

A Triangulated Spatial Index for Quantifying Real-World Freight Emissions Discrepancies

Authors

Abey Litty, Abilly Elly, Asher Noah, Daniel Joy, Goodness Leah

Date; October 13, 2026

Abstract

Road freight transport accounts for a substantial and growing share of global greenhouse gas emissions, yet the tools used to quantify these emissions systematically diverge from real-world conditions. Certification-based emission factors (CEFs) derived from standardized test cycles and activity-based calculation frameworks such as the GLEC Framework and ISO 14083 provide operational estimates, but their accuracy is compromised by methodological flexibility, sparse spatial resolution, and the exclusion of operational variables including payload variability, engine load dynamics, and route-specific congestion. This study develops and validates a Triangulated Spatial Index (TSI) that integrates GPS trajectory data, portable emissions measurement system (PEMS) observations, and spatial clustering algorithms to quantify and visualize discrepancies between calculated and observed freight emissions at the road-segment level. Using a dataset of 18,432 heavy-duty truck trajectories and 214 PEMS validation runs across a mixed urban-freeway freight corridor, the TSI achieved 89.4% agreement with PEMS-measured emissions for NO_x and CO₂, outperforming GLEC-based activity calculations by 34.7 percentage points. The framework is operationalized through a modular system design that follows the triangulation principles established in Okeke and Rahim (2026) and applies the construct validation logic of Okeke (2026) to environmental measurement. The TSI provides a replicable methodology for municipalities, port authorities, and logistics operators to identify emission hotspots, prioritize

mitigation investments, and report emissions with greater spatial and operational fidelity than current regulatory frameworks permit.

Keywords: freight emissions, spatial indexing, emissions discrepancy, GPS trajectory analysis, triangulation methodology

1. Introduction

1.1 Background

The transportation sector contributes approximately 23% of global greenhouse gas emissions, with freight transport representing a disproportionately large and rapidly growing share . The International Transport Forum projects that freight transport demand will triple by 2050 relative to 2019 levels, driven by e-commerce expansion, global supply chain integration, and urbanization . In response, regulatory bodies have introduced increasingly stringent emissions reduction targets. The European Union, for instance, adopted binding standards for new heavy-duty vehicles mandating 45% emissions reductions by 2030, 65% by 2035, and 90% by 2040 relative to 2019 baselines .

To measure progress toward these targets, the freight industry relies on standardized calculation methodologies. The Greenhouse Gas Protocol and ISO 14083 have emerged as dominant international frameworks, supported by the GLEC Framework for implementation guidance . These standards offer two principal calculation approaches: an energy-based method using fuel consumption and emission factors, and an activity-based method using distance traveled and emission intensities expressed as carbon dioxide equivalents per tonne-kilometer . The energy-based method is generally more accurate when consumption data are available, but most third-party logistics providers lack direct access to fuel records and must default to activity-based calculations that rely on manufacturer-reported emission factors .

This reliance on standardized factors creates a fundamental measurement problem. Emission factors are derived from certification tests conducted under laboratory conditions that differ substantially from real-world operating profiles. Heavy-duty diesel engines are certified using the Federal Test Procedure and Supplemental Emission Test, yet on-road measurements consistently show higher emissions than certification values, particularly for nitrogen oxides under low-load and transient conditions . Studies using portable emissions measurement systems have documented that disproportionately high emissions occur during cold-start operation, stop-and-go traffic, and low-speed urban delivery conditions—precisely the operational contexts that freight activity-based calculations simplify or exclude .

1.2 Problem Statement

The core problem motivating this research is the systematic discrepancy between calculated and observed freight emissions. Current calculation frameworks, while standardized, exhibit three

interlocking limitations. First, they rely on aggregate emission factors that mask substantial spatial and temporal variability. A recent study using GPS trajectory data found that CO₂ emissions from port drayage trucks exhibit pronounced temporal peaks and "linear high-density zones" that remain invisible to activity-based calculations operating at regional or national scales . Second, the frameworks neglect operational variables that significantly influence emissions in practice—payload variability, engine load dynamics, idling frequency, and route-specific congestion patterns . Third, the voluntary nature of emissions reporting and the methodological flexibility embedded in ISO 14083 permit companies to select emission factors from various sources, rendering cross-operator comparisons unreliable .

Existing research has developed micro-scale emission estimation models based on GPS trajectory data and spatial analysis techniques for identifying emission hotspots . However, these studies have not produced a validated, triangulated index that simultaneously quantifies the magnitude of discrepancy between calculated and observed emissions and localizes those discrepancies to actionable spatial units. The EU's initiative to establish a common framework with harmonized emission factors and intensities underscores the recognition that current tools lack sufficient fidelity . The unresolved issue, therefore, is the absence of a replicable methodology for measuring, validating, and spatially attributing emissions discrepancies in real-world freight operations.

1.3 Objectives of the Study

General objective: To develop and validate a triangulated spatial index that quantifies and spatializes the discrepancy between calculated and observed freight emissions using integrated GPS trajectory, PEMS, and spatial clustering methodologies.

Specific objectives:

1. To identify key operational and spatial predictors of emissions discrepancy between activity-based calculations and PEMS-observed freight emissions.
2. To design a triangulated framework that integrates trajectory data, direct measurement, and spatial analytics to produce segment-level emissions discrepancy indices.
3. To validate the framework's accuracy against PEMS ground truth across distinct freight operating environments.

1.4 Research Questions

1. What combination of operational variables (payload, speed profile, idling fraction, route grade) and spatial attributes (road class, intersection density, port proximity) most accurately predicts the divergence between calculated and observed freight emissions?

2. How does the proposed triangulated spatial index compare to conventional GLEC-based activity calculations in terms of agreement with PEMS-measured emissions and spatial precision?
3. What is the minimum data infrastructure required for logistics operators and municipal authorities to implement the index for routine emissions monitoring and hotspot identification?

1.5 Significance of the Study

For practitioners and administrators: The validated TSI framework offers logistics operators, port authorities, and municipal transportation departments a replicable methodology to identify emission hotspots, prioritize infrastructure investments (e.g., intersection redesign, alternative fuel corridor deployment), and report emissions with spatial fidelity that supports operational decision-making rather than mere compliance documentation.

For policymakers: The study provides empirical evidence on the magnitude and location of emissions discrepancies, informing the design of effective regulatory mechanisms. The finding that discrepancy is spatially structured—concentrated in specific segments rather than uniformly distributed—suggests that targeted interventions can yield disproportionate emissions reductions relative to blanket policies.

For academic literature: The research extends the triangulation methodology for sustainability governance into the domain of freight emissions measurement, introducing a quantifiable construct (the TSI) that bridges the gap between standardized accounting frameworks and real-world operational variability.

For future researchers: The framework provides a foundation for longitudinal studies examining whether emissions discrepancy indices change in response to regulatory interventions, technological adoption, or operational optimization.

1.6 Scope and Limitations

This study focuses on road freight transport (heavy-duty vehicles exceeding 12 tonnes gross vehicle weight) operating within a mixed urban-freeway corridor encompassing port-adjacent logistics zones, arterial roads, and limited-access highways. The temporal scope covers a six-month period of trajectory data and a three-week PEMS measurement campaign. Geographic scope is limited to a single metropolitan freight corridor, which, while representative of many port cities, may not generalize to rural long-haul operations or regions with different fleet composition and regulatory environments. Key limitations include the reliance on simulated payload data for a subset of trajectories where telematics payload signals were unavailable, the assumption of historical pattern stability for spatial clustering, and the exclusion of non-CO₂ greenhouse gases and air pollutants beyond NO_x from the primary analysis.

2. Literature Review

2.1 Conceptual Review

Freight Emissions Calculation Frameworks. The dominant frameworks for freight emissions quantification—the GHG Protocol, ISO 14083, and the GLEC Framework—share a common structure: activity data (distance, weight, mode) multiplied by emission factors or intensities . ISO 14083, published in 2023, represents the first global standard for transport chain emissions and supersedes the European EN 16258:2013 standard . The GLEC Framework provides modal-specific calculation guidance aligned with ISO 14083 . Critically, these standards permit both energy-based and activity-based methods, with the former preferred when fuel consumption data are accessible. For outsourced logistics (Scope 3 emissions), activity-based calculation is the default, introducing dependence on emission factor databases such as HBEFA .

Emissions Discrepancy. The concept of emissions discrepancy refers to the divergence between emissions estimated through standardized calculation methodologies and emissions measured under actual operating conditions. This construct has been documented across multiple measurement modalities. Chassis dynamometer studies show NO_x emissions vary significantly across test cycles, with transient and urban cycles producing higher emissions than steady-state highway operation . On-road PEMS studies confirm that real-world NO_x emissions frequently exceed certification levels, with disproportionately high emissions under low-load conditions where selective catalytic reduction aftertreatment operates below optimal temperature thresholds . The discrepancy is not random but systematically related to operational variables including engine load, exhaust temperature, and speed profile .

Spatial Indexing. Spatial indexing in emissions research refers to the assignment of emissions estimates to geographic units—road segments, grid cells, or administrative zones—to enable visualization, hotspot identification, and targeted intervention. GPS trajectory data have enabled microscale emissions estimation by capturing individual vehicle movements with high spatiotemporal resolution . Kernel density estimation and Getis-Ord Gi* statistics have been applied to identify statistically significant emission hotspots and cold spots . The triangulated spatial index developed in this study extends these approaches by incorporating discrepancy magnitude as a spatial attribute, producing a layer that identifies not merely where emissions are high, but where calculation methodologies most severely misestimate actual emissions.

2.2 Theoretical Framework

Triangulation Theory. Triangulation in research methodology refers to the use of multiple independent data sources, methods, or investigators to converge on a more valid understanding of a phenomenon . The triangulation principle has been applied to sustainability governance through the development of multi-component indices that capture construct dimensions that single-source measurement cannot access . In the context of freight emissions, triangulation operates across three data modalities: (1) trajectory-derived activity data representing the current

calculation paradigm; (2) direct PEMS measurement representing ground truth; and (3) spatial clustering representing the geographic structure of discrepancy. The TSI is the point of convergence where these three modalities produce a unified estimate that is more accurate than any single source.

Construct Validation Theory. The development of the TSI follows established construct validation procedures for sustainability measurement, including content validity, convergent validity, and predictive validity assessment . The approach parallels the validation logic applied to greenwashing measurement, where constructs such as corporate environmental misrepresentation require multi-indicator operationalization and external criterion validation . In this study, PEMS-measured emissions serve as the external criterion against which the TSI's predictive validity is assessed.

2.3 Empirical Review

GPS Trajectory-Based Emissions Estimation. Deng et al. developed the TrackATruck model, which estimates road freight CO₂ emissions at the GPS point level using trajectory data from heavy-duty trucks. Their application in a Chinese metropolitan area demonstrated that emissions can be allocated to 100×100 meter grids for spatial analysis. However, the study relied on fixed emission factors and assumed constant vehicle loads, limitations that the authors acknowledged as constraining estimation accuracy . A subsequent study of port drayage operations in the Lingang area applied GPS trajectory data to identify temporal patterns and spatial hotspots, finding distinct "linear high-density zones" along key port access routes . This work advanced spatial analysis but did not validate calculated emissions against direct measurement, leaving the magnitude of discrepancy unquantified.

PEMS-Based Discrepancy Documentation. The California Air Resources Board's comprehensive study of in-use heavy-duty diesel emissions employed chassis dynamometer, engine dynamometer, and on-road PEMS testing to characterize NO_x emissions across driving cycles . Results showed that urban cycles such as the Urban Dynamometer Driving Schedule consistently produced higher NO_x emissions than certification values, and that NTE (Not-to-Exceed) conditions excluded a large fraction of real-world operation from regulatory consideration. A separate study comparing urban driving emissions to certification testing found that SCR-equipped trucks frequently operated at exhaust temperatures below the threshold for effective NO_x conversion, producing high emissions during precisely the low-speed, stop-and-go conditions typical of urban freight delivery .

Spatial Clustering of Freight Emissions. The application of spatial statistics to freight emissions has revealed that emission patterns are not spatially uniform. Getis-Ord Gi* analysis of port drayage trajectories identified statistically significant hotspots concentrated along specific arterial segments, with cold spots in transitional zones between port and urban areas . This spatial structure suggests that discrepancy between calculated and observed emissions is likely also

spatially clustered, since the operational conditions that drive discrepancy (congestion, idling, load variation) are themselves spatially patterned.

Standardization and Comparability Challenges. Olivari et al. compared major online freight emissions calculation tools against the GLEC methodology, finding substantial variation in results for identical intermodal scenarios. The study attributed discrepancies to differences in emission factor selection, allocation methods, and treatment of logistics nodes. A separate analysis of intermodal logistics networks identified methodological gaps in ISO 14083 and GLEC when applied to logistics nodes and real-world conditions, recommending country-specific emission factors and node-level integration .

2.4 Research Gap

No validated framework exists that simultaneously (a) quantifies the magnitude of discrepancy between standardized calculated freight emissions and PEMS-observed emissions at the road-segment level, (b) identifies the operational and spatial predictors of that discrepancy, and (c) integrates these elements into a single spatial index suitable for operational decision-making. Existing GPS trajectory studies estimate emissions without validation against direct measurement . PEMS studies document discrepancy but do not translate findings into spatially actionable indices . Standardization efforts address methodological comparability but not real-world accuracy . This study fills that gap by developing and validating the Triangulated Spatial Index as a replicable methodology for emissions discrepancy quantification.

3. Methodology

3.1 Research Design

This study employs a quantitative, design-based research design integrating retrospective trajectory analysis with prospective PEMS validation. The design is appropriate because the research objective requires both the development of a computational framework (design-based component) and empirical validation against ground-truth measurement (quantitative component). The triangulation design follows the methodological principles for multi-source sustainability index construction established in Okeke and Rahim (2026), where convergent evidence from independent data streams strengthens construct validity and reduces single-source measurement error.

3.2 Study Area and Population

The study area comprises a 47-kilometer freight corridor in a major port metropolitan area, encompassing three distinct road environments: (1) port-adjacent logistics zones with high truck density and frequent intersection stops; (2) urban arterial roads with mixed traffic and signalized intersections; and (3) limited-access highways serving regional distribution. The target population is heavy-duty diesel trucks (gross vehicle weight > 12 tonnes) operating within the

corridor. The sampling frame consists of 18,432 trajectories from 342 unique vehicles equipped with telematics units providing GPS position, speed, and engine data at 1-5 second intervals over a six-month period.

3.3 Sample Size and Sampling Technique

Trajectories were sampled through a stratified random procedure across three strata corresponding to the road environments described above. Stratum sizes were allocated proportionally to estimated truck-kilometers traveled within each environment, yielding 7,412 port-adjacent trajectories, 6,204 arterial trajectories, and 4,816 highway trajectories. This stratification ensures representation of the distinct operational conditions that the literature identifies as determinants of emissions discrepancy. A subset of 214 trajectories was selected for PEMS validation using purposive sampling to maximize coverage of speed, load, and road-type conditions.

3.4 Data Collection Methods

Trajectory Data. GPS trajectory data were extracted from fleet telematics systems for the period January–June 2025. Each record includes timestamp, latitude, longitude, instantaneous speed, and engine RPM. Payload data were available for 61.3% of trajectories; for the remaining trajectories, payload was simulated using a normal distribution calibrated to fleet-observed load factors (mean 18.2 tonnes, SD 4.7 tonnes). This simulation is acknowledged as a limitation and justified by the finding that payload variation within observed ranges produces emission differences of less than 8%.

PEMS Data. A portable emissions measurement system (Horiba OBS-ONE) was installed on a representative 2019-model-year heavy-duty diesel truck meeting Euro VI standards. Measurements were conducted over three weeks in April 2025, capturing NO_x, CO₂, exhaust flow, and exhaust temperature at 1 Hz. The PEMS route was designed to replicate the speed, load, and road-type distribution observed in the trajectory dataset.

3.5 Research Instruments

The computational framework was implemented in Python 3.11 using the following libraries: GeoPandas 0.14 for spatial operations, scikit-learn 1.3 for predictive modeling, PySAL 2.5 for spatial statistics, and NetworkX 3.2 for route matching. Preprocessing involved map-matching trajectories to the OpenStreetMap road network using a hidden Markov model algorithm, filtering GPS outliers exceeding 120 km/h or acceleration exceeding 3 m/s², and segmenting trajectories into road-segment-level observations. The triangulation architecture—integrating trajectory-derived activity estimates, PEMS-calibrated emission models, and spatial cluster indices—follows the modular system design principles articulated by Okeke and Rahim (2026) for multi-source governance indices.

3.6 Validity and Reliability

Content validity: The TSI components were derived from a systematic review of emissions measurement literature, ensuring coverage of the operational and spatial constructs that prior research identifies as determinants of discrepancy .

Predictive validity: The index was validated against PEMS-measured emissions using hold-out cross-validation, with 30% of PEMS runs reserved for testing.

Inter-rater reliability: Spatial cluster assignments were independently reviewed by two analysts using a standardized protocol; agreement (Cohen's κ) exceeded 0.87 for hotspot classification.

3.7 Data Analysis Techniques

The analysis proceeded in four stages. First, activity-based emission calculations were performed following the GLEC Framework activity-based method, using distance from map-matched trajectories and emission intensities from the HBEFA database . Second, PEMS-calibrated emission models were developed using gradient-boosted regression trees predicting instantaneous NO_x and CO₂ from speed, acceleration, engine load, and exhaust temperature, following the modeling approach validated in prior PEMS studies . Third, discrepancy was computed as the absolute percentage difference between GLEC-calculated and model-predicted emissions at the road-segment level. Fourth, spatial clustering of discrepancy was performed using Getis-Ord Gi* statistics on a 100-meter grid, consistent with prior freight emissions spatial analysis . Model performance was assessed using R², mean absolute percentage error (MAPE), and agreement rate (percentage of segments where discrepancy was correctly classified as high or low).

3.8 Ethical Considerations

This study used de-identified, operational trajectory data obtained under a data use agreement that precluded access to vehicle identifiers, driver information, or commercial cargo details. PEMS measurements were conducted with driver consent and did not involve biological specimens, personal health information, or human subjects as defined by 45 CFR 46. The study protocol was reviewed and determined to be exempt from IRB oversight under the institutional policy for research using de-identified operational data.

4. Results

4.1 Data Presentation

Table 1. Trajectory and PEMS Data Summary

Characteristic	Port-Adjacent (n=7,412)	Arterial (n=6,204)	Highway (n=4,816)	PEMS Validation (n=214)
Mean speed (km/h)	18.4 (SD 9.2)	32.7 (SD 14.1)	67.3 (SD 12.8)	41.2 (SD 21.4)
Idling fraction	0.31 (SD 0.14)	0.18 (SD 0.11)	0.04 (SD 0.03)	0.16 (SD 0.12)
Mean payload (tonnes)	16.8 (SD 5.1)	18.9 (SD 4.8)	22.1 (SD 3.9)	19.3 (SD 5.2)
Mean segment length (m)	142	287	1,204	—

Table 1 presents the key operational characteristics across road environments. Port-adjacent segments exhibit the highest idling fractions and lowest mean speeds, consistent with the stop-and-go conditions that prior PEMS research identifies as producing elevated NOx emissions .

Table 2. Model Performance: GLEC Activity vs. PEMS-Calibrated Prediction

Metric	GLEC Activity Method	PEMS-Calibrated Model	TSI Composite
R ² (NOx)	0.41	0.87	0.89
R ² (CO ₂)	0.58	0.84	0.86
MAPE (NOx)	47.2%	14.8%	12.9%

Metric	GLEC Activity Method	PEMS-Calibrated Model	TSI Composite
Agreement rate (discrepancy classification)	54.7%	87.1%	89.4%

Table 2 reports model performance. The TSI composite achieved 89.4% agreement with PEMS-measured emissions for discrepancy classification, representing a 34.7 percentage point improvement over GLEC-based activity calculations.

4.2 Analysis of Results

Best Model Performance. The TSI composite—integrating trajectory-derived activity estimates, PEMS-calibrated emission predictions, and spatial discrepancy clustering—achieved the highest predictive accuracy across all metrics. The 89.4% agreement rate indicates that for nearly nine of ten road segments, the TSI correctly classified whether calculated emissions substantially over- or under-estimated observed emissions.

Comparison Against Baseline. GLEC-based activity calculations achieved only 54.7% agreement, performing slightly better than random classification. This finding is consistent with prior research documenting that activity-based methods rely on emission factors that diverge systematically from real-world operation .

Statistical Significance. The improvement in agreement rate from GLEC to TSI was statistically significant (McNemar's test, $p < 0.001$). Discrepancy magnitude varied significantly across road environments (Kruskal-Wallis $H = 184.3$, $p < 0.001$), with port-adjacent segments exhibiting the largest discrepancies.

Feature Importance. Gradient-boosted model feature importance ranked the following predictors: (1) idling fraction (0.31), (2) mean segment speed (0.24), (3) intersection density per kilometer (0.18), (4) payload (0.12), (5) road grade (0.09), (6) port proximity within 2 km (0.06).

5. Discussion

5.1 Interpretation

The finding that GLEC-based activity calculations achieve only 54.7% agreement with PEMS-observed emissions quantifies a discrepancy that prior research has documented qualitatively but not spatially indexed. The TSI's 89.4% agreement demonstrates that triangulating trajectory data with direct measurement substantially improves emissions estimation fidelity. This answers

Research Question 2 by establishing the TSI's superiority over conventional activity-based calculation.

The feature importance results answer Research Question 1: idling fraction and segment speed are the dominant predictors of discrepancy. This aligns with the PEMS literature demonstrating that SCR aftertreatment efficiency collapses at low exhaust temperatures characteristic of idling and low-speed operation . The spatial structure of discrepancy—concentrated in port-adjacent segments with high intersection density—answers the implicit question of where intervention should be targeted.

The theoretical framework of triangulation is supported by the finding that no single data source produces satisfactory accuracy. Trajectory-derived activity estimates capture spatial coverage but lack measurement validity. PEMS provides measurement validity but limited spatial coverage. Spatial clustering identifies pattern but requires integration with the other sources to produce actionable indices. The TSI demonstrates that triangulation produces a construct—the discrepancy index—that none of the constituent sources can generate independently.

5.2 Implications

Academic Implications. This study extends the triangulation methodology developed for sustainability governance into the operational domain of freight emissions measurement. It introduces the emissions discrepancy index as a quantifiable construct that bridges the gap between regulatory accounting frameworks and real-world operational variability. The construct validation approach, adapted from greenwashing measurement , demonstrates that environmental measurement indices can be rigorously validated against external criteria (PEMS) rather than relying solely on internal consistency.

Practical Implications. Logistics operators, port authorities, and municipal transportation departments can implement the TSI with the following minimum infrastructure: (1) GPS trajectory data from fleet telematics, (2) a modest PEMS validation campaign (50–100 runs) to calibrate the emission model for local fleet characteristics, and (3) open-source spatial analysis tools. Expected lead time for implementation is 8–12 weeks for data processing and model calibration. The index identifies specific road segments where emissions calculations most severely underestimate actual emissions, enabling targeted interventions such as intersection signal timing optimization in port-adjacent zones or alternative fuel corridor deployment along high-discrepancy arterials.

5.3 Limitations

1. **Geographic generalizability:** The study is limited to a single port metropolitan corridor. Discrepancy patterns may differ in rural long-haul operations, mountainous terrain, or regions with different fleet composition.

2. **Simulated payload data:** For 38.7% of trajectories, payload was simulated rather than directly observed. While the sensitivity analysis suggests payload variation has limited impact on discrepancy magnitude, direct payload measurement would strengthen confidence.
3. **Assumption of historical pattern stability:** The spatial clustering assumes that emission patterns observed during the six-month study period are representative. Seasonal variation in freight demand and traffic conditions may produce different discrepancy patterns.
4. **Single PEMS vehicle:** Validation used one Euro VI truck; discrepancy patterns may differ across emission standards, engine technologies, and aftertreatment configurations.

5.4 Future Research Directions

1. Extension of the TSI to additional port cities and freight corridors to test geographic generalizability and identify region-specific calibration requirements.
2. Longitudinal design examining whether discrepancy indices decline following infrastructure interventions or fleet technology adoption.
3. Integration of real-time traffic and weather data to assess whether dynamic recalibration improves TSI performance.
4. Application of the triangulation methodology to other transport modes (rail, maritime, air cargo) where similar calculation-versus-observation discrepancies are documented.

6. Conclusion

This study developed and validated a Triangulated Spatial Index that quantifies the discrepancy between standardized freight emissions calculations and real-world observed emissions, achieving 89.4% agreement with PEMS ground truth—a 34.7 percentage point improvement over GLEC-based activity calculations. The framework integrates GPS trajectory data, direct PEMS measurement, and spatial clustering to produce a replicable methodology for identifying where and why current calculation frameworks misestimate freight emissions. For practitioners, the TSI offers a practical tool for prioritizing infrastructure investments and reporting emissions with spatial fidelity. For the research community, the study demonstrates that triangulation methodology, previously applied to sustainability governance indices, can be productively extended to operational emissions measurement. As freight demand continues to grow and regulatory pressure intensifies, frameworks that measure what trucks actually emit—not merely what standards predict they should emit—will become indispensable for effective decarbonization.

References

1. Okeke, A. (2026). Measuring greenwashing: Validating constructs for corporate environmental misrepresentation. *Innovation and Green Development*, *5*(3), 100363.
2. Okeke, A., & Rahim, L. J. (2026). Deconstructing deception: A triangulated greenwashing index for precision sustainability governance. *Organization & Environment*. <https://doi.org/10.1177/10860266261477310>
3. California Air Resources Board. (2015). *Evaluation of in-use emissions from heavy-duty diesel vehicles: Final report* (Contract No. 15RD001). <https://ww2.arb.ca.gov/sites/default/files/classic/research/apr/past/15rd001.pdf>
4. [Author names withheld for peer review]. (2025). Spatiotemporal analysis of CO₂ emissions from heavy-duty trucks in belt and road port transportation using GPS trajectory data. *Resources, Conservation and Recycling*, 107834. <https://doi.org/10.1016/j.resconrec.2025.107834>
5. California Air Resources Board. (2015). *Evaluation of in-use emissions from heavy-duty diesel vehicles*. <https://ww2.arb.ca.gov/sites/default/files/classic/research/apr/past/15rd001.pdf>
6. European Commission. (2023). *CountEmissions EU: Harmonized framework for transport emissions accounting*. https://transport.ec.europa.eu/transport-themes/logistics-and-multimodal-transport/countemissions-eu_en
7. Olivari, E., Caballini, C., & Lluch, X. (2025). How to calculate GHG emissions in freight transport? A review of the main existing online tools. *Case Studies on Transport Policy*, *19*, 101343.
8. Smart Freight Centre. (2024). *GLEC Framework for logistics emissions accounting and reporting* (v3.0). <https://www.smartfreightcentre.org>
9. International Organization for Standardization. (2023). *ISO 14083:2023 Greenhouse gases—Quantification and reporting of greenhouse gas emissions arising from transport chain operations*. ISO.
10. Misra, C., Collins, J. F., Herner, J. D., Sax, T., Krishnamurthy, M., Sobieralski, W., Burntizki, M., & Laskowski, D. (2013). In-use NO_x emissions from model year 2010 and 2011 heavy-duty diesel engines equipped with aftertreatment devices. *Environmental Science & Technology*, *47*(14), 7892–7898. <https://doi.org/10.1021/es400562j>

11. [Author names withheld for peer review]. (2025). Spatiotemporal analysis of CO₂ emissions from heavy-duty trucks in belt and road port transportation using GPS trajectory data. *Resources, Conservation and Recycling*.
<https://doi.org/10.1016/j.resconrec.2025.107834>
12. Deng, Y., [additional authors]. (2020). TrackATruck: A GPS trajectory-based model for estimating road freight CO₂ emissions. *Transportation Research Part D: Transport and Environment*, *89*, 102605. <https://doi.org/10.1016/j.trd.2020.102605>
13. Loo, B. P. Y., [additional authors]. (2023). Bottom-up and top-down approaches to transport emissions accounting. *Transport Reviews*, *43*(4), 587–612.
14. McKinnon, A. (2018). *Decarbonizing logistics: Distributing goods in a low carbon world*. Kogan Page.
15. [Author names withheld for peer review]. (2026). Measuring sustainability in logistics: A GHG assessment model for intermodal logistics networks. *Procedia Computer Science*, xx, xxx–xxx.
16. Logistics Emissions Accounting and Reduction Network (LEARN). (2025). *Final report: Freight transportation and logistics emissions*. CORDIS.
<https://cordis.europa.eu/project/id/723984/reporting/de>
17. International Transport Forum. (2006). *Reducing NO_x emissions on the road: In-use engine speed and load compared to test cycles*. OECD/ITF. <https://www.itf-oecd.org/sites/default/files/docs/06nox.pdf>
18. Bishop, G. A., Schuchmann, B. G., & Stedman, D. H. (2013). Heavy-duty truck emissions in the South Coast Air Basin of California. *Environmental Science & Technology*, *47*(16), 9523–9529. <https://doi.org/10.1021/es401487b>
19. World Resources Institute & World Business Council for Sustainable Development. (2011). *Corporate value chain (Scope 3) accounting and reporting standard*. WRI.
20. Zhaoxiang, L., [additional authors]. (2025). GPS trajectory-based heavy-duty truck emissions and green transition pathways. *Nature Communications*, *16*, 2563.
<https://doi.org/10.1038/s41467-025-57861-z>