A Risk-Normalized Effectiveness Index for Vehicle Overloading Control

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ABSTRACT

This study proposes an Effectiveness Index (EI) that integrates inspection coverage, targeting accuracy, and risk derived from Weigh-In-Motion (WIM) data to assess vehicle overloading control. Using data from 6.054.617 vehicles during the observation period from November 2023 to July 2025 in South Sumatra, the index was applied to two enforcement units. Results show that Unit Kertapati achieved a moderate effectiveness score of 43.6, while Unit Talang Kelapa was classified as ineffective with a score of 6.7. The analysis reveals that increasing inspection coverage yields a higher marginal gain in effectiveness than improving targeting accuracy alone. This EI framework offers a scalable, data-driven tool for benchmarking performance and optimizing resource allocation in vehicle overloading control.

Keywords-vehicle overloading; enforcement benchmarking; enforcement effectiveness; performance index; weigh-in-motion; traffic risk; risk-normalized metrics

I. INTRODUCTION

Transport networks, particularly the road network, play a crucial role in economic and social advancement and well-being [1]. Road quality reflects a region's economic level, and timely detection and maintenance of road damage are crucial for protecting lives and property, while preventing further damage [2]. Much of this risk stems from the behavior of heavy vehicle drivers, who are a key determinant of traffic conflicts [3]. To achieve road safety goals, strict law enforcement must be coupled with long-term, coherent, and sustainable awareness programs [4]. Heavy vehicle congestion not only damages roads but also significantly increases the risk of conflict and the frequency of accidents along the road network [5]. Vehicle Damage Factors (VDFs) exhibit non-linear relationships to axial loads, where even small proportions of overweight traffic significantly increase road maintenance costs [6]. Traffic of overloaded trucks is one of the main causes of pavement damage, leading to structural deterioration and safety risks [7]. Overloading has an exponentially destructive impact on road pavements, with increased axle loads accelerating road deterioration [8]. Overloading significantly reduces pavement service life and accelerates structural deterioration, leading to earlier failure than originally designed [9]. Although the physical and structural impacts of overloading are well documented in the literature, the analytical focus has remained largely on pavement engineering rather than on evaluating enforcement policies intended to mitigate these risks. Rising operational costs and budget constraints require law enforcement agencies to optimize their strategies, shifting from random controls to more cost-effective approaches [10].

The current literature extensively covers why roads fail under load but fails to provide a standardized, objective framework for measuring how effectively enforcement units perform their duties, representing a critical research gap. The use of systematic, data-driven evaluation methods is crucial to avoid subjective bias and achieve more accurate distribution plans [1]. This study proposes an Effectiveness Index (EI) that transforms historical Weigh-In-Motion (WIM) data into strategic information to help law enforcement units conduct more targeted and efficient controls [12]. To create value in public policy, EI integrates inspection coverage, target accuracy, and load risk. WIM systems enable continuous and reliable measurement and recording of the weight of every passing vehicle [13]. Utilizing WIM data as the basis enables a more objective, real-time assessment of law enforcement performance, in line with the development of modern heavy-vehicle monitoring systems [14].

While existing enforcement measures primarily focus on volumetric outputs—such as the total number of citations issued or vehicles weighed—they often overlook the actual damage potential of non-intercepted overloaded vehicles. In contrast, the proposed EI introduces a risk-normalized perspective. By integrating WIM data, the EI accounts for the severity of axle loads and the coverage gaps of enforcement activities, providing a more precise diagnostic tool for infrastructure protection than traditional quantity-based metrics. While these indicators are useful for monitoring operational activities, they often fail to account for differences in traffic risk environments, particularly in freight corridors where the prevalence of overloaded vehicles may vary substantially.

Based on this perspective, this study addresses gaps in law enforcement by proposing a risk-normalized EI. Unlike conventional performance measures that emphasize quantity-based policy outcomes, this framework provides a balanced assessment of risk. This index is applied to a case study of law enforcement units in South Sumatra, Indonesia, to reveal performance gaps not captured by traditional metrics, thereby strengthening evidence-based policymaking in overload control.

II. METHODOLOGY

A. Conceptual Framework

Composite indicators and safety performance indicators have been widely used in transport policy evaluation to capture complex interactions among multiple safety factors. Previous studies have developed composite road safety indicators that integrate policy implementation, behavioral outcomes, and accident statistics to benchmark national safety performance [15]. Similarly, safety performance indicators have been promoted as an important tool for monitoring the effectiveness of transport safety policies and guiding regulatory interventions. These approaches highlight the value of integrating multiple dimensions of system performance into a single evaluative indicator. However, most existing indicators focus primarily on safety outcomes or policy implementation rather than operational enforcement effectiveness. Unlike these approaches, the proposed EI focuses specifically on enforcement performance, integrating inspection activity, targeting accuracy, and traffic-based violation risk into a single risk-normalized indicator [16].

The conceptual framework and workflow of the EI are presented in Figure 1, illustrating the sequence from enforcement data acquisition and indicator derivation to the aggregation of components into a composite effectiveness score and subsequent performance classification.

The framework assumes that enforcement effectiveness improves when a larger proportion of freight vehicles is inspected and when inspections are more precisely targeted toward overloaded vehicles, relative to the prevailing level of overloading risk within the traffic stream.

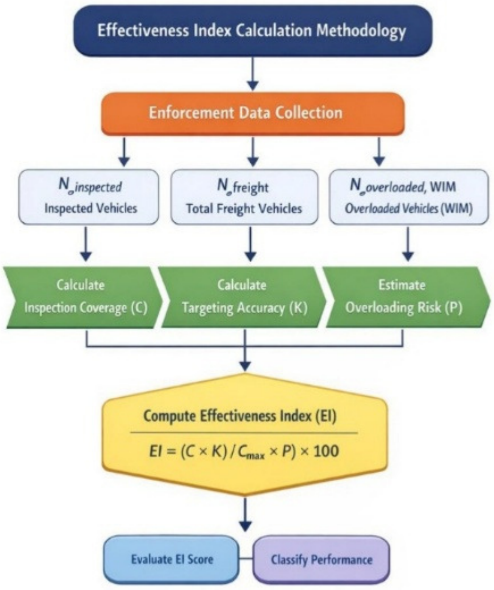

Fig. 1. Methodology flowchart for computing the EI.

B. Definition of Variables

To ensure robust aggregation, the EI adopts a multiplicative formulation. Three primary performance variables are defined:

1) Inspection Coverage (C)

Inspection coverage represents the proportion of freight vehicles that are physically inspected at a given enforcement site within a defined time period. It is calculated by:

$$C = \frac{N_{inspected}}{N_{freight}} \quad (1)$$

where $N_{inspected}$ is the number of freight vehicles inspected and $N_{freight}$ is the total number of freight vehicles passing through the enforcement corridor.

2) Targeting Accuracy (K)

Targeting accuracy measures the proportion of inspected vehicles that are confirmed as overloaded. It reflects the effectiveness of vehicle selection and screening strategies:

$$K = \frac{N_{overloaded,detected}}{N_{inspected}} \quad (2)$$

where $N_{overloaded,detected}$ is the number of inspected vehicles found to be overloaded.

3) Overloading Risk (P)

Overloading risk represents the empirical prevalence of overloaded freight vehicles in the traffic stream, derived from WIM data:

$$P = \frac{N_{overloaded,WIM}}{N_{freight,WIM}} \quad (3)$$

This parameter captures the baseline enforcement difficulty at a given location, as sites with higher prevalence pose greater operational challenges.

C. Formulation of the Effectiveness Index

The EI is formulated to integrate inspection coverage and targeting accuracy, normalized by overloading risk and maximum feasible inspection capacity:

$$\mathrm{EI} = \frac{C \times K}{C_{max} \times P} \times 100 \quad (4)$$

where C_{max} denotes the maximum realistic inspection coverage, representing operational capacity constraints such as staffing, processing time, and lane throughput. The multiplication by 100 scales the index to a 0–100 range for interpretability.

This formulation ensures that enforcement units operating in high-risk environments are not unfairly penalized, while those operating in lower-risk contexts are not disproportionately advantaged.

D. Mathematical Properties of the Effectiveness Index

To ensure consistent interpretability of the composite indicator, the EI adopts a multiplicative aggregation structure. This formulation preserves important mathematical properties commonly recommended in composite indicator construction, particularly monotonicity and limited compensability among indicator components [15, 17].

Monotonicity implies that improvements in any performance component should increase the overall index value. Given the EI formulation, the partial derivatives of the index with respect to its key components demonstrate this property. Specifically, the derivatives with respect to inspection coverage (*C*) and targeting accuracy (*K*) are positive:

$$\frac{\partial I}{\partial C} = \frac{K}{C_{max} P} \times 100 > 0$$

$$\frac{\partial I}{\partial K} = \frac{C}{C_{max} P} \times 100 > 0$$

These expressions indicate that improvements in inspection coverage or targeting accuracy, holding other factors constant, will consistently increase the EI. Conversely, the derivative with respect to overloading risk (*P*) is negative:

$$\frac{\partial I}{\partial P} = -\frac{CK}{C_{max} P^2} \times 100 < 0$$

This inverse relationship reflects the risk parameter's normalizing role: as the probability of overloaded vehicles increases, greater enforcement effort is required to maintain the same level of effectiveness

Furthermore, the multiplicative structure reduces excessive compensatory effects among indicators. High performance in one dimension cannot fully offset deficiencies in another, ensuring that enforcement effectiveness reflects the joint performance of inspection coverage, targeting accuracy, and risk exposure. Such aggregation structures are widely recommended for constructing composite performance indicators to maintain a balanced representation of multidimensional system performance [15, 17].

E. Determination of Maximum Inspection Capacity (C_{max})

The value of C_{max} is set at 0.30, reflecting a realistic upper bound on the proportion of freight vehicles that can be inspected without causing significant traffic disruption or operational bottlenecks. This value is based on:

1) Observed Throughput Constraints at Weighbridge Facilities

The physical capacity of weighbridges, which typically only have 2-4 inspection lanes, limits weighing to 8-20 vehicles per hour, while peak logistics volumes can reach 100-300 vehicles per hour. This infrastructure condition results in a realistic cumulative capacity of only about 30% of total freight traffic [18, 19].

2) Average Inspection Processing Times

Static weighing, which takes 5-8 minutes per vehicle, or up to 15 minutes if a full documentation check is required, inherently limits the number of vehicles that can be handled. A 30% inspection target is the optimal threshold for maintaining thoroughness without compromising the smooth flow of traffic in key corridors [18, 20].

3) Staffing and Infrastructure Limitations of Enforcement Units

Law enforcement units with moderate levels of automation that combine low-speed WIM systems and manual procedures are technically limited to a capacity range of 0.25-0.30. In addition to staffing and budget constraints, the need for routine equipment calibration and maintenance to maintain data accuracy also limits the system's uptime [21-23].

F. Data Sources and Computation Procedure

1) Enforcement Operational Data

Operational records from vehicle weight enforcement units were used to compute:

1. The total number of freight vehicles passing through inspection corridors,
2. The number of inspected vehicles.
3. The number of overloaded vehicles detected.

These data were used to estimate *C* and *K* for each enforcement site.

2) Weigh-In-Motion Data

Traffic-based overloading prevalence (*P*) was derived from WIM datasets obtained from the national highway authority.

G. Data Utilization and Computation Workflow

After calculating the *C*, *K*, and *P* values, (4) was applied to compute the standardized effectiveness scores. The enforcement performance was classified using predefined effectiveness thresholds.

H. Performance Classification Thresholds

Table I presents the EI classification thresholds used to group enforcement performance into five categories, ranging from Ineffective to Highly Effective. The classification thresholds were defined by the authors to enhance the interpretability of EI results and to support comparative performance assessment and policy-oriented analysis across enforcement units.

TABLE I. EI PERFORMANCE CLASSIFICATION CATEGORIES

EI Range	Performance Category
< 29	Very Low Effectiveness
30–49	Low Effectiveness
50–69	Moderate Effectiveness
70–79	High Effectiveness
80–100	Excellent Effectiveness

This threshold determination uses a standards-based adaptation method from the ASTM D6433 Pavement Condition Index (PCI) standard [24, 25]. The selection of five classification levels is based on the principle of cognitive ergonomics, which optimizes human ability to distinguish between performance categories without increasing the complexity of interpretation [26, 27]. In addition, each category is directly linked to specific managerial actions, ranging from maintaining best practices at the Excellent level to systematic restructuring at the Very Low level.

I. Sensitivity Considerations

A sensitivity analysis was conducted to examine how variations in inspection coverage, targeting accuracy, and overloading risk influence EI scores. This analysis supports robustness assessment and ensures that the index behaves consistently across a range of realistic enforcement scenarios.

III. DATA AND CASE STUDY

A. Study Area and Institutional Context

The case study was conducted in South Sumatra Province, Indonesia, a major freight corridor within the national road network. The province plays a strategic role in regional logistics, supporting the movement of bulk commodities, including coal, palm oil products, construction materials, and interprovincial freight. Vehicle overloading enforcement in the study area is conducted by the Motor Vehicle Weighing Implementation Unit, which operates fixed roadside weighing and inspection facilities that inspect freight vehicles, identify overloading violations, and apply regulatory sanctions in accordance with national transport policies.

B. Enforcement Units Included in the Study

Two enforcement units were selected to illustrate the application of the proposed EI.

1) Motor Vehicle Weighing Implementation Unit Kertapati

Located in a high-traffic logistics corridor, Motor Vehicle Weighing Implementation Unit (MVWIU) Kertapati serves as a primary enforcement site for freight vehicles traveling through urban and industrial zones. The unit is characterized by moderate inspection throughput and relatively high targeting accuracy, reflecting selective enforcement practices.

2) Motor Vehicle Weighing Implementation Unit Talang Kelapa

MVWIM Talang Kelapa operates along a major freight access route connecting industrial and distribution centers. Compared with Kertapati, this unit exhibits lower inspection throughput but maintains moderate targeting accuracy, making it a useful contrast case for evaluating enforcement effectiveness under constrained inspection capacity.

C. Operational Enforcement Data

Operational data were obtained from law enforcement records during the observation period from November 2023 to July 2025, including the total number of freight vehicles passing through the law enforcement corridor, the number of vehicles inspected, and the number of vehicles confirmed to be overloaded, totalling 6,054,617 vehicles. Based on these records, two key performance indicators, *C* and *K*, were derived to measure law enforcement intensity and targeting effectiveness. Table II summarizes the calculated values of these indicators for each law enforcement unit, highlighting variations in inspection efforts and the selection of overloaded vehicles across locations. These values represent the empirical proportion of overloaded vehicles within the traffic stream and serve as baseline indicators of enforcement difficulty and exposure to overloading risk at each site, thereby providing critical contextual input for the computation of the EI.

TABLE II. INSPECTION COVERAGE AND TARGETING ACCURACY PERFORMANCE OF ENFORCEMENT UNITS

Enforcement Unit	Inspection Coverage (*C*)	Targeting Accuracy (*K*)
MVWIU Kertapati	9.8%	18%
MVWIU Talang Kelapa	2.0%	16%

D. Weigh-In-Motion Data and Overloading Risk Estimation

The considered WIM-derived *P* values for each enforcement corridor are presented in Table III, showing that the Kertapati corridor exhibits a slightly higher proportion of overloaded vehicles than the Talang Kelapa corridor.

TABLE III. *P* BY ENFORCEMENT CORRIDOR BASED ON WIM DATA

Enforcement Corridor	Overloading Prevalence (*P*)
Kertapati	24.0%
Talang Kelapa	16.0%

IV. RESULTS AND DISCUSSION

A. Computation of the Effectiveness Index

The computed EI scores and associated performance indicators for each enforcement unit are presented in Table IV.

TABLE IV. COMPUTED EI AND PERFORMANCE INDICATORS

Enforcement Unit	*C*	*K*	*P*	EI	Performance Category
MVWIUKertapati	0.098	0.24	0.18	43.6	Low Effectiveness
MVWIUTalang Kelapa	0.020	0.16	0.160	6.7	Very Low Effectiveness

B. Interpretation of Case Study Relevance

The selected case study demonstrates the practical applicability of the proposed EI in real-world enforcement settings. The contrast between the two enforcement units illustrates how enforcement effectiveness depends not only on detection precision but also on inspection coverage relative to prevailing overloading risk. This case study provides empirical evidence that performance gaps across enforcement sites can be systematically quantified, offering a foundation for targeted operational improvements, resource prioritization, and performance benchmarking.

C. EI Result Analysis

The observed proportions of overloaded vehicles in the study locations, 18% in Kertapati and 16% in Talang Kelapa, indicate a significant potential to accelerate pavement deterioration. Even moderate levels of overloading can substantially increase pavement damage due to the nonlinear relationship between axle load and structural response, in which pavement deterioration increases exponentially with incremental axle load. Consequently, a relatively small share of overloaded trucks can generate a disproportionately large share of total pavement damage, leading to faster accumulation of structural distress and higher maintenance requirements [28].

The computed EI reveals substantial variation in enforcement performance between the two studied vehicle weight control units.

Although the MVWIU Kertapati demonstrates relatively high targeting accuracy, its effectiveness remains constrained by limited inspection coverage. In contrast, the MVWIU Talang Kelapa exhibits markedly lower overall effectiveness, primarily due to extremely low inspection coverage, despite maintaining moderate detection precision.

Empirical studies on ODOL traffic in Indonesia further show that excessive axle loads increase the VDF and reduce the effective design life of flexible pavements. Higher overload proportions, therefore, shorten pavement service life and increase rehabilitation costs, particularly on freight corridors with high heavy-vehicle traffic volumes such as the national road networks in Sumatra. This confirms that even overload levels below 20% can significantly influence pavement performance and infrastructure sustainability when sustained over time.

D. Relative Contribution of Coverage and Targeting Accuracy

A comparative sensitivity assessment indicates that increasing inspection coverage yields a larger marginal improvement in EI than increasing targeting accuracy, particularly under moderate-to-high overloading prevalence.

For example, holding targeting accuracy constant, increasing inspection coverage at Talang Kelapa from 2% to 10% would raise the EI score from 6.7 to approximately 33.5, shifting performance from ineffective to low-to-moderate effectiveness. By contrast, improving targeting accuracy alone without expanding inspection coverage would yield more limited gains. These findings indicate that increasing inspection coverage delivers greater marginal gains in enforcement effectiveness than improving targeting accuracy alone, particularly in contexts with moderate-to-high overloading prevalence-risk-normalized performance comparison.

By incorporating WIM-based overloading prevalence, the EI enables risk-normalized performance evaluation across enforcement sites. This ensures that units operating in corridors with higher overloading rates are not unfairly penalized, while those in lower-risk environments are not disproportionately advantaged.

In this study, MVWIU Kertapati operates under a slightly higher overloading risk (18%) than MVWIU Talang Kelapa (16%), yet still achieves substantially higher effectiveness. This demonstrates that performance differences are driven more by operational execution than by traffic risk alone, reinforcing the validity of the proposed normalization approach.

The comparative insights from Kertapati and Talang Kelapa offer policy implications that extend beyond the regional context of South Sumatra. By demonstrating that high citation volumes do not always correlate with risk mitigation, this study advocates for a national shift in performance evaluation. For policymakers, the proposed EI framework provides a scalable diagnostic tool to identify critical infrastructure segments where enforcement resources are underperforming relative to the actual load risk. This approach supports the transition toward "Smart Enforcement" in developing countries, where data-driven resource allocation is essential to overcome budget and personnel constraints in road asset management.

E. Sensitivity and Robustness Analysis

To evaluate the operational behavior and structural integrity of the proposed index, a sensitivity analysis was performed to examine how the Effectiveness Index (EI) responds to variations in C, K, and P. The analysis focuses on interpreting the behavioral patterns and synergy between these dimensions as follows:

1) Operational Variable Response and Inter-Dimensional Synergy

The analysis reveals a clear positive relationship between C and the resulting EI score. Notably, higher levels of K produce steeper increases in the EI value as coverage expands. This synergistic effect suggests that while increasing inspection volume is beneficial, its impact on the overall enforcement effectiveness is significantly amplified when supported by precise vehicle selection strategies.

2) Non-Linear Risk Normalization

In contrast to the positive drivers of performance, the EI score exhibits a non-linear decrease as the probability of overloaded vehicles (P) in the traffic stream increases. This inverse relationship validates the risk parameter as a robust normalization factor. By accounting for baseline enforcement difficulty, the index ensures that units operating in high-risk corridors, which require greater enforcement capacity to maintain effectiveness, are not unfairly penalized compared to units in lower-risk environments.

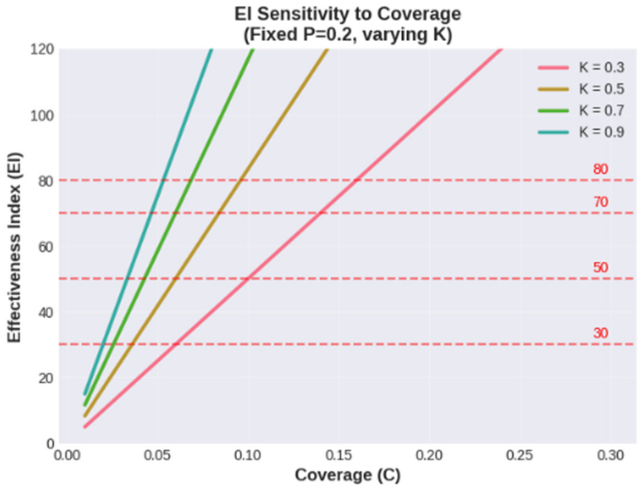

Fig. 2. EI sensitivity to coverage.

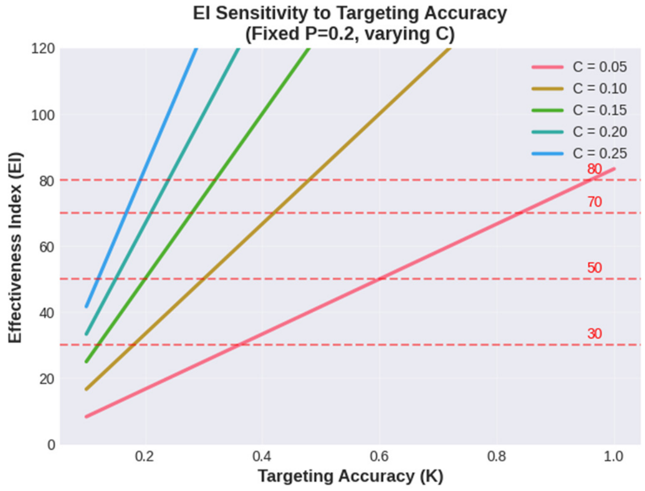

Fig. 3. EI sensitivity to targeting accuracy.

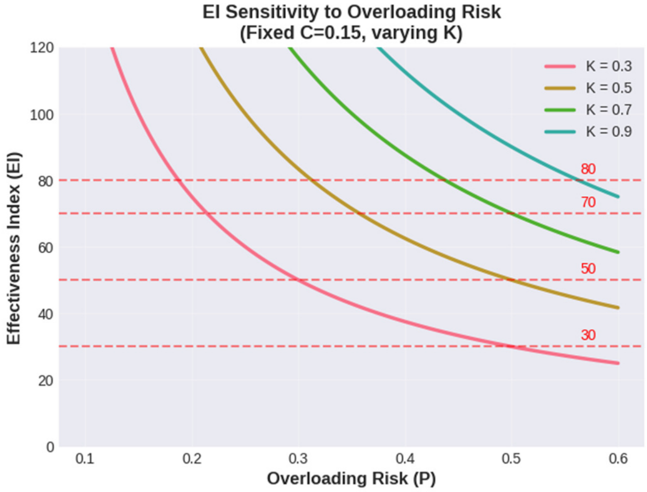

Fig. 4. EI sensitivity to overloading risk.

3) Threshold Contour Analysis for Strategic Planning

The threshold contours in Figure 5 illustrate the specific combinations of coverage (*C*) and targeting accuracy (*K*) required to achieve moderate (EI=50) and high (EI=70) effectiveness levels. As the overloading risk (*P*) increases, the contours shift, indicating that a higher degree of either *K* or *C* is mandatory to maintain the same performance classification. These contours provide a practical roadmap for agencies to determine the minimum operational requirements needed to reach a targeted effectiveness category under varying traffic conditions.

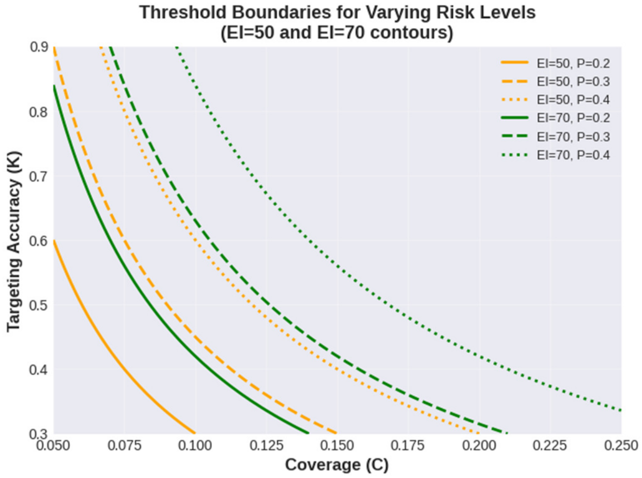

Fig. 5. Threshold boundaries for varying risk levels.

F. Implications for Enforcement Strategy

1) Balancing Coverage and Precision

Effective overloading enforcement requires a balanced combination of inspection coverage and targeting accuracy. Overemphasis on selective inspections may yield high violation detection rates but low overall deterrence impact if inspection intensity remains limited.

2) Priority on Inspection Expansion in Low-Performing Units

For low-performing units such as Talang Kelapa, expanding inspection coverage is the most impactful pathway to improving effectiveness. This may include operational adjustments such as increasing inspection shifts, reducing processing time, or leveraging WIM systems for pre-screening.

3) Data-Driven Performance Benchmarking

The EI provides a quantitative benchmarking tool for comparing enforcement units and identifying performance gaps. Agencies can use EI scores to strategically allocate resources, prioritize high-impact corridors, and monitor performance trends over time.

G. Policy and Institutional Relevance

From a policy perspective, the findings underscore the need to move beyond conventional enforcement metrics based solely on inspection counts or recorded violations. Instead, data-driven and risk-aware effectiveness indicators, such as the proposed EI, offer a more meaningful and practical basis for benchmarking enforcement performance by accounting for both operational intensity and exposure to enforcement difficulty. The proposed index supports evidence-based decision-making by enabling transport authorities to set realistic performance targets, optimize inspection strategies, and strengthen accountability mechanisms in vehicle overloading control programs.

H. Limitations and Future Research

This study is subject to several limitations. The case study focuses on a limited number of enforcement units within a single province, and the observation period may not capture seasonal or long-term variations in freight patterns. Additionally, WIM-based prevalence estimates may be influenced by sensor accuracy and calibration constraints.

While this study is limited to two enforcement units in South Sumatra, the findings provide a robust foundation for broader application across Indonesia's logistics networks. Empirical studies on Overdimension and Overloading (ODOL) traffic in Indonesia further show that excessive axle loads increase VDF and reduce the effective design life of flexible pavements. Higher overload proportions, therefore, shorten pavement service life and increase rehabilitation costs, particularly on freight corridors with high heavy-vehicle traffic volumes such as national road networks in Sumatra. This confirms that even overload levels below 20% can significantly influence pavement performance and infrastructure sustainability when sustained over time [29].

Future research should extend the index's application to broader geographic contexts, incorporate longitudinal data, and explore integration with behavioral compliance indicators to assess driver responses to enforcement strategies. Furthermore, incorporating cost-benefit analyses would be valuable to quantify the economic trade-offs between enforcement operational expenditures and the resulting savings in pavement maintenance costs. These additions, along with pavement performance metrics, will further validate and enhance the framework. The use of the risk-normalized EI as a scalable benchmarking tool could also be tested in different jurisdictions to standardize enforcement performance evaluation

V. CONCLUSION

This study proposed an Effectiveness Index (EI) as a risk-aware and comprehensive metric for evaluating vehicle overloading enforcement by integrating inspection coverage, targeting accuracy, and Weigh-In-Motion (WIM)-derived overloading risk. Applications to enforcement units in South Sumatra demonstrated performance variation and confirmed that detection accuracy alone is insufficient, while adequate inspection coverage is essential for achieving meaningful enforcement effectiveness. The risk-normalized formulation enables fair comparison across heterogeneous traffic conditions. The robustness of this framework was further validated through sensitivity analysis, which revealed that while EI is highly responsive to targeting accuracy, the overloading risk (P) serves as a critical normalization factor, preventing performance bias in high-risk corridors. Consequently, the risk-normalized EI serves as a novel, scalable benchmarking tool that standardizes performance evaluation across diverse geographic and operational contexts. Overall, the proposed framework provides a data-driven and policy-relevant tool for benchmarking enforcement performance, optimizing resource allocation, and supporting evidence-based decision-making.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author. Some traffic and enforcement data are presented directly within the tables of this manuscript.

AI USE AND DECLARATION OF GENERATIVE AI USE

During the preparation of this work, the authors used AI tools to improve the language and flow of the text. The authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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