscore the need to identify and regulate high-emission units within the fleet. The distribution of CO is right-skewed, suggesting that although the majority of petrol vehicles emit relatively modest CO levels, a significant group exists that has with highly CO concentrations, often associated with "lambda" deviations. The HC distribution exhibits significant fluctuation, underscoring the notion that incomplete combustion is common among specific vehicle clusters, especially of older vehicles.

The "opacity" values for diesel vehicles exhibit a broader error and a more uniform distribution, with a considerable proportion of vehicles surpassing the permissible thresholds. This suggests that a substantial portion of the diesel vehicles makes a significant contribution to particle pollution. These distributions visually corroborate the regression and clustering results: a limited selection of vehicles generates a disproportionately large fraction of the overall emissions. Identifying and targeting these vehicles can result in substantial enhancement in air quality with minimum regulatory intervention.

IV. DISCUSSION

The thorough examination of vehicle emissions in Tirana uncovers significant patterns that align with established literature while offering fresh, context-specific insights. The robust association between "lambda" deviations and increased CO and HC emissions in petrol vehicles corroborates previous research [17], which illustrates how inadequately calibrated engines or defective oxygen sensors can significantly enhance pollutant emissions. The inverse correlation between production year and "opacity" in diesel vehicles corroborates the findings of the authors in [13] who highlight that older diesel engines often produce considerably more particulate matter due to their antiquated combustion methods and insufficient filtration systems.

Authors in [17] state that Real Driving Emissions (RDE) represent an essential procedure in the implementation of clean transport zones in Poland, and establishing a link between a vehicle's air pollutant emissions and its age (15 years) can support making transport or delivery planning more sustainable and choosing less carbon-intensive means of transport to reduce the negative impact of transport on the environment.

The regression model for petrol vehicles accounted for approximately 57% of the CO emissions variance, utilizing year, mileage, and vehicle group as variables. This illustrates the capacity of even restricted inspection data to produce significant prediction insights. This corroborates the findings of [11], where basic yet structured datasets were employed to predict greenhouse gas emissions.

The cluster analysis showed three distinct types of emission behavior among petrol vehicles, paralleling the categorization procedures employed in [18] for AI-based energy management systems. These techniques highlight the significance of machine learning and clustering in environmental diagnostics.

The subpar performance of Random Forest and Gradient Boosting models, indicated by negative R^2 values, suggests that the dataset's constraints are more significant than the inadequacies of the methods themselves. These techniques generally necessitate:

- Extensive datasets to discern intricate patterns without over fitting.
- This study lacked comprehensive feature sets, which would have covered variables such as air intake pressure, engine temperature, fuel injection settings, and service history.
- Inconsistencies partially hindered data normalization and quality assurance in the inspection procedures.

The models failed to derive significant structure from the limited variables, underscoring the efficacy of interpretable linear models in data-scarce scenarios. Subsequent research may address these constraints by incorporating IoT-based real-time vehicle telemetry or centralized emission databases.

The ramifications from the policy standpoint are significant. Most of the sampled diesel vehicles did not pass the "opacity" tests, signifying significant noncompliance with environmental regulations, showcasing that immediate intervention is required. Public policies should prioritize vehicle replacement programs targeting Euro 0–3 categories, which comprise the majority of Albanian fleets [19]. Incentives for adopting electric and hybrid vehicles, according to the proposals of the EU and CE Delft [20], implementing CO_2-based taxation [7], and establishing more stringent inspection processes will enhance fleet quality and diminish harmful emissions.

Nonetheless, this study has several drawbacks. The research utilized current datasets from governmental portals and pre-existing datasets from standardized technical inspections, which, while dependable, omit critical explanatory variables such as engine condition, service records, driving behavior, and fuel quality—elements recognized to significantly affect emissions [12, 21]. The absence of standardized data-gathering protocols may restrict generalizability. Secondly, the statistical models are very simplistic despite the use of multivariate regression and clustering. Advanced modeling techniques, including nonlinear regression, machine learning ensembles, and time-series forecasting, may reveal further aspects of the emission issue [12]. Authors in [22] provide a significant framework, while authors in [18] bring solutions to the complex interactions of environmental and social factors with new remote sensing models for urban planning, by identifying the hottest zones. The data collection lacks maintenance records, engine conditions, driving behavior, and fuel quality. Albania is concerned about for the quality of fuel and the widespread occurrence of inferior components and maintenance services [23]. The lack of these parameters may lead to underestimating the severity or misattribution of pollution sources.

Notwithstanding these constraints, this work addresses a critical research gap in Albanian environmental research. By integrating real-world data, statistical modeling, and policy analysis, it provides an empirical basis for forthcoming legislation, advocacy, and investment in sustainable urban mobility.

V. CONCLUSIONS

This study offers a thorough, data-driven examination of vehicle emissions in Tirana, emphasizing the substantial impact of vehicle-specific attributes on pollutant concentrations. The findings demonstrate that petrol vehicles with "lambda" deviations produce significantly elevated CO and HC emissions, especially in older models. Likewise, diesel vehicles exhibited persistently high "opacity" levels, particularly those manufactured before 2005, highlighting the effects of technology obsolescence and inadequate maintenance—a worry previously noted in [7, 18].

The statistical study indicated that simple linear regression models were somewhat effective in forecasting CO emissions (R^2 = 0.57). More sophisticated machine learning techniques like Random Forest and Gradient Boosting exhibited subpar performance with the given data. These findings align with those of [3, 12] where the need for broad and comprehensive datasets to leverage sophisticated predictive models' capabilities properly is emphasized. The absence of data on essential variables—such as maintenance records, fuel quality, and driving behavior—restricts the explanatory capacity of non-linear models, thereby underscoring the practical use of interpretable, conventional methods given the existing limitations.

These ideas possess considerable ramifications for public policy. The prevalence of Euro 0–3 vehicles in the Albanian fleet [14] necessitates immediate renewal activities. A comprehensive policy framework should encompass CO_2 pricing, direct incentives for adopting low-emission vehicles, and enhancing municipal initiatives that promote electric transportation [24]. These improvements will mitigate pollution, improve public health, and match Albania's transport sector with EU environmental criteria [22].

Future research should progress in three principal areas: (1) Implementing longitudinal studies to assess the temporal impacts of policy interventions and fleet renewal, (2) utilizing advanced modeling techniques, including neural networks and ensemble learning, when more comprehensive data is accessible; and (3) incorporating spatial variables—such as traffic density, road topology, and use of IoT technology for traffic management [21], to enhance the comprehension of the urban aspect of transport-related emissions.

Technological advancements, such as the Three-Way Catalysts (TWCs) for petrol vehicles and Diesel Particulate Filters (DPFs), are essential for reducing vehicle pollutant emissions. In diesel vehicles, incomplete combustion results in the production of soot particles. The mass and number of particles are fundamentally contingent upon the combustion quality within the engine. The injection pump functions at elevated pressure to meet the engine's requirements for effective combustion, resulting in an alteration in injection that diminishes soot particle generation throughout the combustion process. Nonetheless, greater injection pressure and effective fuel atomization do not inherently reduce the emitted particle size. The measurements indicated that the particle size distribution in the exhaust gases is independent of the combustion principle employed in the engine and remains consistent across different engine types. Technical solutions for reducing particulate emissions have been made through endomotor measures, which involve efficient optimization of combustion so that polluting substances are not generated from the beginning, and locomotor measures, which consist of reducing soot particles using a filtration system in the exhaust gases, with or without additional additives, depending on the distance from the engine of the particulate filter.

The heightened emission levels identified in this study have direct consequences to urban public health. CO and HC are recognized for inducing respiratory and cardiovascular strain, especially in heavily populated urban areas such as Tirana [23]. "Opacity", indicative of particulate matter from diesel vehicles, correlates with $PM_{2.5}$ exposure, heightening the risk of asthma, bronchitis, and premature mortality [1]. The prevalence of a substantial segment of the vehicle fleet classified as Euro 0–3 underscores the pressing necessity for transport reforms focused on public health. Vehicles account for 44.2% and Euro 4 vehicles account for 33.5% of the total. Compared to 2021, Euro 5 vehicles have increased by 221% and Euro 4 vehicles by 48%. Meanwhile, Euro 6 vehicles have increased by 195%. This brings about the necessity of awareness and financial policies that bring benefits to vehicle users that pollute the environment less and thus help improve the quality of life in Tirana. Albania is a clear example of a country whose energy system justifies the transition to electromobility. In 2024, the percentage of the electricity provided by renewable sources is: hydro ~93-94%, and solar PV: ~6.5% [25]. Electric mobility naturally fits with the strengths of renewable energy. Furthermore, Albania is developing new solar projects such as the 140 MW Karavasta and additional photovoltaic/wind auctions. Regional grid integration (e.g. with Italy via the planned submarine cable) could stabilize electricity imports and exports.

The empirical finding that petrol and diesel vehicles emit up to six times more NO_x and $PM_{2.5}$ than gas fueled variants has direct health relevance. Chronic exposure to elevated NO_x and $PM_{2.5}$ levels is causally linked to asthma exacerbations, reduced lung function, and increased cardiovascular mortality. In mixed fleet urban environments, a 15% shift from diesel to gas could lower average $PM_{2.5}$ emisions by 1.5 μg/m³—potentially reducing premature cardiac events by 2–4%. Consequently, policies incentivizing cleaner fuel adoption or retrofitting older fleets may yield measurable health benefits.

This study contributes to the growing body of evidence advocating for sustainable transport reform in Albania. By connecting empirical data with policy analysis, it establishes a basis for targeted initiatives to improve environmental and public health outcomes in Tirana and other rapidly expanding urban areas.

VI. RECOMMENDATIONS

This paper, based on empirical results and corroborated by the literature, suggests a comprehensive array of policy options to mitigate transport-related emissions in Albania and facilitate alignment with EU environmental objectives:

- Establish a taxing mechanism for vehicles based on CO_2 emissions. Substituting uniform ecological levies with a progressive tax system predicated on CO_2 emissions would deliver a distinct financial incentive for low-emission vehicles. This methodology, endorsed in [17] and implemented in many EU member states, promotes consumer adoption of ecologically sustainable options. Albanian policy may focus on the high-emitting Euro 0–3 fleet indicated in this analysis [11].
- Promote the utilization of electric and hybrid vehicles. Much of Tirana's vehicle fleet consists of obsolete and environmentally detrimental vehicles. CE Delft [8] and national policy talks [9] recommend that the government should establish substantial financial incentives to encourage the purchase of electric and hybrid vehicles. These measures may encompass import tax exemptions, purchasing subsidies, VAT reductions, and advantageous lending programs. National expansion of municipal efforts, such as the electric taxi fleet advocated by the Municipality of Tirana, is warranted.
- Allocate resources to sustainable public transport and environmentally friendly urban infrastructure. A sustained decrease in urban pollution necessitates a transition from reliance on private vehicles [25]. Essential interventions are the expansion of public transit networks, the construction of protected bicycle lanes and pedestrian pathways, and the establishment of low-emission zones. These investments generate environmental and public health advantages while fostering social fairness.
- Augment the technical inspection and emissions monitoring system [22]. Given group-specific and age-related pollution trends, inspection centers should include more sophisticated diagnostic instruments to identify high emitters. Many other pollutant compounds have not been analyzed, but are the subject of research worldwide. Authors in [26] use the BAT-CELL Bio-Ambient-Tests method to measure exhaust gas emissions, and thus determine toxicity by correlating them with the results of chromatographic analysis. As in other EU contexts, data-sharing protocols between inspection centers and regulatory bodies might enhance enforcement and policy responsiveness [4].
- Establish comprehensive emission data systems. Albania should create a centralized digital platform for tracking emissions, inspection outcomes, and vehicle lifetime information to enable sophisticated environmental assessment and decision-making. Authors in [12] assert that these datasets are crucial for implementing AI and machine learning in emissions forecasting.

Collectively executed, these ideas can significantly diminish vehicle emissions, enhance public health, and establish Albania on a credible trajectory toward climate neutrality and conformity with EU environmental standards [18, 21].

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DATA AVAILABILITY

Data will be made available on request.

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