

Article

Assessing Road-Segment-Level Operational Environmental Burdens of Electric Vehicles: A Composite Index for Urban Transportation Planning

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Abstract

The rapid transition toward electric mobility is widely recognized as a key strategy for improving urban environmental quality. However, while electric vehicles eliminate tailpipe emissions, they continue to contribute to environmental pressures through non-exhaust sources such as tire wear, road surface abrasion, and particle resuspension. This study develops a composite index framework for assessing road-segment-level operational environmental burdens associated with electric traffic, focusing on traffic operations, electric vehicle load characteristics, non-exhaust emission potential, and meteorological dispersion conditions. The framework does not constitute a life-cycle assessment and does not include battery production, electricity-generation mix, or other upstream environmental impacts. The framework combines four dimensions of influence: traffic operations, electric vehicle characteristics, non-exhaust emission processes, and meteorological dispersion conditions. Indicator selection was performed using the Delphi method, while indicator weights were determined through the Analytic Hierarchy Process (AHP). The methodological contribution lies not in the individual methods applied, but in their integration into a road-segment-level assessment framework specifically designed to identify and prioritize environmentally sensitive locations under traffic electrification scenarios. The resulting model incorporates sixteen indicators aggregated into a single environmental impact index that enables the ranking, classification, and prioritization of urban road segments according to their environmental burden. A case study conducted on selected urban streets demonstrates that non-exhaust emission indicators, particularly tire wear and particle resuspension, represent the most influential factors in the assessment process. Within the illustrative five-segment case study, the relative road-segment ranking remained unchanged under the electrified-traffic scenario, while the structure of the assessed burden shifted toward non-exhaust processes. The proposed framework provides a practical decision-support tool for urban planners and transport authorities by enabling the identification of environmentally sensitive locations, prioritization of infrastructure interventions, and support for sustainable mobility strategies in increasingly electrified urban transport systems.



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1. Introduction

Modern urban traffic is one of the dominant sources of environmental pollution, especially in large cities with high traffic volumes. Traditionally, the negative impacts of traffic have been primarily associated with exhaust gas emissions from internal combustion engine vehicles, with pollutants such as nitrogen dioxide (NO₂) and suspended particulate matter (PM₁₀ and PM_{2.5}) identified as key factors in air quality degradation [1–3]. However, the rapid development and deployment of electric vehicles (EVs) introduce a new paradigm in the analysis of the environmental impact of traffic. Although electric vehicles eliminate exhaust gas emissions during operation, numerous studies indicate that their overall environmental impact is not negligible [4–6]. In particular, non-exhaust sources of pollution—such as tire wear, brake system wear, and the resuspension of particles from the roadway—which can represent a dominant source of suspended particles in urban areas [7–9], are increasingly emphasized. In addition, the environmental impact of electric vehicles cannot be considered in isolation from traffic flow characteristics and environmental conditions. Factors such as vehicle speed, driving mode (stop-and-go), and the degree of congestion, as well as meteorological conditions such as wind speed, temperature, and air humidity, have a significant influence on the generation and dispersion of pollutants [10,11]. At the same time, EV-specific characteristics, particularly greater vehicle mass associated with battery systems, may increase non-exhaust particle emissions, while battery size and energy consumption influence broader life-cycle environmental impacts [12,13].

The existing literature is dominated by approaches that analyze individual aspects of the impact of traffic on the environment, while integrated models that combine multiple heterogeneous factors remain relatively rare [14,15]. Many established road-traffic emission models and empirical studies were developed primarily for conventional gasoline- and diesel-powered vehicle fleets [16–18]. A particular challenge lies in the fact that different indicators have varying measurement units, value ranges, and directions of influence, which complicates their direct comparison and integration into a single analytical framework [19–22]. Starting from these challenges, this paper develops a composite index to assess the environmental impact of electric vehicles at the level of a road segment in urban conditions. The proposed model integrates operational traffic flow indicators, load characteristics of electric vehicles, non-exhaust sources of pollution, and meteorological dispersion conditions into a single quantitative measure of environmental burden, representing an important input for traffic system planning processes.

Urban transportation planning increasingly relies on data-driven and multi-criteria assessment tools capable of identifying critical locations within the road network. While traditional approaches focus primarily on traffic performance indicators such as capacity, delay, or safety, contemporary planning frameworks require the integration of environmental considerations into road network assessment. In this context, environmental burden may be considered an additional dimension of urban road segment performance, supporting sustainable mobility planning and prioritization of infrastructure interventions.

The transition toward electric mobility creates a new challenge for urban planners. Although exhaust emissions are significantly reduced, non-exhaust emissions remain spatially concentrated along specific road segments. Therefore, identifying environmentally sensitive locations within urban networks becomes an important planning task comparable to traditional road safety assessment procedures. Such an approach enables transportation planners to better prioritize infrastructure investments, traffic management measures, and environmental mitigation strategies within increasingly electrified urban transport systems.

The aim of this study is to develop a methodological framework that supports urban transportation planning by assessing road-segment-level operational environmental burdens associated with electric traffic, identifying relevant indicators, determining their

weights using the Delphi and AHP methods, and constructing a composite index for ranking and classifying road segments under a full traffic-electrification scenario. In a modern approach to transportation planning that emphasizes the sustainability of urban transport systems, such a composite index could play an important role in developing sustainable solutions and measures.

The novelty of the proposed framework does not arise from the independent use of the Delphi method, AHP, or composite index construction, all of which are established methodological approaches. Rather, it lies in their integration into a planning-oriented framework specifically developed for assessing environmental burden at the urban road-segment level under traffic electrification conditions. The framework simultaneously incorporates traffic operations, electric vehicle characteristics, non-exhaust emission processes, and meteorological dispersion conditions within a single hierarchical structure. It further enables the spatial ranking of road segments and the comparison of environmentally critical locations between conventional and electrified traffic scenarios, thereby translating environmental assessment results into information directly applicable to transportation planning and intervention prioritization.

2. Literature Review

Air pollution originating from road traffic has been one of the central issues of urban environmental research for decades, with primary attention traditionally focused on exhaust emissions, particularly nitrogen dioxide (NO₂), suspended particles PM₁₀ and PM_{2.5}, and carbon monoxide [23–25]. However, contemporary literature increasingly emphasizes that the analysis of traffic-related pollution can no longer be limited to exhaust emissions alone, but must also encompass broader processes of pollutant generation and dispersion in urban environments. It is particularly highlighted that, in urban conditions, the spatial distribution of pollution is highly heterogeneous and depends not only on traffic intensity but also on traffic flow composition, street morphology, and local meteorological conditions [26,27]. With the growing prevalence of electric vehicles, research focus is gradually shifting from reducing exhaust emissions to evaluating their overall environmental impact. Although electric vehicles eliminate local exhaust emissions, several recent studies indicate that their environmental advantage is not absolute, as non-exhaust sources of pollution persist and, under certain conditions, may become dominant [28–30].

In particular, it is noted that electric vehicles are often heavier than conventional vehicles due to battery systems, which can increase tire and pavement wear, and consequently, particle emissions [31–33]. This paradigm shift is clearly reflected in recent reviews and modeling approaches, where EVs are considered as vehicles with reduced exhaust emissions but still significant non-exhaust impacts [33,34]. In this context, research focusing on tire wear, brake system wear, and the resuspension of particles from road surfaces has gained particular importance in the recent literature [35,36]. Zhang et al. [37] provide a comprehensive review of the mechanisms underlying the formation of tire wear particles, their measurement methods, and the key factors influencing emissions, identifying vehicle weight, speed, driving behavior, and surface characteristics as the primary determinants. Similarly, Costagliola et al. [33] indicate that, due to the decarbonization of traffic, the relative importance of non-exhaust particles in total transport-related pollution will continue to increase, while He et al. [38] emphasize that non-exhaust particles should not be viewed solely as a vehicle-related issue, but also as a consequence of the accumulation and resuspension of particles from roadways and urban surfaces.

In addition to the characteristics of the vehicles themselves, numerous studies confirm that traffic flow operating conditions have a decisive influence on pollution levels [39–41]. Parameters such as traffic volume, average speed, stop-and-go driving patterns, and the

degree of congestion not only affect exhaust emissions but also the intensity of non-exhaust processes, particularly under conditions of frequent acceleration and braking [39,40]. In this context, it is especially important that recent reports and studies indicate that non-exhaust emissions are more pronounced in urban areas characterized by frequent stops, accelerations, and directional changes, directly linking them to the traffic flow indicators considered in this paper [40,41]. A substantial body of research highlights that meteorological conditions play a key role in shaping pollutant concentrations in urban areas [42–44]. Wind speed, precipitation, relative humidity, and temperature do not directly affect emission generation but significantly influence their dispersion, retention, and transformation within the atmospheric layer above the roadway [43,44]. More recent studies emphasize that traffic-related pollution cannot be adequately explained without incorporating local meteorology and urban morphology, particularly in streets exhibiting a pronounced “street canyon” effect and reduced ventilation [45,46]. In the regional and local context, particularly relevant research has been conducted in Serbia. Basarić et al. [47] demonstrated that, on the busiest streets of Novi Sad, the highest concentrations of NO₂ and PM₁₀ are associated not only with total traffic volume but also with the share of freight vehicles and characteristics of the urban environment. On the other hand, a recent study conducted in Belgrade [48] indicates that pollution is not evenly distributed even across spatially proximate locations, but is strongly influenced by the presence of green areas, street orientation, wind exposure, and traffic intensity. These findings are particularly important as they confirm that assessing environmental burden at the road-section level must be based on a combination of traffic, spatial, and meteorological indicators.

Beyond pollution assessment itself, recent studies increasingly emphasize the importance of integrating environmental indicators into urban transportation planning and road network management. Contemporary planning frameworks are moving toward multi-dimensional evaluation of urban road segments, where environmental burden is considered alongside traditional performance measures such as traffic efficiency, accessibility, and safety. In this context, spatial identification of environmentally critical locations has become an important component of sustainable mobility planning, supporting the prioritization of infrastructure investments, traffic management measures, and environmental mitigation strategies. However, despite growing interest in integrated urban assessment frameworks, relatively few studies have proposed practical tools capable of evaluating environmental burden at the urban road-segment level under future traffic electrification scenarios.

From a methodological perspective, composite, hybrid, and multi-criteria models have increasingly been applied in transportation and road-infrastructure decision support to integrate heterogeneous indicators, quantify complex impacts, and support prioritization [49–52]. In the more specific field of sustainable transport assessment, composite indices are particularly useful because they enable environmental, technical, social, and operational indicators to be combined within a unified evaluation framework [53–55]. Ayadi et al. [53] point out that composite indexes are particularly suitable for evaluating and planning complex transport systems, as they enable the integration of a large number of heterogeneous indicators into a single performance measure. At the same time, studies in the field of indicator framework development confirm that combining expert-based methods for indicator selection with multi-criteria approaches for weight determination represents one of the most methodologically sound approaches, especially under conditions of limited availability of direct data [54,55].

Previous indicator-based approaches can be classified into several related but methodologically distinct streams. General transport sustainability indices typically combine environmental, economic, and social indicators at the city, regional, or national level. Other studies assess environmental effects at the road-segment level but primarily focus on

conventional traffic pollutants, noise, carbon emissions, or safety. Research concerning electric vehicles commonly evaluates direct and indirect emissions, energy-source effects, or life-cycle impacts, whereas studies of non-exhaust emissions identify the principal determinants of tire wear and particle resuspension without integrating them into a road-segment planning index. Table 1 provides a structured comparison of representative approaches and the framework proposed in this study.

Table 1. Comparison of representative indicator-based transport and environmental assessment frameworks.

Study	Assessment Unit	Main Indicators or Dimensions	Methodological Approach	Main Distinction from the Present Study
Zito and Salvo [56]	European cities	Transport performance indicators describing urban mobility policies, transport sustainability, development, and infrastructure	Transport Performance Indicators and a Normalized Transport Sustainability Index	City-level comparison of transport policies; does not specifically address EV characteristics, non-exhaust emissions, or individual road segments.
Haghshenas and Vaziri [57]	Cities worldwide	Nine indicators covering environmental, economic, and social dimensions of urban transport	Composite urban sustainable transport index based on standardized indicators	Designed for comparison among cities rather than the assessment and prioritization of individual road segments.
Reisi et al. [58]	Statistical local areas in Melbourne	Nine environmental, social, and economic transport sustainability indicators	PCA/FA-based weighting, dimension-specific sub-indices, and a composite transport sustainability index	Provides sub-city assessment but does not focus on EV-related load, non-exhaust emissions, or meteorological dispersion conditions.
Auttha and Klungboonkrong [59]	Urban road segments	CO ₂ emissions, PM _{2.5} and CO concentrations, traffic noise, and pedestrian accident risk	Environmental-effect prediction models combined with FAHP, fuzzy scoring, and TOPSIS	Assesses multiple effects at the road-segment level but focuses predominantly on conventional traffic impacts and does not integrate EV load, tire wear, particle resuspension, and meteorological dispersion within one index.
Basarić et al. [47]	Selected urban streets	Traffic volume, traffic composition, fleet characteristics, surrounding urban conditions, meteorological factors, NO ₂ , and PM ₁₀	Traffic and air-pollution modelling based on empirical road-segment data	Provides segment-level evidence on conventional traffic pollution but does not develop a composite index or examine an EV scenario.
Manojlović et al. [14]	Vehicle and national energy-system level	Direct and indirect CO ₂ and NO _x emissions, vehicle energy demand, and electricity-generation mix	Comparative emissions assessment of conventional and electric vehicles	Evaluates propulsion- and electricity-related environmental impacts but does not address non-exhaust emissions or road-segment ranking.
Timmers and Achten [60]	Vehicle-category and non-exhaust emission level	Vehicle mass, tire wear, brake wear, road wear, PM ₁₀ , and PM _{2.5} emissions	Review and comparison of non-exhaust PM emission factors for conventional and electric vehicles	Demonstrates the importance of vehicle mass and non-exhaust emissions but does not develop a spatial or planning-oriented composite index.
Zhang et al. [37]	Tire-wear process level	Vehicle mass, speed, driving behaviour, tire characteristics, road-surface characteristics, particle formation, and measurement methods	Comprehensive review of tire-wear particle formation and influencing factors	Supports the selection of tire-wear indicators but does not integrate them with traffic operations, EV load, and meteorological conditions at the road-segment level.
Present study	Urban road segment	Traffic operations, EV load, non-exhaust pollution, and meteorological dispersion conditions	Delphi indicator selection, AHP weighting, directional normalization, group-specific sub-indices, composite index, and sensitivity and uncertainty analyses	Integrates EV-specific and non-exhaust factors into a road-segment screening, ranking, and intervention-prioritization framework.

The structured comparison reveals that several indicators included in the proposed framework have previously been used in transport and environmental assessment. Traffic volume, vehicle composition, speed, conventional pollutant concentrations, energy consumption, vehicle mass, tire wear, pavement characteristics, and meteorological conditions

are all supported by earlier studies. However, these indicators have generally been examined within separate analytical streams. Broad transport sustainability indices operate mainly at the city or regional level and emphasize environmental, social, and economic performance. Existing road-segment frameworks predominantly assess conventional pollutants, noise, carbon emissions, or safety, while EV studies usually focus on energy-source or life-cycle effects. Non-exhaust emission studies identify tire wear and particle resuspension mechanisms but rarely translate them into a road-segment decision-support index. Accordingly, the contribution of the present study lies not in introducing each indicator individually, but in integrating four complementary groups, traffic operations, EV load, non-exhaust pollution, and meteorological dispersion, within a single road-segment-level framework. The model further combines expert-based indicator selection, AHP weighting, sub-index analysis, uncertainty testing, and planning-oriented prioritization. Few of the identified studies simultaneously provide this electrification-specific indicator structure, road-segment resolution, robustness assessment, and direct linkage to pavement maintenance, traffic management, and environmental monitoring decisions.

3. Methodology

The methodology adopted in this study consists of several sequential phases aimed at developing a composite index for assessing road-segment-level operational environmental burdens associated with electric traffic. The procedure includes the formation of an expert panel, identification and selection of relevant indicators using the Delphi method, determination of indicator weights through the Analytic Hierarchy Process (AHP), development of the composite index, and its illustrative application through an exploratory case study. The conceptual and analytical framework adopted in this research is presented in Figure 1.

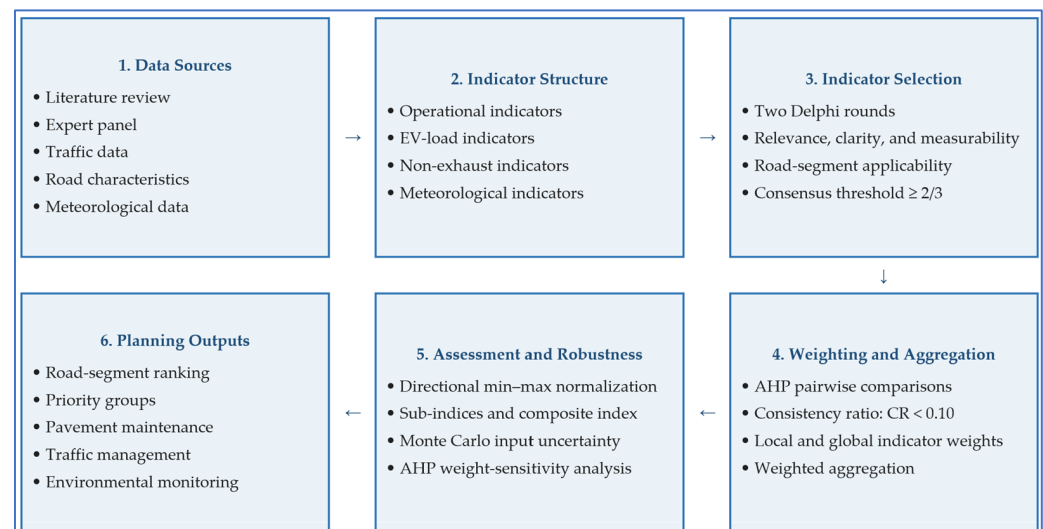


Figure 1. Numbers indicate the six sequential stages of the framework, while arrows indicate the direction of the analytical workflow.

Assessing the environmental impacts of electric vehicles at the urban road-segment level requires the integration of numerous technical, operational, environmental, and meteorological factors. To address this complexity, a combined Delphi–AHP–Composite Index approach was adopted. The Delphi method was applied to identify and refine relevant indicators through expert consensus, while the Analytic Hierarchy Process was used to determine their relative importance. Subsequently, a composite index was developed to integrate the selected indicators into a single assessment measure suitable for ranking and classifying urban road segments. The combination of these methods was considered

particularly suitable for the objectives of this study because it enables systematic indicator selection, transparent weighting procedures, and practical application within urban transportation planning.

3.1. Formation of an Expert Panel

In order to define relevant indicators for assessing the environmental burden of urban road segments and supporting transportation planning under traffic electrification, an expert evaluation procedure was conducted using the Delphi method. A multidisciplinary panel of experts was formed to ensure a comprehensive approach to addressing the problem, taking into account various aspects of traffic, energy, and environmental protection. The expert panel consisted of specialists in traffic engineering, electrical engineering, urban planning, environmental protection, meteorology, and mechanical engineering. Three experts from each field were included, with the requirement that they hold a PhD and have at least one published scientific paper related to the research topic. This ensured a high level of expertise, multidisciplinary, and reliability in the decision-making process. This panel structure allowed for the integration of different perspectives and the reduction in subjectivity in defining indicators and their significance. The research was conducted from 18 January 2026, to 29 March 2026. Participation of experts in the research was voluntary. Before completing each questionnaire, experts were required to confirm that they were familiar with the goals, rules, and procedures of the research, that their participation was voluntary, that they did not require any compensation for their participation, and that they would participate in the evaluation process professionally, conscientiously, and responsibly. This ensured the ethical and procedural integrity of the conducted research. The panel consisted of 18 experts, which is consistent with recommendations from the Delphi literature suggesting that panels composed of 10–30 experts are generally sufficient to achieve reliable consensus in specialized research domains [61,62]. The selected panel size was considered adequate to ensure both disciplinary diversity and effective management of the iterative evaluation process.

3.2. Application of the Delphi Method

The Delphi method was implemented through several iterative phases, with the aim of reaching a consensus among experts regarding the selection and structure of indicators. The method was conducted through anonymous expert responses, allowing for the revision of opinions in subsequent rounds, thereby ensuring objectivity and reducing the influence of dominant opinions. In the first phase, experts identified and defined the key aspects of the impact of electric vehicles on the urban environment. Special emphasis was placed on the fact that electric vehicles do not generate exhaust emissions, but their impact still exists through non-exhaust processes, operational traffic characteristics, and the conditions for the dispersion of pollutants. Based on the conducted discussion and analysis, four main groups of indicators were defined:

- Operational indicators of traffic flow
- Indicators of electric vehicle load
- Non-exhaust pollution indicators
- Meteorological indicators of dispersion

This division allows for a systematic examination of both the factors that generate environmental burden and the factors that influence the formation and retention of pollutants in urban conditions. Furthermore, the proposed structure enables the evaluation and prioritization of urban road segments according to their environmental burden, providing a basis for transportation planning and infrastructure management decisions.

The Delphi procedure was conducted in two iterative rounds. During the first round, experts proposed and evaluated potential indicators according to their relevance to the research objective, applicability at the urban road-segment level, clarity of definition, practical measurability, and potential overlap with other indicators. Based on the experts' responses and comments, indicators with similar meanings were merged, ambiguous indicators were reformulated, and indicators considered insufficiently relevant or unsuitable for assessment at the road-segment level were excluded. During the second round, the revised set of indicators was returned to the expert panel for final evaluation. Consensus was defined as agreement by at least two-thirds of the panel, corresponding to a minimum of 12 of the 18 experts. Indicators meeting this threshold were retained. Indicators that did not meet the threshold were reconsidered and either reformulated, when their underlying concept was still considered relevant, or excluded because of insufficient relevance, redundancy, limited measurability, or incompatibility with the defined unit of analysis. All 16 indicators included in the final framework reached the specified consensus threshold in the second Delphi round.

The first-round questionnaire invited the experts to propose and evaluate candidate indicators and to comment on their relevance, clarity, measurability, applicability at the urban road-segment level, and allocation to the proposed indicator groups. Based on the first-round responses, 24 initially proposed indicators were reviewed. Four pairs of overlapping indicators were merged, five indicators were reformulated to improve their clarity and measurability, and four indicators were excluded because of insufficient relevance, redundancy, or limited applicability at the urban road-segment level. The resulting set of 16 indicators was then presented to the same experts in the second-round questionnaire, in which they evaluated the inclusion, formulation, and allocation of each indicator to the proposed groups. Consensus was defined as agreement by at least two-thirds of the expert panel, corresponding to a minimum of 12 of the 18 experts. All 16 indicators retained in the final framework exceeded this threshold. Final agreement ranged from 72.2% to 94.4%, corresponding to agreement by 13 to 17 experts, with a mean agreement of 83.3%. No additional indicators required reconsideration after the second round.

3.3. Definition and Selection of Indicators

In this research, the subject of evaluation is a road segment in an urban street network. To ensure the comparability of results, the analysis is based on a predefined road segment, that is, on a standardized observation unit. For this reason, the length of the section is not included as a separate indicator, but as a methodologically defined characteristic of the analyzed spatial unit. This allows the selected indicators to describe the actual intensity and nature of the environmental burden on the observed section, without the influence of variability in its length. In the second phase of the Delphi procedure, within each of the defined levels, experts proposed a set of potential indicators, after which a selection and alignment process was conducted. Based on the conducted Delphi procedure and the achieved consensus among experts, a final set of 16 indicators was defined, organized into four main groups. The selection of indicators was made to encompass operational traffic characteristics, specifics of electric vehicles, non-exhaust sources of pollution, and meteorological conditions for dispersion. The indicators are presented in Table 2.

The final set of 16 indicators was selected to provide a balanced representation of the principal mechanisms that determine environmental burden at the urban road-segment level. The indicators cover four complementary dimensions: traffic operating conditions, electric vehicle characteristics, the generation of non-exhaust particles, and meteorological conditions affecting their dispersion. Their selection was based on the literature review

and the two-round Delphi procedure, during which overlapping or insufficiently relevant indicators were merged, reformulated, or excluded. Tire wear and particle resuspension were retained because they are consistently identified in the literature as two of the most important sources of non-exhaust particulate emissions, particularly under increasing traffic electrification. In the proposed framework, TWI and RPI are intentionally defined as simplified relative indicators rather than detailed physical emission models. Their purpose is to capture differences in tire-wear and resuspension potential among road segments using variables that are generally available to transportation planners, while more detailed measurements or calibrated emission models may be incorporated when such data are available. The road segment was selected as the basic unit of analysis because it represents a common planning and management unit in urban transportation systems. Assessing environmental burden at the road-segment level allows transportation planners to identify critical locations within the urban network and prioritize interventions aimed at improving environmental sustainability.

Table 2. Defined indicators, measurement methods, calculation formulas, and impacts.

GROUP 1—Traffic Operational Indicators				
Group	Indicator	How to measure	Formula	Impact
G1I1	Traffic flow (q)	Vehicle counting (counters, video, radar) [vehicle/h]	$q = N/t$	Higher traffic flow increases non-exhaust environmental burden.
G1I2	Average speed (v)	GPS, video analysis, travel time	$v = L/t$	Low and variable speeds increase emissions
G1I3	Stop-and-go index (SGI)	Proportion of acceleration/braking time	$SGI = t_{sg}/t$	Higher SGI, higher wear and emissions
G1I4	Congestion level (X)	Flow and capacity ratio	$X = q/C$	More congestion, more braking and particles
GROUP 2—EV System Load Indicators				
Group	Indicator	How to measure	Formula	Impact
G2I1	Average vehicle mass ($\bar{m}$)	Technical data of vehicles, databases	$\bar{m} = \Sigma m/n$	Greater mass, greater tire wear
G2I2	Percentage of heavy EVs (%)	Vehicle classification	$\% = (N_{heavy}/N) \cdot 100$	The higher the proportion, the higher the particulate emissions
G2I3	Longitudinal Road Gradient (i)	Geodetic data	$i = \Delta h/L \times 100$	Higher slope, higher load and wear
G2I4	Specific Energy Consumption (e)	Vehicle data or simulation	$e = E/L$	Higher consumption, higher indirect load
GROUP 3—Indicators of Non-Exhaust Pollution				
Group	Indicator	How to measure	Formula	Impact
G3I1	Tire wear index (TWI)	Relative screening score based on available tire-wear data, vehicle and tire characteristics, pavement condition, and operating conditions	Ordinal score (1–5) or measured/calibrated tire-wear value.	Higher values indicate greater tire-wear particle generation potential.
G3I2	Resuspension of particles (RPI)	Relative screening score based on road-dust loading, pavement condition, traffic-induced turbulence, and local operating conditions.	Ordinal score (1–5) or measured/calibrated resuspension value.	Higher values indicate greater road-dust resuspension potential.
G3I3	Acceleration/braking intensity (ACI)	Relative screening score based on the magnitude and frequency of acceleration and braking events obtained from GPS, sensors, video analysis, or simulation.	Ordinal score (1–5)	Higher values indicate more intensive acceleration and braking and greater non-exhaust emission potential.
G3I4	PCI-based pavement condition score	Visual assessment or conversion of available PCI data into a five-point condition score.	Ordinal score (1–5)	Lower values indicate poorer pavement condition and greater tire and pavement wear potential.

Table 2. Cont.

GROUP 4—Meteorological Indicators of Dispersion				
Group	Indicator	How to measure	Formula	Impact
G4I1	Wind speed (WS)	Weather station	—	Higher wind, lower concentration
G4I2	Relative humidity (RH)	Weather station	—	Higher humidity, more secondary particles
G4I3	Precipitation (P)	Weather station	—	Precipitation reduces pollution
G4I4	Temperature (T)	Weather station	—	Temperature influences particle transformation and dispersion conditions.

The units and measurement scales of the indicators are as follows: traffic flow, q , is expressed in vehicles per hour; average speed, v , in kilometres per hour; SGI and congestion level, X , are dimensionless; average vehicle mass, $\bar{m}$, is expressed in kilograms; the share of heavy EVs and road gradient are expressed as percentages; specific energy consumption, e , is expressed in kWh/km; wind speed is expressed in m/s; relative humidity in percent; precipitation in millimetres; and temperature in degrees Celsius. In the illustrative case study, TWI, RPI, and ACI were assessed using a five-point ordinal screening scale, where 1 indicates very low, 2 low, 3 moderate, 4 high, and 5 very high generation or intensity potential. Pavement condition was represented using a five-point score, where 1 indicates very poor, 2 poor, 3 fair, 4 good, and 5 very good condition. Pavement condition was therefore treated as an inverse indicator during normalization. The symbols used in the formulas are defined as follows: N is the number of observed vehicles; t is the relevant observation or travel time; L is the road-segment length; t_{sg} is the time spent in stop-and-go conditions; C is road-segment capacity; m is the mass of an individual vehicle; n is the number of vehicles included in the calculation; N_{heavy} is the number of heavy electric vehicles; Δh is the elevation difference along the segment; E is the energy consumed over the analyzed distance; Δv is the change in speed; and Δt is the time interval during which the speed change occurs.

Potential overlap among conceptually related indicators was explicitly considered during indicator selection. Traffic flow, average speed, and vehicle mass describe directly observable traffic and vehicle characteristics, whereas TWI and RPI represent process-level outcomes related to tire-wear generation and road-dust resuspension. Therefore, TWI and RPI were not calculated as deterministic products of the input variables in the composite-index calculation. The proportional relationships shown in the initial framework were intended only to indicate the expected direction of influence and have now been replaced by independent relative screening scores or measured/calibrated values. Similarly, SGI, congestion level, and ACI describe related but distinct aspects of traffic operation. SGI represents the proportion of time spent under unstable stop-and-go conditions, congestion level represents the relationship between traffic demand and road capacity, and ACI represents the intensity of individual acceleration and braking events. These indicators may be correlated in congested environments, but they are not conceptually interchangeable and may differ substantially under other traffic conditions.

3.4. Evaluation of Indicators and Determination of Weights Using the AHP Method

In the final phase of the research, the significance of the defined groups and indicators was evaluated with the aim of determining their relative contribution to the overall environmental impact of electric vehicles at the urban road-segment level. For the purposes of determining weights, the Analytic Hierarchy Process (AHP) was applied, which enables hierarchical evaluation of criteria based on their mutual comparisons. AHP was selected because the proposed model has a clearly defined hierarchical structure consisting of an

overall assessment objective, four indicator groups, and four indicators within each group. The method enables expert judgments concerning heterogeneous environmental, traffic, technical, and meteorological indicators to be expressed on a common ratio scale, while its consistency ratio provides a transparent check of the logical coherence of the pairwise comparisons. AHP was also considered suitable because the model-development phase relied on multidisciplinary expert knowledge, whereas sufficiently large and complete empirical datasets were not available for deriving stable objective weights. Data-driven weighting methods, such as entropy weighting or principal component analysis, were not adopted because the available five-segment dataset represents an illustrative application rather than a representative calibration sample. Weights derived from such a limited dataset would be highly sample-dependent and could reflect the variability of the selected segments rather than the general importance of the indicators. Equal weighting was also considered less appropriate because it would assume that all indicators contribute equally, contrary to the expert-based structure established through the Delphi procedure. Other multi-criteria techniques may be useful for ranking alternatives, but AHP was selected specifically for deriving transparent hierarchical weights and examining the consistency of expert judgments. The hierarchical structure of the model consists of three levels:

- goal (assessment of environmental burden of urban road segments under traffic electrification);
- four groups of indicators;
- indicators within each group.

Within the AHP method, experts performed pairwise comparisons of elements using Saaty's intensity of importance scale, where the values have the following meaning [63,64]:

- 1—equal importance
- 3—moderate advantage of one element over another
- 5—strong advantage
- 7—very strong advantage
- 9—extreme advantage
- 2, 4, 6, 8—intermediate values

For each group of indicators, a 4×4 pairwise comparison matrix was formed, while an additional matrix was used to compare the indicator groups themselves. The elements of the matrix are defined as the ratio of importance between the two observed elements, where the following applies:

$$a_{ij} = \frac{1}{a_{ji}}, a_{ii} = 1$$

Based on the pairwise comparison matrices, the local weight vectors were determined using column normalization. Each matrix element was first divided by the sum of its corresponding column, after which the local weight of each element was calculated as the arithmetic mean of the normalized values in the corresponding row:

$$\bar{a}_{ij} = \frac{a_{ji}}{\sum_{k=1}^n a_{kj}}$$

$$w_i = \frac{1}{n} \sum_{j=1}^n \bar{a}_{ij}$$

where

- $\bar{a}_{ij}$ —normalized value of the element in row i and column j ;
- a_{ij} —element of the pairwise comparison matrix;
- w_i —local weight of the i th element;

- n —number of elements in the pairwise comparison matrix.

In order to check the consistency of expert assessments, the consistency index (CI) and consistency ratio (CR) were calculated:

$$CI = \frac{\lambda_{max} - n}{n - 1}$$

$$CR = \frac{CI}{RI}$$

where

- λ_{max} —the maximum eigenvalue of the matrix
- RI—random index

The consistency of assessments is considered acceptable if:

$$CR < 0.10$$

The final weights of the indicators determined are a product of the weight of the associated group and the local weight of the indicator within that group:

$$W_j = W_g \cdot w_{j|g}$$

where

- W_j —global weight of the indicator
- W_g —weight of the group to which the indicator belongs
- $w_{j|g}$ —local weight of the indicator within the group

The resulting global weights were used to form a composite index, which is defined as:

$$I = \sum_{j=1}^m W_j \cdot z_j$$

where

- I —composite impact index
- z_j —normalized indicator value

Each expert completed five pairwise-comparison matrices: one matrix comparing the four indicator groups and four matrices comparing the indicators within their respective groups. The consistency ratio was first calculated separately for each matrix completed by each expert. Matrices with $CR \geq 0.10$ were returned to the corresponding expert for reconsideration before the aggregation stage. After the individual judgments satisfied the adopted consistency requirement, the corresponding pairwise-comparison values were combined using the element-wise geometric mean. This aggregation procedure preserves the reciprocal structure of the matrices and produces one group matrix and four indicator-level matrices representing the collective expert judgment. The final priority vectors were calculated from these five aggregated matrices. Consistency ratios were then calculated again for each aggregated matrix to verify the coherence of the collective judgments. All five aggregated matrices satisfied the adopted criterion of $CR < 0.10$. Therefore, consistency was assessed at both levels: for the individual expert matrices before aggregation and for the aggregated group matrices used to derive the final weights.

3.5. Application of the Composite Index in Transportation Planning

The proposed composite index is intended to serve as a screening and prioritization tool for urban transportation planning. After the indicator values are collected and

normalized, each road segment receives an overall environmental burden score, a corresponding impact category, and four group-specific sub-index values. The overall index enables planners to rank road segments and identify locations requiring priority attention, while the sub-indices indicate the principal factors contributing to the identified burden. For pavement maintenance planning, road segments characterized by high non-exhaust sub-index values, particularly those associated with tire wear, particle resuspension, and poor pavement condition, may be prioritized for detailed pavement inspection, surface rehabilitation, road cleaning, or the application of pavement materials with improved durability and lower particle-generation potential. The index does not replace technical pavement-condition assessment but helps determine where more detailed inspections and maintenance resources should be directed first.

For traffic management, segments with high operational and EV-load sub-index values may be considered for measures such as signal-timing optimization, reduction in stop-and-go traffic, speed harmonization, management of heavy-vehicle movements, or changes in traffic routing. Alternative traffic-management scenarios may also be assessed by recalculating the index after modifying the relevant input indicators. For environmental monitoring, high-ranking segments may be selected as priority locations for the installation of air-quality sensors, road-dust sampling, or more frequent measurements of particulate matter. Meteorological sub-index values may additionally support the identification of periods in which unfavorable dispersion conditions require intensified monitoring. Repeated calculation of the index can also be used to compare conditions before and after an intervention and to monitor changes over time. Accordingly, the proposed index should be interpreted as a decision-support and screening instrument rather than as a substitute for direct emission measurements, detailed engineering assessment, or regulatory environmental standards. Its principal planning function is to identify where additional investigation or intervention is most urgently required and which category of measures should be considered.

For the illustrative case study, agreement between the road-segment ranking based on measured NO₂ concentrations under conventional traffic conditions and the ranking obtained using the EV composite index was assessed using Spearman's and Kendall's rank correlation coefficients. Because the analysis included only five road segments, exact significance values were used, and the results were interpreted as exploratory evidence of rank agreement rather than as a basis for broader statistical inference. Model robustness was additionally examined through Monte Carlo input-uncertainty analysis and sensitivity analysis of the AHP-derived weights.

Potential indicator redundancy was additionally examined using pairwise Spearman rank correlations among the conceptually related indicators and exclusion-based sensitivity tests. In the exclusion tests, selected indicators or related indicator groups were removed, the remaining global weights were renormalized to sum to one, and the composite index and road-segment rankings were recalculated.

4. Results

4.1. Weights of Indicator Groups

The results presented in Table 3 indicate the relative importance of different groups of indicators within the proposed model for assessing the environmental impact of electric vehicles. The highest weight is assigned to the group of non-exhaust pollution indicators (0.34), confirming that under electrified traffic conditions, the dominant environmental impact arises from processes such as tire wear and particle resuspension. The groups of electric vehicle load indicators and meteorological dispersion indicators have equal significance (0.24 each), highlighting the importance of both vehicle technical characteristics

and energy demands, as well as the conditions governing the dispersion of pollutants in urban environments. On the other hand, operational traffic indicators have the lowest weight (0.18), suggesting that although they are important for describing traffic flow, their direct impact on pollution becomes relatively less significant under full electrification compared to non-exhaust and meteorological factors. Overall, the results validate the hierarchical structure of the proposed model and point to a paradigm shift in traffic pollution analysis, where the focus moves from exhaust emissions toward non-exhaust processes and the conditions influencing their dispersion. From a transportation planning perspective, these findings indicate that future urban road network assessments should consider non-exhaust pollution indicators as an important criterion when identifying environmentally critical road segments and prioritizing mitigation measures.

Table 3. Relative Weights of Indicator Groups.

Indicator Group	Weight
Operational Indicators	0.18
EV Load Indicators	0.24
Non-Exhaust Pollution	0.34
Meteorological Indicators	0.24

The results presented in Table 4 show the local weights of indicators within each group, determined using the Analytic Hierarchy Process (AHP) method. Within the group of operational indicators, the stop-and-go index has the highest importance (0.32), highlighting the significance of dynamic traffic conditions in the generation of non-exhaust emissions. In the group of electric vehicle load indicators, the highest weights are assigned to specific energy consumption (0.30) and average vehicle mass (0.29), emphasizing the importance of both energy-related and physical vehicle characteristics in shaping the overall environmental impact. The most pronounced results are observed within the non-exhaust pollution group, where the tire wear index (0.30) and the particle resuspension index (0.29) dominate, further confirming the key role of these processes under electrified traffic conditions. Within the meteorological dispersion indicators, precipitation has the highest importance (0.30), followed by wind speed and temperature (0.26 each), indicating the crucial role of atmospheric conditions in determining pollutant concentrations in urban environments.

Table 4. Local Weights of Indicators within the Defined Groups.

Indicator Group	Indicators	Local Weight
Operational Indicators	Traffic Flow (q)	0.26
	Average Speed (v)	0.18
	Stop-and-Go Index (SGI)	0.32
	Level of Congestion (X)	0.24
EV Load Indicators	Average Mass ($\bar{m}$)	0.29
	Share of Heavy EVs	0.24
	Road Gradient (i)	0.17
	Specific Energy Consumption (e)	0.30
Non-Exhaust Pollution	TWI	0.30
	RPI	0.29
	ACI	0.22
	PCI	0.19
Meteorological Indicators	Wind Speed (WS)	0.26
	Relative Humidity (RH)	0.18
	Precipitation (P)	0.30
	Temperature (T)	0.26

Table 5 presents the global weights of the indicators obtained using the Analytic Hierarchy Process (AHP), along with their corresponding rankings. The highest importance is assigned to non-exhaust pollution indicators, particularly the Tire Wear Index (TWI) and the Resuspension of Particles Index (RPI), confirming their dominant role under electrified traffic conditions. Indicators describing vehicle energy load and meteorological conditions are also highly ranked, while operational traffic indicators occupy lower positions. The obtained results indicate a shift in priorities in pollution analysis, where non-exhaust processes emerge as the key factor in environmental impact assessment.

Table 5. Global Weights and Ranking of Indicators for Assessing the Impact of Electric Vehicles.

Rank	Group	Indicator	Global Weight
1	Non-Exhaust	TWI	0.1020
2	Non-Exhaust	RPI	0.0986
3	Non-Exhaust	ACI	0.0748
4	EV	Specific Energy Consumption (e)	0.0720
5	Meteorology	Precipitation (P)	0.0720
6	EV	Average mass ($\bar{m}$)	0.0696
7	Non-Exhaust	PCI	0.0646
8	Meteorology	Wind Speed (WS)	0.0624
9	Meteorology	Temperature (T)	0.0624
10	Operational	SGI	0.0576
11	EV	Share of Heavy EVs	0.0576
12	Operational	Traffic Flow (q)	0.0468
13	Meteorology	RH	0.0432
14	Operational	Congestion Level (X)	0.0432
15	EV	Road Gradient (i)	0.0408
16	Operational	Average Speed (v)	0.0324

The ranking of indicators provides useful information for transportation planners and urban authorities. Indicators with the highest global weights may be considered priority variables when evaluating environmental burden across urban road networks. In particular, the dominance of tire wear and particle resuspension indicators suggests that future planning strategies should not focus solely on vehicle electrification but also on pavement quality, traffic operations, and management of heavy vehicle movements.

4.2. Composite Index Construction and Indicator Normalization

For the purpose of quantitatively assessing the impact of electric vehicles on environmental quality along the observed urban road segment, a composite index was developed based on a hierarchical structure of indicators and weights obtained using the Analytic Hierarchy Process (AHP). The model integrates operational traffic characteristics, electric vehicle load, non-exhaust pollution sources, and meteorological dispersion conditions into a unified measure of environmental impact. Given the defined model structure, a corresponding sub-index was constructed for each group of indicators, representing a weighted sum of normalized indicator values within that group:

$$I_g = \sum_{i=1}^4 w_{gi} \cdot z_{gi}, g = 1, 2, 3, 4,$$

where

- w_{gi} —local weight of the i th indicator within the g th group;
- z_{gi} —normalized value of the i th indicator.

Based on the defined sub-index, the final composite index of electric vehicle impact is determined as:

$$I_{EV} = W_1 I_1 + W_2 I_2 + W_3 I_3 + W_4 I_4$$

where

- W_1, W_2, W_3, W_4 —weights of the indicator groups;
- I_{EV} —composite index of electric vehicle impact for the observed road segment.

This approach enables the assessment of both individual aspects of impact and the overall environmental burden caused by electric vehicles at the road segment level.

4.3. Indicator Normalization

Given that the indicators have different units of measurement and value ranges, they were normalized prior to inclusion in the model, transforming all variables into a dimensionless scale within the interval [0, 1]. This procedure ensures their mutual comparability and proper integration within the composite index framework. For indicators where higher values correspond to a greater negative environmental impact, the following normalization was applied:

$$z_{gi} = \frac{x_{gi} - x_{gi}^{min}}{x_{gi}^{max} - x_{gi}^{min}}$$

This formula was applied to the following indicators: traffic flow (q), stop-and-go index (SGI), congestion level (X), average vehicle mass ($\bar{m}$), share of heavy EVs, road gradient (i), specific energy consumption(e), tire wear index (TWI), particle resuspension index (RPI), acceleration/braking intensity (ACI), relative humidity (RH), and air temperature (T). For indicators where higher values correspond to a lower negative environmental impact, inverse normalization was used:

$$z_{gi} = \frac{x_{gi}^{max} - x_{gi}}{x_{gi}^{max} - x_{gi}^{min}}$$

This approach was applied to: average traffic speed (v), pavement quality index (PCI), wind speed (WS), and precipitation (P). In this way, all indicators are aligned in the same direction, such that higher values of normalized indicators consistently correspond to a more unfavorable environmental impact.

Linear min–max normalization was selected because the primary purpose of the proposed index is the comparative screening, ranking, and prioritization of road segments rather than the direct prediction of pollutant concentrations or emission quantities. The procedure preserves the ordering and relative position of the observed indicator values, transforms indicators expressed in different measurement units to a common [0, 1] scale, and enables their transparent integration using the AHP-derived weights. The application of linear normalization does not imply that the underlying physical relationships between all indicators and environmental burden are globally linear. Rather, it represents a first-order monotonic approximation within the ranges observed in the case study. Indicator-specific nonlinear functions were not applied because generally accepted thresholds or empirically calibrated response functions were not available for all 16 indicators. Introducing different nonlinear transformations without such empirical support would add assumptions to the model and reduce its transparency and reproducibility. The direction of each indicator was determined according to whether an increase in its value represents a more or less unfavorable environmental condition. Average speed was treated as an inverse indicator within the observed urban operating range, in which lower speeds are associated with congested and unstable traffic conditions. Road gradient refers to the absolute magnitude

of the longitudinal gradient. For indicators whose environmental effects may be more complex, particularly temperature and relative humidity, the adopted direction should be interpreted as applicable to the limited range and conditions represented in the case study rather than as a universal relationship.

4.4. Index Interpretation

The obtained composite index enables a quantitative assessment of the level of environmental burden across the observed road segments. Unlike predefined uniform intervals, the classification boundaries in this study were determined based on the statistical distribution of the calculated index values. The introduction of a quartile-based classification approach stems from the need to avoid predefined threshold values, which are commonly used in models relying on fixed intervals. Given that the distribution of composite index values depends on the specific characteristics of the analyzed segments, the application of statistical distribution measures allows the classification to be adapted to real data. The quartile-based approach is widely applied in environmental analyses and traffic engineering, particularly in cases where no predefined standards or threshold values exist for the considered indicator. Moreover, this approach is consistent with recommendations from the literature in the field of multi-criteria analysis and is also applied in environmental studies, where the importance of data-driven methods in defining classification thresholds is emphasized [65,66]. In this way, greater objectivity is ensured and the influence of subjective decision-making by researchers is reduced. To objectively define the categories, a quartile-based approach was applied using the distribution of index values. Based on the calculated quartiles (Q_1 , Q_2 , Q_3), the following categories were defined:

- $I_{EV} < Q_1$, low impact
- $Q_1 \leq I_{EV} < Q_2$, moderate impact
- $Q_2 \leq I_{EV} < Q_3$, high impact
- $I_{EV} \geq Q_3$, very high impact

This approach enables an adaptive classification aligned with the data distribution, thereby avoiding arbitrary threshold definitions and enhancing the model's sensitivity to real differences among the observed road segments.

The resulting categories represent relative environmental-burden levels within the analyzed sample and should not be interpreted as absolute environmental risk levels, regulatory classes, or externally validated thresholds. Because the case study includes only five road segments, the quartile boundaries are sample-dependent and may change if segments are added or removed. Accordingly, the classification is used only for illustrative screening and prioritization, while the development of stable and transferable thresholds requires application to a substantially larger and more diverse dataset.

4.5. Illustrative Case Study: Application of the Proposed Model

The case study is intended as an illustrative proof-of-concept application of the proposed framework rather than as a comprehensive empirical validation. The five road segments were not used to develop the structure or weights of the model, which were established independently through the literature review, Delphi procedure, and AHP analysis. Instead, the selected segments were used to demonstrate the calculation, ranking, classification, and interpretation of the composite index under contrasting traffic and environmental conditions. Consequently, the results should be interpreted as evidence of the model's operational applicability within the analyzed example, rather than as proof of its general robustness or transferability to other urban networks.

4.5.1. Analysis of Real Traffic Pollution in Urban Conditions—Conventional Vehicles

The illustrative application uses five cross-sections selected from the fifteen urban street locations analyzed by Basarić et al. [47]. In the original study, locations P1–P3 were situated on the urban transit-road network, where freight-vehicle traffic was permitted, while locations P4–P15 represented major urban transport routes within the central street network of Novi Sad. Segments P2 and P3 were located along Partizanska Street, a major transit corridor characterized by a particularly high proportion of goods vehicles. The five locations were selected purposively to provide contrasting traffic and pollution conditions rather than to constitute a statistically representative sample of the Novi Sad road network. P2 and P3 represent locations with high freight-vehicle shares and the highest modeled NO₂ concentrations; P7 represents the location with the highest traffic volume among the selected segments; and P10 and P12 represent locations with lower freight-vehicle shares and lower pollution levels. This selection enables an illustrative examination of whether the proposed index differentiates road segments with substantially different traffic compositions and environmental conditions. Detailed information on exact coordinates, segment lengths, numbers of lanes, speed limits, and surrounding land use was not consistently reported for all selected cross-sections in the original dataset. Therefore, these attributes were not reconstructed retrospectively, and a map was not produced to avoid presenting uncertain spatial information. The available traffic and environmental characteristics used in the present analysis are summarized in Table 6. Based on the results presented in Table 6, it can be observed that segments P2 and P3 have the highest NO₂ values, primarily due to the high share of heavy-duty vehicles in the traffic flow, which was identified in the study as a key factor contributing to increased pollution. On the other hand, segments such as P10 and P12 are characterized by lower pollutant concentrations despite relatively high traffic volumes, indicating a significant influence of traffic flow composition rather than traffic intensity. It is particularly noteworthy that segment P7, although having the highest traffic volume, does not belong to the group with the highest pollution levels. This finding supports evidence from the literature that the share of heavy vehicles and traffic operating conditions have a greater impact on emissions than traffic volume itself. The differences among the selected segments provide contrasting traffic and pollution conditions suitable for illustrating the application of the proposed composite index and comparing the resulting road-segment rankings under the electric vehicle scenario.

Table 6. Characteristics of Selected Road Segments and Pollution Levels [47].

Road Segment	AADT (veh/Day)	Heavy Vehicles (%)	PM10 (µg/m ³)	NO ₂ (µg/m ³)	Pollution Level	Road-Network Context
P2	29,829	25.0	36.9	64.4	Very high	Urban transit corridor; freight traffic permitted; Partizanska Street
P3	30,470	20.62	36.0	63.1	Very high	Urban transit corridor; freight traffic permitted; Partizanska Street
P7	47,343	6.34	31.0	51.3	Moderately High	Major urban transport route in the central street network
P10	40,216	5.53	28.1	45.1	Moderate	Major urban transport route in the central street network
P12	33,396	6.30	29.6	42.6	Low	Major urban transport route in the central street network

4.5.2. Assessment of Environmental Impact Under the Electrified Traffic Scenario

Table 7 presents the values of indicators for the selected road segments under the electric vehicle (EV) scenario. Certain indicator values that were not directly available in

the original study were estimated based on expert assessments, relevant literature, and the characteristics of the traffic flow. The estimation was performed by taking into account the road type, traffic intensity, share of heavy-duty vehicles, and typical urban conditions, thereby ensuring the consistency of the input data for further analysis. Based on the defined indicators shown in Table 2, the developed composite index model was applied to assess the environmental impact of electric vehicles at the level of the observed road segments.

Table 7. Indicator Values for Selected Road Segments.

Road Segment	q (veh/h)	v (km/h)	SGI	$X = q/C$	$\bar{m}$ (kg)	Heavy EVs (%)	i (%)	e (kWh/km)	TWI	RPI	ACI	PCI	WS (m/s)	RH (%)	P (mm)	T (°C)
P2	1800	28	0.65	0.85	1900	25.0	1.5	0.22	5	5	5	3	2.5	65	1.0	12
P3	1850	30	0.60	0.80	1850	20.62	1.2	0.21	5	5	5	3	2.5	65	1.0	12
P7	2600	40	0.45	0.70	1700	6.34	0.8	0.18	4	4	4	4	3.0	60	0.5	13
P10	2200	42	0.35	0.65	1650	5.53	0.5	0.17	3	3	3	4	3.2	58	0.5	13
P12	2000	45	0.30	0.60	1600	6.30	0.3	0.16	3	3	3	4	3.5	55	0.5	13

Certain input values required for the EV scenario were not directly available from the original empirical study. Traffic flow was derived from the reported AADT values, while the remaining unavailable indicators were estimated using the observed traffic composition, road-segment characteristics, representative values from the literature, and the assessment of the expert panel. The same assumptions and assessment criteria were applied consistently across all five road segments. The estimated values should therefore be interpreted as comparative inputs for illustrating the application of the proposed framework rather than as direct field measurements.

The resulting sub-index and composite-index values are presented in Table 8. It can be concluded that segments with a higher share of heavy-duty vehicles (P2 and P3) have more pronounced values of indicators related to vehicle load and non-exhaust processes, particularly in terms of the Tire Wear Index (TWI), Resuspension of Particles Index (RPI), and Acceleration/Braking Intensity (ACI). In contrast, segments with a lower share of heavy vehicles (P10 and P12) are characterized by lower values of these indicators, indicating a reduced potential for generating non-exhaust pollution. Furthermore, the results show that segments P2 and P3 have the highest values of the composite IEV index, which is a consequence of the combined influence of traffic operational characteristics and intensified non-exhaust processes. A particularly significant contribution is observed from indicators within the non-exhaust pollution and EV load categories, which are directly associated with higher vehicle mass and a greater proportion of heavy vehicle categories in the traffic flow. Segment P7 occupies an intermediate position in terms of index value, indicating a moderate level of environmental burden in the analyzed scenario. This result reflects a balance between relatively high traffic intensity and a lower share of heavy vehicles. On the other hand, segments P10 and P12 have the lowest index values, indicating more favorable conditions in terms of overall environmental burden. From a transportation planning perspective, the obtained classification enables the identification of environmentally sensitive road segments within the urban network. Segments classified as high and very high impact may require priority consideration during pavement maintenance planning, traffic management optimization, environmental monitoring, or implementation of sustainable mobility measures. Conversely, segments with low environmental burden may be considered less critical in future intervention programs.

Table 8. Sub-Index Values and Composite IEV Index for Selected Road Segments.

Road Segment	Operational Sub-Index (I_1)	EV Sub-Index (I_2)	Non-Exhaust Sub-Index (I_3)	Meteorological Sub-Index (I_4)	Composite Index (I_{ev})	Rank	Category
P2	0.740	1.000	1.000	0.440	0.819	1	Very High
P3	0.641	0.805	1.000	0.440	0.754	2	High
P7	0.546	0.277	0.405	0.780	0.490	3	Moderate
P10	0.255	0.127	0.000	0.692	0.242	4	Low
P12	0.065	0.009	0.000	0.560	0.148	5	Low

To examine whether the ranking depended on the assumption of linear normalized contributions, a sensitivity check was performed using two alternative monotonic transformations of the normalized values: a concave square-root transformation and a convex squared transformation. The AHP-derived weights remained unchanged. Under both transformations, the ranking of the road segments remained P2, P3, P7, P10, and P12, from the highest to the lowest environmental burden. This result indicates that the prioritization of the analyzed segments is robust to reasonable deviations from the linear normalization assumption. Nevertheless, future applications may introduce indicator-specific nonlinear or threshold-based functions when sufficiently detailed empirical relationships are available.

In practical planning terms, segments P2 and P3 would be selected for priority investigation because they exhibit the highest composite index values and pronounced contributions from the EV-load and non-exhaust sub-index. These locations would therefore justify more detailed pavement-condition assessment, monitoring of particulate matter and road dust, and evaluation of measures aimed at reducing stop-and-go traffic and managing heavy-vehicle movements. Segment P7 would represent a secondary priority, whereas P10 and P12 would require less immediate intervention under the analyzed scenario. This example illustrates how the composite index and its sub-index can be used jointly to determine both the priority of a road segment and the type of planning response that should be considered.

Based on the distribution of the composite index values, the classification of road segments was performed using a quartile-based approach. The defined threshold values enabled the categorization of segments into low, moderate, high, and very high impact levels, thereby providing additional interpretative value to the results. The obtained results indicate that, even under conditions of full traffic electrification, a significant portion of environmental burden originates from non-exhaust processes, the intensity of which depends on traffic flow characteristics, vehicle structure, and driving conditions. This confirms the importance of an integrated approach in assessing the environmental impact of electric vehicles, going beyond the traditional focus on exhaust emissions alone.

Figure 2 complements the numerical results presented in Table 8 by illustrating the contribution of the four sub-indices and the resulting composite index for each road segment. The graphical representation shows that P2 and P3 are characterized by particularly high EV-load and non-exhaust sub-index values, whereas P10 and P12 exhibit substantially lower overall environmental burden.

4.5.3. Sensitivity and Uncertainty Analysis

A Monte Carlo uncertainty analysis was conducted to examine the extent to which uncertainty in the estimated input values may affect the composite index and road-segment ranking. Two uncertainty scenarios were considered. In the moderate scenario, the estimated and derived continuous indicators were independently varied within $\pm 10\%$ of their baseline values. In the stress scenario, the corresponding range was increased to $\pm 20\%$. The ordinal TWI, RPI, ACI, and PCI values were varied within ± 1 point of their baseline

scores and constrained to the original 1–5 scale. The share of heavy EVs was held constant because it was based on the heavy-vehicle shares reported in the original empirical study. For each scenario, 10,000 simulations were performed. Continuous indicator values were sampled independently from uniform distributions defined by the corresponding $\pm 10\%$ and $\pm 20\%$ ranges, while the ordinal indicators were sampled from the allowable integer values within ± 1 point of their baseline scores.

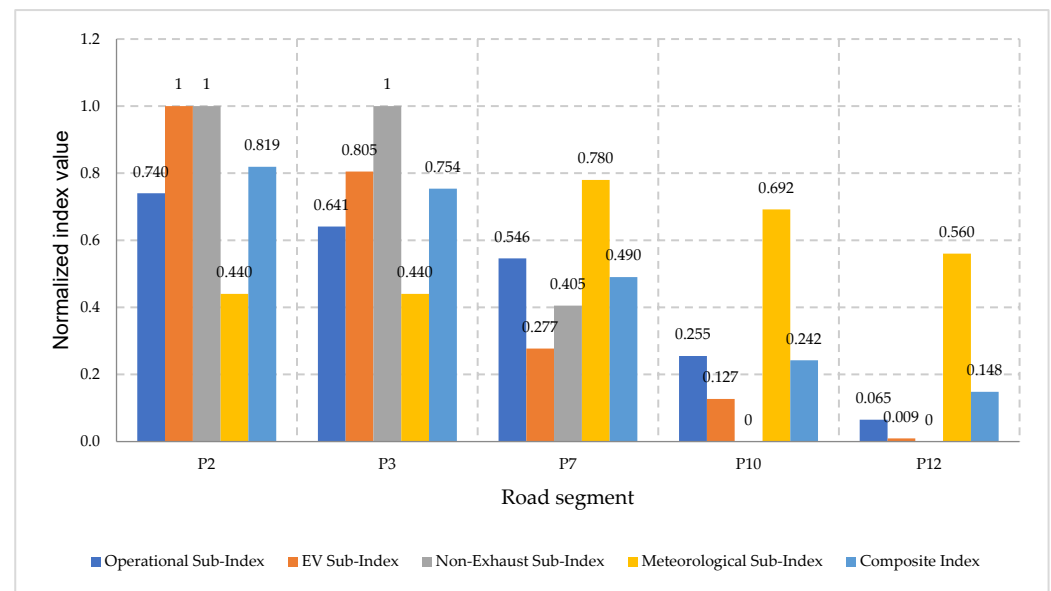


Figure 2. Sub-index and composite-index values for the selected road segments under the EV scenario.

In every iteration, the indicator values were resampled, the min–max normalization procedure was repeated, and the sub-indices and final composite index were recalculated. The AHP-derived weights were held constant in order to isolate the effect of input-data uncertainty. Under the moderate uncertainty scenario, the complete baseline ranking P2–P3–P7–P10–P12 was preserved in 67.4% of the simulations, while the mean Spearman rank correlation with the baseline ranking was 0.965. P2 and P3 jointly occupied the first two positions in 99.7% of the simulations, P7 remained in third position in 99.4%, and P10 and P12 jointly occupied the final two positions in 99.7% of the simulations. Under the $\pm 20\%$ stress scenario, the complete baseline ranking was preserved in 52.3% of the simulations, and the mean Spearman rank correlation was 0.944. P2 and P3 remained the two highest-priority segments in 98.3% of the simulations, P7 remained in third position in 96.4%, and P10 and P12 remained the two lowest-priority segments in 98.1%.

These findings indicate that the broader prioritization structure is robust to the assumed uncertainty ranges. However, the exact ordering of segments with relatively similar index values, particularly P2 and P3 and, to a lesser extent, P10 and P12, is sensitive to variations in the estimated inputs. The results should therefore be interpreted primarily in terms of priority groups rather than as an exact and immutable ranking of individual segments. More precise empirical input data would reduce this uncertainty in future applications.

A separate weight-sensitivity analysis was performed to examine the dependence of the results on the AHP-derived weights. In 10,000 simulations, each global indicator weight was independently varied within $\pm 20\%$ of its baseline value and the complete set of weights was subsequently renormalized to sum to one. An equal-weight scenario was also examined. The road-segment ranking P2–P3–P7–P10–P12 remained unchanged in all weight-perturbation simulations and under the equal-weight scenario. These findings

indicate that, for the illustrative dataset, the resulting ranking is not driven solely by the exact values of the expert-derived AHP weights.

An exploratory redundancy assessment was also conducted for the conceptually related indicators using Spearman rank correlations. The strongest associations were observed between SGI and congestion level ($\rho = 1.000$), between SGI and ACI ($\rho = 0.949$), and between congestion level and ACI ($\rho = 0.949$). TWI was strongly associated with vehicle mass ($\rho = 0.949$) and inversely associated with average speed ($\rho = -0.949$), while RPI was moderately associated with traffic flow ($\rho = -0.632$) and strongly inversely associated with average speed ($\rho = -0.949$). Given the limited number of road segments and the partly estimated ordinal inputs, these coefficients were interpreted as exploratory indicators of possible overlap rather than as definitive evidence of statistical redundancy. To examine whether these associations materially affected the model results, exclusion-based sensitivity tests were performed. The ranking P2–P3–P7–P10–P12 remained unchanged when TWI and RPI were simultaneously excluded, when vehicle mass, average speed, and traffic flow were simultaneously excluded, and when only one of SGI, congestion level, or ACI was retained from that related indicator group. In all tested cases, the Spearman correlation between the recalculated and baseline rankings was $\rho = 1.000$. These results indicate that the observed road-segment prioritization is not dependent on the simultaneous inclusion of the potentially overlapping indicators. Nevertheless, future applications using larger empirical datasets should examine redundancy through broader correlation matrices, variance-inflation measures, or dimension-reduction procedures.

4.5.4. Comparative Analysis and Rank-Agreement Assessment

The results presented in Table 9 show identical ordering of the five road segments according to measured NO₂ concentrations and the composite IEV index. This descriptive correspondence was further examined using formal rank-agreement statistics. P2 and P3 remain the highest-ranked segments, while P7, P10, and P12 retain their relative positions. This finding provides an initial indication that the proposed index captures differences among the selected segments in a manner consistent with the available empirical evidence. However, the unchanged ranking should not be interpreted as proof that the spatial distribution of environmental burden will remain stable across an entire urban network or in other cities. The finding is limited to the selected segments and reflects their specific traffic composition, operating conditions, and estimated EV-scenario indicators. A larger multi-location dataset is required to examine the robustness, spatial stability, and external validity of the proposed framework. Accordingly, the present comparison should be considered an exploratory assessment of model behavior rather than a definitive validation.

Table 9. Comparison of Measured Pollution Levels and Model Results for the EV Scenario.

Road Segment	Conventional Vehicles		Electric Vehicles		Comparison
	NO ₂ (µg/m ³)	Rank	IEV	Rank (EV)	ΔRank
P2	64.4	1	0.819	1	0
P3	63.1	2	0.754	2	0
P7	51.3	3	0.490	3	0
P10	45.1	4	0.242	4	0
P12	42.6	5	0.148	5	0

To quantify the agreement between the two rankings, Spearman's and Kendall's rank correlation coefficients were calculated using the measured NO₂ concentrations and the corresponding IEV values. The analysis produced a Spearman rank correlation of $\rho = 1.000$ and a Kendall rank correlation of $\tau = 1.000$. The exact two-sided significance value was $p = 0.0167$ for both measures. These results indicate complete rank agreement

among the five analyzed road segments. Nevertheless, the statistical result should be interpreted cautiously because it is based on only five purposively selected segments from a single city. The coefficients confirm agreement within the illustrative dataset but do not establish general model validity or transferability to broader urban road networks. The rank-agreement results should therefore be considered together with the input-uncertainty and weight-sensitivity analyses.

These results indicate that the proposed index may be used as a screening tool for identifying environmentally critical road segments within urban road networks. Similar to road safety screening procedures, the index enables transportation planners to prioritize locations where mitigation measures, pavement improvements, traffic management interventions, or environmental monitoring activities may be required. Consequently, the framework provides practical support for sustainable urban transportation planning under future traffic electrification scenarios. Furthermore, the preservation of segment ranking between conventional and electrified traffic scenarios suggests that the proposed index can support long-term planning decisions. Urban planners may use the framework to identify locations that are likely to remain environmentally sensitive even after large-scale adoption of electric vehicles, thereby improving the effectiveness of future infrastructure and environmental policies.

To facilitate visual interpretation, the measured NO₂ concentrations for conventional traffic were normalized to the [0, 1] interval and compared with the composite-index values obtained for the EV scenario, as shown in Figure 3. NO₂ concentrations were normalized using min–max normalization solely to facilitate visual comparison. The normalized NO₂ values and the EV composite index do not represent the same physical quantity. The figure indicates a similar relative ordering of the five road segments, although the differences between the two series should not be interpreted as direct differences in physical pollution quantities.

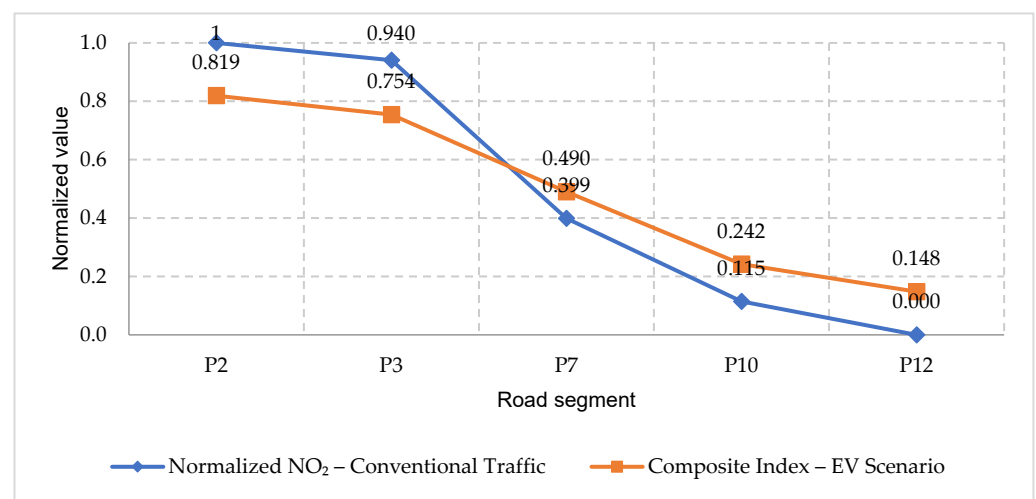


Figure 3. Comparison of normalized conventional-traffic NO₂ concentrations and the EV composite index for the selected road segments.

5. Discussion

5.1. Key Results and Interpretation of the Model

The results are consistent with current research trends concerning the environmental impacts of road traffic. A gradual transition from the analysis of exhaust emissions to an integrated consideration of non-exhaust processes and the total environmental burden is evident. The obtained indicator weights clearly show that under electrified traffic conditions, non-exhaust pollution indicators have a dominant influence, primarily the tire wear

index (TWI) and the particle resuspension index, which is in accordance with findings from contemporary literature [35,37]. The presented results are consistent with the view that the elimination of tailpipe emissions changes the relative importance of pollution sources, with non-exhaust processes becoming more prominent. Namely, under electrified traffic conditions, emissions of suspended particles occur primarily as a consequence of mechanical processes, such as tire wear, pavement wear and particle resuspension, which was also confirmed in papers analyzing the influence of vehicle mass and driving dynamics on particle generation [33,38]. The finding that indicators describing the load of electric vehicles, such as average mass and specific energy consumption, have a high relative importance in the model is particularly significant. This is directly related to the fact that electric vehicles, due to the presence of battery systems, have a greater mass compared to conventional vehicles, which additionally affects the intensity of wear and particle emissions [6,12]. This confirms that the electrification of traffic does not eliminate the problem of pollution, but transforms it into a different form. From the perspective of urban transportation planning, these findings suggest that future road network assessments should extend beyond traditional traffic performance measures and explicitly incorporate environmental burden indicators. The dominance of non-exhaust pollution indicators demonstrates that environmental sustainability in electrified transport systems depends not only on vehicle technology but also on infrastructure characteristics and traffic operating conditions. Consequently, environmental burden may be considered an additional performance dimension when evaluating urban road segments and prioritizing interventions within the transport network.

5.2. Influence of Traffic and Meteorological Factors

The results of the case study additionally confirm the importance of the traffic flow composition in shaping environmental burden. It was observed that sections with a higher share of heavy vehicles achieve the highest values of the composite index, regardless of the propulsion system type. This finding is consistent with previous research that indicates that the share of heavy vehicles has a greater impact on the level of pollution than the intensity of traffic itself [47]. This further confirms the justification of including traffic flow composition indicators in the model. A significant contribution of this paper is also reflected in the integration of meteorological indicators in the assessment of the traffic impact. The obtained results indicate that factors such as wind speed, precipitation and temperature play an important role in determining the concentration of pollutants, which is in accordance with modern research on urban microclimate and pollution dispersion [11]. In this way, the need to include external environmental factors in pollution assessment models was confirmed. A particularly important result of the paper refers to the stability of the road-segment ranking in different scenarios. Within the illustrative dataset, the transition to the EV scenario did not change the relative ranking of the five selected road segments. This result suggests that traffic composition and operating conditions may continue to influence the location of environmentally sensitive segments after electrification. However, because the analysis includes only five segments from one city, this finding should be regarded as preliminary and should not be generalized to complete urban networks without broader empirical testing [67,68].

These findings also indicate that the environmental burden associated with electric traffic is not determined solely by vehicle mass, propulsion technology, and infrastructure characteristics, but may also be influenced by advanced vehicle-control and traffic-management strategies. In this context, Wang et al. [69] demonstrated that trajectory smoothing for power-heterogeneous connected and autonomous vehicle platoons at signalized intersections can reduce speed fluctuations and unnecessary stopping, thereby improving traffic efficiency and lowering energy consumption. Within the framework proposed in this

study, the effects of such a strategy could be represented through reduced values of the stop-and-go index, acceleration/braking intensity, congestion level, and specific energy consumption. Consequently, trajectory smoothing may reduce the operational component of the composite index and may also indirectly mitigate non-exhaust burdens associated with repeated acceleration and deceleration. The proposed model could therefore be applied not only to identify environmentally critical road segments, but also to compare baseline conditions with scenarios involving cooperative automated driving, eco-driving, adaptive signal control, or other traffic-smoothing measures. Future research should quantify these effects using empirical or microsimulation data under different connected and autonomous vehicle penetration rates and mixed-traffic conditions.

From a methodological perspective, the combined application of the Delphi and AHP methods proved to be an effective approach for defining and evaluating indicators under conditions of limited data availability. This approach enables the inclusion of expert knowledge and the systematic determination of weights, in line with recommendations from the literature on multi-criteria analysis and composite indicator development [53,64]. An important practical implication is that transportation planners may use the proposed framework to identify locations where environmental mitigation measures should be prioritized. Road segments characterized by high environmental burden may require targeted actions such as pavement rehabilitation, optimization of traffic operations, management of heavy vehicle movements, implementation of green infrastructure, or intensified environmental monitoring. The results therefore demonstrate the potential of the proposed index as a decision-support tool for sustainable urban mobility planning.

5.3. Implications for Urban Transportation Planning

The results obtained in this study have several implications for urban transportation planning. First, they indicate that the transition to electric mobility alone may not eliminate environmentally critical locations within urban road networks, since non-exhaust processes remain significant sources of pollution. Second, the proposed composite index enables transportation planners to identify and rank environmentally sensitive road segments, thereby supporting evidence-based decision making. Finally, the framework may be incorporated into broader urban sustainability assessment systems together with traditional transport indicators such as traffic performance, accessibility, and road safety. In this way, environmental burden becomes an additional criterion for evaluating and managing urban road infrastructure under future mobility scenarios. In addition, the framework may support the ex ante assessment of intelligent traffic-management measures by recalculating the composite index after modifying the SGI, ACI, congestion, and energy-consumption inputs under connected and autonomous vehicle trajectory-smoothing scenarios.

5.4. Methodological Contribution and Research Limitations

From a methodological perspective, the contribution of this study lies in the design of an integrated assessment architecture rather than in the individual Delphi, AHP, or normalization procedures. The framework connects expert-based indicator selection, hierarchical weighting, directional normalization, sub-index construction, and road-segment classification within a single procedure tailored to electrified urban traffic. Its distinguishing feature is the ability to assess both the magnitude and spatial distribution of environmental burden and to translate the resulting rankings into priorities for infrastructure maintenance, traffic management, and environmental monitoring. However, certain limitations of the study should be taken into account. First of all, part of the input data for the EV scenario is based on expert assessment, which may affect the accuracy of the results. Directly measured non-exhaust pollution data were not available for the selected road segments; therefore,

the comparison with conventional-traffic NO₂ concentrations should be interpreted as an exploratory assessment of ranking agreement rather than as external validation of the composite index. Also, the model does not include all relevant factors, such as the long-term effects of battery production and the energy mix, which may also have a significant impact on the overall environmental balance of electric vehicles [70,71]. Despite the mentioned limitations, the results of the research clearly indicate the need to redefine the approach to the analysis of traffic pollution in urban areas. Beyond its environmental assessment function, the proposed framework contributes to the development of practical planning tools for urban transport systems. Unlike conventional pollution studies that primarily quantify environmental impacts, the proposed index enables ranking, classification, and comparison of urban road segments according to their environmental burden. This provides a structured basis for prioritizing interventions and allocating resources within urban transportation planning processes. The proposed model represents a step towards an integrated assessment of the impact of electric vehicles, taking into account the complex interaction of traffic, technical and meteorological factors.

6. Conclusions

This paper developed a methodological framework for assessing road-segment-level operational environmental burdens associated with electric traffic by integrating traffic-operational, EV-load, non-exhaust, and meteorological indicators. Using the Delphi and AHP methods [61,64], the weights of the indicators were defined, which enabled the development of a composite index for the quantitative evaluation of the environmental burden at the road segment level. The results of the research indicate that under the electrified traffic conditions, non-exhaust processes have a dominant influence, primarily tire wear and particle resuspension, as well as vehicle characteristics such as mass and share of heavy vehicles. In the illustrative case study, the relative ranking of the five analyzed road segments remained unchanged under the electrified traffic scenario, although the intensity and structure of environmental burden differed. This preliminary finding requires verification using larger and more diverse urban road-segment datasets. The proposed model enables the identification and ranking of environmentally sensitive road segments and may serve as a decision-support tool for sustainable urban transportation planning. By integrating environmental burden into road network assessment, the framework provides planners with an additional criterion for prioritizing infrastructure interventions and mobility management measures. Future research can be directed toward the inclusion of additional factors and the application of the model using larger and more detailed empirical datasets.

6.1. Practical Application of the Framework

The results of this research have significant practical application in urban transportation planning and traffic management. The proposed composite index enables the identification of critical sections from the aspect of environmental burden, which can support decision-making related to traffic management of heavy vehicles and improvement of the road infrastructure quality. Furthermore, the framework may support the prioritization of pavement maintenance programs, environmental monitoring activities, traffic management strategies, and sustainable mobility interventions. Similar to road safety screening procedures, the proposed index allows urban authorities to identify locations requiring additional attention and resource allocation. It is particularly significant that the model highlights the importance of non-exhaust sources of pollution, which implies the need to introduce measures aimed at reducing tire wear, upgrading pavement structures, and optimizing traffic regimes. Also, the model can be applied as a tool for evaluating the effects

of different scenarios of the development of the traffic system, including full or partial electrification of the vehicle fleet. In the context of sustainable transportation planning, it is important to emphasize the comprehensiveness of the developed methodological framework, which considers both technological improvements in the automotive industry and meteorological data that, as a result of climate change, have a significant impact on the traffic system.

6.2. Research Limitations

Despite the achieved results, certain limitations of the research should be taken into account. Part of the input data for the electrified traffic scenario is based on expert assessment and secondary sources, which may affect the accuracy of the results obtained. Also, the model does not include all potential factors that affect the overall environmental impact of electric vehicles, such as the effects of battery production and the structure of the energy mix. Additionally, the analysis was conducted on a limited number of sections, which may affect the general applicability of the results. In addition, the study was conducted within a single urban context, and therefore the transferability of the proposed classification thresholds to other cities should be interpreted with caution. Future research should include a larger number of locations and more detailed empirical data in order to further improve the robustness of the model. A further limitation concerns the empirical scope of the case study, which includes only five road segments located in a single city. These segments were selected to illustrate the application of the framework under contrasting traffic and pollution conditions and do not constitute a statistically representative sample of the urban road network. Therefore, the case-study results cannot establish the general robustness, spatial stability, or transferability of the proposed index. External validation will require application to a substantially larger number of road segments, preferably across several cities and under different traffic, pavement, climatic, and urban-morphological conditions.

6.3. Future Research Directions

Future research should focus on improving the model through the inclusion of additional indicators, as well as the application of advanced modeling methods, including machine learning and simulation approaches. It is particularly important to develop models that incorporate real-time and spatial data, thus enabling a dynamic assessment of traffic-related environmental impacts. Also, further research may include extending the model to the analysis of the entire life cycle of electric vehicles, as well as integration with urban planning and sustainable development policies. Applying the model across different urban environments would enable the assessment of its transferability and further improvement of the methodological approach. Future studies may also integrate the proposed framework with GIS-based urban planning tools, smart-city platforms, and sustainable mobility assessment systems, thereby enhancing its practical applicability in transportation planning and policy development. Future research should also examine connected and autonomous vehicle trajectory smoothing and adaptive signal control as mitigation scenarios within the proposed framework, particularly under mixed-traffic conditions and different levels of CAV penetration.

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