

Article

Real-World Emission Factors for Andean Light-Duty Vehicles Based on a PSV_{m10}-Validated Driving Cycle Across 0–4000 m Altitude

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Abstract

Emission inventories for high-altitude Andean cities rely on sea-level certification cycles that misrepresent real-world combustion conditions. This study derives altitude-resolved emission factors (EFs) for light-duty gasoline vehicles across 0–4000 m a.s.l. in Ecuador using the purpose-built Andean Ecuador Driving Cycle (AEDC), validated against naturalistic data via the Percentile Speed Vector metric (PSV_{m10}; IGS = 1.89 vs. IGS = 2.30 for the WLTC). Ten vehicles (Euro III–V) were instrumented with OBD-II and portable analysers recording CO, NO, HC, and CO₂ at 1 Hz over a four-year campaign (2021–2025; ≈2000 h). K-Means clustering on PSV_{m10} identified five operating regimes (silhouette ≈0.384). Under dynamically equivalent AEDC conditions, NO, CO, and HC all peaked in the 1000–2000 m band (NO: 0.188 g km^{−1}, 6.7× the sea-level value; CO: 4.47 g km^{−1}, +50%; HC: 0.047 g km^{−1}, +292%), fell in the 2000–3000 m band, and partially rebounded above 3000 m (NO: 0.186 g km^{−1}); CO₂ instead declined monotonically with altitude (182 to 119 g km^{−1}, −35%), tracking a near-stable-to-slightly-declining fuel consumption (8.56 to 8.11 L/100 km) consistent with reduced aerodynamic drag at altitude partially offsetting the density penalty. These results show that altitude affects pollutants through distinct, non-monotonic mechanisms rather than a uniform trend, so that single-coefficient altitude corrections introduce systematic bias in Andean emission inventories.

Keywords: real-world driving emissions; Andean Ecuador Driving Cycle (AEDC); altitude correction; Vehicle Specific Power; PSV_{m10} metric; light-duty vehicles; emission factors; high-altitude combustion; Ecuador



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1. Introduction

Road transport is responsible for approximately 23–25% of global energy-related CO₂ emissions, with light-duty vehicles (LDVs) accounting for a substantial share of both greenhouse gases and criteria pollutants (CO, HC, NO) in urban environments [1,2]. In Ecuador, LDVs represent roughly 70% of the registered fleet and constitute a primary source of urban air pollution [3]. The challenge is amplified by the country's pronounced altitudinal gradient: cities range from coastal Guayaquil (4 m a.s.l.) to highland Quito

(2850 m), Ambato (2577 m), and Riobamba (2754 m), while inter-city routes regularly cross passes above 4000 m [4].

At altitude, reduced atmospheric pressure diminishes intake-air density, lowers the mass of oxygen admitted per cycle, and forces the engine management system to enrich the air–fuel mixture. The resulting combustion inefficiency increases CO and HC output while simultaneously altering NO kinetics through reduced flame temperatures [5–7]. Empirical studies in China and Latin America have confirmed CO increments of up to $2.5\times$ at 2400 m relative to 700 m [8], and particle-number increases of up to 20-fold [9]. Yet most national emission inventories in the Andes apply correction factors derived from North American or European campaigns that rarely exceed 1500 m [10], introducing systematic bias whose magnitude grows with altitude.

A key methodological gap compounds this problem: no representative driving cycle exists for Ecuadorian operating conditions. Standard cycles (WLTC, FTP-75, NEDC) were designed for near-sea-level conditions and do not reproduce the kinematic aggressiveness, stop-and-go frequency, and sustained-grade climbing characteristic of Andean traffic patterns [11,12]. Cycle choice directly governs measured emission factors [13,14], making it impossible to construct reliable altitude-resolved inventories without a locally validated cycle.

The Vehicle Specific Power (VSP) framework, originally developed at MIT and adopted by the US EPA in the MOVES model [15,16], provides a physically interpretable descriptor of instantaneous engine load. The present study extends this framework by introducing PSV_{m10}, a 10-s moving-median formulation that captures the accumulated energy history of the vehicle, improving the predictive association with fuel consumption and emissions over instantaneous VSP [17].

Against this background, the study pursues three objectives:

1. Construct and validate the Andean Ecuador Driving Cycle (AEDC)—a representative driving cycle for Ecuadorian LDVs—using the PSV_{m10} statistical similarity framework.
2. Measure on-road emission factors for CO, NO, HC, and CO₂ across a continuous altitude range of 0–4000 m under dynamically equivalent driving conditions.
3. Characterise the altitude dependence of each pollutant and provide a quantitative basis for correcting Andean emission inventories.

The paper is organised as follows. Section 2 reviews altitude effects on internal combustion engines and driving-cycle construction methods. Section 3 describes the vehicle fleet, instrumentation, data collection campaigns, PSV_{m10} computation, and the AEDC construction and validation procedure. Section 4 presents the validated cycle, operating-regime clusters, and altitude-resolved emission factors. Section 5 interprets the results in the context of existing models and policy implications. Section 6 summarises the main findings and recommends future work.

2. Background

2.1. Altitude Effects on Light-Duty Gasoline Engines

As atmospheric pressure decreases with altitude, volumetric efficiency (η_v) falls proportionally with air density, reducing the oxygen mass admitted per cycle. Modern spark-ignition engines with closed-loop λ -control partially compensate via the manifold absolute pressure (MAP) sensor, but compensation is incomplete during transients, sustained grade climbing, and cold-start events. The net effect depends on the interaction between altitude, driving dynamics, and engine management strategy [5,18].

For CO and HC, the dominant mechanism is mixture enrichment under partial or full load, which promotes incomplete combustion. Observed increments in real-world campaigns range from +30% at 1500 m to more than 150% at 3000 m relative to sea-level

baselines [8,19]. NO behaviour in real-world conditions differs markedly from laboratory predictions: while controlled chamber tests show monotone NO reduction with altitude due to lower adiabatic flame temperatures, on-road studies reveal a dual or “N-shaped” response in which moderate altitudes generate elevated engine loads that raise combustion temperatures and increase NO, until very high altitudes (>2500 m) where oxygen scarcity dominates and NO decreases [20]. A predominantly monotone NO decline with altitude, consistent with the flame-temperature mechanism, has also been reported for gasoline fleets by Lyu et al. [19] and, in the diesel segment, by Lapuerta et al. [5], while the dual (N-shaped) response of Wang et al. [20] and Qi et al. [6] represents a second regime. The present study (Section 4.4) finds a third pattern for a fully Andean, gasoline-only fleet: an initial dual-response-like rise and fall up to 3000 m, consistent with Wang H. et al. and Qi et al., followed by a previously undocumented secondary rise above 3000 m, underscoring that the altitude–NO relationship is more heterogeneous across fleets, cycles, and altitude ranges than a single monotone or dual-response model can capture.

2.2. Driving Cycle Construction and the PSV_{m10} Method

A driving cycle must reproduce the kinematic and energetic signatures of real-world traffic to yield representative emission factors. Micro-trip concatenation, the method used here, segments naturalistic data into stop-to-stop fragments and selects and concatenates them to minimise deviation from a target statistical vector [11,12].

The Percentile Speed Vector method (PSV_{m10}) evaluates representativeness by comparing the speed–acceleration joint probability density of a candidate cycle against the naturalistic reference via a Global Similarity Index (IGS) computed as a normalised Euclidean distance:

$$\text{IGS} = \sqrt{\sum_{k=1}^K \left(\frac{p_{\text{cycle},k} - p_{\text{ref},k}}{p_{\text{ref},k}} \right)^2} \quad (1)$$

where $p_{\text{cycle},k}$ and $p_{\text{ref},k}$ denote the k -th kinematic metric of the candidate cycle and of the naturalistic reference, respectively (speed mean, speed P95, standard deviation, idle fraction, PKE, etc.). Lower IGS values indicate higher representativeness; the cycle developed here achieved $\text{IGS} = 1.89$ against experimental data vs. $\text{IGS} = 2.30$ for the WLTC class 3b, the latter computed by the authors by applying the same IGS procedure to the published WLTC class-3b speed–time trace against the Ecuadorian naturalistic reference, following the methodology validated in [17].

PSV_{m10} was preferred over the regulatory RDE completeness metrics $v \cdot a_{95\text{th}}$ and Relative Positive Acceleration (RPA) because those indices are designed to verify that a trip covers a sufficient dynamic range for certification purposes, whereas the present study required an instantaneous, continuously varying load descriptor that could be binned and matched at the 1-Hz level to isolate altitude effects from driving dynamics. $v \cdot a_{95\text{th}}$ and RPA are trip-level scalars unsuitable for this purpose. PSV_{m10}’s superior association with fuel consumption and emissions relative to instantaneous VSP was established via the Granger-causality analysis summarised in Table 5 and detailed in [17]; this evidence, rather than a claim of superiority over the regulatory metrics themselves, is the basis for adopting PSV_{m10} here. It should also be noted that an equivalent PSV_{m10} value between two segments indicates equivalent instantaneous power demand history, not an identical full speed–acceleration trajectory; for this reason, altitude-band matching (Section 3.8) combines PSV_{m10} with five additional kinematic descriptors rather than relying on PSV_{m10} alone.

The residual PSV_{m10} variable is defined as the retrospective moving median of the instantaneous VSP over a 10-s window:

$$PSV_{m10}(t) = \text{median}\{VSP(\tau) : \tau \in [t - 10, t)\} \quad (2)$$

Granger causality testing across windows of 1–20 s was used as descriptive, not confirmatory, evidence for window selection: none of the tested windows reached conventional statistical significance at $\alpha = 0.05$ (all $p > 0.05$; Table 5). The 10-s window was, therefore, selected primarily on physical grounds—it best matches engine-system inertia and drive-train response delay—and is reported alongside the window with the lowest (though still non-significant) p -value among physically plausible options ($p = 0.0566$), following [17]. This choice is revisited as a limitation in Section 5.4.

3. Materials and Methods

3.1. Study Region and Measurement Routes

Measurements were conducted along the central Andean corridor of Ecuador, spanning from coastal Guayaquil (4 m a.s.l.) to the Chimborazo Refuge approach road (4050 m). The corridor covers the principal inter-city routes linking the coast to the major highland cities and passes through representative urban, peri-urban, and mountain-road traffic environments (Table 1), illustrated in Figure 1.

Table 1. Measurement corridors and altitudinal coverage.

Corridor	Key Cities/Waypoints	Alt. Range (m)	Env. Type
Coastal	Guayaquil	4–50	Urban
Sierra low	Ambato, Riobamba	2500–2800	Urban/peri
Inter-city	Guayaquil–Quito	4–3600	Mixed
High-altitude	Riobamba–Chimborazo	2754–4050	Mountain

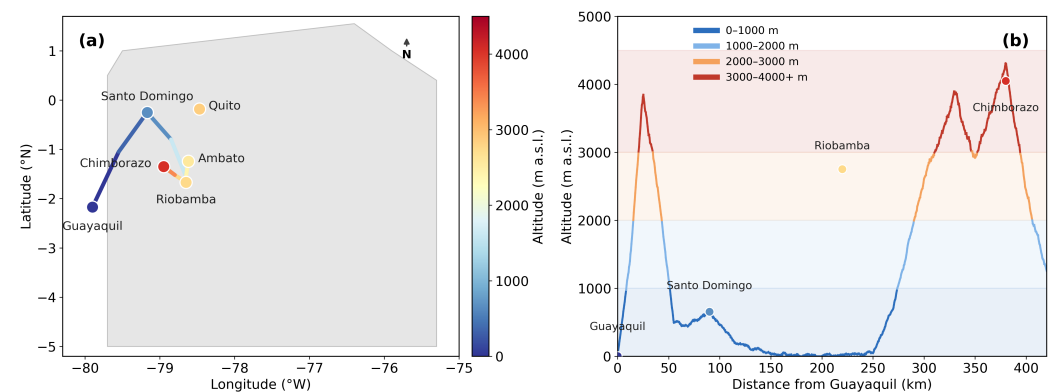


Figure 1. Experimental measurement routes in Ecuador covering 0–4050 m a.s.l.: (a) route map (latitude vs. longitude) coloured by altitude, showing the Guayaquil–Santo Domingo–Ambato–Riobamba–Quito corridor and the Riobamba–Chimborazo Refuge spur; (b) altitude profile along each route as a function of distance from Guayaquil, coloured by 1000 m altitude band. The main corridors are Guayaquil–Riobamba–Quito (west–east, sea level to 3600 m) and Riobamba–Chimborazo Refuge (up to 4050 m). Source: authors, from GPS data 2021–2025.

3.2. Vehicle Fleet

Ten light-duty gasoline vehicles representative of the Ecuadorian fleet were instrumented (Table 2). Selection criteria included displacement coverage (1000–2500 cm³), emission standard diversity (Euro III–V), and body-type variety (sedan, hatchback, SUV, van, pick-up). A total of ten trained drivers participated, one independently assigned to each vehicle (V01–V10) for the full four-year campaign; this design holds driving style constant within each vehicle’s record (rather than eliminating driver variability altogether),

so that any residual driver-specific effect is absorbed into the per-vehicle baseline and does not vary systematically with altitude band, since every driver covered the full 0–4000 m range repeatedly over the campaign. Trips were distributed across different times of day and traffic conditions over the four-year period, but time-of-day, traffic density, and driver-fatigue state were not independently logged or statistically controlled; this is acknowledged as a limitation in Section 5.4.

Table 2. Instrumented vehicle fleet characteristics.

ID	Model	Type	Euro	Disp. (cc)	Mass (kg)	Max Torque (Nm)
V01	Chevrolet N300	Van	III	1173	1230	106
V02	Kia Rio	Sedan	IV	1399	1133	136
V03	Hyundai i20	Hatch	V	1397	1263	137
V04	Chevrolet Sail	Sedan	V	1397	1074	138
V05	Chevrolet Aveo	Sedan	IV	1498	1040	128
V06	Toyota Yaris	Sedan	IV	1498	1040	128
V07	Nissan Sentra	Sedan	IV	1598	1350	153
V08	Toyota Corolla	Sedan	IV	1799	1211	165
V09	Audi Q5	SUV	V	1984	1830	350
V10	Mazda BT-50	Pick-up	IV	2237	1740	190

3.3. Instrumentation and Data Acquisition

Each vehicle was equipped with an OBD-II ELM327 interface recording engine speed (RPM), calculated load, throttle position, coolant temperature, short- and long-term fuel trims, and mass air flow (MAF) at 1 Hz via a custom Python–PostgreSQL data pipeline (Table 3). Altitude and vehicle speed were derived from an integrated GPS/barometer sensor (GPS accuracy ± 2 m; barometric accuracy ± 0.5 hPa).

Table 3. OBD-II parameters recorded via SAE J1979.

Parameter	PID (Hex)	Unit
Engine RPM	0C	rpm
Vehicle speed	0D	km h ^{−1}
Calculated engine load	04	%
Throttle position	11	%
Short-term fuel trim B1	06	%
Long-term fuel trim B1	07	%
Engine fuel rate	5E	L/h
Coolant temperature	05	°C
MAF air flow rate	10	g/s

Exhaust emissions were measured with BrainBee AGS-688 (Brain Bee S.p.A., Parma, Italy) and KANE AutoPlus (Kane International Ltd., Welwyn Garden City, United Kingdom) portable analysers (Table 4), calibrated to ISO 17025 [21] and EPA 40 CFR Part 1065 standards before each measurement session. These instruments are workshop-grade gas analysers designed primarily for stationary idle/tailpipe testing rather than PEMS-class mobile RDE work; they were adapted for on-road use here with a tailpipe-mounted sampling probe, a heated sample line, and a 12 V vehicle-powered pump/battery pack, following the same adaptation approach used in prior on-road studies with workshop analysers [7,22]. This adaptation is a limitation relative to certified PEMS units (Section 5.4): it does not provide exhaust mass-flow measurement, so concentrations (% , ppm) were converted to mass-based EFs (g km^{−1}) using the fuel-based carbon-balance method, combining measured CO, HC, and CO₂ concentrations with the OBD-derived fuel-rate signal (PID 5E) and vehicle speed. NO was measured via electrochemical detection; cross-validation against a

parSYNC[®] FLEX-PNC reference system (3DATX Corporation, Buffalo, NY, USA), itself run in parallel on-road on a subset of trips, showed a mean difference of ± 30 – 50 ppm above 2500 m, within the tolerance specified in ISO 16183 for portable electrochemical sensors; this cross-validation also confirmed acceptable agreement for CO and HC concentrations (within instrument-stated accuracy, Table 4) under real driving conditions. All signals were synchronised by adaptive event-based alignment (cross-correlation Pearson $r > 0.8$ per kilometre segment) to compensate for the 5.8 s PEMS transport delay relative to the 0.002 s OBD-II latency.

Table 4. Portable emission analyser specifications.

Species	Principle	Range	Resolution	Accuracy
CO ₂	NDIR	0–20%	0.01%	$\pm 0.01\%$
CO	NDIR	0–15%	0.01%	$\pm 0.01\%$
HC	NDIR	0–10,000 ppm	1 ppm	$\pm 0.01\%$
NO	Electrochem.	0–5000 ppm	20 ppm	± 20 ppm
O ₂	Electrochem.	0–25%	0.01%	$\pm 0.01\%$

3.4. Data Collection Campaigns

Campaigns were conducted continuously from 2021 to 2025, accumulating approximately 2000 h of on-road driving (≈ 200 h per vehicle; ≈ 50 h per vehicle per year), corresponding to ≈ 7.2 million raw 1-Hz records across all three data streams (OBD-II, PEMS, GPS/barometer). Of these, 103,033 records ($\approx 1.4\%$) were retained as valid, simultaneously time-aligned 1-Hz observations after quality filtering. This comparatively low retention rate reflects four compounding, deliberately conservative criteria rather than sensor unreliability: (i) the requirement of a full, simultaneously valid OBD-II + PEMS + GPS/barometer record at every 1-Hz step, discarding any step where one of the three streams was missing or out of range; (ii) the event-based cross-correlation alignment ($r > 0.8$ per kilometre segment, Section 3.3) needed to compensate the 5.8 s PEMS transport delay, which rejects entire kilometre segments rather than individual samples whenever alignment quality is insufficient; (iii) exclusion of non-driving time (parked, idling engine-off periods, and logger stand-by intervals), which the raw ≈ 2000 h logging duration includes but which does not represent on-road driving; and (iv) removal of atypical driving-behaviour records (sensor artefacts and non-representative manoeuvres) using Tukey $IQR \times 1.5$ suppression applied to instantaneous acceleration and instantaneous fuel consumption (IFC). For the pooled fleet, this yields empirical IQR-based bounds of approximately ± 0.5 m/s² around the (near-zero, idle-dominated) acceleration median and an upper IFC bound of ≈ 25 L/100 km (dataset Q1 = 5.0, Q3 = 13.0 L/100 km); records with instantaneous acceleration magnitude > 5 m/s² (beyond the 99.9th percentile of ± 3 – 4.4 m/s² observed under normal driving, and inconsistent with sustained acceleration capability implied by the fleet's mass and torque ratings, Table 2: e.g., 1040–1830 kg and 106–350 Nm) or instantaneous fuel consumption > 25 L/100 km (roughly 2–3 $\times$ the fleet's typical cruising range of 8–10 L/100 km, Table 9) were treated as behavioural/sensor-artefact outliers rather than genuine driving events and excluded together with the criteria in (i)–(iii). Standard quality-control removal of physically inconsistent values (negative speeds, out-of-range accelerations) and sessions with GPS dropout > 30 s were applied on top of this alignment-driven filtering. OBD-II fields (Table 3) served two roles in this pipeline: engine-state screening (excluding cold-start and open-loop λ intervals via coolant temperature and fuel-trim signals) and, via the fuel-rate signal (PID 5E), the carbon-balance conversion of PEMS concentrations to mass-based EFs described in Section 3.3; OBD-II signals were not used as direct predictors of emissions or fuel consumption in the PSV_{m10}/EF analysis, which relies solely on the

kinematic (speed, acceleration, altitude) variables defined in Equation (3). The resulting matched dataset covered five altitudinal bands of 1000 m width from 0 to >4000 m a.s.l. A full quantitative breakdown of rejected records by cause (stream misalignment, GPS dropout, non-driving time, and behavioural/IQR outliers) is maintained in the authors' processing log and is available from the corresponding author upon reasonable request.

Use of Generative AI Tools

Claude (Anthropic, <https://claude.ai>, accessed on 3 November 2025) was used during the preparation of this manuscript for the following tasks: (1) structuring and formatting manuscript sections in LaTeX based on content provided by the authors; (2) generating Python (matplotlib) scripts for figure production from the experimental dataset prepared by the authors; and (3) organising references into MDPI citation style. All scientific content, experimental design, data acquisition, statistical analysis, results, and conclusions are entirely the work of the authors, who reviewed, edited, and take full responsibility for all content of this publication.

3.5. VSP and PSV_{m10} Computation

Instantaneous VSP was computed as (Equation (3)):

$$VSP(t) = \frac{1}{M} [F_w(t) + R_x(t) + W(t) + F_i(t)] \cdot v(t) \quad (3)$$

where $F_w = 0.5 \rho A C_d v_r^2$ is the aerodynamic drag, $R_x = f_r M g \cos \alpha$ the rolling resistance, $W = M g \sin \alpha$ the grade force, $F_i = M a$ the inertial force, M the vehicle mass, and v the vehicle speed. No dedicated inclinometer was used; the grade angle α was estimated indirectly at each 1-s step as $\alpha(t) = \arctan(\Delta z(t) / \Delta d(t))$, where Δz is the altitude change between consecutive GPS/barometer fixes and Δd the corresponding horizontal distance travelled. Because barometric altitude is more precise over short intervals than GPS altitude, Δz was computed from the barometric channel (± 0.5 hPa, ≈ 4 m resolution near sea level), while Δd was computed from GPS position; the resulting $\alpha(t)$ series was smoothed with a 5-s moving median to suppress fix-to-fix noise before use in Equation (3). This indirect, sensor-fusion approach to grade estimation is consistent with common practice in VSP-based studies that lack a dedicated inclinometer [16] and is acknowledged as a source of additional uncertainty in Section 5.4. Air density ρ was corrected for altitude and temperature using barometric pressure readings. The PSV_{m10} variable was then derived as the 10-s retrospective moving median of VSP (Equation (2)): at each 1-Hz time step t , VSP was computed from Equation (3) for every sample in the preceding 10-s window $[t - 10, t)$, and $PSV_{m10}(t)$ was set to the median of that 10-sample set, so that one PSV_{m10} value is produced per second, smoothing transient VSP spikes while preserving the underlying load trend. Window selection combined the (non-significant) Granger causality trend of Table 5 with physical interpretability, as described in Section 2.2. A direct graphical comparison of the instantaneous VSP and PSV_{m10} time series for a representative trip is not included in the present figure set but is available from the authors' processing pipeline upon reasonable request.

Table 5. Granger causality p -values for different PSV_{m10} window lengths (1-step lag). Selected window: 10 s. No window reached $p < 0.05$; values are reported as descriptive evidence only and should not be interpreted as statistically significant.

Window (s)	p -Value	Remark
1	0.0389	Lowest p -value; physically unrealistic (too short for drivetrain response)
2	0.0564	Not significant; window still short
9	0.0591	Not significant
10	0.0566	Selected—best physically motivated window; not statistically significant
13	0.0826	Not significant; weaker trend

3.6. K-Means Operating-Regime Segmentation

Unsupervised K-Means clustering was applied to PSV_{m10} and instantaneous acceleration as segmentation variables, deliberately excluding response variables (fuel consumption, emissions) to avoid circular methodology. All data processing, clustering, statistical testing, and figure generation were carried out in Python 3.11.9 using pandas 2.2.2, scikit-learn 1.5.1, SciPy 1.13.1, and matplotlib 3.9.0. The optimal number of clusters was determined jointly by the elbow method (inflection at $K = 5$) and the silhouette coefficient, evaluated over $K = 2$ to 8, with the maximum silhouette (≈ 0.384) obtained at $K = 5$; adjacent values ($K = 4$ and $K = 6$) yielded consistently lower silhouette scores, supporting $K = 5$ as the stable optimum rather than an isolated local maximum. The five resulting operating regimes are described in Table 6 and illustrated in Figure 2.

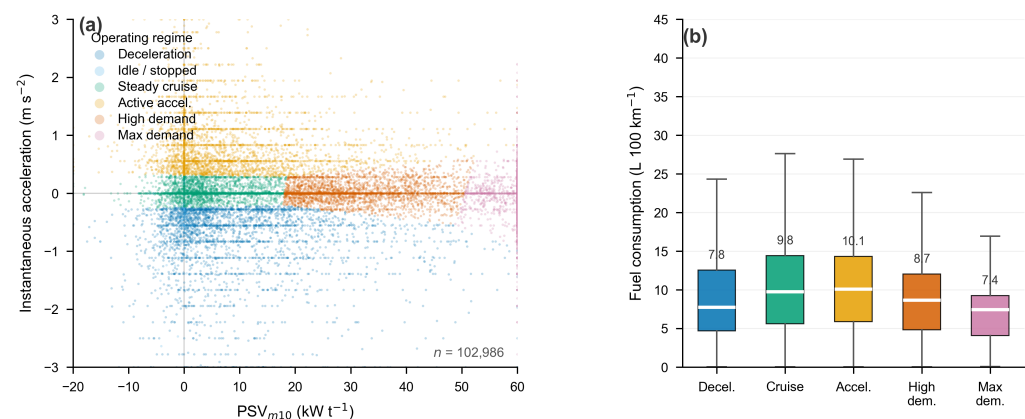


Figure 2. K-Means operating regimes in PSV_{m10} –acceleration space ($n = 103,033$ records): (a) scatter of instantaneous acceleration vs. PSV_{m10} coloured by operating regime; (b) fuel-consumption distribution (box plots, median and IQR) by operating regime. Five clusters are identified: low demand (C4, labelled “Idle/stopped” in panel (a) for descriptive clarity, given its near-zero acceleration and strongly negative PSV_{m10}), deceleration (C3), steady cruise (C1), active acceleration (C0), and high sustained demand (C2); the “Max demand” category shown in panel (a) is not a sixth cluster but the $PSV_{m10} > 40 \text{ kW t}^{-1}$ sub-range of C2 (C2b), plotted separately for visual detail, consistent with the five-cluster K-Means segmentation of [17]. Silhouette coefficient ≈ 0.384 at $K = 5$. Source: authors.

Table 6. K-Means operating regimes ($n = 103,033$ records). Values: median [Q25–Q75]. C4 excluded from EF calculation (near-zero speed). C2b is not an independent K-Means cluster: it is a $PSV_{m10} > 40 \text{ kW t}^{-1}$ sub-range within cluster C2, reported separately for finer resolution in the fuel/EF breakdown; the underlying K-Means segmentation identified exactly five clusters (C0–C4), consistent with [17].

Cl.	Label	PSV_{m10} (kW t^{-1})	Accel. (m s^{-2})	Fuel ($\text{L}/100 \text{ km}$)	CO (g km^{-1})	NO (g km^{-1})
C4	Low demand	−8.03	0.00	—	—	—
C3	Deceleration	−0.67	−0.98	7.7 [4.7–12.5]	2.4 [0.5–5.9]	0.079 [0.006–0.40]
C1	Steady cruise	+0.65	0.00	9.7 [5.6–14.4]	3.4 [0.8–7.4]	0.126 [0.005–0.60]
C0	Active accel.	+1.69	+0.59	10.1 [5.9–14.3]	3.5 [0.7–7.8]	0.086 [0.007–0.47]
C2	High demand	+12.07	+0.07	8.7 [4.9–12.0]	4.2 [1.4–7.5]	0.131 [0.017–0.45]
C2b	Max demand	>40	+0.07	7.4 [4.1–9.2]	3.8 [1.3–6.5]	0.091 [0.026–0.54]

3.7. AEDC Construction and Validation

All measurements reported in this study, including the altitude-resolved emission factors of Section 4, were obtained exclusively from on-road driving; no chassis dynamometer was used at any stage. The AEDC itself is a statistical construct: a representative speed–time trace, assembled and validated as described below, that serves as the target kinematic vector against which real on-road segments are matched (Section 3.8). The AEDC was not physically driven by the fleet; instead, its speed–time profile and derived PSV_{m10} distribution define the reference against which naturalistic on-road segments in each altitude band are selected for direct comparison, so that emission factors are always computed from genuinely-driven, real-world data under altitude-band-specific but kinematically equivalent conditions. Matching is performed via PSV_{m10} bins (Section 3.8) rather than by replaying the AEDC speed curve itself, because the AEDC trace corresponds to one specific realisation of the target kinematics recorded on particular roads; no naturalistic segment from a different route and altitude band could be expected to reproduce that exact speed trace second-by-second, whereas PSV_{m10} -bin matching selects segments with equivalent instantaneous power demand regardless of the specific road or speed trajectory, which is the physically relevant quantity for emissions and fuel consumption. Physical reproduction of the AEDC on a chassis dynamometer—including road-load and altitude/grade simulation, which would require an altitude chamber or intake air-density correction beyond standard dynamometer capability—is identified as a valuable direction for future controlled validation (Section 5.4) but was outside the scope of the present on-road campaign. The AEDC was constructed via stochastic micro-trip concatenation using the stop-to-stop segmentation criterion. Because each source micro-trip was recorded on real Andean roads, the altitude and grade-force history embedded in its PSV_{m10} /VSP time series (via the $W = Mg \sin \alpha$ term, Equation (3)) reflects actual sustained-grade climbing rather than a synthetic profile; the AEDC therefore, inherits the sustained-grade characteristics of the naturalistic dataset directly, rather than reproducing them through an explicit grade-simulation step. The naturalistic dataset was split into n micro-trips; each was characterised by the same kinematic metrics used to define the target vector (mean speed, speed standard deviation, speed P95, idle fraction, mean positive acceleration, PKE, and PSV_{m10}). Candidate micro-trips were ranked by normalised Euclidean distance to the target vector, and four were selected (IDs 213, 93, 456, 261; ordered D→C→A→B) to form the final cycle. Nine stitch boundaries were smoothed to eliminate physically unreproducible acceleration spikes, reducing peak acceleration from $+12.62 \text{ m/s}^2$ to $+3.61 \text{ m/s}^2$ and peak deceleration from -10.56 to -4.17 m/s^2 while retaining >92% of the original PKE.

Representativeness was quantified via the IGS (Equation (1)) and a set of individual kinematic and energetic metrics (Table 7). The validated AEDC speed–time profile and CDF comparison with the WLTC are shown in Figure 3.

Table 7. AEDC kinematic parameters and comparison with the naturalistic dataset and WLTC class 3b.

Parameter	Unit	AEDC	Dataset	WLTC 3b
Duration	s	1370	—	1800
Distance	km	19.4	—	23.3
Mean speed	km h ^{−1}	50.94	48.10	46.5
Max speed	km h ^{−1}	111	—	131.3
Speed std. dev.	km h ^{−1}	29.29	25.33	30.0
Speed P95	km h ^{−1}	95.0	88.0	—
Idle fraction	%	8.75	6.09	13.4
Mean pos. accel.	m/s ²	0.766	0.361	0.35
PKE	m/s ²	0.383	0.357	0.34
PSV _{m10} mean	kW/t	2.67	2.84	—
IGS vs. dataset	—	1.89	1.00	2.30

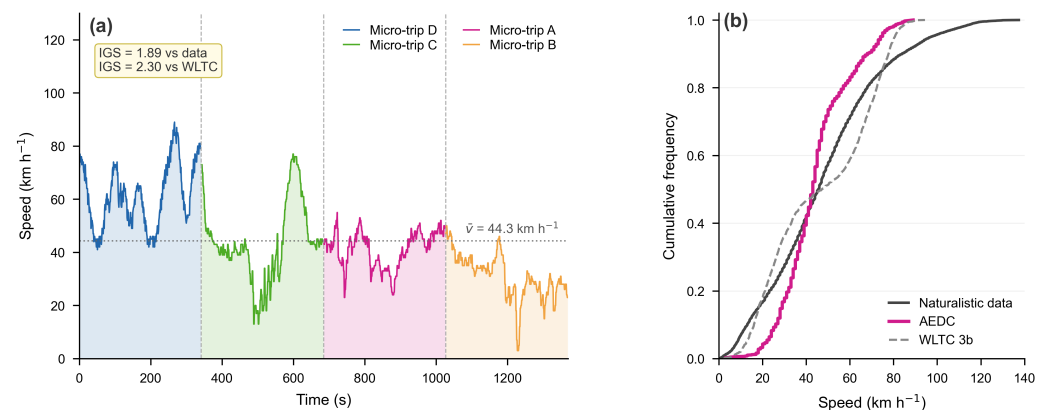


Figure 3. AEDC speed–time profile (1370 s, 19.4 km, mean speed 50.94 km h^{−1}, max speed 111 km h^{−1}): (a) speed–time trace, with the four concatenated micro-trips (D→C→A→B) indicated by alternating shading; (b) cumulative speed–frequency distribution of the AEDC compared against the naturalistic reference data and the WLTC class-3b cycle (IGS = 1.89 and 2.30, respectively). Nine stitch boundaries were smoothed to reduce peak acceleration from +12.62 to +3.61 m/s². Source: authors.

3.8. Altitude-Resolved Emission Factor Estimation

To isolate the effect of altitude from driving style, equivalent AEDC segments were identified in each 1000 m altitudinal band using a multi-variable matching procedure. All non-overlapping windows of duration equal to the AEDC (1370 s) available within each altitudinal band were treated as candidates. Each candidate was characterised by the same six kinematic descriptors used to define the AEDC target vector (mean speed, speed standard deviation, acceleration standard deviation, idle fraction, PKE, and 10-s PSV_{m10}). Because these descriptors span heterogeneous units and magnitudes (e.g., speed in km h^{−1} vs. idle fraction in %), each metric k was standardised via z -score normalisation across the full pool of candidate windows in the corresponding altitudinal band before combination:

$$z_{i,k} = \frac{x_{i,k} - \mu_k}{\sigma_k} \quad (4)$$

where $x_{i,k}$ is the value of metric k for candidate window i , and μ_k and σ_k are the mean and standard deviation of metric k across all candidates in that band. The six standardised metrics were then combined, with equal weighting, into a single composite distance score

(Euclidean norm in z-score space) against the similarly standardised AEDC target vector. Z-score standardisation (rather than min–max scaling) was chosen because it is robust to the differing native ranges of the six metrics without compressing all candidates into a fixed $[0, 1]$ interval that would be sensitive to the single most extreme candidate in each band. For each band, the candidate of minimum distance (highest kinematic equivalence) was selected (Table 8). A formal sensitivity check—re-ranking candidates under alternative weighting schemes and reporting the distance-score gap to the second-best candidate in each band—was not performed in the present analysis and is recommended as a robustness check for future revisions of the matching procedure (Section 5.4). As noted in Section 2.2, equivalence in PSV_{m10} alone does not guarantee equivalence in full driving trajectory; this is why the composite score combines PSV_{m10} with five additional, largely independent kinematic descriptors rather than relying on PSV_{m10} in isolation.

Instantaneous emission rates (g/s) were matched to AEDC time steps by PSV_{m10} bin (± 0.5 – 5.0 kW/t tolerance, minimum 10 samples per bin), outliers were suppressed by the Tukey $IQR \times 1.5$ criterion, and the median was taken as the representative value. Final EFs ($g\ km^{-1}$) were obtained by integrating median rates over the cycle distance.

Table 8. Equivalent-AEDC segments selected per altitudinal band: distance score and integral multi-variable proximity index.

Band (m)	Distance Score	Similarity (%)	Proximity Index (%)
0–1000	4.691	100.0	48.8
1000–2000	3.540	100.0	56.6
2000–3000	2.889	100.0	49.1
>3000	4.744	100.0	41.7

4. Results

4.1. AEDC Validation

The AEDC reproduces the naturalistic dataset with high fidelity in the metrics that govern fuel consumption and average emissions: mean speed error 5.9%, PKE error 7.2%, and speed P95 error 7.9% (Table 7). The Wasserstein distance between the PSV_{m10} distributions of the AEDC and the full dataset was 1.36, with 87.4% overlap in the central 0–20 kW/t region that accounts for the majority of on-road operation. The AEDC is, therefore, considered representative for estimating average fuel consumption and emission rates across the Ecuadorian fleet operating in Andean and coastal conditions.

The largest deviations appear in mean positive (+112%) and negative (+129%) acceleration, which reflect an intentional trade-off made during stitch-boundary smoothing (Section 3.7): preserving energetic fidelity (PKE) while eliminating physically unreproducible acceleration spikes at micro-trip junctions required moderating the most extreme transient events, at the cost of amplifying the relative deviation in mean acceleration metrics. This trade-off also improves the AEDC’s suitability for future chassis-dynamometer replication, even though the present study derives all emission factors from on-road data (Section 3.7).

4.2. Operating Regime Characterisation

The five K-Means clusters show a monotone progression from low-energy (C4, median fuel 3.07 L/100 km) to high-energy regimes (C2, median 10.08 L/100 km), with Kruskal–Wallis $p < 0.001$ and statistically distinct pairwise medians across all ten cluster-pair comparisons after Bonferroni correction for multiple comparisons (Dunn’s post-hoc test, family-wise $\alpha = 0.05$; the full pairwise test-statistic and adjusted- p table is available from the authors upon reasonable request), confirming that PSV_{m10} -based segmentation captures

operationally meaningful differences in energy demand. C1 (steady cruise) contains the largest number of observations ($n = 61,193$), confirming it as the dominant on-road regime.

Peak fuel consumption (7.42 L/h) was observed in the 2000–3000 m band under high-demand conditions (C2), where altitude-related power loss converges with the steep grades typical of the Andean transition zone. Above 4000 m, the high-demand bin ($PSV > 40 \text{ kW/t}$) disappears from the dataset ($n < 30$), indicating that the engine cannot sustain such loads at extreme altitude.

Notably, the volumetric fuel-consumption metric (L/100 km) does not rank clusters in the same order as absolute fuel flow (L/h): the max-demand regime (C2b) shows a lower median L/100 km (7.4) than steady cruise (C1, 9.7), even though its instantaneous fuel flow and power output are higher. This apparent contradiction is consistent with the well-established, non-monotonic relationship between engine load and brake-specific fuel consumption in spark-ignition engines: sustained high-load operation (C2/C2b) is closer to the engine's peak thermal-efficiency region and covers more distance per unit time, so consumption per kilometre can be lower despite higher consumption per hour; steady cruise (C1), by contrast, often involves partial-throttle pumping losses and, at extreme altitude, ECU-driven mixture enrichment at moderate loads that penalise the per-kilometre metric even though absolute engine demand is lower. This distinction between per-hour and per-kilometre fuel metrics should be kept in mind when interpreting Figure 4 and Table 6 jointly.

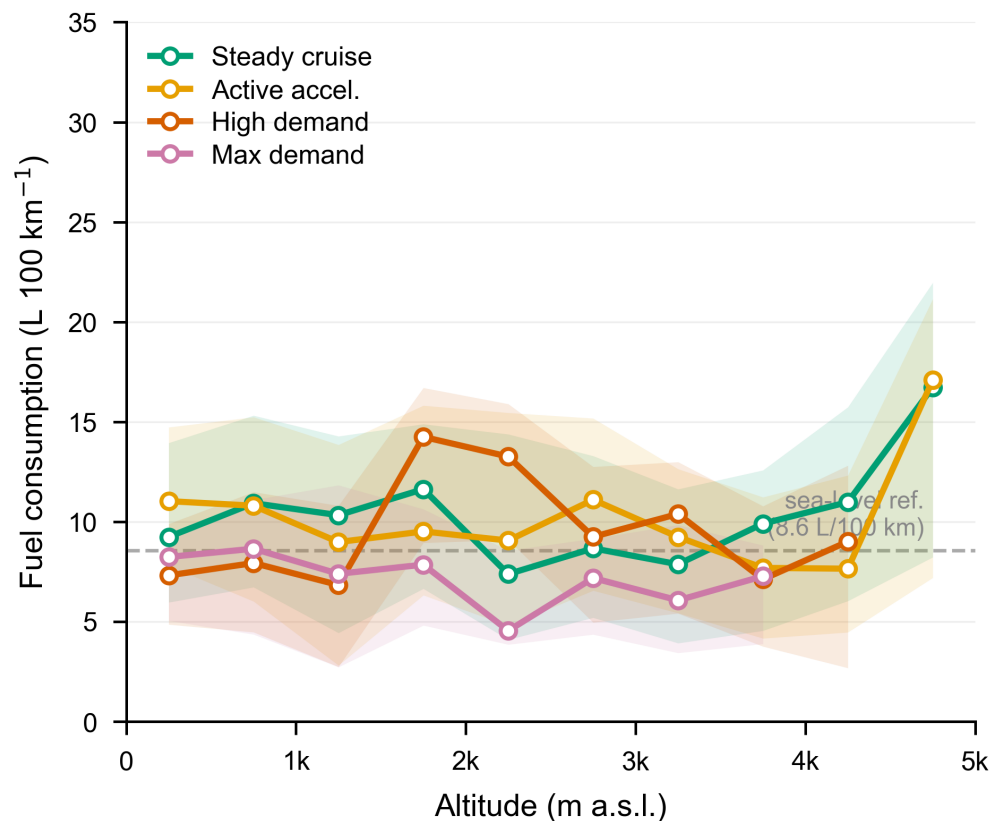
4.3. Fuel Consumption vs. Altitude

Under dynamically equivalent AEDC segments, fuel consumption is comparatively flat across the altitude range, with a mild hump rather than a strong monotonic trend (Figure 4; Table 9). From 0–1000 m (8.56 L/100 km) to 1000–2000 m (8.79 L/100 km, +2.7%) consumption rises slightly, consistent with the transition from coastal to highland conditions and the mixture enrichment described in Section 2.1. Beyond 2000 m, consumption declines progressively, to 8.20 L/100 km in the 2000–3000 m band and 8.11 L/100 km above 3000 m (−5.3% relative to sea level, −7.7% relative to the 1000–2000 m peak). This decline, rather than the increase reported in some prior high-altitude studies [4,18,23], is consistent with reduced aerodynamic drag ($F_w \propto \rho$, Equation (3)) at lower air density increasingly offsetting, and beyond ≈ 2000 m outweighing, the enrichment-driven fuel penalty for the driving intensity sampled by the equivalent AEDC segments; ECU barometric correction may further limit over-fuelling at sustained moderate loads. This finding should be interpreted for the specific driving intensity of the matched AEDC segments (Table 8) and not extrapolated to all load conditions, since Section 4.2 shows that high-load regimes and steady-cruise regimes respond oppositely to altitude in per-kilometre fuel terms.

Table 9. Altitude-resolved emission factors and fuel consumption under equivalent AEDC conditions (g km^{-1} ; fuel in L/100 km). Values: median [95% CI] ^a.

Band (m)	CO (g km^{-1})	NO ^b (g km^{-1})	HC (g km^{-1})	CO ₂ (g km^{-1})	Fuel (L/100 km)
0–1000	2.97 [2.91–3.03]	0.028 [0.026–0.029]	0.012 [0.012–0.012]	182 [181–183]	8.56
1000–2000	4.47 [4.29–4.64]	0.188 [0.178–0.199]	0.047 [0.042–0.050]	165 [160–169]	8.79
2000–3000	2.98 [2.91–3.05]	0.071 [0.069–0.074]	0.015 [0.015–0.015]	140 [138–142]	8.20
>3000	3.91 [3.82–4.01]	0.186 [0.182–0.191]	0.017 [0.017–0.018]	119 [117–120]	8.11

^a Bootstrapped 95% CI, $B = 500$. ^b Electrochemical detection; ± 30 –50 ppm above 2500 m.



Shaded area: interquartile range (Q25–Q75). Dashed line: sea-level median reference.

Figure 4. Fuel consumption ($\text{L } 100 \text{ km}^{-1}$) vs. altitude under dynamically equivalent AEDC conditions, stratified by K-Means operating regime. Consumption rises slightly to a maximum in the 1000–2000 m band ($8.79 \text{ L}/100 \text{ km}$) and then declines progressively above 2000 m to $8.11 \text{ L}/100 \text{ km}$ above 3000 m, consistent with reduced aerodynamic drag at lower air density increasingly offsetting the enrichment-driven fuel penalty. Shaded area: interquartile range (Q25–Q75). Dashed line: sea-level median reference. Source: authors.

4.4. Altitude-Resolved Emission Factors

Table 9, Figures 5 and 6 report the EFs derived under equivalent AEDC driving conditions. Figure 5 shows the full EF distribution across altitude bands and PSV_{m10} bins as a heatmap; Figure 6 presents the altitude trend by operating regime.

4.4.1. NO Response

The altitude trends shown in Figure 6 are discussed below. NO is lowest at sea level (0.028 g km^{-1}), rises sharply to a peak in the 1000–2000 m band (0.188 g km^{-1} , $6.7 \times$ the sea-level value), falls to 0.071 g km^{-1} in the 2000–3000 m band, and rebounds to 0.186 g km^{-1} above 3000 m—essentially returning to the 1000–2000 m peak. NO therefore, does not decline monotonically with altitude over the range studied; instead it follows a double-peak (“W”-shaped) pattern. The initial rise from sea level to 1000–2000 m and the subsequent fall to 2000–3000 m are consistent with the dual-response mechanism reported by Wang et al. [20] and Qi et al. [6], in which moderate-altitude engine loading initially raises combustion temperature and NO before oxygen scarcity suppresses it at higher elevation. The secondary rise above 3000 m has not, to our knowledge, been previously documented and may reflect altitude-specific enrichment strategies (e.g., knock-protection or cold-intake enrichment) that become active only at the sustained loads and low air density of the

Chimborazo-approach corridor; this interpretation is exploratory given the limited data density above 4000 m (Section 5.4) and warrants targeted follow-up.

4.4.2. CO Response

CO displays a non-monotonic pattern similar in shape to NO: lowest at sea level (2.97 g km^{-1}), peaking at 4.47 g km^{-1} (+50%) in the 1000–2000 m band, falling back to 2.98 g km^{-1} in the 2000–3000 m band, and partially rebounding to 3.91 g km^{-1} above 3000 m. The intermediate peak reflects the region where mixture enrichment from reduced air density generates incomplete combustion without yet significantly limiting engine load, while the 2000–3000 m dip and the >3000 m rebound broadly track the same double-peak structure discussed for NO above, suggesting a shared, load-dependent enrichment mechanism across both pollutants.

4.4.3. HC Response

HC follows the same double-peak shape, at much lower absolute levels: 0.012 g km^{-1} at sea level, peaking at 0.047 g km^{-1} (+292%) in the 1000–2000 m band, falling to 0.015 g km^{-1} in the 2000–3000 m band, and rising again to 0.017 g km^{-1} above 3000 m. Because HC, CO, and NO share the same qualitative altitude pattern (peak at 1000–2000 m, trough at 2000–3000 m, partial rebound above 3000 m), this is consistent with a common driver—altitude-dependent mixture enrichment interacting with engine load—rather than three independent mechanisms.

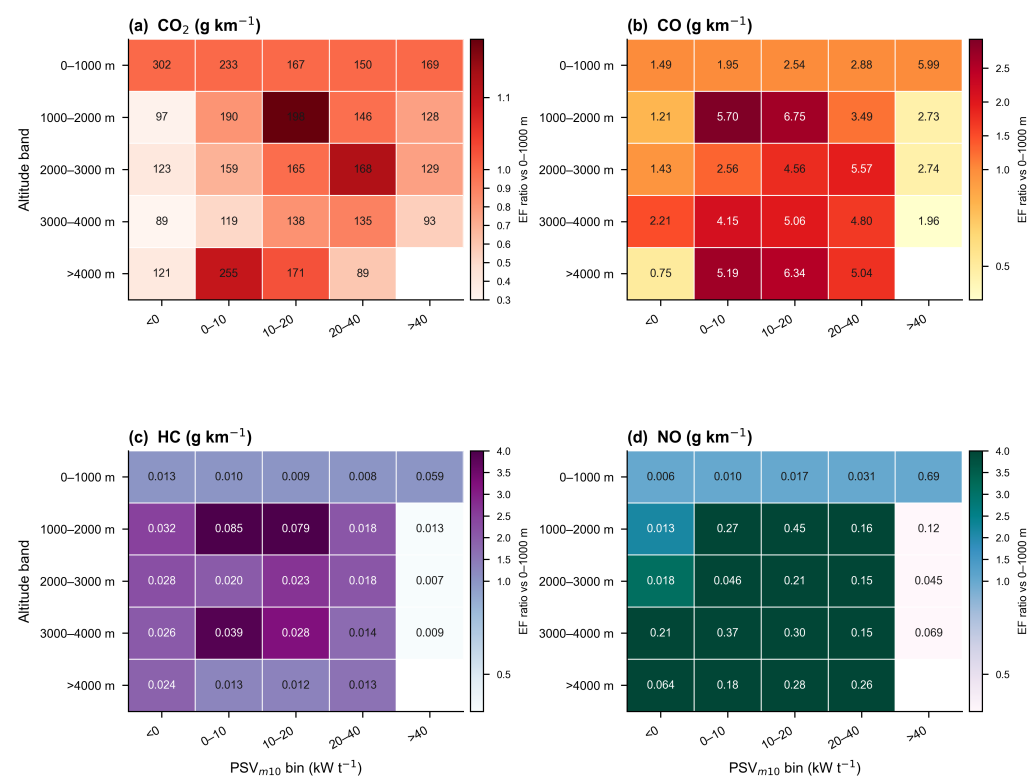


Figure 5. Emission factor heatmap: median EF by altitude band and PSV_{m10} bin (kW t^{-1}) under equivalent AEDC conditions, for (a) CO₂ (g km^{-1}); (b) CO (g km^{-1}); (c) HC (g km^{-1}); (d) NO (g km^{-1}). Values annotated in each cell. Colour scale normalised to the 0–1000 m band. Source: authors.

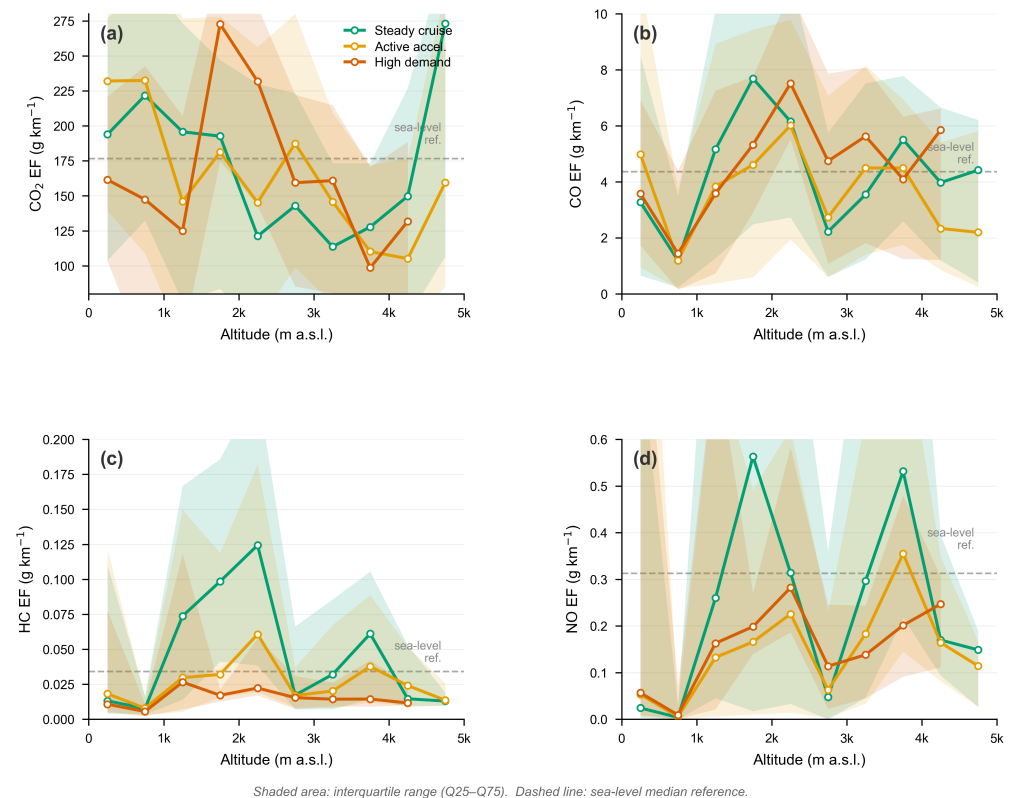


Figure 6. Altitude-resolved emission factors (g km^{-1}) by operating regime (steady cruise, active acceleration, high demand) for (a) CO_2 ; (b) CO; (c) HC; (d) NO, under equivalent AEDC driving conditions (0–4000 m a.s.l.). NO, CO, and HC all peak in the 1000–2000 m band and partially rebound above 3000 m after a mid-altitude dip; CO_2 declines monotonically with altitude. Lines show the median trend per regime and shaded bands the interquartile range (Q25–Q75) across the matched AEDC segments; the dashed line marks the sea-level median reference. Source: authors.

4.4.4. CO_2 Response

In contrast to NO, CO, and HC, CO_2 declines monotonically with altitude, from 182 g km^{-1} at sea level to 165, 140, and 119 g km^{-1} in successive bands (−35% overall). This tracks the comparatively flat-to-declining fuel-consumption trend (Section 4.3) rather than the double-peak pattern of the other three pollutants, indicating that CO_2 is governed primarily by net fuel burned per kilometre (itself moderated by reduced aerodynamic drag at altitude) rather than by the combustion-completeness fluctuations that drive CO, HC, and NO. The contrast between CO_2 's monotone decline and the non-monotone response of the other three pollutants confirms that altitude affects these species through distinct physicochemical mechanisms and that a single altitude-correction coefficient cannot be applied uniformly across pollutants (Section 5.1).

The absence of a strictly proportional CO_2 –fuel-consumption relationship in Table 9 is expected rather than anomalous: under complete combustion, carbon exits almost entirely as CO_2 and the two quantities scale together, but the mixture-enrichment fluctuations that accompany altitude (Section 2.1) divert a variable fraction of fuel carbon into CO and HC instead of CO_2 . Because this diversion follows the double-peak pattern described above (largest around 1000–2000 m and again above 3000 m) rather than a monotonic trend, the CO_2 /fuel ratio is not expected to decrease smoothly with altitude either; instead, CO_2 tracks fuel consumption directly while the CO/HC share of total carbon output fluctuates with the enrichment regime, decoupling CO_2 from a purely proportional relationship with fuel consumption at any single altitude band.

5. Discussion

5.1. Altitude Sensitivity by Pollutant

The results demonstrate that altitude affects individual pollutants through distinct and sometimes opposing mechanisms. NO, CO, and HC, all controlled to varying degrees by mixture stoichiometry and combustion completeness, share a double-peak (peak at 1000–2000 m, trough at 2000–3000 m, partial rebound above 3000 m) altitude response, with NO showing the largest relative excursion ($6.7\times$ from its sea-level minimum to its 1000–2000 m peak). CO₂, in contrast, declines monotonically with altitude, tracking net fuel consumption rather than combustion-completeness fluctuations. This differentiated, non-monotonic response has direct implications for emission inventory modelling: applying a single, monotonic altitude correction factor to all pollutants, as is common in COPERT 5 and IVE, will necessarily over-correct some species while under-correcting others, and may have the wrong sign in some altitude bands for NO, CO, and HC.

Table 10 places the present findings in the context of recent PEMS-based altitude studies. Wang et al. [8] reported CO increments of up to $2.5\times$ at 2400 m relative to 700 m for gasoline LDVs under RDE-compliant cycles in China; our peak CO increment of $1.5\times$ (4.47 g km^{-1} at 1000–2000 m vs. 2.97 g km^{-1} at sea level) is directionally consistent but smaller in magnitude. The lower relative increment observed here likely reflects the broader altitude range sampled (0–4000 m vs. 700–2400 m) and the use of dynamically equivalent AEDC segments, which isolate the altitude signal from driving-style variability. Lyu et al. [19] measured CO and NO from LPG taxis and gasoline vehicles in a high-altitude Chinese city ($\approx 2500\text{ m}$), finding NO values of $0.03\text{--}0.08\text{ g km}^{-1}$ —in close agreement with our 0.071 g km^{-1} at 2000–3000 m. Qi et al. [6] and Wang H. et al. [20] reported a dual (N-shaped) response for NO (increase then decrease with altitude), corroborating the initial rise from sea level to our 1000–2000 m peak followed by the decline to 2000–3000 m; neither study, however, reports the secondary rebound we observe above 3000 m, which may be specific to the extreme-altitude, sustained-grade conditions of the Chimborazo-approach corridor and merits dedicated follow-up. Notably, none of these studies employed a locally validated driving cycle; the use of the AEDC and PSV_{m10} matching methodology constitutes a methodological advance that reduces confounding by driving dynamics.

Table 10. Comparison of CO and NO emission factors from recent PEMS-based altitude studies. All values refer to moving conditions only. n.r. = not reported.

Study	Region	Alt. (m)	CO (g km^{-1})	NO (g km^{-1})	Cycle
Wang et al. [8]	China	700–2400	1.2–3.0	0.04–0.18	RDE
Lyu et al. [19]	China	~ 2500	1.5–4.2	0.03–0.08	On-road
Qi et al. [6]	China	500–4500	0.8–5.1	0.02–0.25	On-road
Lyu et al. [24]	China	~ 2500	1.1–3.8	n.r.	WLTC
This study	Ecuador	0–4000	2.97–4.47	0.028–0.188	AEDC

The CO range observed here ($2.97\text{--}4.47\text{ g km}^{-1}$) falls within the range reported by Chinese studies ($0.8\text{--}5.1\text{ g km}^{-1}$) but is narrower and sits toward the middle of that range, which is consistent with the use of the AEDC under dynamically equivalent conditions reducing (though not eliminating) the driving-aggressiveness component of the altitude signal. When raw on-road data are used without kinematic matching (as in most prior studies), differences in road gradient, traffic density, and driving behaviour across altitudinal bands may further inflate the apparent altitude effect beyond what is reported here. This methodological distinction is relevant for inventory modellers who require altitude correction factors that are independent of driving style.

More broadly, apparent inconsistencies between the present results and other altitude-emissions studies (Table 10) should not be read as contradictory evidence about the physical effect of altitude itself, but as evidence that driving patterns, road-gradient distribution, traffic congestion, and ambient conditions are frequently confounded with altitude in study designs that do not control for driving dynamics. Because most cited studies compare raw on-road samples collected at different altitudes without an explicit kinematic-equivalence step, part of their reported altitude sensitivity plausibly reflects these confounders rather than altitude per se. The present AEDC/PSV_{m10} matching framework was designed specifically to reduce this source of disagreement, and the resulting narrower, more conservative CO range (Table 10) is consistent with that interpretation; a direct test of this hypothesis would require applying the same kinematic-matching procedure to the published datasets of Wang et al. [8], Lyu et al. [19], and Qi et al. [6], which is suggested as future collaborative work. The lower CO increment observed here relative to Wang et al. [8] ($1.5\times$ vs. $2.5\times$) is, therefore, attributable to a combination of at least two factors that cannot be fully disentangled with the present data: the methodological control introduced by AEDC matching (discussed above), and possible differences in vehicle technology and after-treatment calibration between the Ecuadorian Euro III–V fleet studied here and the vehicles sampled by Wang et al. [8]; distinguishing between these two explanations would require harmonised testing of comparable vehicle technologies across both regions.

5.2. Implications for Andean Emission Inventories

Ecuador's national emission inventory currently relies on COPERT 5 handbook EFs derived primarily from European sea-level test data. The present results suggest that a sea-level-anchored NO factor would substantially underestimate NO at most Andean urban altitudes: cities near 1000–2000 m (e.g., Ambato, Riobamba) could see NO underestimated by a factor of up to $\approx 6.7\times$ relative to a sea-level baseline, and cities above 3000 m by a similar margin, while the 2000–3000 m band would be comparatively better represented by such a baseline. A single sea-level CO factor would likewise underestimate CO by $\approx 50\%$ in mid-altitude urban environments (1000–2000 m, e.g., Ambato, Riobamba) where mixture enrichment is most pronounced, while overestimating it modestly in the 2000–3000 m band. The non-monotonic, pollutant-specific nature of these biases means a single altitude-correction multiplier cannot correct COPERT 5 EFs for Andean cities; altitude- and pollutant-specific correction factors, informed by data such as Table 9, are needed instead. Accurate altitude-resolved EFs are essential for cities such as Quito, Riobamba, and Cuenca, which account for a large share of Ecuador's vehicular fleet and population.

5.3. Role of the AEDC and PSV_{m10} Framework

A key methodological contribution is the use of the AEDC to provide dynamically equivalent comparison conditions across altitudinal bands. Without this control, differences in driving dynamics between highland and lowland routes would confound the altitude signal in emission factors. The PSV_{m10} descriptor further refines this control by accounting for the accumulated energy history of the vehicle, capturing transient effects that instantaneous VSP misses. The five K-Means operating regimes provide a physically interpretable segmentation that can be integrated into existing models such as MOVES or IVE as an additional stratification variable.

5.4. Limitations

Several limitations should be noted.

First, NO was measured with electrochemical sensors rather than the chemiluminescence method required by EU RDE regulations; the estimated uncertainty of ± 30 – 50 ppm above 2500 m is small relative to the 1000–2000 m and >3000 m NO peaks (≈ 0.19 g km^{−1})

but is non-negligible relative to the 2000–3000 m trough (0.071 g km^{-1}), so the depth of that trough in particular should be interpreted with some caution; it limits quantitative comparability with regulatory databases in general, and absolute NO values reported here should be treated as indicative rather than regulatory-grade until cross-validated against a chemiluminescence reference across the full altitude range in future work.

Second, data density above 4000 m is limited ($n = 7139$), and the high-demand operating regime ($\text{VSP} > 40 \text{ kW/t}$) is statistically under-represented at extreme altitude, so conclusions in that zone should be treated as exploratory.

Third, the fleet covers ten gasoline spark-ignition vehicles of Euro III–V emission standards only; diesel, hybrid, and CNG vehicles are excluded, and Euro III–V after-treatment technology is older than current Euro VI calibration and catalyst strategies, so the reported EFs should not be extrapolated to Euro VI or newer fleets. The ten-vehicle sample, while spanning a deliberately broad range of displacement, body type, and emission standard (Table 2), remains modest in absolute size; cluster-level medians and altitude trends should be interpreted as representative of this fleet rather than as population-level estimates for the entire Ecuadorian LDV fleet, and results with wide interquartile ranges (Table 9) in particular warrant cautious generalisation.

Fourth, environmental variables such as relative humidity and fuel quality were not independently controlled; both plausibly affect the results reported here beyond their interaction with altitude alone. Relative humidity is a well-established covariate of NO formation (humidity-based correction factors are standard in regulatory NO_x testing), so uncontrolled humidity variation across sampling days may add scatter to, though not necessarily bias, the reported altitude–NO relationship; fuel-quality variation across the sampling region and period could similarly affect CO and HC formation independently of altitude.

Fifth, grade angle was estimated indirectly from consecutive GPS/barometer altitude and distance differentials (Section 3.5) rather than measured with a dedicated inclinometer, and the PSV_{m10} window length (10 s) was selected primarily on physical grounds because none of the tested Granger-causality windows reached conventional statistical significance (Section 2.2, Table 5); both choices are standard practice in VSP-based studies without specialised grade or causality-testing instrumentation but add uncertainty that a dedicated slope sensor or a larger panel (for adequately powered causality testing) would reduce.

Sixth, the equivalent-AEDC segment-matching procedure (Section 3.8) was not subjected to a formal weighting-sensitivity analysis, and the AEDC has not yet been physically reproduced on a chassis dynamometer nor directly compared, under identical post-processing, against WLTC-based or fully naturalistic (unmatched) emission and fuel-economy estimates; both are recommended next steps to further strengthen the case for AEDC adoption in Andean inventory work.

6. Conclusions

This study presents a set of real-world emission factors for a ten-vehicle fleet of Euro III–V light-duty gasoline vehicles, derived under dynamically equivalent driving conditions across a continuous 0–4000 m altitude gradient in Ecuador, underpinned by the PSV_{m10} -validated Andean Ecuador Driving Cycle (AEDC). Findings are specific to gasoline spark-ignition vehicles of this technology generation and to the fleet, routes, and period sampled; extrapolation to diesel, hybrid, CNG, or Euro VI-and-newer fleets, or to statistically robust population-level estimates, should await confirmation with larger, more diverse samples (Section 5.4). The main findings for the studied fleet are:

1. The AEDC (1370 s, 19.4 km, IGS = 1.89) provides a statistically representative alternative to the WLTC for the Ecuadorian fleet, with a PSV_{m10} distribution overlap of 87.4% with naturalistic data.
2. NO, CO, and HC emission factors follow a shared, non-monotonic (“double-peak”) altitude pattern: all three peak in the 1000–2000 m band (NO: 0.188 g km^{-1} , $6.7 \times$ the sea-level value; CO: 4.47 g km^{-1} , +50%; HC: 0.047 g km^{-1} , +292%), fall in the 2000–3000 m band, and partially rebound above 3000 m—most markedly for NO (0.186 g km^{-1} , nearly back to its 1000–2000 m peak). NO therefore, does not show a simple monotonic decrease with altitude over the range studied.
3. CO_2 , by contrast, declines monotonically with altitude (from 182 to 119 g km^{-1} , −35%), tracking net fuel consumption rather than the combustion-completeness fluctuations that govern NO, CO, and HC; this confirms that altitude affects individual pollutants through distinct physicochemical mechanisms.
4. Fuel consumption is comparatively flat across the altitude range studied, with a mild maximum in the 1000–2000 m band (8.79 L/100 km , +2.7% vs. sea level) followed by a decline to 8.11 L/100 km above 3000 m (−5.3% vs. sea level), consistent with reduced aerodynamic drag at lower air density increasingly offsetting the enrichment-driven fuel penalty for the driving intensity of the matched AEDC segments.

These results highlight that single-coefficient altitude corrections applied uniformly across all pollutants will introduce systematic bias in Andean emission inventories. Future work should extend the fleet coverage to diesel, hybrid, CNG, and Euro VI vehicles with a larger sample size; expand measurements above 4000 m; cross-validate NO against a chemiluminescence reference and grade estimates against a dedicated inclinometer; directly compare emissions and fuel economy between the AEDC, the WLTC, and unmatched naturalistic data (ideally also via chassis-dynamometer replication of the AEDC); and develop altitude-specific correction modules for integration into COPERT and IVE.

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Informed Consent Statement: Verbal informed consent was obtained from all vehicle owners and drivers prior to their participation in the measurement campaign.

Data Availability Statement: The raw OBD-II and emission dataset, the AEDC speed–time profile, and the K-Means cluster assignments are available upon reasonable request to the corresponding author. A summary dataset will be deposited in a public repository upon acceptance.

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Abbreviations

AEDC	Andean Ecuador Driving Cycle
CO	Carbon monoxide
CO ₂	Carbon dioxide
EF	Emission factor
ECU	Engine Control Unit
GPS	Global Positioning System
HC	Total hydrocarbons
IGS	Global Similarity Index
IQR	Inter-quartile range
LDV	Light-duty vehicle
MAF	Mass air flow
MAP	Manifold absolute pressure
NO	Nitric oxide
OBD	On-board diagnostics
PEMS	Portable emissions measurement system
PKE	Positive kinetic energy
PSV _{m10}	Residual Vehicle Specific Power (10-s moving median)
RDE	Real Driving Emissions
TWC	Three-way catalyst
VSP	Vehicle Specific Power
WLTC	Worldwide harmonised Light vehicles Test Cycle

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