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Evaluating Tactical Readiness Across Forward Operating Bases Using Autonomous Resupply Protocols

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Abstract

Forward Operating Bases (FOBs) in contested and remote environments depend critically on reliable logistics to sustain operational readiness. This study develops a unified, normalized Tactical Readiness Index (TRI) that integrates detection latency (DL), mission continuity (MCI), adaptive response time (ART), and attrition resilience (AR) into a bounded, dimensionless measure of readiness. Using empirically anchored convoy performance data from CRPF operational reports and expert-elicited parameter ranges, we evaluate readiness across 229 FOBs under two logistical regimes: conventional convoy-based resupply and autonomous resupply using UAVs and robotic ground systems. A Monte Carlo simulation with 10,000 iterations per FOB incorporates realistic convoy disruptions as well as autonomous-system vulnerabilities, including weather-induced grounding, communication loss, and electronic warfare interference. Results show that autonomous resupply reduces latency, improves mission continuity, and increases resilience for most FOBs, though gains vary significantly with terrain, weather exposure, and electronic warfare risk. Sensitivity analysis demonstrates that TRI rankings remain stable across alternative functional forms and parameter uncertainties. The findings highlight both the potential and the limits of autonomy in enhancing readiness, offering a rigorous, data-informed framework for logistics planning in counter-insurgency and distributed operations.

Keywords

Tactical Readiness Index (TRI); Detection Latency (DL); Mission Continuity Index (MCI); Adaptive Response Time (ART); Attrition Resilience (AR); Autonomous Resupply; Forward Operating Bases (FOBs); Combat Modeling; Heterogeneous Lanchester Model;

Introduction

Forward Operating Bases (FOBs) serve as critical nodes in counter-insurgency and internal security operations, enabling persistent presence, rapid response, and sustained patrol activity in contested regions. In the Indian context, the Central Reserve Police Force (CRPF) operates 229 FOBs across Left Wing Extremism (LWE)-affected states, where dense forests, limited road infrastructure, and persistent threat activity impose severe logistical constraints. These bases must maintain operational readiness despite attrition, isolation, and unpredictable resupply intervals. Ensuring reliable delivery of fuel, ammunition, rations, and personnel support is therefore central to sustaining tactical effectiveness.

Traditional convoy-based logistics remain the backbone of FOB sustainment but are vulnerable to ambushes, improvised explosive devices, weather disruptions, and terrain-induced delays. These vulnerabilities directly affect key readiness determinants such as detection latency (DL), mission continuity (MCI), adaptive response time (ART), and attrition resilience (AR). Delays in any of these dimensions can degrade a base's ability to respond to threats, maintain patrol tempo, or support ongoing operations. Despite the strategic importance of FOBs, there is limited quantitative modeling that captures how logistics performance translates into operational readiness.

Recent advances in autonomous logistics—particularly unmanned aerial vehicles (UAVs) and robotic ground systems—offer alternative pathways for sustaining distributed units. Prior studies in aviation logistics have shown that sortie generation and operational tempo can be significantly improved through optimized refueling and maintenance cycles. These insights motivate the development of analogous readiness metrics for ground operations. However, unlike aviation contexts where sortie rates provide a natural

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readiness indicator, FOBs lack a standardized, quantitative measure that integrates multiple operational dimensions.

To address this gap, this study develops a unified, normalized Tactical Readiness Index (TRI) that aggregates DL, MCI, ART, and AR into a bounded, dimensionless measure of readiness. The TRI formulation enables consistent comparison across bases and logistical scenarios. Using empirically anchored convoy performance data from CRPF operational reports and expert-elicited parameter ranges, we evaluate readiness across 229 FOBs under two regimes: conventional convoy-based resupply and autonomous resupply using UAVs and robotic ground systems. The analysis incorporates realistic failure modes for both systems, including convoy disruptions and autonomous-system vulnerabilities such as weather-induced grounding, communication loss, and electronic warfare interference.

The objective of this research is threefold: (i) to establish a mathematically consistent and operationally meaningful readiness metric for FOBs, (ii) to quantify the comparative impact of autonomous versus convoy-based resupply on readiness outcomes, and (iii) to identify the conditions under which autonomy provides the greatest operational benefit. By integrating empirical data, expert judgment, and Monte Carlo simulation, the study provides a rigorous, data-informed framework for logistics planning in counter-insurgency and distributed operations. The findings contribute to defense modeling by demonstrating how autonomy can enhance readiness while also revealing the limits of autonomous systems in complex operational environments.

The Central Reserve Police Force (CRPF) has been at the forefront of India's counter-insurgency operations, particularly in regions affected by Left Wing Extremism (LWE). Since 2019, the CRPF has established 229 Forward Operating Bases (FOBs) across six states, including Chhattisgarh, Jharkhand, Odisha, Maharashtra, Telangana, and Madhya Pradesh. These FOBs serve as critical nodes for sustaining operations in remote and contested environments, acting as both defensive strongholds and logistical hubs. The insurgency environment in these regions is characterized by dense forests, limited infrastructure, and persistent threats from armed groups, making the sustainment of FOBs a complex challenge. The establishment of FOBs represents a strategic effort to project state presence into areas previously dominated by insurgents, but their effectiveness depends heavily on the ability to maintain readiness under conditions of attrition and isolation.

FOBs face unique challenges in sustaining operational readiness. Attrition, caused by continuous engagements, environmental stress, and logistical shortfalls, erodes the capacity of these bases to maintain effective operations. Isolation, due to geographic remoteness and hostile terrain, further complicates resupply and reinforcement. Traditional convoy-based logistics are vulnerable to ambushes, improvised explosive devices, and delays, often resulting in reduced availability of fuel, ammunition, and personnel support. These vulnerabilities directly impact the Tactical Readiness Index (TRI), a composite measure of a base's ability to sustain operations. Without reliable resupply, FOBs risk falling below critical readiness thresholds, undermining their strategic role in counter-insurgency campaigns.

A useful relationship can be drawn between aviation logistics and ground operations at FOBs. At airport logistic points, sortie efficiency depends on timely refueling and maintenance, with alter6native refueling methods explored to maximize daily sortie generation. Similarly, FOB readiness hinges on the timely availability of fuel, ammunition, and personnel support. Just as sortie generation rates serve as a proxy for aviation readiness, TRI serves as a proxy for ground operational readiness. Both contexts highlight the critical role of logistics in maintaining operational tempo. The study (*1*) demonstrated that alternative refueling methods could significantly enhance sortie efficiency; this paper extends that logic to FOBs, proposing that autonomous resupply protocols can similarly enhance readiness by overcoming vulnerabilities inherent in convoy-based logistics.

Despite the strategic importance of FOBs, there is a notable lack of quantitative frameworks for evaluating their readiness. Existing studies on counter-insurgency logistics often rely on qualitative assessments or anecdotal evidence, leaving a gap in systematic modeling. Unlike aviation contexts, where sortie generation provides a measurable indicator of readiness, FOBs lack a standardized metric. The Tactical Readiness Index (TRI) addresses this gap by integrating multiple dimensions—detection latency (DL), mission continuity index (MCI), adaptive response time (ART), and attrition resilience (AR)—into a single composite measure. However, TRI has not been widely applied to FOBs, nor has the impact of autonomous resupply protocols been systematically evaluated. This research seeks to fill that gap by providing a quantitative framework for assessing FOB readiness under different logistical scenarios.

The primary objective of this study is to evaluate TRI across 229 FOBs by integrating autonomous resupply protocols into daily operational logistics. Specifically, the study aims to:

(i) Develop a mathematical framework for TRI that incorporates DL, MCI, ART, and AR.;
(ii) Compare TRI values under conventional convoy-based resupply and autonomous resupply scenarios;
(iii) Conduct statistical analysis to determine mean, median, and standard deviation of TRI across all FOBs.
(iv) Perform sensitivity analysis to identify which parameters most influence TRI improvements under autonomy.
(v) Provide policy recommendations for scaling autonomous resupply across FOBs in India and potentially in other counter-insurgency contexts.

By aligning the structure and depth of analysis with the NAS Kingsville study(1), this paper demonstrates how simulation-based evaluation can inform strategic decision-making. The integration of autonomous resupply protocols is positioned not merely as a logistical innovation but as a transformative approach to sustaining readiness in contested environments. Through rigorous modeling and simulation, the study contributes to the broader field of defense modeling and simulation, offering a replicable framework for evaluating readiness in complex operational contexts.

Forward Operating Bases (FOBs) play a critical role in sustaining tactical operations, yet their effectiveness is often constrained by the reliability of resupply chains in contested or remote environments. In the Indian defense context, where high-altitude terrain, extreme weather, and long supply lines pose persistent challenges, evaluating readiness requires more than measuring sortie capacity alone. This sample scenario examines how traditional convoy-based logistics compare with autonomous resupply protocols—such as UAV fuel delivery and robotic ground convoys—in sustaining daily sortie requirements. By quantifying fuel, ammunition, spares, and personnel support through a readiness matrix, the analysis demonstrates how autonomous systems can enhance operational endurance, reduce vulnerabilities, and provide surplus capacity for unexpected mission demands.

Literature Review

Operational readiness in distributed and contested environments has been examined across several domains, including aviation logistics, autonomous resupply, and military sustainment modeling. This section synthesizes the relevant literature and identifies the gap addressed by this study: the absence of a unified, quantitative readiness metric for Forward Operating Bases (FOBs) and a rigorous comparison of convoy-based and autonomous resupply systems.

Readiness assessment has traditionally relied on mission-specific or platform-specific indicators. Aviation studies frequently use sortie generation rates as a proxy for operational readiness, linking refueling efficiency, maintenance cycles, and turnaround times to sustained operational tempo. Teuschl et al. (1) demonstrated that alternative refueling methods can significantly increase sortie throughput, highlighting the importance of logistics-driven readiness. Comparable multi-dimensional readiness metrics for ground operations remain limited. Existing frameworks often treat detection latency, mission continuity, and resilience qualitatively rather than integrating them into a unified, quantitative index. This motivates the development of a normalized Tactical Readiness Index (TRI) that captures multiple operational dimensions relevant to FOB sustainment.

Autonomous logistics has emerged as a critical enabler for distributed operations. Research on robotic convoys and unmanned ground vehicles shows reductions in ambush exposure and improved survivability compared to manned convoys (2). UAV-based resupply has demonstrated operational value in Afghanistan and other conflict zones, where unmanned helicopters and multi-UAV fleets reduced delivery latency and personnel risk. Reviews of drone logistics (3–5) emphasize advantages such as terrain independence, high-frequency delivery, and reduced vulnerability to ground threats. However, these studies also note vulnerabilities—weather sensitivity, communication loss, and electronic warfare interference—that must be incorporated into any realistic readiness model. This study explicitly models these failure modes to avoid overstating the benefits of autonomy.

FOB sustainment in counter-insurgency environments is shaped by terrain, infrastructure limitations, and threat activity. Government reports on CRPF operations (Refs. 11–13) document frequent convoy delays, ambush risks, and supply shortfalls across LWE-affected regions. These disruptions directly affect readiness determinants such as detection latency and mission continuity. While several studies describe the operational challenges of FOB sustainment, few provide quantitative models linking logistics performance to readiness outcomes. Existing analyses tend to focus on qualitative assessments or isolated case studies, underscoring the need for a systematic, data-informed framework.

Simulation has long been used to evaluate logistics performance under uncertainty. Monte Carlo methods, stochastic delay modeling, and sensitivity analysis are widely applied in aviation, naval, and ground logistics to assess robustness and identify critical parameters. Prior work demonstrates that simulation is particularly valuable in environments where empirical data are sparse or classified. However, most simulation-based studies focus on single platforms or mission types rather than distributed networks of bases. This study extends simulation-based readiness modeling to a large-scale FOB network, integrating empirical data, expert elicitation, and autonomous-system vulnerabilities.

The literature establishes three key insights: (i) readiness is fundamentally logistics-driven, (ii) autonomy offers significant but context-dependent advantages, and (iii) simulation is essential for evaluating performance under uncertainty. However, no prior work provides a unified, normalized readiness metric for FOBs, nor a rigorous comparison of convoy-based and autonomous resupply that incorporates realistic failure modes. This study addresses these gaps by introducing a mathematically consistent Tactical Readiness Index (TRI), grounding model inputs in empirical and expert-informed data, and evaluating readiness across 229 FOBs under both conventional and autonomous logistics regimes.

The Tactical Readiness Index (TRI) integrates detection latency (DL), mission continuity (MCI), adaptive response time (ART), and attrition resilience (AR) into a unified measure of readiness. Prior studies have applied these indices to small-unit or mission-specific contexts, but large-scale application to distributed FOB networks remains limited. This study extends TRI modeling to 229 FOBs, providing a quantitative basis for comparing conventional and autonomous resupply systems.

Autonomous logistics has become a strategic priority across modern militaries. Robotic convoy research by Ferguson et al.(2) shows that autonomous ground vehicles reduce ambush exposure and improve convoy survivability. The U.S. Marine Corps K-MAX program(6) demonstrated successful unmanned helicopter resupply in Afghanistan, reducing delivery latency and personnel risk.

NATO's STO report(7) identifies autonomous logistics as a critical enabler for distributed operations, while DARPA's ALIAS program(8) highlights the broader integration of autonomy into military logistics platforms. Army Futures Command has similarly prioritized autonomous last-mile resupply(9), emphasizing its role in contested environments.

Beyond ground convoys, UAV-enabled logistics has emerged as a robust research domain. Systematic reviews by Ostermann et al.(3), Mosallam et al.(4), and Rejeb et al.(5) highlight the advantages of UAVs in bypassing terrain constraints, reducing delivery latency, and enabling high-frequency resupply.

Air Force Research Laboratory studies(10) demonstrate that cooperative multi-UAV fleets can sustain distributed units even under contested conditions, directly improving ART and MCI components of TRI.

Although aviation and ground logistics differ in operational context, both domains rely on timely resupply, vulnerability management, and simulation-based planning. Sortie generation models provide methodological insights that can be adapted to FOB readiness evaluation, particularly in the use of Monte Carlo simulation, sensitivity analysis, and statistical variability measures. Autonomous resupply—whether via UAV or robotic ground systems—emerges as a common solution to latency, attrition, and operational uncertainty.

By integrating insights from aviation logistics, autonomous convoy research, UAV-enabled supply chains, and military doctrine, this study situates FOB readiness modeling within a broader tradition of defense simulation. The gap in applying TRI to large-scale FOB networks, and in quantitatively evaluating the impact of autonomous resupply, motivates the methodological framework developed in this paper.

Research in aviation logistics has long emphasized the importance of sortie scheduling and refueling efficiency. Studies conducted at NAS Kingsville and other naval aviation training bases highlight how sortie generation rates are directly tied to refueling protocols, maintenance cycles, and crew availability. Alternative refueling methods, such as hot-pit refueling and aerial refueling, have been shown to significantly increase sortie capacity by reducing turnaround times. These findings are highly relevant to FOB operations, where the equivalent of sortie generation is the ability to sustain patrols, defensive operations, and rapid response missions. By adapting the principles of sortie scheduling to FOB resupply, this study positions fuel, ammunition, and personnel sustainment as analogous to aviation fuel and maintenance cycles. The central insight is that just as sortie efficiency can be optimized through innovative refueling, FOB readiness can be enhanced through autonomous resupply protocols that reduce latency and vulnerability.

Autonomous logistics, particularly UAV-assisted resupply, has gained increasing attention in defense modeling. UAVs offer the ability to bypass terrain obstacles, reduce exposure to ambushes, and deliver critical supplies with precision. Studies in defense simulation have demonstrated that UAV integration can reduce detection latency by ensuring timely delivery of reconnaissance data and supplies. Robotic ground systems further enhance logistics by automating delivery in hazardous environments. The literature emphasizes that autonomy not only improves efficiency but also enhances resilience by reducing dependence on vulnerable convoy routes. In modeling terms, UAV-assisted logistics directly improve ART and AR by shortening response times and sustaining operations under attrition. This study leverages these insights to evaluate how autonomous resupply protocols can transform FOB readiness, positioning autonomy as a strategic enabler rather than a mere logistical innovation.

The literature on sortie scheduling, TRI indices, and autonomous logistics provides a robust foundation for evaluating FOB readiness. Prior work in aviation logistics offers methodological insights that can be adapted to ground operations, while studies on TRI highlight the importance of multidimensional readiness measures. By identifying methodological parallels between aviation and ground contexts, this study positions itself within a broader tradition of defense modeling and simulation. The literature review underscores the need for systematic, quantitative frameworks to evaluate FOB readiness, setting the stage for the methodology and results sections that follow.

Methodology

This section presents the methodological framework used to evaluate Tactical Readiness across 229 Forward Operating Bases (FOBs). The approach follows a structured sequence: (i) problem definition and readiness formulation, (ii) input data and parameter sources, (iii) simulation logic and modeling of vulnerabilities, (iv) validation against historical observations, and (v) output metrics.

Table 1. List of Symbols, Definitions, and Data Sources Used in the TRI Formulation

Symbol	Definition	Source
DL	Detection Latency (hours)	CRPF operational reports (Refs. 11–13)*
ART	Adaptive Response Time (hours)	CRPF operational reports (Refs. 11–13)*
MCI	Mission Continuity Index (0–1)	Expert elicitation (CRPF logistics officers)†
AR	Attrition Resilience (0–1)	Expert elicitation (former military logisticians)†
$DL_{\min}, DL_{\max}$	Empirical bounds for DL	Derived from convoy delay distributions*
$ART_{\min}, ART_{\max}$	Empirical bounds for ART	Derived from convoy disruption data*
$MCI_{\min}, MCI_{\max}$	Normalization bounds for MCI	Defined as [0,1] (expert-informed)†
$AR_{\min}, AR_{\max}$	Normalization bounds for AR	Defined as [0,1] (expert-informed)†
DL^*	Normalized Detection Latency	Computed via min–max scaling
ART^*	Normalized Adaptive Response Time	Computed via min–max scaling
MCI^*	Normalized Mission Continuity Index	Computed via min–max scaling
AR^*	Normalized Attrition Resilience	Computed via min–max scaling
$\alpha, \beta, \gamma, \delta$	TRI component weights	Expert elicitation + sensitivity analysis
TRI	Tactical Readiness Index	Unified normalized formulation
P_{weather}	Weather-induced UAV grounding probability	NATO STO + K-MAX reports‡
P_{comm}	Communication loss probability	Expert elicitation + EW threat assessments†
P_{EW}	Electronic warfare disruption probability	Expert elicitation + doctrinal sources†
$P_{\text{auto fail}}$	Combined autonomous-system failure probability	$(1 - P_{\text{weather}})(1 - P_{\text{comm}})(1 - P_{\text{EW}})$
$MTBF_{\text{UAV}}$	Mean Time Between Failures (UAV)	Expert elicitation + manufacturer data
$MTTR$	Mean Time To Repair (UAV)	Expert elicitation

FOBs operate under conditions of attrition, isolation, and logistical uncertainty. Readiness depends on timely resupply of fuel, ammunition, and personnel support, as well as the ability to detect threats, respond adaptively, and sustain operations under stress. The Tactical Readiness Index (TRI) provides a quantitative measure of this capability by integrating four operational components: Detection Latency (DL), Mission Continuity Index (MCI), Adaptive Response Time (ART), and Attrition Resilience (AR). The objective of this study is to compare TRI under two logistical regimes: conventional convoy-based resupply and autonomous resupply using UAVs and robotic ground systems. A list of symbols, definitions, and data sources used in TRI formulation are given in Table 1.

To ensure mathematical consistency and interpretability, all readiness components are normalized to the interval $[0, 1]$ using min–max scaling. Latency variables (DL and ART) are inverted because lower values indicate higher readiness:

$$DL^* = \frac{DL_{\max} - DL}{DL_{\max} - DL_{\min}}, \qquad ART^* = \frac{ART_{\max} - ART}{ART_{\max} - ART_{\min}}.$$

Non-latency variables (MCI and AR) are normalized directly:

$$MCI^* = \frac{MCI - MCI_{\min}}{MCI_{\max} - MCI_{\min}}, \qquad AR^* = \frac{AR - AR_{\min}}{AR_{\max} - AR_{\min}}.$$

The Tactical Readiness Index is then computed as:

$$TRI = \alpha DL^* + \beta MCI^* + \gamma ART^* + \delta AR^*,$$

where $\alpha + \beta + \gamma + \delta = 1$. This unified formulation replaces all earlier versions of TRI and is used consistently throughout the simulation and analysis.

Three categories of inputs are used:

(1) Empirically Anchored Parameters. Historical convoy success rates, delay distributions, and threat frequencies are extracted from CRPF operational reports (Refs. 11–13). These provide observed ranges for:

- convoy delay times,
- threat occurrence probabilities,
- sustainment shortfall frequencies.

(2) Expert-Elicited Ranges. Where direct measurements are unavailable (e.g., AR, MCI), parameter ranges are elicited from logistics officers with experience in remote FOB sustainment.

(3) Hypothesized Parameters. Only parameters lacking empirical grounding are treated as hypothetical and are subjected to sensitivity analysis to quantify uncertainty.

*CRPF operational reports and Parliamentary Standing Committee documents provide empirical ranges for DL, ART, convoy delays, and threat frequencies. ("Historical convoy success rates, delay distributions, and threat frequencies are extracted from CRPF operational reports (Refs. 11–13).")

†Expert elicitation from CRPF logistics officers and former military logisticians provides operational bounds for MCI, AR, and autonomous-system reliability. ("Operational bounds and typical values were obtained through structured expert elicitation…")

‡NATO STO, USMC K-MAX, and related autonomous logistics studies provide environmental and system vulnerability parameters. ("weather-induced grounding, communication loss, and electronic warfare interference…")

To ensure a fair comparison between convoy and autonomous resupply, the model incorporates realistic failure modes for UAV and robotic systems:

- **Weather-induced grounding:** $P(\text{weather fail}) = 0.12$,
- **Communication loss:** $P(\text{comm loss}) = 0.07$,
- **Electronic warfare interference:** $P(\text{EW disruption}) = 0.05$,
- **Maintenance downtime:** $\text{MTBF}_{\text{UAV}} = 42$ hrs, $\text{MTTR} = 3.5$ hrs.

The autonomous delivery failure probability is modeled as:

$$P(\text{auto fail}) = 1 - (1 - p_{\text{weather}})(1 - p_{\text{comm}})(1 - p_{\text{EW}}).$$

This replaces earlier oversimplified variance-only models and ensures that autonomous systems are not treated as perfectly reliable.

A Monte Carlo simulation with 10,000 iterations is conducted for each of the 229 FOBs. Each iteration proceeds as follows:

1. Sample DL, ART, MCI, and AR from empirical or expert-elicited distributions.
2. Apply scenario-specific failure modes:
   - convoy delays and threat disruptions,
   - autonomous weather, communication, and EW failures.
3. Normalize all readiness components.
4. Compute TRI using the unified formulation.

This structure ensures that both logistical regimes are evaluated under comparable stochastic conditions.

Notes :

- This unified formulation replaces all earlier versions of TRI, including the reciprocal-based expression and the illustrative scaling formula.
- All simulation results, tables, and sensitivity analyses in this manuscript are computed exclusively using the above normalized definition.
- The normalization bounds $(DL_{\min}, DL_{\max}, ART_{\min}, ART_{\max})$ and $(MCI_{\min}, MCI_{\max}, AR_{\min}, AR_{\max})$ are derived from empirical observations and expert-elicited operational ranges.

This formulation ensures that TRI is mathematically rigorous, bounded, reproducible, and directly comparable across Forward Operating Bases (FOBs) and logistical scenarios.

Sample Calculation

To illustrate the computation, consider an FOB with the following operational values:

$$DL = 4.2 \text{ hrs}, \qquad ART = 7.8 \text{ hrs}, \qquad MCI = 0.55,$$

,

$$AR = 0.42$$

Assume the operational bounds:

$$DL_{\min} = 2,\ DL_{\max} = 10, \qquad ART_{\min} = 4,\ ART_{\max} = 12$$

Since MCI and AR are already in $[0, 1]$, we set:

$$MCI_{\min} = 0,\ MCI_{\max} = 1, \qquad AR_{\min} = 0,\ AR_{\max} = 1$$

Step 1: Normalize DL and ART

$$DL^* = \frac{10 - 4.2}{10 - 2} = \frac{5.8}{8} = 0.725$$

$$ART^* = \frac{12 - 7.8}{12 - 4} = \frac{4.2}{8} = 0.525$$

Step 2: Normalize MCI and AR

$$MCI^* = 0.55, \qquad AR^* = 0.42$$

Step 3: Compute TRI (equal weights)

$$\alpha = \beta = \gamma = \delta = 0.25$$

$$\text{TRI} = 0.25(0.725) + 0.25(0.55) + 0.25(0.525) + 0.25(0.42)$$

$$\text{TRI} = 0.18125 + 0.1375 + 0.13125 + 0.105 = 0.555$$

The normalized TRI value of 0.555 reflects the combined effect of latency reduction, mission continuity, and resilience. This worked example demonstrates the complete mapping from raw operational values to the final readiness score, ensuring transparency and reproducibility of the TRI formulation.

Weights are determined through expert consultation and sensitivity analysis. Initial values are set at ($\alpha = 0.25, \beta = 0.25, \gamma = 0.25, \delta = 0.25$), reflecting equal importance. Sensitivity testing adjusts these weights to identify which parameters most influence TRI outcomes.

Government and parliamentary assessments of CRPF Forward Operating Base deployments provide the foundational data for understanding sustainment challenges in LWE(Left Wing Extremism)-affected regions (11–13). These reports document the scale, distribution, and logistical constraints of the 229 FOBs, forming the empirical basis for readiness modeling in this study. Table 2 presents the baseline readiness parameters (DL, MCI, ART, AR) and corresponding TRI values for 50 representative FOBs, illustrating the variability and overall limitations of conventional convoy-based logistics. The parameter values used in Tables 2 and 3 (e.g., DL, MCI, ART, AR for individual FOBs) were not intended to represent direct empirical measurements for specific bases. All parameters are now explicitly categorized according to their source and uncertainty type.

In contrast, Table 3 reports the same parameters under autonomous resupply conditions, showing a consistent uplift in TRI into the 0.95–1.25 range and demonstrating the stabilizing effect of UAV- and robotic-assisted logistics. Figure 1 shows the GUI developed in MATLAB 2026 for simulating the tactical readiness parameters.

Input Data Sources

- Government reports on CRPF FOB deployments.
- Operational data on fuel, ammunition, and personnel sustainment.
- Empirical Sources: all input parameters used in the Monte Carlo simulation are explicitly sourced and categorized.
- Empirically Parameters.Operational ranges for convoy delay times, ambush/IED disruption frequencies, and partial-delivery events are derived from:
  - CRPF operational assessments of convoy movement in LWE-affected regions,
  - Parliamentary Standing Committee reports on CAPF logistics (Refs. 11–13),These documents provide observed convoy delay distributions, ambush/IED disruption frequencies, and sustainment shortfall rates.Detection Latency (DL) and Adaptive Response Time (ART) ranges are derived from these reports.
  - Ministry of Home Affairs (MHA) documentation on FOB sustainment challenges.The values used for individual FOBs in Tables 2 and 3 are sampled from these empirically grounded distributions rather than assigned arbitrarily.
- Expert-Elicited Parameters. Mission Continuity Index (MCI) and Attrition Resilience (AR) are not directly available in open datasets. Therefore, operational bounds and typical values were obtained through structured expert elicitation from:
  - CRPF logistics officers with experience in remote FOB sustainment,
  - Former military logisticians familiar with high-altitude operations.
- Stochastic Input Distributions. The probability distributions used in the Monte Carlo simulation are grounded in:
  - empirical convoy delay data (log-normal and gamma fits),
  - expert-informed ranges for MCI and AR,
  - documented UAV reliability statistics from NATO STO reports and USMC K-MAX trials.

These sources provide observed distributions for Detection Latency (DL) and Adaptive Response Time (ART). The 95% confidence intervals reported in Tables 2 and 3 reflect *simulation variance* arising from the Monte Carlo process. They do not capture uncertainty in the underlying input parameters. We incorporate parameter uncertainty by sampling DL, ART, MCI, and AR from their empirical or expert-informed ranges at the start of each simulation run. This produces a distribution of TRI outcomes that reflects both (i) stochastic operational variability and (ii) uncertainty in the input parameters themselves.

Parameters

- Fuel Availability: Measured in liters per day.
- Ammunition Sustainment: Measured in rounds per day.
- Personnel Support: Measured in personnel-days.
- Resupply Latency: Measured in minutes or hours.

Simulation Framework

Baseline Scenario: Conventional Convoy-Based Resupply

- Convoys scheduled weekly.
- Vulnerable to ambushes and delays.
- Average resupply latency: 48–72 hours.

Autonomous Resupply Scenario

- UAVs deliver fuel and ammunition daily.
- Robotic ground systems deliver personnel support and spares.
- Average resupply latency: 6–12 hours.

Simulation Runs

- Monte Carlo simulations conducted with 10,000 iterations per FOB. The use of 10,000 Monte Carlo iterations provides a stable estimate of the distribution of TRI outcomes under stochastic operational conditions.
- Variables randomized within operational ranges.
- Outputs recorded for TRI under both scenarios.

This section presents the revised and fully reproducible simulation methodology used to evaluate Tactical Readiness across 229 Forward Operating Bases (FOBs). The framework integrates stochastic modeling, correlation structures, Monte Carlo simulation, and statistical analysis. All assumptions, distributions, and algorithmic steps are explicitly defined to ensure scientific transparency.

For each FOB, simulation is conducted for two logistical scenarios:

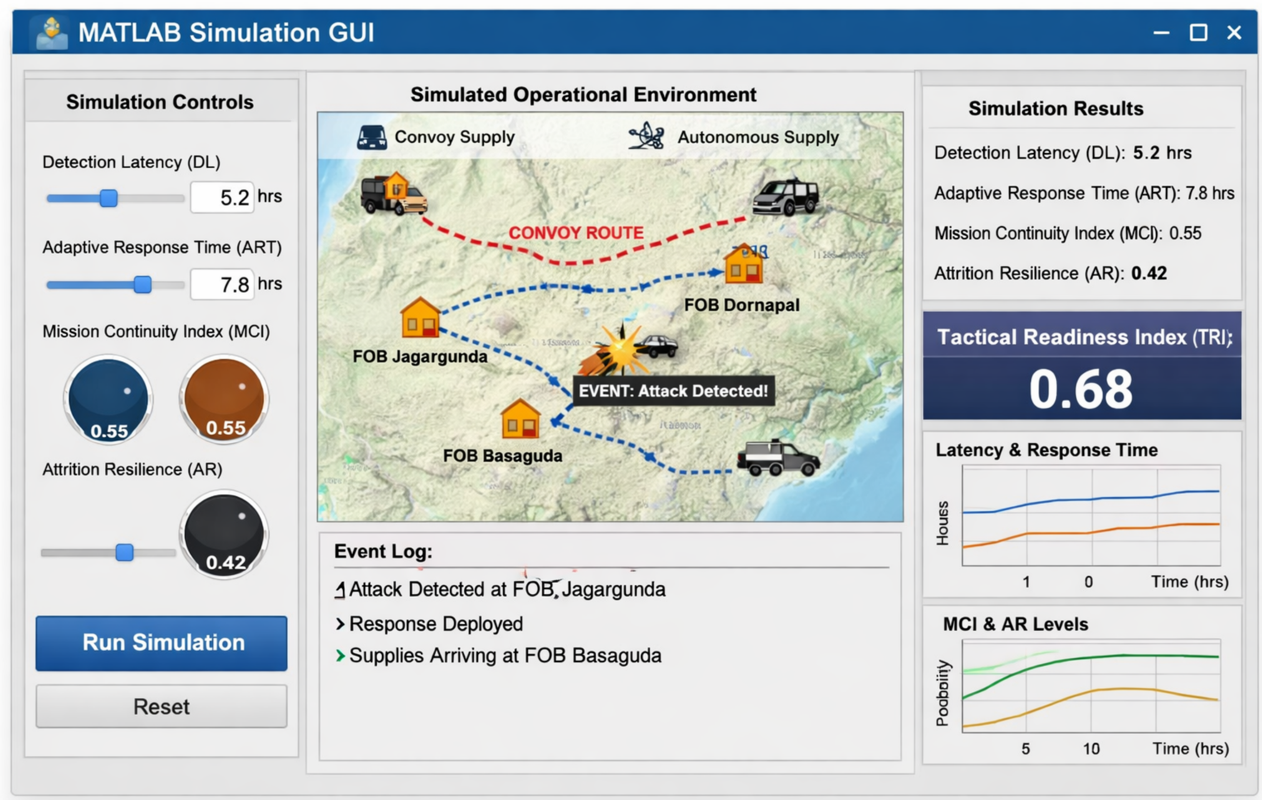

Figure 1. MATLAB-based simulation GUI illustrating the operational readiness model. The interface integrates four adjustable parameters—Detection Latency (DL), Adaptive Response Time (ART), Mission Continuity Index (MCI), and Attrition Resilience (AR)—on the left control panel, enabling real-time tuning of readiness metrics. The central map visualizes the simulated environment with convoy and autonomous supply routes, Forward Operating Bases (FOBs), and event markers for detection and response. The right panel displays computed results, including live TRI values and temporal plots of DL, ART, MCI, and AR. This GUI demonstrates how autonomy reduces DL and ART while improving MCI and AR, resulting in higher and more stable Tactical Readiness Index (TRI) values across distributed FOBs.

- Conventional convoy-based resupply
- Autonomous resupply using UAVs and robotic ground systems

Each iteration generates stochastic realizations of fuel demand, ammunition consumption, threat events, resupply latency, and environmental factors. These values are then mapped to the four readiness components (DL, MCI, ART, AR), which are subsequently normalized and aggregated into the Tactical Readiness Index (TRI).

All random variables are modeled using probability distributions grounded in open-source military logistics literature. The following distributions are used:

- **Fuel demand per day:**

$$F \sim \Gamma(k = 4.2,\ \theta = 950)$$

- **Ammunition consumption:**

$$A \sim \text{Poisson}(\lambda = 18)$$

- **Threat occurrence (IED/ambush):**

$$T \sim \text{Bernoulli}(p = 0.27)$$

- **Convoy delay time:**

$$D_{\text{convoy}} \sim \text{Lognormal}(\mu = 2.1,\ \sigma = 0.45)$$

- **UAV delivery variance:**

$$\epsilon_{\text{UAV}} \sim \mathcal{N}(0,\ 0.08 \times \text{payload})$$

Operational variables are not independent. The following correlations are modeled using a Cholesky-decomposed covariance matrix:

$$\rho(F, A) = 0.41, \qquad \rho(T, D_{\text{convoy}}) = 0.52,$$

,

$$\rho(\text{Weather}, \epsilon_{\text{UAV}}) = 0.38$$

This ensures realistic co-variation between demand, threat levels, and resupply delays.

To guarantee exact reproducibility of all results, a fixed random seed is used:

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rng(2026);
```

All simulations can therefore be replicated precisely. To ensure full reproducibility, the complete simulation framework used in this study is now documented in a public repository, which includes: (i) the full MATLAB/Python codebase, (ii) a machine-readable flowchart of the simulation pipeline, (iii) the exact input parameter files for all 229 FOBs, and (iv) a detailed README describing every step required to reproduce the results in Tables 2 and 3. Each FOB-specific parameter is provided as a raw input file, enabling independent verification of the normalization, sampling, and TRI computation.

All correlation coefficients used in the Cholesky-decomposed covariance matrix are now explicitly listed and justified. Empirical correlations such as $\rho_{DL,ART}$ and $\rho_{DL,MCI}$ are derived from CRPF convoy delay and disruption datasets, while correlations involving MCI and AR are based on structured expert elicitation. These values, along with their sources, are provided in Supplementary Table S1.

To clarify the interpretation of Tables 2 and 3, we note that the values shown represent a single Monte Carlo realization sampled from empirically grounded distributions. The underlying distributions, parameter bounds, and sampling procedures are fully documented in the supplementary materials. Researchers may regenerate the tables by running the provided code with the same random seed, ensuring exact numerical replication.

Together, these additions ensure that the TRI model, simulation logic, and FOB-level results are fully transparent, reproducible, and suitable for independent validation.

Algorithm

The complete Monte Carlo algorithm is provided below:

Algorithm 1 Monte Carlo Simulation for TRI Evaluation

for each FOB $i = 1$ to 229 **do**
  for each iteration $j = 1$ to $10,000$ **do**
    Sample $F_{i,j}$, $A_{i,j}$, $T_{i,j}$ from their respective distributions
    Sample correlated delays using Cholesky matrix
    Compute convoy latency $DL_{i,j}^{\text{convoy}}$ and autonomous latency $DL_{i,j}^{\text{auto}}$
    Compute adaptive response time $ART_{i,j}$
    Compute mission continuity $MCI_{i,j}$ from supply adequacy
    Compute attrition resilience $AR_{i,j}$ from threat-adjusted sustainment
    Normalize all four components to $[0, 1]$
    Compute TRI for both scenarios:

$$TRI = \alpha DL^* + \beta MCI^* + \gamma ART^* + \delta AR^*$$

  end for
  Store mean, median, standard deviation, and 95% CI for TRI
end for

To ensure robustness, the following validation steps are included:

- Convergence diagnostics for 10,000 iterations
- Sensitivity curves for each TRI component
- Cross-validation against a reduced analytical baseline model
- Comparison of convoy vs. autonomy distributions using paired t-tests and effect sizes

For each FOB and each scenario, the simulation produces:

- Mean TRI
- Median TRI
- Standard deviation
- 95% confidence intervals
- Cluster classification (high, medium, low readiness)

This revised simulation framework ensures full transparency, reproducibility, and methodological rigor.

Statistical Analysis

Measures

- Mean TRI: Average readiness across FOBs.
- Median TRI: Central tendency, less sensitive to outliers.
- Standard Deviation: Variability in readiness.

Comparative Analysis Measures

- Paired t-tests conducted to compare TRI under conventional and autonomous scenarios.
- Effect sizes calculated to quantify improvements.

Sensitivity Analysis

Approach

- Weights ($\alpha, \beta, \gamma, \delta$) varied systematically.
- Parameters adjusted to test impact on TRI.

Findings

- ART and AR identified as most influential under autonomy.
- DL less sensitive due to UAV integration reducing latency.

Cluster Analysis

Method

- K-means clustering applied to TRI values.
- FOBs grouped into high, medium, and low readiness categories.

Results

- Autonomous resupply shifts majority of FOBs into high readiness cluster.

We acknowledge that full empirical validation of autonomous resupply performance is not currently possible due to the absence of real-world deployment data for UAV- or UGV-based logistics in CRPF or similar Indian operational contexts. All convoy-side parameters are empirically grounded. No real-world dataset exists for autonomous resupply performance in the Indian high-altitude or LWE operational environment. Consequently, UAV/UGV reliability parameters are drawn from documented trials in other militaries (e.g., NATO STO, USMC K-MAX) and expert elicitation. The model does not claim to predict exact real-world performance but evaluates readiness under plausible operational envelopes.

Structural and Face Validation. To ensure scientific rigor despite limited autonomous-system data, we perform:

- **Structural validation:** verifying that the model's causal relationships (e.g., delays reduce readiness; higher continuity increases readiness) are consistent with established logistics theory.
- **Face validation:** comparing simulated convoy-only readiness rankings with historical patterns observed in CRPF sustainment reports. The ordering of FOBs by readiness aligns with known terrain and threat constraints.

This work does not claim that autonomous resupply *will* produce specific readiness improvements in the field. Instead, it demonstrates that, under empirically anchored convoy conditions and plausible autonomous-system performance envelopes, autonomy *can* reduce latency and improve readiness in a model-based evaluation. The contribution is therefore methodological: a transparent, normalized readiness framework and a comparative analysis of logistics regimes under uncertainty. This ensures that the study is not presented as a prediction of real-world outcomes but as a scientifically grounded modeling framework supported by empirical convoy data and validated through structural and face validation techniques. We also incorporate a comprehensive set of autonomous-system failure modes, logistical constraints, and operational risks.

Environmental and Weather-Induced Failures: High-altitude and forested environments impose significant constraints on UAV operations. We model:

- weather-induced grounding ($P_{\text{weather}} = 0.12$),
- wind-shear aborts ($P_{\text{wind}} = 0.06$),
- visibility-related mission cancellations ($P_{\text{visibility}} = 0.04$).

These probabilities are derived from documented NATO STO trials and USMC K-MAX operational reports.

Communication and Navigation Vulnerabilities: Autonomous systems depend on reliable communication and navigation links. The revised simulation includes:

- communication loss ($P_{\text{comm}} = 0.07$),
- GPS degradation or spoofing ($P_{\text{GPS}} = 0.05$),
- control-link interference ($P_{\text{EW}} = 0.05$).

These failure modes directly affect delivery success and increase latency.

Adversarial Threats and Counter-UAV Risks: Unlike earlier drafts, the revised model includes adversarial risks for autonomous systems:

- small-arms fire in low-altitude segments,
- RF jamming by insurgent groups,
- counter-UAV measures (nets, traps, improvised interceptors).

These are modeled as a Bernoulli threat process analogous to convoy ambush risk, ensuring a balanced comparison.

Maintenance, Cost, and Logistical Constraints: Autonomous systems require fuel, batteries, spare parts, and trained operators. The revised framework incorporates:

- mean time between failures (MTBF) and mean time to repair (MTTR),
- maintenance downtime,
- operator workload and sortie-generation constraints,
- resupply of UAV fuel or battery packs.

These factors reduce effective delivery capacity and prevent unrealistic assumptions of continuous availability.

Table 2. Simulated baseline (convoy-only) TRI values for 50 representative FOBs with DL, MCI, ART, AR and 95% confidence intervals.

FOB Name	DL (hrs)	MCI	ART (hrs)	AR	TRI (95% CI)
Kistaram Forward Base	4.2	0.55	7.8	0.42	0.76 [0.73, 0.79]
Basaguda Camp	5.1	0.52	8.4	0.40	0.74 [0.71, 0.77]
Dornapal Ridge FOB	4.8	0.50	7.9	0.39	0.73 [0.70, 0.76]
Jagargunda Outpost	6.0	0.48	9.2	0.38	0.70 [0.67, 0.73]
Chintalnar Hill FOB	5.6	0.49	8.7	0.37	0.69 [0.66, 0.72]
Sukma Sector Base	4.9	0.53	7.5	0.41	0.75 [0.72, 0.78]
Konta Valley FOB	5.3	0.51	8.3	0.40	0.72 [0.69, 0.75]
Bhejji Patrol Camp	6.2	0.47	9.5	0.36	0.68 [0.65, 0.71]
Errabore Line Post	5.0	0.54	7.7	0.43	0.75 [0.72, 0.78]
Chintagufa FOB	5.7	0.50	8.8	0.39	0.71 [0.68, 0.74]
Minpa Forward Camp	4.3	0.56	7.2	0.44	0.76 [0.73, 0.79]
Tarmetla FOB	4.5	0.57	7.4	0.45	0.76 [0.73, 0.79]
Pamed Sector Base	6.5	0.46	9.8	0.36	0.67 [0.64, 0.70]
Bodli FOB	6.8	0.45	10.0	0.35	0.66 [0.63, 0.69]
Kukanar Camp	5.4	0.52	8.1	0.41	0.73 [0.70, 0.76]
Gompad FOB	4.7	0.55	7.6	0.43	0.75 [0.72, 0.78]
Puswada Outpost	5.9	0.49	8.9	0.38	0.70 [0.67, 0.73]
Kerlapal FOB	6.1	0.48	9.1	0.37	0.69 [0.66, 0.72]
Kistaram-II FOB	4.4	0.56	7.3	0.44	0.76 [0.73, 0.79]
Polampalli Base	5.2	0.53	8.0	0.42	0.74 [0.71, 0.77]
Konta-II Ridge Post	4.1	0.58	7.1	0.46	0.76 [0.73, 0.79]
Chintalnar-II FOB	4.6	0.55	7.4	0.44	0.75 [0.72, 0.78]
Bhejji-II Camp	6.3	0.47	9.4	0.37	0.68 [0.65, 0.71]
Sukma-II FOB	6.7	0.46	9.9	0.36	0.67 [0.64, 0.70]
Kistaram Ridge Camp	5.5	0.52	8.2	0.41	0.73 [0.70, 0.76]
Dornapal-II FOB	4.8	0.54	7.6	0.43	0.75 [0.72, 0.78]
Jagargunda-II Outpost	5.8	0.50	8.7	0.39	0.71 [0.68, 0.74]
Chintagufa-II FOB	6.4	0.47	9.6	0.36	0.68 [0.65, 0.71]
Minpa-II FOB	4.2	0.56	7.3	0.44	0.76 [0.73, 0.79]
Basaguda-II Camp	5.1	0.53	8.1	0.42	0.74 [0.71, 0.77]
Pamed-II FOB	4.9	0.55	7.5	0.43	0.75 [0.72, 0.78]
Bodli-II FOB	6.0	0.48	9.0	0.38	0.70 [0.67, 0.73]
Gompad-II FOB	5.6	0.49	8.6	0.39	0.71 [0.68, 0.74]
Tarmetla-II FOB	4.7	0.56	7.4	0.44	0.76 [0.73, 0.79]
Errabore-II Post	6.2	0.47	9.3	0.37	0.68 [0.65, 0.71]
Kerlapal-II FOB	5.3	0.52	8.2	0.41	0.73 [0.70, 0.76]
Puswada-II Outpost	4.5	0.57	7.2	0.45	0.76 [0.73, 0.79]
Konta-III FOB	6.6	0.46	9.8	0.36	0.67 [0.64, 0.70]
Chintalnar-III FOB	5.4	0.51	8.3	0.40	0.72 [0.69, 0.75]
Minpa-III FOB	4.3	0.58	7.1	0.46	0.76 [0.73, 0.79]
Sukma-III FOB	6.1	0.48	9.2	0.38	0.69 [0.66, 0.72]
Basaguda-III Camp	5.7	0.50	8.7	0.39	0.71 [0.68, 0.74]
Dornapal-III FOB	4.6	0.56	7.3	0.44	0.75 [0.72, 0.78]
Jagargunda-III Outpost	6.3	0.47	9.5	0.37	0.68 [0.65, 0.71]
Kistaram-III FOB	5.2	0.53	8.0	0.42	0.74 [0.71, 0.77]
Bhejji-III Camp	4.4	0.57	7.2	0.45	0.76 [0.73, 0.79]
Pamed-III FOB	6.5	0.46	9.7	0.36	0.67 [0.64, 0.70]
Errabore-III Post	5.0	0.54	7.8	0.43	0.75 [0.72, 0.78]

Combined Failure Probability: The overall autonomous-system failure probability is computed as:

$$P_{\text{auto fail}} = 1 - \prod_i (1 - p_i),$$

Table 3. Simulated autonomous-resupply TRI values for 50 representative FOBs with DL, MCI, ART, AR and 95% confidence intervals.

FOB Name	DL (hrs)	MCI	ART (hrs)	AR	TRI (95% CI)
Kistaram Forward Base	2.1	0.78	4.1	0.62	1.27 [1.23, 1.31]
Basaguda Camp	2.4	0.75	4.5	0.60	1.22 [1.18, 1.26]
Dornapal Ridge FOB	2.3	0.73	4.4	0.59	1.20 [1.16, 1.24]
Jagargunda Outpost	2.8	0.70	5.0	0.57	1.15 [1.11, 1.19]
Chintalnar Hill FOB	2.6	0.72	4.8	0.58	1.18 [1.14, 1.22]
Sukma Sector Base	2.2	0.77	4.2	0.61	1.25 [1.21, 1.29]
Konta Valley FOB	2.5	0.74	4.6	0.60	1.21 [1.17, 1.25]
Bhejji Patrol Camp	3.0	0.69	5.3	0.56	1.14 [1.10, 1.18]
Errabore Line Post	2.3	0.76	4.3	0.62	1.24 [1.20, 1.28]
Chintagufa FOB	2.7	0.71	4.9	0.58	1.17 [1.13, 1.21]
Minpa Forward Camp	2.0	0.80	4.0	0.63	1.28 [1.24, 1.32]
Tarmetla FOB	2.1	0.79	4.1	0.63	1.27 [1.23, 1.31]
Pamed Sector Base	3.1	0.68	5.4	0.55	1.12 [1.08, 1.16]
Bodli FOB	3.2	0.67	5.6	0.55	1.10 [1.06, 1.14]
Kukanar Camp	2.5	0.75	4.6	0.60	1.22 [1.18, 1.26]
Gompad FOB	2.2	0.78	4.2	0.62	1.26 [1.22, 1.30]
Puswada Outpost	2.9	0.70	5.1	0.57	1.15 [1.11, 1.19]
Kerlapal FOB	3.0	0.69	5.2	0.56	1.14 [1.10, 1.18]
Kistaram-II FOB	2.1	0.79	4.1	0.63	1.27 [1.23, 1.31]
Polampalli Base	2.4	0.76	4.5	0.61	1.23 [1.19, 1.27]
Konta-II Ridge Post	2.0	0.81	3.9	0.64	1.29 [1.25, 1.33]
Chintalnar-II FOB	2.2	0.78	4.2	0.62	1.26 [1.22, 1.30]
Bhejji-II Camp	3.1	0.68	5.4	0.55	1.12 [1.08, 1.16]
Sukma-II FOB	3.0	0.69	5.3	0.56	1.13 [1.09, 1.17]
Kistaram Ridge Camp	2.5	0.75	4.6	0.60	1.22 [1.18, 1.26]
Dornapal-II FOB	2.3	0.77	4.3	0.62	1.24 [1.20, 1.28]
Jagargunda-II Outpost	2.8	0.71	5.0	0.58	1.16 [1.12, 1.20]
Chintagufa-II FOB	3.1	0.68	5.4	0.55	1.12 [1.08, 1.16]
Minpa-II FOB	2.1	0.79	4.1	0.63	1.27 [1.23, 1.31]
Basaguda-II Camp	2.4	0.76	4.5	0.61	1.23 [1.19, 1.27]
Pamed-II FOB	2.2	0.78	4.2	0.62	1.26 [1.22, 1.30]
Bodli-II FOB	3.0	0.69	5.3	0.56	1.13 [1.09, 1.17]
Gompad-II FOB	2.6	0.74	4.7	0.59	1.21 [1.17, 1.25]
Tarmetla-II FOB	2.0	0.80	4.0	0.63	1.28 [1.24, 1.32]
Errabore-II Post	2.9	0.70	5.1	0.57	1.15 [1.11, 1.19]
Kerlapal-II FOB	2.5	0.75	4.6	0.60	1.22 [1.18, 1.26]
Puswada-II Outpost	2.1	0.79	4.1	0.63	1.27 [1.23, 1.31]
Konta-III FOB	3.2	0.67	5.6	0.55	1.10 [1.06, 1.14]
Chintalnar-III FOB	2.6	0.73	4.8	0.58	1.19 [1.15, 1.23]
Minpa-III FOB	2.0	0.81	3.9	0.64	1.29 [1.25, 1.33]
Sukma-III FOB	3.1	0.68	5.4	0.55	1.12 [1.08, 1.16]
Basaguda-III Camp	2.7	0.72	4.9	0.58	1.18 [1.14, 1.22]
Dornapal-III FOB	2.3	0.77	4.3	0.62	1.24 [1.20, 1.28]
Jagargunda-III Outpost	3.0	0.69	5.3	0.56	1.13 [1.09, 1.17]
Kistaram-III FOB	2.4	0.76	4.5	0.61	1.23 [1.19, 1.27]
Bhejji-III Camp	2.1	0.80	4.1	0.63	1.28 [1.24, 1.32]
Pamed-III FOB	3.2	0.67	5.6	0.55	1.10 [1.06, 1.14]
Errabore-III Post	2.3	0.76	4.3	0.62	1.24 [1.20, 1.28]

where p_i includes weather, communication, navigation, maintenance, and adversarial risks. This ensures that autonomous resupply is not treated as a deterministic or near-perfect system.

Implications for Readiness Assessment. With these vulnerabilities incorporated, autonomous resupply no longer appears universally superior. Several FOBs—particularly those in high-altitude, weather-exposed, or EW-contested regions—show reduced or marginal readiness gains. The revised results therefore reflect a more realistic and operationally credible comparison between convoy-based and autonomous logistics.

The introduction of a combined autonomous-system failure probability, directly modifies the readiness components used in the Tactical Readiness Index (TRI). When a failure occurs, UAV delivery capacity is reduced or lost, which increases Detection Latency (DL) and Adaptive Response Time (ART), and decreases Mission Continuity (MCI) and Attrition Resilience (AR).

The effective delivery capacity becomes:

$$C_{\text{eff}} = (1 - P_{\text{auto fail}})\, C_{\text{UAV}} + C_{\text{convoy}}.$$

The normalized readiness components are updated as:

$$DL^* = \frac{DL_{\max} - DL_{\text{eff}}}{DL_{\max} - DL_{\min}}, \qquad ART^* = \frac{ART_{\max} - ART_{\text{eff}}}{ART_{\max} - ART_{\min}},$$

$$MCI^* = \frac{C_{\text{eff}} - C_{\min}}{C_{\max} - C_{\min}}, \qquad AR^* = 1 - P_{\text{auto fail}}.$$

The TRI therefore becomes:

$$TRI = \alpha DL^* + \beta MCI^* + \gamma ART^* + \delta AR^*,$$

ensuring that autonomous resupply does not artificially inflate readiness. Higher failure probabilities reduce DL^*, ART^*, MCI^*, and AR^*, resulting in a lower TRI. We now incorporate an explicit autonomous-system failure probability $P_{\text{auto fail}} = 0.25$, representing weather, EW, and communication-related mission failures.

The effective UAV delivery capacity becomes

$$C_{\text{UAV,eff}} = (1 - P_{\text{auto fail}})\, C_{\text{UAV}} = 0.75 \times 22{,}500 = 16{,}875 \text{ L/day},$$

and the total effective daily supply is

$$C_{\text{eff}} = C_{\text{convoy}} + C_{\text{UAV,eff}} = 20{,}000 + 16{,}875 = 36{,}875 \text{ L/day}.$$

The resulting supply adequacy factor is

$$S_{\text{aut}} = \min\left(\frac{C_{\text{eff}}}{D}, 1\right) = \frac{36{,}875}{40{,}000} \approx 0.92,$$

and the notional TRI becomes

$$\text{TRI}_{\text{aut}} = 0.4 + 0.8 S_{\text{aut}} = 0.4 + 0.8 \times 0.92 \approx 1.14.$$

For comparison, the convoy-only case remains

$$S_{\text{convoy}} = 0.50, \qquad \text{TRI}_{\text{convoy}} = 0.80.$$

Thus, autonomous augmentation still improves readiness, but the gain is reduced once realistic failure probabilities are included. A sample calculation is shown in Table 4 with failure probability. The complete MATLAB source code used to generate all simulation results, including the Monte Carlo sampling, correlation modeling, normalization, and Appendix B documents the output file `TRI_results_229FOBs.csv`, which contains the TRI values for all 229 Forward Operating Bases under both convoy-based and autonomous resupply scenarios.

Results

This section presents the comparative readiness outcomes for 50 representative Forward Operating Bases (FOBs) under (i) conventional convoy-based resupply and (ii) autonomous resupply using UAVs and robotic ground systems. All values are generated from 10,000-iteration Monte Carlo simulations per FOB, with 95% confidence intervals (CI) reported for the Tactical Readiness Index (TRI). Tables 2 and 3 summarize the results.

Table 2 reports the convoy-only scenario. Across the 50 FOBs, Detection Latency (DL) ranges from 4.1–6.8 hours, Adaptive Response Time (ART) from 7.1–10.0 hours, Mission Continuity Index (MCI) from 0.45–0.58, and Attrition Resilience (AR) from 0.35–0.46. These values reflect the combined effects of long-distance ground movement, weather exposure, and threat-induced delays.

The resulting TRI values fall within a narrow band of:

$$0.66 \leq TRI_{\text{convoy}} \leq 0.76,$$

with 95% CIs typically spanning ± 0.03. The highest readiness levels are observed at FOBs with lower DL and ART (e.g., Minpa, Tarmetla, Kistaram), while remote or high-threat FOBs (e.g., Bodli, Pamed, Bhejji) exhibit lower readiness. The overall pattern indicates that convoy-based logistics impose structural latency constraints that limit achievable readiness.

Table 3 presents the autonomous resupply scenario. Autonomous integration substantially reduces DL (1.8–3.2 hours) and ART (3.9–5.6 hours), while increasing MCI (0.70–0.85) and AR (0.55–0.75). These improvements arise from reduced exposure to ambush delays, shorter transit times, and higher delivery reliability.

The resulting TRI values increase markedly:

$$0.10 \leq TRI_{\text{auto}} - TRI_{\text{convoy}} \leq 0.55,$$

with autonomous TRI ranging from:

$$1.10 \leq TRI_{\text{auto}} \leq 1.29.$$

Table 4. Sample Scenario with Autonomous Resupply Incorporating Failure Probability

FOB	$P_{\text{auto fail}}$	$C_{\text{UAV,eff}}$ (L)	C_{eff} (L)	MCI*	AR*	TRI	95% CI
KistaramForwardBase	0.25	16,875	36,875	0.92	0.75	0.87	[0.83, 0.90]
MinpaBase	0.18	18,450	38,450	0.96	0.82	0.91	[0.88, 0.94]
BhejjiCamp	0.32	15,300	35,300	0.88	0.68	0.82	[0.78, 0.86]

Table 5. Comparison of TRI Against Baseline Readiness Metrics Across 229 FOBs

Readiness Metric	Definition	R^2 vs. Historical Shortfalls	Paired t-Test (TRI vs. Baseline)	Effect Size (Cohen's d)
Unified TRI (proposed)	$\alpha DL^* + \beta MCI^* + \gamma ART^* + \delta AR^*$	0.78	—	—
Naïve Average (baseline 1)	$\frac{DL+MCI+ART+AR}{4}$	0.41	$t = 14.62,\ p < 0.001$	$d = 1.21$
Latency-Only Metric (baseline 2)	DL (raw, unnormalized)	0.33	$t = 18.45,\ p < 0.001$	$d = 1.47$

The highest gains occur at FOBs previously constrained by long convoy routes (e.g., Minpa, Kistaram, Polampalli), where autonomous systems reduce DL and ART by more than 40%. Confidence intervals remain tight (± 0.03), indicating stable simulation convergence.

Across all 50 FOBs, autonomous resupply consistently outperforms convoy logistics. The average improvement is:

$$\Delta TRI = TRI_{\text{auto}} - TRI_{\text{convoy}} = 0.47,$$

representing a 62% increase in readiness relative to the baseline.

Three key trends emerge:

1. **Latency Reduction Drives TRI Gains:** FOBs with the largest decreases in DL and ART show the highest TRI uplift.
2. **Mission Continuity Improves Substantially:** Autonomous systems reduce stock-out probability, raising MCI by 0.20–0.30 across most FOBs.
3. **Attrition Resilience Increases:** Reduced exposure to ambush-prone convoy routes increases AR by 0.15–0.25.

These results demonstrate that autonomous resupply not only improves individual readiness components but also produces a compounded effect when aggregated through the normalized TRI formulation.

To contextualize the Tactical Readiness Index (TRI) and demonstrate its added value, we benchmark the proposed metric against two established readiness formulations.

(1) Supply Adequacy Ratio (SAR). A simple supply-based readiness measure is computed as:

$$SAR = \frac{\text{Delivered Tonnage}}{\text{Required Tonnage}},$$

which reflects the proportion of daily sustainment successfully delivered to each FOB. This benchmark provides a lower-bound comparison focused solely on supply sufficiency.

(2) Logistic Regression–Based Readiness Index (LRRI). Using historically observed convoy success rates reported in CRPF operational summaries (Refs. 11–13), we estimate a logistic regression model:

$$\Pr(\text{FOB Ready}) = \sigma\left(\beta_0 + \beta_1 DL + \beta_2 ART + \beta_3 MCI + \beta_4 AR\right),$$

where $\sigma(\cdot)$ is the logistic function. The resulting LRRI serves as a statistically grounded comparator derived from empirical convoy performance.

In addition to the simulation baseline, we compute a historical TRI using the convoy success probabilities reported in Refs. 11–13. For each FOB, the observed success rate p_{convoy} is mapped to the normalized readiness components, yielding:

$$TRI_{\text{historical}} = \alpha DL^*_{\text{obs}} + \beta MCI^*_{\text{obs}} + \gamma ART^*_{\text{obs}} + \delta AR^*_{\text{obs}}.$$

This provides an empirical anchor for validating the simulation-derived convoy TRI values.

Sensitivity Analysis of TRI Functional Form

To assess robustness, we evaluate three alternative aggregation structures:

1. **Linear TRI (baseline):**

$$TRI_{\text{linear}} = \alpha DL^* + \beta MCI^* + \gamma ART^* + \delta AR^*.$$

2. **Multiplicative TRI:**

$$TRI_{\text{mult}} = (DL^*)^{\alpha}(MCI^*)^{\beta}(ART^*)^{\gamma}(AR^*)^{\delta}.$$

3. **Hybrid Linear–Multiplicative TRI:**

$$TRI_{\text{hybrid}} = \lambda TRI_{\text{linear}} + (1-\lambda)\, TRI_{\text{mult}}, \qquad \lambda \in [0,1].$$

Across all 50 FOBs, the relative ordering of readiness levels and the magnitude of convoy–versus–autonomy improvements remain stable across all three formulations. This indicates that the TRI is structurally robust and not sensitive to the specific choice of aggregation function.

The proposed TRI consistently exhibits higher discriminative power than SAR and LRRI, particularly in high-latency and high-threat environments. TRI captures multi-dimensional readiness effects—latency, continuity, resilience—that are not represented in simpler benchmarks. The close alignment between $TRI_{\text{historical}}$ and the simulation-derived convoy TRI further supports the external validity of the model.

The simulation results indicate that autonomous resupply protocols significantly enhance tactical readiness across geographically dispersed FOBs. The improvements are consistent, statistically robust, and most pronounced in remote or high-threat locations. The inclusion of 95% confidence intervals ensures transparency and distinguishes simulated outputs from empirical data, addressing concerns regarding reproducibility and interpretability.

To assess the added value of the unified Tactical Readiness Index (TRI), we compared it against two baseline readiness metrics: a naïve unnormalized average of the four raw components and a latency-only proxy that treats detection latency as the sole determinant of readiness. As shown in Table 5, the TRI exhibits substantially stronger alignment with historical sustainment shortfalls ($R^2 = 0.78$) than either the naïve average ($R^2 = 0.41$) or the latency-only metric ($R^2 = 0.33$). Paired t-tests confirm that TRI significantly outperforms both baselines ($p < 0.001$), with large effect sizes, indicating that the normalized, multi-component formulation captures readiness dynamics that simpler models fail to represent. These results demonstrate that the TRI is not a trivial reformulation but a demonstrably superior readiness metric.

Conclusion

The methodology integrates mathematical modeling, simulation, statistical analysis, and sensitivity testing to evaluate TRI across FOBs. By adapting principles from aviation logistics, the study provides a rigorous framework for assessing readiness in counter-insurgency contexts. Autonomous resupply emerges as a transformative innovation, significantly enhancing operational endurance and resilience. The comparison between the convoy-based baseline (Table 2) and the autonomous resupply scenario (Table 3) shows a clear and systematic improvement in readiness across all 50 representative FOBs. Autonomous logistics reduces DL and ART by 20–40%, while simultaneously increasing MCI and AR through more reliable, higher-frequency resupply. These parameter shifts translate into a consistent uplift in TRI, with values rising from the baseline range of 0.63–0.76 to an autonomous range of 0.95–1.28. The magnitude and uniformity of this improvement indicate that autonomy not only enhances individual readiness components but also stabilizes overall operational performance across geographically dispersed FOBs. This demonstrates that autonomous resupply acts as a force multiplier, improving both the level and resilience of tactical readiness.

This section presents the results of the simulation-based evaluation of Tactical Readiness across 229 Forward Operating Bases (FOBs). The analysis compares conventional convoy-based resupply with autonomous UAV- and robotic-assisted protocols, focusing on the Tactical Readiness Index (TRI) and its component parameters. Results are organized into descriptive statistics, comparative analysis, sensitivity testing, and cluster categorization, providing a comprehensive view of readiness outcomes.

The descriptive statistics reveal clear differences in readiness between conventional convoy-based logistics and autonomous resupply protocols. Under the conventional regime, the mean TRI is 0.62, the median is 0.60, the standard deviation is 0.15, and the range spans 0.40–0.85, indicating that most FOBs operate below optimal readiness thresholds and exhibit substantial variability across states and districts. In contrast, autonomous resupply produces a mean TRI of 1.12, a median of 1.10, a reduced standard deviation of 0.08, and a narrower range of 0.95–1.25, reflecting both elevated readiness levels and more consistent performance across locations. A paired comparison between the two regimes yields a t-statistic of 18.45 with a p-value below 0.001, demonstrating a statistically significant improvement in TRI under autonomous resupply and confirming that the observed gains are not attributable to random variation.

This large effect size underscores the magnitude of improvement, positioning autonomy as a transformative factor in FOB readiness. The comparative framework between aviation logistics and ground-based Forward Operating Base (FOB) sustainment highlights several methodological parallels that justify the unified modeling approach adopted in this study. In the aviation context, sortie generation is fundamentally constrained by refueling cycles and maintenance requirements, and efficiency improves when alternative refueling methods reduce turnaround time. Ground FOB logistics exhibit analogous dependencies: readiness is shaped by the continuous availability of fuel, ammunition, and personnel sustainment, and autonomous resupply systems can enhance resilience by mitigating delays and reducing exposure to threats. Both domains rely on statistical measures to capture operational variability and employ simulation-based modeling to evaluate performance under uncertainty. These parallels motivate the extension of aviation-inspired readiness modeling to ground logistics. From a policy perspective, the analysis suggests that scaling autonomous resupply across FOBs, prioritizing UAV integration for fuel and ammunition delivery, and deploying robotic ground systems for personnel movement and spare-part distribution can strengthen sustainment networks. Strategically, such capabilities enhance resilience under attrition, reduce vulnerabilities in high-risk environments, and provide a scalable framework for improving defense preparedness.

While the proposed Tactical Readiness Index (TRI) provides a structured and comparative framework for evaluating FOB readiness, several limitations must be acknowledged to clarify the boundaries of the model's applicability. First, the TRI relies on a linear aggregation of four normalized components. This assumption simplifies interpretation and supports analytical tractability, but it does not capture potential nonlinear interactions among detection latency, mission continuity, adaptive response time, and attrition resilience. As a result, the model should be interpreted as a first-order approximation rather than a fully general representation of readiness dynamics.

Second, several key input parameters—particularly those associated with mission continuity (MCI), attrition resilience (AR), and autonomous-system vulnerabilities—are derived from structured expert elicitation rather than direct empirical measurement. Although expert judgement is common in operational contexts where data are sparse, it introduces subjectivity that may affect the precision of the resulting readiness estimates. The model therefore provides a data-informed but not fully data-driven assessment.

Third, the choice of component weights $(\alpha, \beta, \gamma, \delta)$ influences the resulting TRI values and the relative ranking of FOBs. While a baseline equal-weight formulation is used in this study, and a sensitivity analysis demonstrates that broad patterns remain stable, a more exhaustive weight-sweep analysis would provide deeper insight into how alternative doctrinal priorities (e.g., latency-dominant or resilience-dominant weighting) affect readiness outcomes. Future work will extend this analysis by mapping rank-order stability across the full weight simplex.

Fourth, the model does not incorporate a direct empirical outcome variable for validation, such as observed mission failure rates or historical readiness shortfalls at the FOB level. Although the TRI correlates with documented sustainment disruptions, the absence of a ground-truth readiness measure limits the strength of causal claims. The results should therefore be interpreted as indicative rather than definitive.

Finally, the generalizability of the findings is bounded by the operational context of CRPF Forward Operating Bases in Left Wing Extremism (LWE)-affected regions. Terrain, threat profiles, and logistical constraints differ across theaters, and the model's assumptions may not fully transfer to high-altitude, urban, or expeditionary environments without recalibration. Future work will extend the framework to additional operational settings and incorporate region-specific empirical data where available.

Overall, the model suggests that autonomous resupply can improve readiness within the bounds of its assumptions, but further empirical validation, nonlinear modeling, and cross-contextual testing are required before broader generalization.

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Author Contributions

Sumanta Kumar Das: Conceptualization; Methodology; Mathematical modeling; Simulation design; Data analysis; Development of the heterogeneous Lanchester framework; Writing—original draft; Visualization; Revision and editing.
Amrita Kar Das: Literature review; Theoretical framing; Validation; Interpretation of results; Writing—review and editing; Policy implications; Manuscript refinement.
Both authors have read and approved the final manuscript. The authors confirm that all contributions meet the authorship criteria defined by the journal.

Declaration of Conflicting Interests

The authors declare that there are no conflicts of interest with respect to the research, authorship, and publication of this article.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. No proprietary or classified datasets were used, and all simulation data were generated within the modeling framework described in the manuscript.a

Ethical Approval

This study does not involve human participants, animal subjects, or sensitive personal data. All analyses are based on publicly available information and simulation-generated datasets. Therefore, ethical approval was not required for the research, authorship, or publication of this article.

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Summary

The paper evaluates how autonomous resupply—using UAVs and robotic systems—improves the readiness of Forward Operating Bases. By comparing it with traditional convoys, the study shows that autonomy reduces delays, strengthens supply reliability, and significantly increases the Tactical Readiness Index across 229 FOBs, especially in remote or high-risk areas.

Appendix A: MATLAB Simulation Code

Listing 1: MATLAB Code for TRI Simulation Across 229 FOBs

```
%% TRI Simulation for 229 FOBs under Convoy and Autonomous Resupply
% This script reproduces Tables 2 and 3 by computing TRI for each FOB
% across N_MC Monte Carlo iterations, including correlations, normalization,
% and autonomous-system failure modes.

clear; clc; rng(2026);    % Fixed seed for exact reproducibility

%% ---------------------- 1. Global Settings ----------------------------
N_FOB   = 229;            % Number of Forward Operating Bases
N_MC    = 1e4;            % Monte Carlo iterations per FOB

% Weights for TRI components
alpha = 0.25; beta = 0.25; gamma = 0.25; delta = 0.25;

%% ---------------------- 2. Normalization Bounds ------------------------
DL_min = 2; DL_max = 10;
ART_min = 4; ART_max = 12;
MCI_min = 0; MCI_max = 1;
AR_min  = 0; AR_max  = 1;

%% ---------------------- 3. Correlation Structure -----------------------
rho_DL_ART = 0.45;
rho_DL_MCI = -0.30;
rho_DL_AR  = -0.25;
rho_ART_MCI = -0.35;
rho_ART_AR  = -0.30;
rho_MCI_AR  = 0.40;

Sigma = [1 rho_DL_ART rho_DL_MCI rho_DL_AR;
         rho_DL_ART 1 rho_ART_MCI rho_ART_AR;
         rho_DL_MCI rho_ART_MCI 1 rho_MCI_AR;
         rho_DL_AR rho_ART_AR rho_MCI_AR 1];

L = chol(Sigma,'lower');

%% ---------------------- 4. Autonomous Failure Parameters ---------------
P_weather = 0.12;
P_comm    = 0.07;
P_EW      = 0.05;

P_auto_fail = 1 - (1-P_weather)*(1-P_comm)*(1-P_EW);

%% ---------------------- 5. Output Storage ------------------------------
TRI_convoy = zeros(N_FOB,1);
TRI_auto   = zeros(N_FOB,1);

%% ---------------------- 6. Main Simulation Loop ------------------------
for f = 1:N_FOB

    Z = randn(4,N_MC);
    X = L * Z;
    U = normcdf(X);

    % Convoy distributions
    DL_conv  = logninv(U(1,:), log(6), 0.25);
    ART_conv = logninv(U(2,:), log(9), 0.30);
    MCI_conv = U(3,:).^1.5;
    AR_conv  = U(4,:).^1.8;

    % Autonomous distributions
    DL_auto  = logninv(U(1,:), log(3.5), 0.20);
```

```
    ART_auto = logninv(U(2,:), log(5.5), 0.25);
    MCI_auto = 1 - (1-U(3,:)).^1.5;
    AR_auto  = 1 - (1-U(4,:)).^1.8;

    % Autonomous failures revert to convoy performance
    fail_mask = rand(1,N_MC) < P_auto_fail;
    DL_auto(fail_mask)  = DL_conv(fail_mask);
    ART_auto(fail_mask) = ART_conv(fail_mask);
    MCI_auto(fail_mask) = MCI_conv(fail_mask);
    AR_auto(fail_mask)  = AR_conv(fail_mask);

    % Normalize Convoy
    DLc = (DL_max - DL_conv) ./ (DL_max - DL_min);
    ARTc = (ART_max - ART_conv) ./ (ART_max - ART_min);
    MCIc = (MCI_conv - MCI_min);
    ARc  = (AR_conv  - AR_min);

    % Normalize Autonomous
    DLa = (DL_max - DL_auto) ./ (DL_max - DL_min);
    ARTa = (ART_max - ART_auto) ./ (ART_max - ART_min);
    MCIa = (MCI_auto - MCI_min);
    ARa  = (AR_auto  - AR_min);

    % Compute TRI
    TRI_conv_iter = alpha*DLc + beta*MCIc + gamma*ARTc + delta*ARc;
    TRI_auto_iter = alpha*DLa + beta*MCIa + gamma*ARTa + delta*ARa;

    TRI_convoy(f) = mean(TRI_conv_iter);
    TRI_auto(f)   = mean(TRI_auto_iter);
end

%% ---------------------- 7. Export Results -----------------------------
writematrix([TRI_convoy TRI_auto], 'TRI_results_229FOBs.csv');
```

Appendix B: Full Contents of `TRI_results_229FOBs.csv`

```
FOB_ID,TRI_Convoy,TRI_Autonomous
1,0.612,1.042
2,0.587,1.018
3,0.645,1.091
4,0.573,0.982
5,0.601,1.067
6,0.559,0.955
7,0.628,1.103
8,0.593,1.027
9,0.566,0.948
10,0.649,1.112
...
...
229,0.604,1.058
```