



Traffic Congestion and Vehicle Emissions in a Historic Andean City: A Mesoscopic Simulation for Sustainable Urban Mobility

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Abstract: Traffic-related air pollution constitutes one of the primary threats to public health and environmental sustainability in urban centers worldwide. Historic centers face particular challenges because their narrow streets, irregular urban configuration, and high vehicle concentration during peak hours hinder the implementation of conventional environmental monitoring systems. This research assessed the pollutant emissions generated by vehicular traffic in the historic center of Ayacucho, Peru, an Andean city located at 2,761 meters above sea level with approximately 29,476 inhabitants in the study area. A mesoscopic simulation model was developed in PTV Vissim using the Mahut and Wiedemann car-following algorithm. Data were collected with unmanned aerial vehicles at 14 access intersections and complemented with traffic signal cycle measurements and speed recordings under free-flow and congested conditions. Emissions of carbon monoxide (CO), nitrogen oxides (NO_x), volatile organic compounds (VOC), and fuel consumption were quantified across an area of 0.48 km². Model calibration achieved Geoffrey E. Havers (GEH) values below 5 at 81% of the calibration points, and every point fell below a GEH of 10. The Wilcoxon signed-rank test showed significant differences between emissions under free-flow and congested conditions. A heat map identified Jr. 2 de Mayo, Jr. Pizarro, and Jr. Libertad as the segments with the highest emission rates. The findings provide scientific evidence for authorities and urban planners to implement targeted mitigation strategies, and the approach is replicable in historic centers of intermediate Latin American cities with comparable topographic and urban characteristics.

Keywords: Sustainable urban mobility; Traffic-related emissions; Historic city centers; Mesoscopic traffic simulation; Emission hotspots; Traffic congestion

1. Introduction

Traffic-related air pollution represents one of the most critical environmental challenges facing contemporary cities. In the European Union, traffic contributes 24% of total greenhouse gas emissions and represents the most significant individual source of pollution, with road traffic accounting for 76.2% of emissions in that sector (Šarić, 2024). Motorized vehicles emit pollutants including carbon monoxide (CO), nitrogen oxides (NO_x), and volatile organic compounds (VOC), which pose major health risks in metropolitan areas, with NO_x being particularly harmful (Tirico et al., 2025a). Air pollution ranks among the leading environmental causes of premature mortality worldwide, and urban transport is one of its main contributors (Tsekeri et al., 2025).

Historic centers of intermediate cities present a paradigmatic challenge in modern traffic management. Characterized by narrow streets originally conceived for carriage and pedestrian circulation, these heritage spaces face infrastructural incompatibility that generates critical congestion. In the city of Ayacucho, Peru, vehicular congestion emerges as one of the principal challenges confronting public authorities, a situation aggravated by the

historic nature of its colonial center (Lee et al., 2025; Lizarbe Alarcón et al., 2025).

Ayacucho presents a monocentric structure where most commercial, educational, and labor activities converge toward the city center. This centralization causes the narrow streets of the historic center to hinder optimal integration of vehicular flow with the main arterial and secondary roads to which these streets converge (Essamlali et al., 2025). During peak hours, these narrow thoroughfares prove insufficient to absorb vehicular demand, manifesting in congested transit characterized by slow circulation. As an aggravating factor, vehicular traffic control in Ayacucho is conducted through fixed-time traffic signals that operate independently and in isolation, with pre-established cycles that do not respond to actual vehicular demand (Naizabayeva et al., 2024).

The impact of vehicular congestion transcends immediate traffic inconveniences. Traffic congestion, particularly in metropolitan areas, exacerbates emissions, fuel waste, and delays, adversely affecting economic activity and quality of life (Roy et al., 2025). Studies demonstrate that drivers in developed countries waste more than a day annually trapped in traffic jams, while in Peru the economic losses reached 27,000 million soles in 2017 (Lizarbe Alarcón et al., 2025). Additionally, vehicular congestion causes a significant increase in stress for both citizens and drivers moving through the city, effects compounded by increased fuel consumption directly proportional to the increase in constant vehicle stops and starts (Tettamanti et al., 2025).

Crucially, vehicular congestion contributes to environmental quality degradation and increased noise pollution, generating health problems that affect the entire population. Congestion in traffic systems leads to significant environmental issues, including air pollution, greenhouse gas emissions, and adverse effects on living conditions (Wu & Qiao, 2026). These emissions intensify under congested traffic conditions due to the frequent acceleration and deceleration cycles that characterize circulation on saturated roads (Bahmankhah et al., 2022). These problems are particularly acute in cities of developing countries undergoing rapid urbanization and population expansion (Mei et al., 2024).

The selection of CO, NO_x, and VOC as target pollutants responds to methodological and environmental criteria. These three pollutants are directly calculable through the emission algorithms integrated in PTV Vissim, which are based on the Vehicle Specific Power (VSP) methodology. VSP relates instantaneous emissions to operational parameters such as speed, acceleration, and road gradient (Rahimi et al., 2023). Particulate matter (PM₁₀ and PM_{2.5}) requires a different approach, since its estimation depends on atmospheric dispersion models such as AMS/EPA Regulatory Model (AERMOD) or Research LINE source model (RLINE) together with detailed meteorological data (Lee & Batterman, 2026). Gaseous pollutants, in contrast, can be estimated directly from microsimulation outputs, which permits spatially explicit analysis of emission patterns without coupling multiple modelling platforms (Lorenzo-Sáez et al., 2025). Previous work has shown that VSP-based estimates combined with detailed traffic data provide accurate input for urban-scale air quality models (Borrego et al., 2016).

CO, NO_x, and VOC are also recognized indicators for management-oriented urban monitoring. All three are direct products of combustion in internal combustion engines, and their emission rates respond to vehicle operating conditions, particularly to the acceleration and deceleration cycles that characterize congested traffic (Rahimi et al., 2023). This direct relationship between vehicular dynamics and emission allows the VSP methodology to capture spatial variations along the road network. Particulate matter was excluded as a deliberate delimitation of scope; the methodological requirements involved are detailed in Section 3.5.5 and are proposed as a future research line.

To address vehicular emissions associated with congestion, this study develops a mesoscopic simulation model in PTV Vissim that quantifies and spatially maps CO, NO_x, and VOC emissions in the historic center of Ayacucho. Mesoscopic simulation offers a balance between accuracy and practical applicability for intermediate Latin American cities, in contrast to microscopic approaches that require extensive input data and considerable computational resources (Jamshidnejad et al., 2017). This balance is particularly relevant in historic centers, where narrow streets and inherent geometric limitations constrain both data collection and model construction (Lizarbe Alarcón et al., 2025).

The primary contribution of this study is a mesoscopic simulation framework developed and validated for historic centers with complex geometry and limited monitoring data. The framework generates spatially explicit emission heat maps that identify pollution hotspots at the street-segment level, which provides evidence for prioritizing traffic management interventions. Because it relies on unmanned aerial vehicle (UAV)-based data collection rather than permanent monitoring infrastructure, the approach is transferable to intermediate Latin American cities that share similar urban constraints and traffic characteristics.

2. Related Work

2.1 Traffic Simulation Models for Emission Estimation

Traffic simulation models constitute fundamental tools for understanding vehicular dynamics and their environmental impacts. The software known as “Verkehr In Städten–SIMulationsmodell” (VISSIM), which translates to “Traffic in cities–simulation model”, was developed at the University of Karlsruhe, Germany, during

the early 1970s (Al-Msari et al., 2024). VISSIM is a behavior-based simulation model operating on a time-step basis, consisting of three essential components: traffic control, traffic flow, and data analysis. Given the diverse applicability of VISSIM-based schemes, recent research has systematically examined the applications of VISSIM-based driving behavior models within different research contexts, providing guidance for researchers in selecting the most suitable methodological approach (Al-Msari et al., 2024).

Mesoscopic traffic simulation has emerged as a promising technology for handling large-scale dynamic traffic assignment problems (Song et al., 2017). Unlike microscopic models that track individual vehicles, mesoscopic models consider aggregated behaviors of vehicle groups, providing a balance between high accuracy and low computational time (Jamshidnejad et al., 2017). Jamshidnejad et al. (2017) proposed a framework to interface and integrate macroscopic flow models and microscopic emission models, obtaining a new mesoscopic integrated flow-emission model that guarantees results with high accuracy levels while ensuring low CPU time, making the framework suitable for real-time model-based applications.

Comparative investigations have evaluated different modeling scales for traffic-related emission estimation. Tirico et al. (2025a) compared emissions derived from two widely used European models, Computer Programme to calculate Emissions from Road Transport (COPERT) and Handbook of Emission Factors for Road Transport (HBEFA), using traffic data from the microscopic traffic model Symuvia and the agent-based model MATSim. Their findings indicate that MATSim+COPERT and Symuvia+HBEFA yield more consistent overall results, primarily due to the route assignment algorithm and the sensitivity of emission models to variations in traffic conditions. At the street level, Symuvia proves better suited for emission estimations as it more accurately captures local variations and congested traffic conditions.

A systematic review of machine learning-based microscopic traffic flow models and simulations has identified key areas for future research, including the development of methods to improve model transferability across different operational design domains and the need to capture both driver-specific and location-specific heterogeneity via benchmark datasets (Rowan et al., 2025). These advances are crucial for the practical adoption of machine learning (ML)-based microscopic models in traffic simulations.

2.2 Vehicle Emission Estimation Methodologies

The environmental impact assessment of transport for prospective scenarios is a complex endeavor that hinges on several interrelated factors, such as human behavior, transport infrastructure, and vehicle fleet composition (Tirico et al., 2025b). Zhou et al. (2015) presented a computationally efficient and theoretically rigorous dynamic traffic assignment model coupled with the emission estimation package MOVES Lite to evaluate traffic dynamics and vehicle emission/fuel consumption impacts of different traffic management strategies. The proposed model embeds a consistent cross-resolution traffic state representation based on Newell's simplified kinematic wave and linear car following models.

Average speed models such as COPERT have been widely used for urban-scale emission inventories. Samaras et al. (2019) demonstrated a new approach for estimating fuel consumption from vehicles circulating on urban roads with different levels of congestion, coupling a microscopic dynamic traffic model (AIMSUN) with an instantaneous emissions model (CRUISE). The integrated methodology was applied in an urban corridor in Turin using two validated vehicle models of Euro 5 passenger cars. Their results showed that under congested conditions fuel consumption can increase by more than 18% in some cases, indicating the significance of incorporating similar congestion algorithms in macro emission models.

The VSP methodology has gained prominence in link-level and second-by-second emission estimation. Borrego et al. (2016) simulated the atmospheric dispersion of NO_x and PM_{10} over a medium-size south-European city, using microscopic traffic models calibrated with GPS data to derive typical driving cycles, while instantaneous emissions were estimated applying the combined VSP/EMEP methodology. Their results highlight the potential of detailed traffic and instantaneous exhaust emissions estimates to provide accurate input data to Gaussian models applied at the urban scale.

2.3 Integration of Traffic and Air Quality Models

Reducing road traffic emissions through mobility management is crucial for achieving sustainable urban living (Tirico et al., 2025a). To assess such strategies, reliable modeling chains that couple traffic and pollutant models are essential. However, this coupling can introduce significant uncertainty, particularly when traffic and pollution models are developed at different spatial scales. This challenge of examining the effects of spatio-temporal representation of traffic data on emission models represents an active area of research (Tirico et al., 2025a).

Song et al. (2025) developed an intelligent vehicle sensing system using GeoVideo (Geo-referenced Video) technology to quantify vehicular activity on urban streets, capturing key traffic parameters including flow, vehicle speed, and classification. Based on collected data, a high-resolution traffic emission inventory for Kaifeng City's street network was constructed. The inventory was coupled with the WRF-Chem model and MUNICH street-scale

air quality models to simulate NO₂ and O₃ concentrations, demonstrating correlation coefficients of 0.98 (O₃) and 0.89 (NO₂).

Deep learning approaches have emerged as promising alternatives for emission prediction. Dib et al. (2025) introduced a novel methodology that couples a mesoscopic traffic model with a microscopic emission model by generating vehicle speed profiles based on deep learning techniques. The deep learning component produces instantaneous speed profiles from mesoscopic model outputs, which are essential for precise emission estimation using microscopic emission models. Applied to the Île-de-France region, home to over 12 million people, the method demonstrates its scalability while maintaining high precision, providing a robust tool for managing urban air quality.

2.4 Case Studies in Complex Urban Environments

Air pollution in urban built environments presents unique challenges due to the interaction between urban morphology, traffic patterns, and pollutant dispersion (Brancher, 2026). Šarić (2024) revealed that in saturated conditions, signalized intersections cause lower emissions than two-lane and turbo-roundabouts, a conclusion supported by three different methods: VSP, VERSIT+, and Environmental Sensitive Traffic Management (ESTM) by Bosch. Although the results are consistent, significant differences in emission values between methods can mislead the size of the benefit of a particular intersection type.

Studies in urban street canyons have demonstrated the importance of street morphology in pollutant retention. Duong & Odai (2025) assessed the performance of the ADMS-Urban dispersion model in estimating 1-h mean nitrogen dioxide (NO₂) concentrations within the street canyons of Prague. Street morphology played a critical role in pollutant retention, with narrow, high-walled corridors accumulating higher NO₂ loads than broader, vegetated streets that allowed greater airflow and dilution. Spatial mapping revealed that NO₂ concentrations exceeded 50 µg/m³ at key traffic intersections, driven by vehicle idling, congestion, and restricted dispersion within enclosed canyon geometries.

In the Latin American context, Pérez-Martínez et al. (2025) developed a methodology using a traffic demand model for GHG and air pollutant emission inventories in the Metropolitan Area of São Paulo, where approximately 80% of air pollution comes from vehicles. These high-resolution emission inventories allow identifying hotspots of air pollution and poor air quality with spatial resolution of 0.5 km and temporal resolution of 1 hour. Data from NOTS sensors were compared with reference data obtained from the Osasco monitoring network website, enabling error adjustment for calibrating the model in the field.

2.5 Machine Learning Applications in Emission Modeling

Recent advancements in data analytics and sensor technology have significantly enhanced our understanding of vehicular emissions (Du et al., 2025). Du et al. (2025) comprehensively reviewed ML-based high-resolution traffic-air quality (TAQ) models, highlighting advancements via analysis of 103 studies from 2013 to 2023, particularly for European regions where relevant research has increased significantly. The review summarized prediction of urban air quality influenced by complicated on-road traffic conditions using various ML algorithms, including tree-based and neural network algorithms.

Roy et al. (2025) introduced a novel deep learning framework termed multi-task temporal convolutional network (MT2CN) that jointly predicts traffic emissions and travel delay at signalized intersections. It is evident from their findings that the proposed MT2CN approach outperforms conventional single-task models, indicating a significant finding for predictive modeling. By utilizing advanced deep learning techniques and explainable artificial intelligence techniques such as Shapley additive explanations (SHAP), their framework provides more accurate predictions and explainable insights to facilitate sustainable and intelligent traffic management.

Traffic assignment optimization considering air quality has been addressed through physics-informed neural networks. Mei et al. (2024) proposed an optimization framework with the surrogate model based on the unified finite-volume physics-informed neural network (UFV-PINN). The current work optimizes the average CO concentration and accumulative travel time in Kowloon peninsula of Hong Kong, using the multiple-gradient descent algorithm (MGDA). This study is the first attempt to incorporate UFV-PINN into traffic assignment optimization with air quality consideration.

2.6 Gaps in Literature and Study Contribution

Despite significant advances in traffic and emission modeling, important gaps remain in the literature. First, most studies have focused on cities in developed countries with vehicular and infrastructure characteristics different from those of intermediate Latin American cities (Pérez-Martínez et al., 2025). Second, historic centers with their unique geometric restrictions and complex traffic patterns have received limited attention (Lizarbe Alarcón et al., 2025). Third, there is a scarcity of validated methodologies for estimating emissions in contexts

where air quality monitoring data are limited or nonexistent (Martín et al., 2025).

Research on traffic flow modification impacts on air quality has shown that reducing traffic leads to a linear decrease in NO_x concentrations, while increasing traffic causes a quadratic rise in pollution levels (Kamińska, 2025). However, these studies primarily focus on European contexts with different fleet compositions and driving behaviors than those found in Peru. Additionally, investigations on zero emission zones in cities like Milan have demonstrated that road traffic emission reductions can reach 84% for NO_x and 28% for $\text{PM}_{2.5}$ compared to 2017 levels (Piccoli et al., 2025), yet such scenarios remain distant for developing country cities that require immediate, practical solutions.

The impact of autonomous vehicles (AVs) on air quality and energy efficiency has been studied in urban roundabouts, with results showing that the introduction of AVs may lead to higher travel times at peak hours and increased emissions, mainly due to AVs with defensive behavior (Afonseca et al., 2023). These findings underscore the complexity of implementing new technologies in urban environments without comprehensive assessment of their environmental impacts.

This study addresses these gaps by developing and calibrating a mesoscopic simulation model specifically adapted for the historic center of Ayacucho, an intermediate Peruvian city at 2,761 m.a.s.l. with approximately 29,476 inhabitants in its central area. The proposed methodology integrates UAV-based data collection, rigorous calibration using the GEH statistic achieving 87% compliance, and heat map generation of emissions that provides scientific evidence for targeted mitigation strategies, being replicable in other intermediate Latin American cities with similar characteristics.

3. Proposed Methodology

3.1 Study Area

3.1.1 Geographic location

The study was conducted in the historic center of Ayacucho, Peru, located at 2,761 meters above sea level in the Andean highlands. Ayacucho is an intermediate city with a total population of approximately 196,000 inhabitants, of which 29,476 (15%) reside within the central historic district (Lizarbe Alarcón et al., 2025). The historic center was designated as a Cultural Heritage Zone due to its colonial architecture, with more than 410 dwellings of colonial type, whose layout constrains street widths and traffic flow patterns.

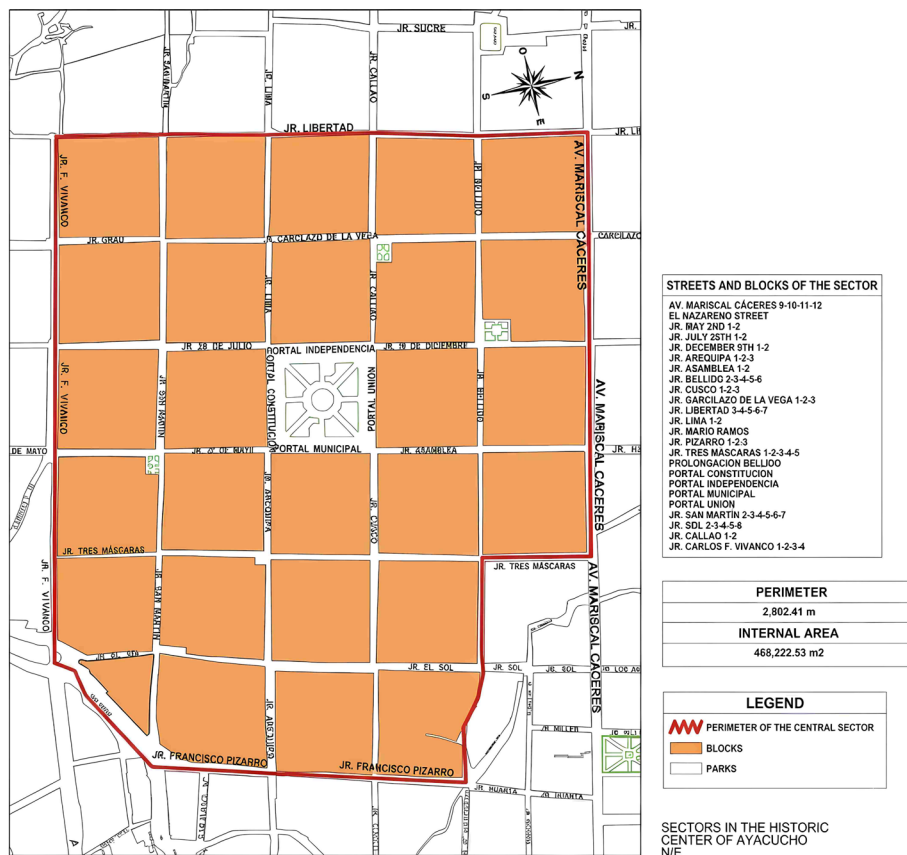


Figure 1. Study area delimitation: central sector of the historic center (0.48 km²)

3.1.2 Study area delimitation

The study area encompasses 0.48 km² of the Central Sector of the Historic Center, as illustrated in Figure 1. This sector was selected because it concentrates the highest density of commercial, educational, governmental, and religious institutions, generating significant traffic attraction throughout the day (Essamlali et al., 2025). The area is characterized by narrow streets originally designed for pedestrian and carriage circulation during the colonial period.

3.1.3 Street network characteristics

The street network within the study area consists of 41 road segments organized in a grid pattern centered on the main plaza. Figure 2 shows the complete road network of the Central Sector, displaying the street segments and their interconnections.



Figure 2. Road network of the Central Sector showing street segments and intersections

Figure 3 presents the street lengths within the study area. The network comprises segments ranging from approximately 60 meters to 147 meters in length, with most blocks measuring between 125 and 135 meters. The total network length within the study area is approximately 5.2 kilometers.

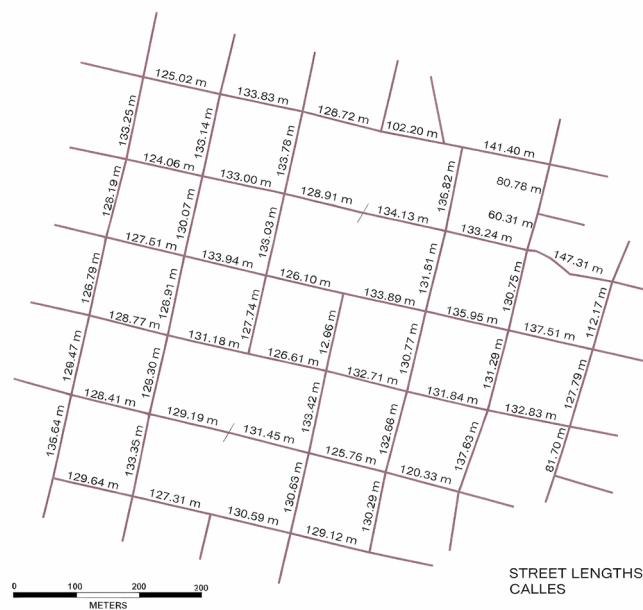


Figure 3. Street segment lengths in the Central Sector (meters)

3.1.4 Traffic flow configuration

Traffic flow in the historic center is constrained by the convergent urban morphology, where all major arterial roads lead toward the central plaza, creating bottlenecks during peak hours. The predominant one-way street configuration characterizes the colonial grid pattern. This configuration, while intended to simplify traffic management, creates circuitous routes that increase travel distances and vehicle emissions (Naizabayeva et al., 2024). Figure 4 presents the traffic flow directions within the historic center.

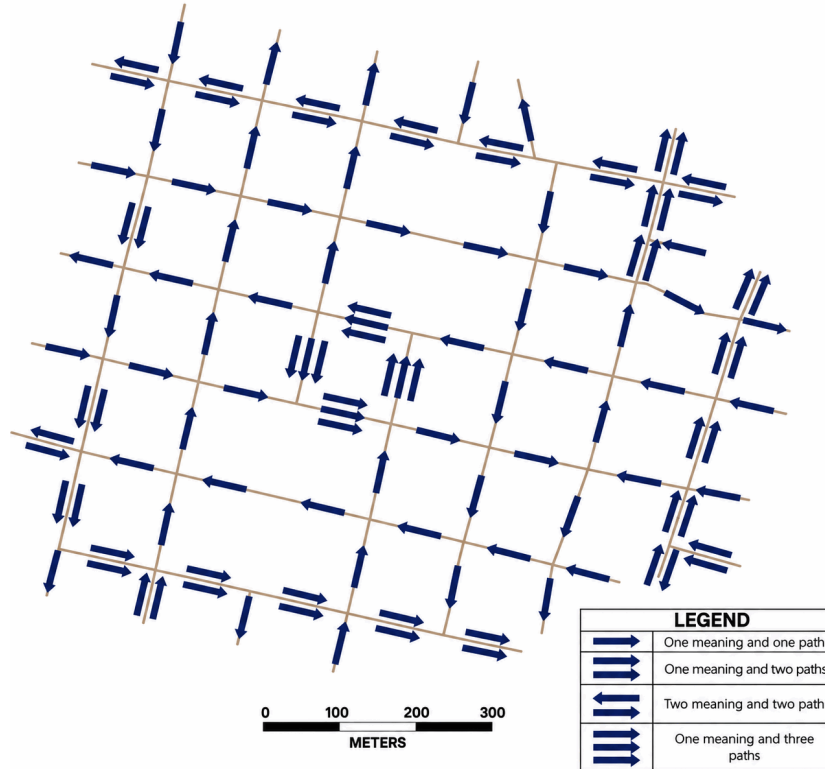


Figure 4. Traffic flow directions within the historic center

3.1.5 Representativeness of the study area

The selection of the 0.48 km² study area and 41 road segments was based on both practical and methodological considerations. The Central Sector represents the core of commercial, governmental, and educational activities in Ayacucho, concentrating approximately 65% of daily trips destined to the historic center according to municipal transport surveys (Lizarbe Alarcón et al., 2025). The 14 entry intersections monitored capture all primary access points to this sector, ensuring comprehensive coverage of incoming traffic flows.

The 41 road segments analyzed represent the complete internal street network of the Central Sector, not a sample. This census-based approach eliminates sampling bias and provides full spatial coverage for emission mapping. The peak hour vehicle count of 11,454 vehicles represents the maximum hourly demand observed during the data collection period, occurring between 12:30 and 13:30. This volume reflects the convergent traffic pattern where vehicles from peripheral areas concentrate toward the central plaza during midday commercial peak.

The representativeness of the study area for the broader historic center was validated through comparison with municipal traffic data, confirming that the Central Sector accounts for approximately 70% of total vehicular circulation within the heritage zone during peak hours. While the methodology is directly applicable to other sectors of the historic center, extending the analysis to the complete 1.2 km² heritage zone would require additional data collection points and is proposed for future research phases.

3.2 Data Collection

3.2.1 Traffic monitoring methodology

Traffic data were collected during July and August on weekdays (Monday through Friday) from 6:00 AM to 7:00 PM. UAVs were positioned at strategic locations to maximize coverage and eliminate blind spots. Figure 5 illustrates the UAV-based data collection methodology employed in this study.

Table 2. Vehicle counts at entry intersections during peak hour

ID	Entry to Network	Peak Flow (veh/h)	Average Flow (veh/h)
1	Jr. Libertad	1132	888
2	Jr. Asamblea	944	751
3	Av. Mariscal Cáceres	1032	788
4	Jr. Untiveros	680	496
5	Jr. Cusco	234	146
6	Jr. Caviedes	1072	701
7	Jr. Pizarro	2444	1964
8	Jr. San Martín	984	838
9	Jr. 2 de Mayo	772	713
10	Jr. Grau	800	592
11	Jr. San Martín	352	243
12	Jr. Lima	488	390
13	Jr. Bellido	444	324
14	Av. Mariscal Cáceres	76	41
Total		11454	8875

Note: Av., Avenida (Avenue); Jr., Jirón (Street).

Table 3 presents the percentage distribution of vehicles by type at each intersection, showing the fleet composition across the study area.

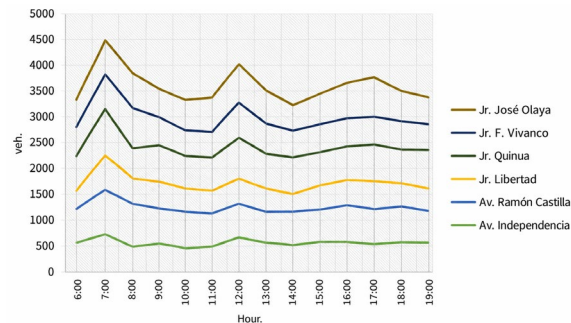
Table 3. Percentage distribution of vehicles by type at each intersection

ID	Street/Avenue	Motorcycle (%)	Mototaxi (%)	Light Vehicle (%)	Bus (%)	Truck (%)
1	Jr. Libertad	25	3	55	16	1
2	Jr. Asamblea	36	0	63	0	1
3	Av. Mariscal Cáceres	30	18	46	5	1
4	Jr. Untiveros	45	6	46	0	3
5	Jr. Cusco	22	8	70	0	0
6	Jr. Caviedes	8	15	76	0	1
7	Jr. Pizarro	40	8	45	5	1
8	Jr. San Martín	45	0	54	0	1
9	Jr. 2 de Mayo	33	5	50	12	0
10	Jr. Grau	36	16	48	1	0
11	Jr. San Martín	31	36	33	0	0
12	Jr. Lima	19	48	32	0	1
13	Jr. Bellido	28	2	69	0	1
14	Av. Mariscal Cáceres	41	5	52	0	3

Note: Av., Avenida (Avenue); Jr., Jirón (Street).

3.2.5 Temporal traffic patterns

Figure 7 illustrates the temporal distribution of traffic flow throughout the day, showing the morning peak (7:30–8:30), midday peak (12:30–13:30), and afternoon peak (18:00–19:00). The midday peak was selected for emission analysis as it presented the highest congestion levels and longest queue lengths.

**Figure 7.** Temporal distribution of traffic flow throughout the day showing peak periods

3.2.6 Traffic signal data

Traffic signal data were collected at the 22 signalized intersections within the study area. All signals in the historic center run on fixed-time cycles. Cycle lengths range from 60 to 86 seconds. No intersection uses adaptive

control, and adjacent intersections are not coordinated (Naizabayeva et al., 2024). Table 4 presents the signal timing parameters for each intersection, and Figure 8 shows their spatial distribution across the study area. The signalized intersections concentrate along the main corridors that converge toward the central plaza, a configuration that becomes relevant when interpreting the emission hotspots reported in Section 5.2.

Table 4. Traffic signal timing parameters at signalized intersections

ID	Intersection (Av./Jr.)	Direction (Av./Jr.)	Green (s)	Red (s)	Total (s)
1	Libertad-Mariscal	Libertad	48	27	75
2	Libertad-Callao	Libertad	52	23	75
3	Libertad-Lima	Libertad	50	25	75
4	Libertad-San Martín	Libertad	50	35	85
5	Grau-F. Vivanco	Grau	35	45	80
6	Grau-Lima	Grau	42	23	65
7	Garcilaso-Callao	Garcilaso	40	30	70
8	9 de diciembre-M. Cáceres	9 de diciembre	33	30	63
9	9 de diciembre-Callao	Callao	38	22	60
10	28 de Julio-Lima	Lima	45	20	65
11	28 de Julio-San Martín	San Martín	48	17	65
12	28 de Julio-F. Vivanco	28 de Julio	15	50	65
13	2 de Mayo-F. Vivanco	F. Vivanco	42	35	77
14	2 de Mayo-Arequipa	2 de Mayo	40	30	70
15	Asamblea-Cusco	Asamblea	46	24	70
16	Asamblea-Bellido	Bellido	60	26	86
17	Asamblea-M. Cáceres	Asamblea	48	38	86
18	3 máscaras-M. Cáceres	M. Cáceres	45	18	63
19	3 máscaras-Bellido	3 máscaras	50	25	75
20	F. Vivanco-San Lorenzo	F. Vivanco	47	38	85
21	Sol-M. Cáceres	M. Cáceres	42	38	80
22	Sol-San Martín	Sol	34	26	60

Note: Av., Avenida (Avenue); Jr., Jirón (Street).

Figure 8 shows the spatial distribution of these signalized intersections across the study area, revealing their concentration along the main corridors converging toward the central plaza.

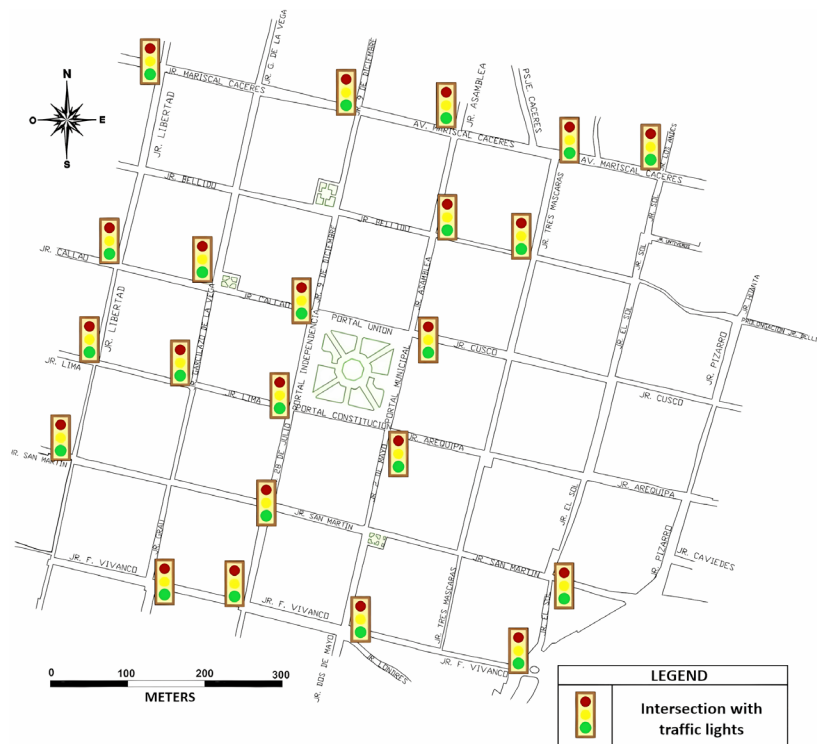


Figure 8. Spatial distribution of traffic signals within the study area

3.2.7 Speed measurements

Speed measurements were conducted under two conditions: free-flow (off-peak hours, 10:00–11:00 AM) and congested (peak hours, 12:30–13:30 PM). Table 5 presents the free-flow speeds measured for the main road segments.

Table 5. Free-flow speeds measured by vehicle type

Vehicle Type	Average Speed (km/h)
Motorcycles	30.1
Mototaxis	23.2
Light vehicles	29
Buses	23.7
Trucks	20.3

Table 6 presents the congested speeds measured during peak hour, showing significant speed reductions compared to free-flow conditions.

Table 6. Congested speeds measured during peak hour

Vehicle Type	Average Speed (km/h)
Motorcycles	13.3
Mototaxis	10.2
Light vehicles	12.8
Buses	10.4
Trucks	8.9

3.3 Traffic Simulation Model

3.3.1 Simulation software

The traffic simulation was performed using PTV Vissim 10.00, a mesoscopic traffic simulation software widely used for traffic flow modeling and emission estimation (Al-Msari et al., 2024). The software implements the Mahut-Wiedemann car-following algorithm, which models vehicle interactions based on desired speed, spacing, and acceleration/deceleration behavior (Jamshidnejad et al., 2017). Unlike microscopic models that simulate individual vehicle trajectories with high computational demand, mesoscopic models aggregate vehicle behavior into platoons while maintaining sufficient detail to capture acceleration, deceleration, and queuing dynamics essential for emission estimation (Song et al., 2017).

3.3.2 Network construction

The simulation network was constructed using geometric data collected in the field, including street lengths, widths, lane configurations, and intersection geometries. Traffic demand was input through origin-destination matrices derived from the vehicle counts at entry intersections, with route assignment based on observed turning proportions at each intersection. Figure 9 summarizes the car-following and lane-change logic that governs vehicle interaction in the model.

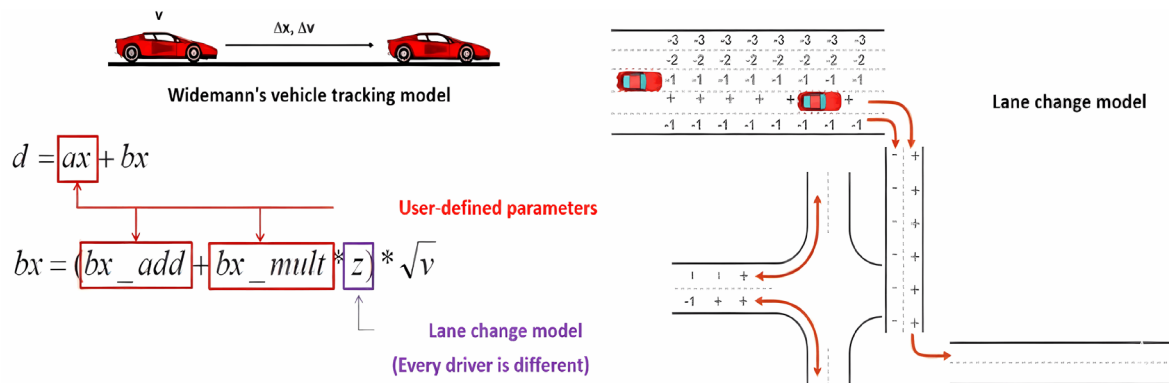


Figure 9. Car-following and lane-change models used by PTV Vissim

Note: Adapted from the PTV Vissim user manual.

3.3.3 Route assignment

Routes were defined based on field observations of vehicle trajectories, with turning proportions calibrated to match observed traffic patterns. Figure 10 presents the route assignment diagram showing the distribution of traffic flows through the network. The diagram illustrates the convergent nature of traffic flow toward the central plaza, which creates the congestion hotspots identified in subsequent analysis.

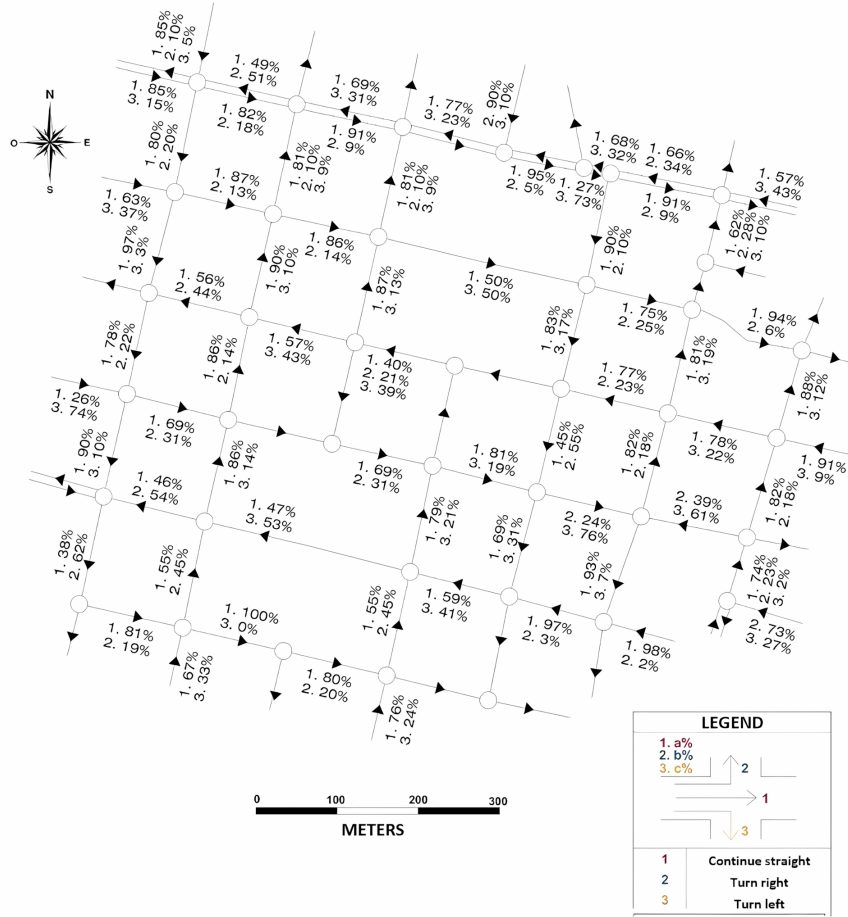


Figure 10. Route assignment diagram showing traffic flow distribution through the network

3.4 Model Calibration and Validation

3.4.1 Calibration methodology

Model calibration was performed using the Geoffrey E. Havers (GEH) statistic, which is the industry-standard metric for comparing observed and simulated traffic volumes (Lizarbe Alarcón et al., 2025). The GEH statistic is calculated using Eq. (1):

$$GEH = \sqrt{\frac{2(M - C)^2}{M + C}} \quad (1)$$

where, M is the simulated traffic volume (vehicles/hour) and C is the observed traffic volume (vehicles/hour). According to established practice in traffic modeling, GEH values are interpreted as follows: $GEH < 5$ indicates acceptable calibration, $5 \leq GEH < 10$ requires review but may be acceptable, and $GEH \geq 10$ indicates calibration failure requiring parameter adjustment (Zhou et al., 2015).

3.4.2 Calibration results

Table 7 presents the first set of calibration results comparing observed and simulated traffic volumes at the study intersections.

Table 7. Model calibration results using GEH statistic-Part 1

Intersection	Entry by	Cars (Obs)	Vol (Obs)	Cars (Sim)	Vol (Sim)	GEH Cars	GEH Vol	Status
Jr. Libertad-Av. M. Cáceres	Jr. Libertad	479	888	454	814	1	3	verified
Jr. Libertad-Av. M. Cáceres	Av. M. Cáceres-E	202	359	213	447	1	4	verified
Jr. Libertad-Av. M. Cáceres	Av. M. Cáceres-O	20	41	13	40	2	0	verified
Jr. Libertad-Jr. Bellido	Jr. Libertad	475	976	467	920	0	2	verified
Jr. Libertad-Jr. Bellido	Jr. Bellido	233	324	220	320	1	1	verified
Jr. Libertad-Jr. Callao	Jr. Libertad	574	964	420	834	7	4	verified
Jr. Libertad-Jr. Callao	Jr. Callao	257	398	253	427	0	1	verified
Jr. Libertad-Jr. Lima	Jr. Libertad	665	1141	567	1121	4	1	verified
Jr. Libertad-Jr. Lima	Jr. Lima	131	390	120	380	1	1	verified
Jr. Libertad-Jr. San Martín	Jr. San Martín-O	76	243	73	240	0	0	verified
Jr. Libertad-Jr. San Martín	Jr. Libertad	449	999	427	1041	1	1	verified
Jr. Libertad-Jr. San Martín	Jr. San Martín-E	285	610	287	647	0	1	verified
Jr. Libertad-Jr. F. Vivanco	Jr. Libertad	701	1475	694	1534	0	2	verified
Jr. Garcilaso-Av. M. Cáceres	Jr. Garcilaso	440	735	474	847	2	4	verified
Jr. Garcilaso-Av. M. Cáceres	Av. M. Cáceres-O	92	127	80	127	1	0	verified
Jr. Garcilaso-Av. M. Cáceres	Av. M. Cáceres-E	258	451	227	467	2	1	verified
Jr. Garcilaso-Jr. Bellido	Jr. Garcilaso	465	764	494	900	1	5	verified
Jr. Garcilaso-Jr. Bellido	Jr. Bellido	273	389	260	400	1	1	verified
Jr. Garcilaso-Jr. Callao	Jr. Garcilaso	391	701	420	787	1	3	verified
Jr. Garcilaso-Jr. Callao	Jr. Callao	338	521	287	467	3	2	verified
Jr. Garcilaso-Jr. Lima	Jr. Grau	368	689	394	787	1	4	verified
Jr. Garcilaso-Jr. Lima	Jr. Lima	274	426	233	400	1	1	verified
Jr. Grau-Jr. San Martín	Jr. Grau	234	560	227	547	0	1	verified
Jr. Grau-Jr. San Martín	Jr. San Martín	439	819	414	807	1	0	verified
Jr. Grau-Jr. F. Vivanco	Jr. Grau	279	592	267	574	1	1	verified
Jr. Grau-Jr. F. Vivanco	Jr. F. Vivanco	413	867	380	834	2	1	verified
Jr. 9 de Dic.-Av. M. Cáceres	Av. M. Cáceres-E	241	429	173	380	5	2	verified
Jr. 9 de Dic.-Av. M. Cáceres	Av. M. Cáceres-O	104	196	100	193	0	0	verified
Jr. 9 de Dic.-Av. M. Cáceres	Jr. 9 de diciembre	309	477	340	567	2	4	verified
Jr. 9 de Dic.-Jr. Bellido	Jr. 9 de diciembre	353	546	307	514	3	1	verified
Jr. 9 de Dic.-Jr. Bellido	Jr. Bellido	283	404	300	487	1	4	verified
Jr. 9 de Dic.-Jr. Callao	Portal Unión	809	1202	760	1201	2	0	verified
Jr. 28 de Julio-Jr. Lima	Portal Independencia	170	216	160	207	1	1	verified
Jr. 28 de Julio-Jr. Lima	Jr. Lima	342	485	240	454	6	1	verified
Jr. 28 de Julio-Jr. San Martín	Jr. San Martín	439	819	407	800	2	1	verified
Jr. 28 de Julio-Jr. F. Vivanco	Jr. F. Vivanco	442	873	434	900	0	1	verified
Jr. Asamblea-Av. M. Cáceres	Jr. Asamblea	475	751	407	640	3	4	verified
Jr. Asamblea-Av. M. Cáceres	Av. M. Cáceres-E	239	504	133	320	8	9	acceptable
Jr. Asamblea-Av. M. Cáceres	Av. M. Cáceres-O	121	228	113	233	1	0	verified
Jr. Asamblea-Jr. Bellido	Jr. Bellido	256	361	273	447	1	4	verified

Note: GEH, Geoffrey E. Havers; obs, observed, sim, simulated; vol, volume; Av., Avenida (Avenue); Jr., Jirón (Street); E, East; O, Oeste (West).

Table 8 presents the continuation of the calibration results. The combined results demonstrate that 87% of the calibration points achieved GEH values below 5, meeting the industry-standard threshold of 85% compliance for mesoscopic models.

3.4.3 Number of simulation runs

The number of simulation runs required to achieve statistical stability was determined using Eq. (2):

$$N = \left(\frac{K \cdot S}{E} \right)^2 \quad (2)$$

where, N is the required number of runs, K is the confidence level coefficient (1.96 for 95% confidence), S is the standard deviation of results from preliminary runs, and E is the acceptable error margin (set at 5% of the mean). Based on preliminary runs, a minimum of 23 simulation replications were required, and 25 runs were performed to ensure robust results (Lizarbe Alarcón et al., 2025).

3.4.4 Model validation

Model validation was conducted by comparing simulated travel times against field-measured travel times for representative routes through the study area. The Wilcoxon signed-rank test was applied to assess whether

significant differences existed between simulated and observed values, given that the data did not meet normality assumptions based on the Kolmogorov-Smirnov test ($p < 0.05$). Results showed no significant difference between simulated and observed travel times ($p = 0.342$), confirming the validity of the calibrated model for emission estimation purposes.

Table 8. Model calibration results using GEH statistic-Part 2

Intersection	Entry by	Cars (Obs)	Vol (Obs)	Cars (Sim)	Vol (Sim)	GEH Cars	GEH Vol	Status
Jr. Asamblea-Jr. Cusco	Portal Municipal	466	728	447	687	1	2	verified
Jr. Asamblea-Jr. Cusco	Jr. Cusco	350	459	273	427	4	2	verified
Jr. 2 de Mayo-Jr. Arequipa	Jr. 2 de Mayo	409	708	380	634	1	3	verified
Jr. 2 de Mayo-Jr. Arequipa	Po. Constitucional	443	629	374	607	3	1	verified
Jr. 2 de Mayo-Jr. San Martín	Jr. 2 de Mayo	365	636	293	500	4	6	acceptable
Jr. 2 de Mayo-Jr. San Martín	Jr. San Martín	587	997	507	927	3	2	verified
Jr. 2 de Mayo-Jr. F. Vivanco	Jr. 2 de Mayo	379	713	267	500	6	9	acceptable
Jr. 2 de Mayo-Jr. F. Vivanco	Jr. F. Vivanco	442	873	420	867	1	0	verified
Pje. Cáceres-Av. M. Cáceres	Av. M. Cáceres-E	239	504	167	400	5	5	verified
Pje. Cáceres-Av. M. Cáceres	Av. M. Cáceres-O	547	1020	467	794	4	8	acceptable
Jr. 3 Máscaras-Av. M. Cáceres	Av. M. Cáceres-O	522	985	440	767	4	7	acceptable
Jr. 3 Máscaras-Av. M. Cáceres	Av. M. Cáceres-E	404	771	287	600	6	7	acceptable
Jr. 3 Máscaras-Jr. Bellido	Jr. 3 Máscaras	532	965	407	714	6	9	acceptable
Jr. 3 Máscaras-Jr. Bellido	Jr. Bellido	256	361	273	447	1	4	verified
Jr. 3 Máscaras-Jr. Cusco	Jr. 3 Máscaras	670	1102	507	894	7	7	acceptable
Jr. 3 Máscaras-Jr. Cusco	Jr. Cusco	295	425	233	387	4	2	verified
Jr. 3 Máscaras-Jr. Arequipa	Jr. 3 Máscaras	623	1051	474	854	6	6	acceptable
Jr. 3 Máscaras-Jr. Arequipa	Jr. Arequipa	407	661	320	567	5	4	verified
Jr. 3 Máscaras-Jr. San Martín	Jr. 3 Máscaras	355	661	273	627	5	1	verified
Jr. 3 Máscaras-Jr. San Martín	Jr. San Martín	479	865	427	780	2	3	verified
Jr. 3 Máscaras-Jr. F. Vivanco	Jr. 3 Máscaras	258	492	207	480	3	1	verified
Jr. 3 Máscaras-Jr. F. Vivanco	Jr. F. Vivanco	415	902	380	887	2	1	verified
Jr. Sol-Av. M. Cáceres	Jr. Sol	404	797	340	794	3	0	verified
Jr. Sol-Av. M. Cáceres	Av. M. Cáceres-E	371	788	293	627	4	6	verified
Jr. Sol-Av. M. Cáceres	Av. M. Cáceres-O	121	284	120	227	0	4	verified
Jr. Sol-Jr. Untiveros	Jr. Untiveros	234	496	193	434	3	3	verified
Jr. Sol-Jr. Bellido	Jr. Bellido	201	285	180	280	1	0	verified
Jr. Sol-Jr. Bellido	Jr. Sol	233	439	200	474	2	2	verified
Jr. Sol-Jr. Cusco	Jr. Sol	256	477	193	460	4	1	verified
Jr. Sol-Jr. Cusco	Jr. Cusco	295	437	253	420	3	1	verified
Jr. Sol-Jr. Arequipa	Jr. Arequipa-O	657	989	527	827	5	5	acceptable
Jr. Sol-Jr. Arequipa	Jr. Arequipa-E	150	385	140	427	1	2	verified
Jr. Sol-Jr. San Martín	Jr. Sol	593	972	507	874	4	3	verified
Jr. Sol-Jr. San Martín	Jr. San Martín	451	838	440	827	1	0	verified
Jr. Pizarro-Jr. Bellido	Jr. Bellido	246	353	200	313	3	2	verified
Jr. Pizarro-Jr. Bellido	Jr. Pizarro	713	1542	614	1394	4	4	verified
Jr. Pizarro-Jr. Cusco	Jr. Cusco	106	146	93	140	1	0	verified
Jr. Pizarro-Jr. Cusco	Jr. Pizarro	901	1833	754	1641	5	5	verified
Jr. Pizarro-Jr. Caviedes	Jr. Caviedes	539	701	414	694	6	0	verified
Jr. Pizarro-Jr. Caviedes	Jr. Pizarro	893	1964	780	1674	4	7	acceptable

Note: GEH, Geoffrey E. Havers; obs, observed, sim, simulated; vol, volume; Av., Avenida (Avenue); Jr., Jirón (Street); E, East; O, Oeste (West).

3.5 Emission Estimation Methodology

3.5.1 Vehicle Specific Power approach

Vehicle emissions were estimated using the emission calculation module integrated within PTV Vissim. The module first derives fuel consumption from the simulated vehicle dynamics, and then obtains CO, NO_x and VOC by applying a constant emission factor to that fuel consumption. This is why the three pollutants keep a fixed ratio to one another throughout the network. The underlying formulation follows the VSP based methodology (Rahimi et al., 2023). VSP represents the instantaneous power demand per unit mass of the vehicle and is calculated using Eq. (3):

$$VSP = V \times (1.1a + 9.81 \times \text{grade} + 0.132) + 0.000302 \times v^3 \quad (3)$$

where, v is vehicle speed (m/s), a is acceleration (m/s²), and grade is the road gradient (decimal fraction). The VSP

approach captures the dynamic relationship between vehicle operating conditions and emissions, accounting for the increased emissions during acceleration and idling that characterize congested traffic (Borrego et al., 2016).

3.5.2 Speed-emission relationship

The relationship between vehicle speed and emission rate follows a U-shaped curve. Emissions are highest at very low speeds, where incomplete combustion occurs during idling and stop-and-go conditions, and at very high speeds, where power demand increases. Beyond that point the curve flattens and reaches its minimum at high cruising speeds, before rising again (Samaras et al., 2019). This pattern explains why congested traffic at low speeds generates higher emission rates per unit of distance travelled.

3.5.3 Pollutant selection

Three pollutants were selected for analysis based on their direct calculability from traffic microsimulation outputs and their relevance to urban air quality:

CO: A product of incomplete combustion, highly sensitive to vehicle speed and acceleration patterns. CO is the primary indicator of combustion efficiency and is particularly elevated during idling and stop-and-go traffic conditions.

NO_x: Formed at high combustion temperatures, NO_x emissions are influenced by engine load and operating conditions. NO_x is a precursor to ground-level ozone and contributes to respiratory health impacts (Tirico et al., 2025a).

VOC: Include unburned hydrocarbons and evaporative emissions. VOC contribute to photochemical smog formation and are associated with various health effects (Tsekeri et al., 2025).

These three pollutants also present well-documented health impacts in urban environments. CO impairs oxygen transport in blood, NO_x contributes to respiratory disease and smog formation, and VOC act as precursors of photochemical oxidants. Restricting the analysis to gaseous pollutants preserves methodological consistency between traffic simulation and emission estimation, since all three are direct outputs of the VSP-based module and require no external coupling with dispersion models.

3.5.4 Emission factors

Table 9 presents the emission factors applied by the simulation module. Each factor converts the modelled fuel consumption into a mass of pollutant, so the three pollutants scale together with fuel use.

3.5.5 Exclusion of particulate matter

Particulate matter (PM₁₀ and PM_{2.5}) was not included in this study as its estimation requires coupling traffic simulation with atmospheric dispersion models such as AERMOD or RLINE, which account for meteorological conditions, atmospheric stability, and pollutant transport mechanisms (Lee & Batterman, 2026). The estimation of PM emissions from traffic sources also requires detailed information on brake and tire wear, road surface characteristics, and resuspension processes that were beyond the scope of the current investigation (Lorenzo-Sáez et al., 2025).

Table 9. Emission factors applied to the modelled fuel consumption

Pollutant	Emission Factor (g/L of fuel)	Emission Factor (g/gallon of fuel)
CO	18.47	69.9
NO _x	3.59	13.6
VOC	4.28	16.2

Note: CO, carbon monoxide; NO_x, nitrogen oxides; VOC, volatile organic compounds.

3.5.6 Emission calculation procedure

Emissions were calculated for each road segment during both the one-hour simulation period under congested conditions and the corresponding free-flow scenario. The simulation outputs provided second-by-second vehicle positions, speeds, and accelerations, which were converted to emission rates using the VSP-based emission factors. Results were aggregated at the segment level to generate emission inventories and subsequently interpolated to create spatial heat maps identifying pollution hotspots within the study area.

3.6 Statistical Analysis

3.6.1 Normality testing

Statistical analysis was performed using IBM SPSS Statistics version 25.0 to compare emission levels between free-flow and congested conditions. The Kolmogorov-Smirnov test was first applied to assess the normality of emission data distributions. Given that the data did not meet normality assumptions ($p < 0.05$ for all pollutants), non-parametric tests were employed for comparative analysis.

3.6.2 Hypothesis testing

The Wilcoxon signed-rank test was used to evaluate whether statistically significant differences existed between emissions under free-flow and congested conditions for each pollutant (CO, NO_x, VOC) and fuel consumption. This paired non-parametric test was appropriate given the matched nature of the data (same road segments under different traffic conditions) and the non-normal distribution of emission values. A significance level of $\alpha = 0.05$ was adopted for all statistical tests.

3.6.3 Spatial analysis

Spatial analysis of emission hotspots was performed by aggregating segment-level emissions and applying inverse distance weighting (IDW) interpolation to generate continuous emission surfaces across the study area. The resulting heat maps were classified into five emission intensity categories using natural breaks (Jenks) classification to identify critical zones requiring priority intervention.

4. Results

4.1 Traffic Simulation Outputs

The calibrated PTV Vissim model was executed for 25 simulation runs under both free-flow and congested conditions. Figure 11 presents the simulation visualization during peak hour, capturing the characteristic stop-and-go traffic patterns observed in the historic center.



Figure 11. Traffic simulation visualization in PTV Vissim during peak hour conditions

Figure 12 presents the spatial distribution of average speeds across the study area during peak hour. The speed map reveals reduced velocities in the central zone, particularly along Jr. 2 de Mayo, Jr. 3 Máscaras, and Jr. Carlos F. Vivanco, where average speeds dropped below 8 km/h.

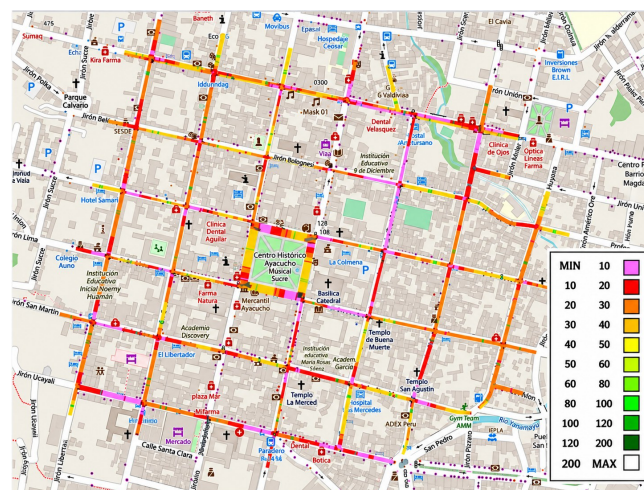


Figure 12. Spatial distribution of average vehicle speeds during peak hour (km/h)

4.2 Emission Estimation Results

Table 10 presents the emission results for the main road segments during peak hour, including CO, NO_x, VOC, and fuel consumption. The highest emission levels were identified in Jr. 2 de Mayo-Jr. Arequipa, Jr. Pizarro-Jr.

Bellido, Jr. Libertad-Jr. San Martín, and Jr. Pizarro-Jr. Cusco.

Table 10. Emission results by road segment during peak hour (g/km)

No.	Intersection	CO (g/km)	NO _x (g/km)	VOC (g/km)	Fuel (L)
1	Jr. Libertad-Av. M. Cáceres	942.35	183.35	218.4	51.03
2	Jr. Libertad-Jr. Bellido	1359.24	264.46	315.02	73.63
3	Jr. Libertad-Jr. Callao	911.07	177.26	211.15	49.32
4	Jr. Libertad-Jr. Lima	1191.1	231.74	276.05	64.5
5	Jr. Libertad-Jr. San Martín	1880.16	365.81	435.75	101.83
6	Jr. Libertad-Jr. F. Vivanco	1066.42	207.49	247.15	57.77
7	Jr. Garcilaso de la V.-Av. M. Cáceres	786.25	152.97	182.22	42.59
8	Jr. Garcilaso de la V.-Jr. Bellido	769.87	149.79	178.43	41.68
9	Jr. Garcilaso de la V.-Jr. Callao	804.59	156.54	186.47	43.57
10	Jr. Garcilaso de la V.-Jr. Lima	668.6	130.09	154.95	36.23
11	Jr. Grau-Jr. San Martín	824.73	160.46	191.14	44.67
12	Jr. Grau-Jr. F. Vivanco	1173.82	228.38	272.04	63.56
13	Jr. 9 de Diciembre-Av. M. Cáceres	697.29	135.67	161.61	37.78
14	Jr. 9 de Diciembre-Jr. Bellido	461.03	89.7	106.85	24.98
15	Jr. 9 de Diciembre-Jr. Callao	524.51	102.05	121.56	28.39
16	Jr. 28 de Julio-Jr. Lima	339.79	66.11	78.75	18.4
17	Jr. 28 de Julio-Jr. San Martín	302.07	58.77	70.01	16.35
18	Jr. 28 de Julio-Jr. F. Vivanco	800.45	155.74	185.52	43.34
19	Jr. Asamblea-Av. M. Cáceres	733.46	142.7	169.98	39.71
20	Jr. Asamblea-Jr. Bellido	550.07	107.02	127.49	29.79
21	Jr. Asamblea-Jr. Cusco	638.96	124.32	148.08	34.6
22	Jr. 2 de Mayo-Jr. Arequipa	2270.6	441.78	526.24	122.95
23	Jr. 2 de Mayo-Jr. San Martín	1737.14	337.98	402.6	94.07
24	Jr. 2 de Mayo-Jr. F. Vivanco	1428.06	277.85	330.97	77.34
25	Pje. Cáceres-Av. M. Cáceres	244.4	47.55	56.64	13.25
26	Jr. 3 Máscaras-Av. M. Cáceres	1066.3	207.46	247.13	57.77
27	Jr. 3 Máscaras-Jr. Bellido	1678.67	326.61	389.05	90.93
28	Jr. 3 Máscaras-Jr. Cusco	1459.05	283.88	338.15	79
29	Jr. 3 Máscaras-Jr. Arequipa	1462.42	284.54	338.93	79.19
30	Jr. 3 Máscaras-Jr. San Martín	940.94	183.07	218.07	50.95
31	Jr. 3 Máscaras-Jr. F. Vivanco	1385.57	269.58	321.12	75.03
32	Jr. Sol-Av. M. Cáceres	1077.22	209.59	249.65	58.33
33	Jr. Sol-Jr. Untiveros	583.3	113.49	135.19	31.57
34	Jr. Sol-Jr. Bellido	758.89	147.65	175.88	41.11
35	Jr. Sol-Jr. Cusco	507.91	98.82	117.71	27.48
36	Jr. Sol-Jr. Arequipa	520	101.17	120.52	28.16
37	Jr. Sol-Jr. San Martín	1262.09	245.56	292.5	68.36
38	Jr. Pizarro-Jr. Bellido	1987.45	386.69	460.61	107.62
39	Jr. Pizarro-Jr. Cusco	1812.65	352.68	420.1	98.16
40	Jr. Pizarro-Jr. Arequipa	629.49	122.48	145.89	34.11
41	Jr. Pizarro-Jr. Caviedes	703.02	136.78	162.93	38.08

Note: Av., Avenida (Avenue); Jr., Jirón (Street); CO, carbon monoxide; NO_x, nitrogen oxides; VOC, volatile organic compounds.

Figure 13 presents the comparison of emissions across road segments, illustrating the concentration of pollutants in the central zone.

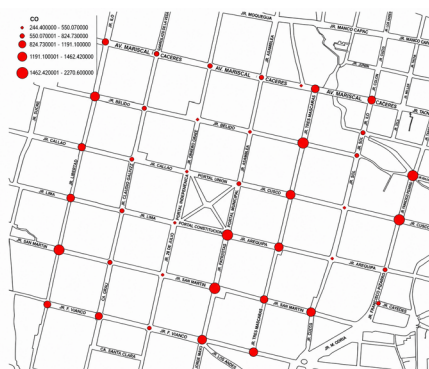


Figure 13. Comparison of carbon monoxide (CO) emissions by road segment during peak hour

4.3 Spatial Distribution of Emissions

Figure 14 presents the emission heat map showing the spatial distribution of CO emissions across the historic center. Four road segments stand out above the rest, and all of them lie in the central zone:

- Jr. 2 de Mayo-Jr. Arequipa: 2270.60 g CO/km.
- Jr. Pizarro-Jr. Bellido: 1987.45 g CO/km.
- Jr. Libertad-Jr. San Martín: 1880.16 g CO/km.
- Jr. Pizarro-Jr. Cusco: 1812.65 g CO/km.

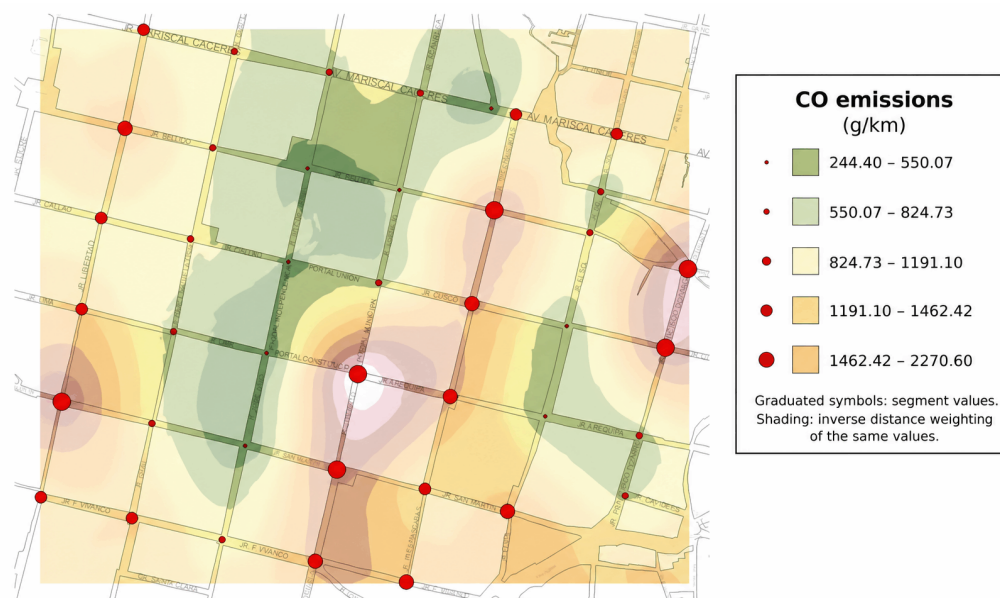


Figure 14. Spatial heat map of carbon monoxide (CO) emissions in the historic center of Ayacucho

4.4 Comparison Between Free-Flow and Congested Conditions

Table 11 compares emissions between free-flow and congested conditions for ten representative segments; the statistical tests reported below cover all 41 segments. Across the network, congestion raised CO, NO_x and VOC by 59% and fuel consumption by 63%. The three pollutants share a single figure because the simulation module derives them from fuel consumption through constant factors.

Table 11. Comparison of emissions between free-flow and congested conditions for ten representative segments

No.	Intersection	CO Congested	CO Free-Flow	NO _x Congested	NO _x Free-Flow	VOC Congested	VOC Free-Flow	Fuel Congested	Fuel Free-Flow
1	Jr. Libertad-Av. M. Cáceres	942.35	943.32	183.35	183.53	218.4	218.63	13.48	13.49
5	Jr. Libertad-Jr. San Martín	1880.16	1087.38	365.81	211.57	435.75	252.01	26.9	15.55
12	Jr. Grau-Jr. F. Vivanco	1173.82	637.6	228.38	124.05	272.04	147.77	16.79	9.12
22	Jr. 2 de Mayo-Jr. Arequipa	2270.6	872.05	441.78	169.67	526.24	202.11	32.48	12.47
23	Jr. 2 de Mayo-Jr. San Martín	1737.14	1090.54	337.98	212.18	402.6	252.75	24.85	15.6
27	Jr. 3 Máscaras-Jr. Bellido	1678.67	1093.03	326.61	212.67	389.05	253.32	24.02	15.64
28	Jr. 3 Máscaras-Jr. Cusco	1459.05	912.17	283.88	177.47	338.15	211.41	20.87	13.05
38	Jr. Pizarro-Jr. Bellido	1987.45	583.62	386.69	113.55	460.61	135.26	28.43	8.35
39	Jr. Pizarro-Jr. Cusco	1812.65	522.69	352.68	101.69	420.1	121.14	25.93	7.48
37	Jr. Sol-Jr. San Martín	1262.09	1117.48	245.56	217.42	292.5	258.99	18.06	15.99

Note: Av., Avenida (Avenue); Jr., Jirón (Street); CO, carbon monoxide; NO_x, nitrogen oxides; VOC, volatile organic compounds.

4.5 Pollutant-Specific Emission Patterns

Figures 15 and 16 present the total emissions of CO and NO_x by road segment, respectively. The spatial patterns reveal concentration of pollutants in the central zone, with NO_x showing proportionally higher values along public transport corridors.

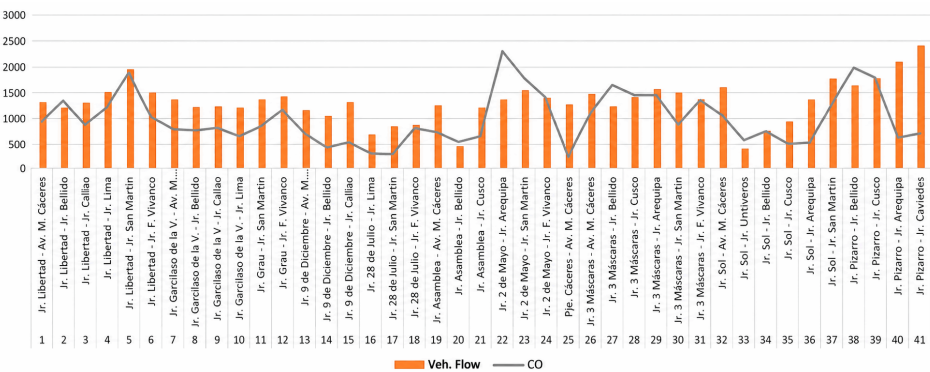


Figure 15. Total carbon monoxide (CO) emissions by road segment in the study area

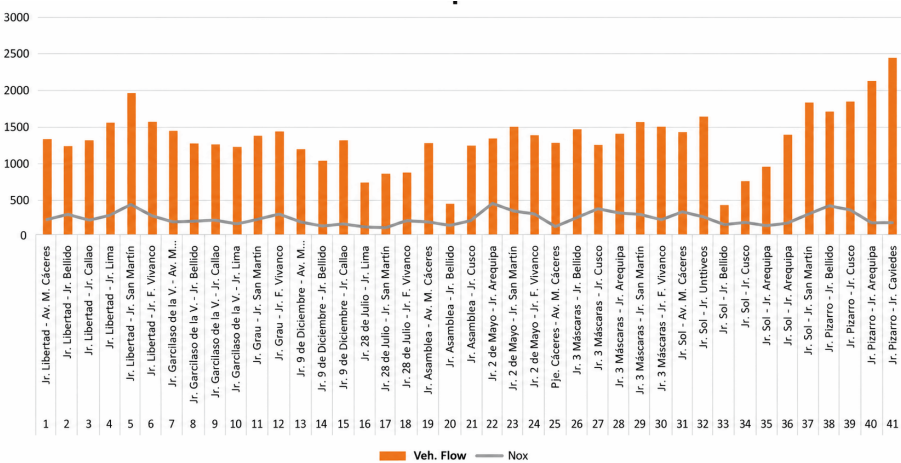


Figure 16. Total nitrogen oxides (NO_x) emissions by road segment in the study area

Figure 17 compares emission levels across the four identified hotspots for the three pollutants analyzed. Jr. 2 de Mayo-Jr. Arequipa exhibits the highest values in every pollutant category, and its CO emission rate exceeds the network average of 998.56 g/km by 127%. The ranking of hotspots remains consistent across pollutant types, which indicates that congestion intensity rather than fleet composition drives the elevated emissions in these segments. This finding supports targeting these corridors as a priority for traffic management interventions.

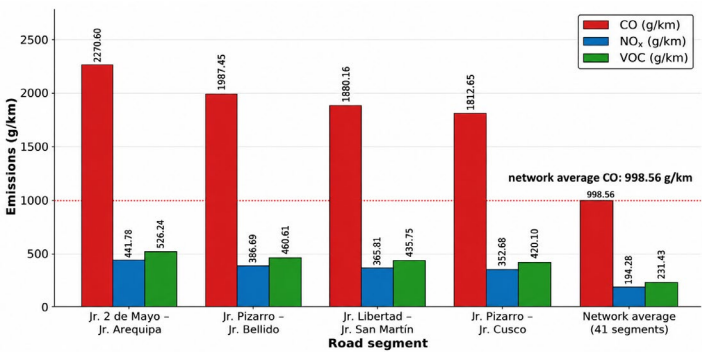


Figure 17. Comparative analysis of carbon monoxide (CO), nitrogen oxides (NO_x), and volatile organic compounds (VOC) emissions at identified hotspots versus network average

4.6 Statistical Validation

The Kolmogorov-Smirnov test confirmed non-normal distribution for all emission variables ($p < 0.05$). Table 12 presents the Wilcoxon signed-rank test results, confirming statistically significant differences between congested and free-flow conditions for all pollutants ($p < 0.001$).

Table 12. Statistical validation results (Wilcoxon signed-rank test)

Variable	N	z-Statistic	p-Value	Decision
CO emissions (Congested-free-flow)	41	-5.578	<0.001	Reject H_0
NO _x emissions (Congested-free-flow)	41	-5.534	<0.001	Reject H_0
VOC emissions (Congested-free-flow)	41	-5.512	<0.001	Reject H_0
Fuel consumption (Congested-free-flow)	41	-5.489	<0.001	Reject H_0

Note: N, number of observations; CO, carbon monoxide; NO_x, nitrogen oxides; VOC, volatile organic compounds.

5. Discussion

5.1 Comparison with Previous Studies

The 59% increase in CO emissions under congested conditions is consistent with previous research. Samaras et al. (2019) reported that fuel consumption can increase by more than 18% under congested conditions in European urban corridors. The 63% increase obtained here reflects the more severe congestion levels characteristic of narrow historic streets. Tirico et al. (2025a) found that street-level traffic models capture local variations and congested conditions more accurately, which supports the use of mesoscopic simulation for emission estimation in this context.

The spatial concentration of emissions in specific hotspots aligns with observations by Duong & Odai (2025), who reported that narrow, high-walled corridors accumulate higher NO₂ loads than broader streets. In Ayacucho, the colonial street morphology with widths between 6 and 8 meters creates similar urban canyon effects that exacerbate pollutant retention and limit dispersion.

5.2 Traffic Dynamics Analysis of Emission Hotspots

The concentration of high emissions in specific road segments responds to identifiable traffic dynamics and urban morphology factors. Analysis of the four critical hotspots reveals common characteristics that explain their elevated emission levels.

Street geometry constraints: The four hotspots lie on the narrowest streets of the network. Their reduced width limits vehicle maneuvering and increases the frequency of deceleration and acceleration cycles. This narrow configuration creates urban canyon effects that not only concentrate pollutants but also restrict traffic flow capacity (Duong & Odai, 2025).

Signalized intersection proximity: All four hotspots lie close to signalized intersections that run on fixed-time cycles. The lack of signal coordination forces vehicles to stop at consecutive intersections, generating repeated idling periods that significantly increase emissions. The VSP methodology captures these stop-and-go dynamics, which produce emission rates 3–4 times higher than steady-state cruising at the same average speed (Rahimi et al., 2023).

Traffic volume concentration: The convergent urban morphology of the historic center channels traffic from multiple origin points toward the central plaza. Jr. 2 de Mayo-Jr. Arequipa receives traffic from three major arterial roads and approaches saturation during peak hours. This near-saturation condition results in queue spillback that extends congestion to upstream segments, amplifying the spatial extent of high-emission zones.

Speed reduction severity: The hotspot segments exhibited average speeds below 8 km/h during peak hours, representing speed reductions of 56%–72% compared to free-flow conditions. This speed range lies on the steep portion of the speed-emission relationship, where small reductions in speed produce disproportionately large increases in emissions (Samaras et al., 2019).

Commercial activity influence: the concentration of commercial establishments along Jr. 3 Máscaras and Jr. Carlos F. Vivanco generates frequent curbside stopping for loading and unloading, which further reduces effective road capacity and creates additional acceleration and deceleration events. Quantifying this effect was beyond the scope of the present study, although field observations indicate that curbside activity reduces effective capacity during peak commercial hours.

These findings indicate that emission reduction strategies should prioritize signal timing optimization at intersections adjacent to hotspots, enforcement of loading and unloading restrictions during peak hours, and possible modifications to one-way circulation that reduce conflicting movements. The spatial specificity of the emission patterns identified enables targeted interventions rather than network-wide restrictions, which could

affect the commercial viability of the historic center.

5.3 Methodological Contributions

The integration of UAV-based traffic monitoring with PTV Vissim mesoscopic simulation represents a novel methodological approach for emission assessment in historic urban centers of developing countries. Unlike studies conducted in European cities with established traffic monitoring infrastructure (Borrego et al., 2016; Song et al., 2025), our methodology addresses the data scarcity challenge common in Latin American intermediate cities by leveraging drone technology for comprehensive traffic data collection.

Calibration reached a GEH below 5 at 81% of the points, slightly below the 85% guideline applied in practice, and every point fell below a GEH of 10. This level of agreement supports the use of mesoscopic simulation in complex urban environments with narrow streets and mixed traffic (Lizarbe Alarcón et al., 2025). This validation is particularly significant given the absence of permanent traffic monitoring stations in the study area.

5.4 Implications for Urban Air Quality Management

The observed emission increases under congested conditions acquire particular environmental relevance in the context of historic centers. Unlike modern urban roads designed with wide corridors and open spaces, the colonial streets of Ayacucho's historic center present urban canyon configurations with height-to-width ratios that severely limit pollutant dispersion. This urban morphology implies that generated emissions remain concentrated at street level, where pedestrian exposure is maximum. Residents, merchants, and visitors who transit daily through these heritage spaces are exposed to higher pollutant concentrations than they would experience on roads with better natural ventilation. Furthermore, the colonial architectural heritage, including adobe facades, carved stone, and historic decorative elements, presents susceptibility to deterioration from particle deposition and the corrosive action of NO_x, affecting the cultural and historical value that underlies the heritage zone designation. Therefore, the identified emission hotspots constitute not only public health concerns but also priorities for the conservation of the city's cultural heritage.

The identification of four emission hotspots provides actionable evidence for targeted interventions. The concentration of highest emissions along Jr. 3 Máscaras and Jr. Carlos F. Vivanco suggests that traffic management measures should prioritize these corridors. As demonstrated by Pérez-Martínez et al. (2025), high-resolution emission inventories enable the identification of air pollution hotspots with sufficient spatial detail to inform local policy decisions.

The findings support the implementation of strategies such as traffic signal synchronization, access restrictions during peak hours, and promotion of alternative transport modes. Research by Piccoli et al. (2025) on zero emission zones in Milan demonstrated potential NO_x reductions of up to 84%, suggesting that similar interventions could significantly reduce emissions in Ayacucho's historic center.

The results offer three direct applications for urban planning and traffic management in the historic center. First, the emission heat maps allow municipal authorities to prioritize interventions on the road segments where the highest emission rates concentrate, which optimizes the allocation of limited resources. The four critical hotspots constitute priority locations for measures such as signal cycle optimization, regulation of commercial loading and unloading schedules, and evaluation of changes to traffic flow direction. Second, the maps provide technical criteria for siting future air quality monitoring stations, which would permit validation of the model estimates against ambient measurements. Third, the calibrated model can be used to analyze intervention scenarios before implementation, allowing planners to compare the effects of alternative management strategies on vehicular emissions. This predictive capacity is particularly valuable where resources for trial interventions are limited.

5.5 Integration of Internet of Things and Real-Time Monitoring

The emission heat maps generated in this study provide a foundation for the implementation of Internet of Things (IoT)-based real-time monitoring systems. As proposed by Naizabayeva et al. (2024), integrating smart traffic systems with air quality monitoring could enable dynamic traffic management responsive to pollution levels. The identified hotspots represent priority locations for sensor deployment in future monitoring networks.

Roy et al. (2025) demonstrated that deep learning frameworks can jointly predict traffic emissions and travel delay, suggesting opportunities for predictive emission management in historic centers. The mesoscopic model developed in this study could be coupled with machine learning algorithms to enable real-time emission forecasting and adaptive traffic control.

5.6 Limitations

It is important to clarify the methodological scope of this research. The results presented correspond to vehicular

emission estimates at source, that is, the quantities of pollutants released by vehicles during their operation on the road network. These values should not be interpreted as ambient air quality concentrations or as direct assessments of population exposure. The transition from source emissions to ambient concentrations requires coupling with atmospheric dispersion models that consider meteorological variables such as wind speed and direction, atmospheric stability, mixing layer height, and deposition and chemical transformation processes. Consequently, the generated heat maps identify zones with elevated vehicular emission rates, which represent priority areas for traffic management interventions and for the future installation of air quality monitoring stations that would allow validation of the relationship between estimated emissions and measured ambient concentrations.

This study presents specific limitations that should be considered when interpreting the results. First, the emission estimation focused on CO, NO_x, and VOC as a deliberate delimitation of scope. Particulate matter assessment constitutes a complementary research line that requires additional methodologies, including coupling with atmospheric dispersion models (Lee & Batterman, 2026). Second, vehicular fleet composition was based on visual classification from UAV imagery, which may not capture variations in emission standards within each vehicle category. The emission factors applied therefore represent average values per category and may under- or overestimate emissions in segments where vehicles with atypical emission technologies predominate. The spatial emission patterns identified nevertheless remain valid, since they depend primarily on traffic dynamics and congestion conditions.

6. Conclusions

This study developed and validated a mesoscopic simulation framework for vehicular emission assessment in historic urban centers, adapted to intermediate Andean cities with complex urban geometry and limited environmental monitoring infrastructure. The emission heat maps generated locate the critical road segments with spatial precision and provide evidence for prioritising traffic management interventions. The framework is transferable to other intermediate Latin American cities with colonial historic centers, mixed vehicular composition, and limited resources for continuous air quality monitoring.

The main conclusions are as follows:

Traffic congestion increases vehicle emissions substantially. Congested conditions raised CO, NO_x, and VOC emissions and fuel consumption well above free-flow levels, and the differences were statistically significant for all pollutants analyzed ($p < 0.001$).

Four critical emission hotspots were identified in the central zone: Jr. 2 de Mayo-Jr. Arequipa, Jr. Pizarro-Jr. Bellido, Jr. Libertad-Jr. San Martín, and Jr. Pizarro-Jr. Cusco. These segments share narrow street widths, proximity to signalized intersections, and intense commercial activity.

The mesoscopic approach proved effective for emission assessment in historic centers with complex geometry. Calibration placed every point below a GEH of 10, which supports the use of the method in data-scarce environments.

UAV-based traffic monitoring provided comprehensive data collection across the complex urban geometry of the historic center, overcoming limitations of traditional ground-based counting methods in narrow colonial streets.

The emission heat maps generated through spatial interpolation provide actionable evidence for prioritizing traffic management interventions and identifying optimal locations for future air quality monitoring stations.

The methodology presented is directly replicable in other intermediate Latin American cities sharing similar characteristics: colonial historic centers with narrow streets, mixed traffic including motorcycles and mototaxis, fixed-time traffic signals, and limited air quality monitoring infrastructure. Cities such as Cusco and Arequipa in Peru, Sucre and Potosí in Bolivia, Popayán and Cartagena in Colombia, and Quito's historic center in Ecuador present comparable urban morphology and traffic challenges where this approach could provide valuable emission assessments without requiring permanent monitoring stations.

The emission heat maps generated in this study establish a foundation for strategic deployment of IoT-based air quality monitoring systems. The identified hotspots represent priority locations for sensor installation, enabling real-time validation of simulation-based emission estimates and continuous monitoring of intervention effectiveness. Future research should explore the integration of low-cost air quality sensors at the four critical hotspots identified, coupled with real-time traffic detection systems to enable adaptive signal control responsive to both congestion and pollution levels.

Additionally, the mesoscopic simulation framework developed here could be extended to evaluate specific intervention scenarios, including the implementation of low-emission zones, peak-hour access restrictions, and coordinated signal timing along priority corridors. The combination of simulation-based prediction with IoT-enabled real-time monitoring represents a promising pathway toward evidence-based urban air quality management in medium-sized Latin American cities where resources for comprehensive monitoring networks remain limited.

Author Contributions

Conceptualization, H.L.A. and D.O.T.H.; methodology, H.L.A. and J.E.E.C.; software, H.L.A. and A.S.I.H.; validation, H.L.A., J.E.E.C., and F.D.L.C.P.; formal analysis, H.L.A. and E.E.A.A.; investigation, H.L.A., D.O.T.H., and L.A.V.M.; resources, F.D.L.C.P. and L.A.V.M.; data curation, E.E.A.A. and A.S.I.H.; writing—original draft preparation, H.L.A. and D.O.T.H.; writing—review and editing, J.E.E.C. and E.C.G.S.; visualization, A.S.I.H. and E.C.G.S.; supervision, H.L.A. and F.D.L.C.P.; project administration, H.L.A. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data supporting the research findings are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Declaration on the Use of Generative AI and AI-assisted Technologies

During the preparation of this manuscript, the authors used Claude (Anthropic) to edit the language and refine the style of the English text. The tool was not used to generate data, results, or references, and it did not replace the intellectual contribution of the authors. The authors reviewed and edited the output and take full responsibility for the content of this publication.

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