

From Narrative to Algorithm: A Risk Mechanism Theory Index for Urban Infrastructure Investment in Sub-Saharan Africa

Author(s): Cesar Marolla

Division of Continuing Education, Harvard University, USA.

Corresponding Author: cesar.marolla@alumni.harvard.edu

Received: July, 2026, Published: October, 2026

ARTICLE INFO

Keywords:

Expected annual loss; Mathematical modeling; Management decision analytics; Risk mechanism design; Risk mechanism theory index; Sub-Saharan Africa; Sustainable urban systems; Urban infrastructure investment

© 2026 by the Author(s). This open-access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license, making research freely available to the public and supporting a greater global exchange of knowledge and human experiments.



ABSTRACT

Rapidly expanding metropolitan areas across Sub-Saharan Africa face systemic risk from hazard-induced disruptions, exacerbated by infrastructure deficits and socioeconomic vulnerabilities. Traditional risk assessment frameworks frequently fail decision-makers by offering static, qualitative narratives that cannot prioritize capital allocation or track resilience over dynamic budget cycles. This paper presents the Risk Mechanism Theory Index (RMTI) framework, a single, decision-ready mathematical model, grounded in Risk Mechanism Design and Theory, and built to assess, quantify, and treat systemic risk across organizational, health, infrastructure, and urban contexts. Structurally, the RMTI reduces every risk environment to three correctly signed dimensions drawn from Table 9.4: RMTre (risk exposure, $L \cdot E$), RMTseen (socio-economic and environmental vulnerability, I), and RMTri (resilience capacity, p), combined into a single bounded 0–1 composite residual score $R = L \cdot E_{sel} \cdot V \cdot (1-p)$. The RMTI is operationalized through a purpose-built calculator that automates the full computational pipeline and is complemented by a Python reference implementation (RMTI-Py) for registry-scale and pipeline use. Both modalities are validated end-to-end against three World Bank-profiled urban infrastructure cases in Sub-Saharan Africa (Bamako, Mali; Lagos, Nigeria; Lilongwe, Malawi) and benchmarked against three comparator cities (Nairobi, Kenya; Dar es Salaam, Tanzania; Lusaka, Zambia). Empirical results demonstrate that targeted \$50 million capital investments reduce composite risk scores by 30.7% to 47.5%, systematically transitioning all three primary environments from Tier 4 (Severe) to Tier 3 (High). The framework provides a transparent, algorithmic pipeline for embedding risk-informed governance into capital-budgeting workflows across sectors, and is offered as a management decision-support tool for institutional investors, development banks, and municipal finance officers seeking a reproducible, data-analytic alternative to narrative-based risk reporting.

1.0 Introduction

Metropolitan regions across Sub-Saharan Africa are undergoing the most rapid urban demographic transition globally (Tabutin et al., 2020). With an annual urban population growth rate of approximately 4.1%, double the global average, the subcontinent's urban populace is projected to double by 2050, accompanied by a 600% expansion in built-up urban land area by 2030 (Muhoza & Zhou, 2025; Saghir & Santoro, 2018; World Bank, 2023). This unprecedented expansion occurs within a context of structural deficit: over 62% of the urban population resides in informal settlements characterized by fragile power grids, insufficient water distribution networks, and a lack of stormwater infrastructure (Agbo et al., 2025; Boanada-Fuchs et al., 2024). Concurrently, the frequency and intensity of severe hazard events such as pluvial flooding, prolonged droughts, and extreme thermal stress, are intensifying across the subcontinent (Calvin et al., 2023; Seneviratne et al., 2021).

The convergence of accelerated urbanization and growing hazard exposure generates a cascading systemic risk environment. Primary shocks propagate through interconnected infrastructure systems, triggering secondary and tertiary failures of disproportionate magnitude, amplified by underlying governance gaps, macroeconomic fragilities, and physical infrastructure interdependencies (Pescaroli & Alexander, 2016; Tang et al., 2026). These cascading dynamics threaten to undo decades of socioeconomic development investment across the subcontinent.

A fundamental impediment to mitigating these risks is the failure of conventional urban risk assessment tools. Traditional methodologies rely primarily on qualitative narratives, classifying a city's risk as "High" or "Medium", that offer no operational utility for municipal finance managers or international development banks (Medaa et al., 2025; Scolobig et al., 2015). Such descriptive indices cannot rank competing infrastructure projects across heterogeneous geographies, nor can they quantify the precise marginal return on resilience investments, satisfy the algorithmic requirements of modern capital-budget cycles, or be re-run on an annual audit cycle (Chen & Ye, 2023; Kapucu et al., 2023).

To resolve this methodological gap, this paper presents the Risk Mechanism Theory Index (RMTI), a deterministic, decision-ready mathematical framework designed to transform risk assessment from a narrative exercise into an executable, repeatable protocol. Grounded in Risk Mechanism Theory—the risk-assessment framework the author introduced in Chapter 9, "Mechanism Design, Risk Mechanism Theory and Its Relation," of Marolla's (2018) book *Information and Communication Technology for Sustainable Development* (pp. 180–188), and extended in Marolla (2025, 2026)—and structured around the three-dimensional indicator backbone of Table 9.4 (Marolla, 2018, p. 186; reproduced here as Table C3): RMTre (risk exposure), RMTseen (socio-economic and environmental vulnerability), and RMTri (resilience level capacity), the RMTI integrates these dimensions into a single, bounded 0–1 composite score tied to five fixed, policy-aligned decision tiers. The framework is operationalized through the RMTI Calculator (Marolla, 2026a), a structured computational workbook that automates the full scoring pipeline, and is complemented by RMTI-Py, a Python reference implementation designed for registry-scale and pipeline deployment. This workflow follows a multi-hazard risk modeling engine, analyzing hazard, exposure, and vulnerability data across different spatio-temporal domains using geoprocessing and spatial sampling operations (Oberndorfer et al., 2020; Paulik et al., 2023).

2.0 Literature Review

Systemic risk is conceptually defined as an emergent property arising from the interaction among hazard conditions, a system's exposure characteristics, and its inherent vulnerability (Calvin et al., 2023; Cho & Kim, 2026; Ouyang et al., 2025). While this paper applies the RMTI to hazard-driven urban contexts in Sub-Saharan Africa, the underlying risk mechanism is domain-agnostic: the same mathematical structure governs organizational, public health, financial systemic, and infrastructure failure risks alike (Marolla, 2018, 2025).

In the Sub-Saharan African urban context specifically, these interactions are compounded by systemic risk mechanisms. These are pathways through which a primary hazard event triggers a cascade of critical infrastructure failures due to underlying governance, economic, and physical fragilities (Agbo et al., 2025; Boanada-Fuchs et al., 2024; Pescaroli & Alexander, 2016). Despite the recognized need for resilient infrastructure investment, capital allocation across the subcontinent remains highly inefficient and analytically underpowered. The World Bank's Africa Climate Resilient Investment Facility (AFRI-RES) framework articulates a structured multi-step adaptation pathway, screening assets for criticality, establishing baseline risk quantification, and designing systemic treatments as the operational standard for development lending (Mikulewicz & Taylor, 2020; Opoku et al., 2024; World Bank, 2023). Executing this pathway, however, requires a rigorous mathematical backbone that existing qualitative tools cannot provide.

Risk Mechanism Theory (Marolla, 2018, 2025) was developed precisely to fill this gap: it provides a unified, evidence-weighted framework for building mechanisms that achieve a desired outcome in the face of risk factors affecting systemic balance, measuring exposure intensity and a system's resilience across any domain. Standard quantitative risk tools frequently rely on unweighted linear scoring matrices that violate the mathematical property of monotonicity: specifically, a rigorous requirement that the model maintain a consistent, unidirectional mathematical relationship between variables (Mazziotta & Pareto, 2025). Consequently, an increase in protective resilience capacity can paradoxically and incorrectly raise the aggregate risk score due to poorly calibrated additive structures (Gotti & Carluccio, 2023; Shaon et al., 2024).

It is important to position the RMTI within the established hazard $\times$ exposure $\times$ vulnerability (HEV) literature from which it draws its conceptual structure. Multiplicative risk formulations have a long precedent: the IPCC AR5 and AR6 assessment frameworks define risk as a function of hazard, exposure, and vulnerability (Calvin et al., 2023); the RiskScape multi-hazard engine similarly structures loss estimation as the product of hazard intensity, asset exposure, and fragility (Paulik et al., 2023); and Oberndorfer et al. (2020) demonstrate multiplicative probabilistic models for road infrastructure. The RMTI's principal conceptual contribution relative to these precedents is threefold. First, it integrates a fourth parameter, resilience (ρ), as an explicit, separable absorption term — thereby making the reduction from inherent to residual risk directly legible as an auditable intermediate output, rather than implicitly embedding resilience in fragility curves or consequence functions. Second, it anchors all four parameters to the Table 9.4 indicator taxonomy from Risk Mechanism Theory (Marolla, 2018, Ch. 9; reproduced as Table C3), providing a pre-registered, domain-agnostic rubric that practitioners without access to quantitative hazard models can apply using the Weight of Evidence grading protocol. Third, the fixed-tier structure and the log-normalized demographic exposure scaling address cross-jurisdictional comparability in ways that site-specific probabilistic models typically do not. The RMTI is therefore best understood as a decision-support overlay that makes multiplicative HEV logic accessible to governance and capital-budgeting workflows, rather than as a replacement for validated hazard models where they exist.

This paper directly addresses these structural deficiencies by formalizing the RMTI in strict accordance with four design rules drawn from Risk Mechanism Theory. First, monotonicity: each input moves the score in one correct, policy-aligned direction; resilience always lowers R, and exposure and vulnerability always raise it. Second, roundedness: the index is constrained to [0, 1] for cross-jurisdictional comparability, with all scores sitting on the same fixed scale. Third, reproducibility: identical inputs yield identical outputs regardless of analyst or institutional context — a finite, deterministic algorithm coded once and re-run on any budget cycle. Fourth, severity-awareness: likelihood is multiplied by consequence, so a high-impact event outranks a frequent but minor disruption (Meyer & Reniers, 2025; Petrova, 2025). The RMTI Calculator and RMTI-Py implement all four rules programmatically, eliminating manual arithmetic error and enabling any practitioner to reproduce published results by entering the same inputs.

3.0 Methodology: Mathematical Framework, Calculator Design, and Python Implementation

The RMTI assessment and computation protocol in this study was executed using the Risk Mechanism Theory Index framework (Marolla, 2018, Ch. 9; 2025, 2026). The framework operationalizes systemic risk, whether urban, organizational, health-related, or infrastructural, as a bounded, multi-dimensional composite system governed by four architectural layers: (a) a core multiplicative risk index, (b) a log-normalized demographic exposure scaling algorithm, (c) an Expected Annual Loss severity module, and (d) a per-capita equity transformation. These four layers are fully implemented in the RMTI Calculator, a four-sheet analytical workbook, and replicated identically in RMTI-Py for pipeline

deployment. The calculator enforces a strict input–output discipline by isolating user-entered warm cells (active, editable input fields) from auto-calculated grey output columns, thereby preserving mathematical reproducibility and auditability across heterogeneous case environments (Ma et al., 2026; Shahata et al., 2022).

3.1 Theoretical Backbone: Risk Mechanism Theory and Table 9.4

The RMTI inherits its indicator structure directly from Risk Mechanism Theory (Marolla, 2018, Ch. 9, pp. 180–188), specifically from the three-dimensional taxonomy of Table 9.4, reproduced in full as Table C3 in Appendix C, so readers do not need to consult the source volume to follow the derivation below. Every risk indicator, regardless of domain or sector, is sorted into one of three families that constitute the backbone of the model:

- **RMTre (Risk Exposure, E):** What the population and infrastructure are exposed to. Exposure and vulnerability raise the score; resilience lowers it. Exposure indicators include natural and man-made hazards, health hazards, food and water scarcity, energy production disruptions, accelerated urbanization, and population growth and inflation. In the RMTI formula, RMTre is operationalized as the joint product $L \cdot E$, where L is the annualized likelihood of the hazard event and E is the proportional share of assets and population within the hazard footprint.
- **RMTseen (Socio-Economic and Environmental Vulnerability, V):** How fragile the system is, and the conditions that deepen harm. Vulnerability indicators include fiscal stability and productivity, inequality and wealth distribution, control of corruption and rule of law, governance and political stability, energy consumption and supply, environmental pollution, urbanization rates, poverty indices, and GDP per capita. In the RMTI formula, RMTseen maps directly to V .

Formula lineage: It is worth making explicit how the RMTI formula used in this paper relates to the composite expression Marolla (2018, p. 182) originally proposed. The 2018 formulation defines $RMTI = (RMTre \cdot RMTseen \cdot RMTri) / Pd$, a direct three-term product divided by population density Pd . Taken literally, multiplying by $RMTri$ (resilience capacity, scored so that a higher value means more resilience) makes resilience a risk amplifier rather than a mitigator – the same monotonicity failure this paper attributes to poorly calibrated additive structures elsewhere in the literature (Gotti & Carluccio, 2023; Shaon et al., 2024). This paper's refinement, formalized in Equations (1)–(2) below, keeps the multiplicative core Marolla (2018) established for risk exposure and vulnerability (L, E, V) but replaces the direct $RMTri$ multiplier with its complement, $(1 - \rho)$, so that resilience is scored on the same $[0, 1]$ scale but enters as the fraction of inherent risk absorbed rather than as a third multiplicative amplifier. This restores strict monotonicity (higher ρ always lowers R) without changing what the underlying Table 9.4 indicators measure. Separately, this paper substitutes the population-density divisor Pd with the log-normalized exposure scaling E_{log} of Equation (4) below, because population density is not reported consistently across the heterogeneous asset types (a transit corridor, a hospital network) scored in the six-city validation, whereas a population-anchored exposure share is available in every case. Both changes are offered as a scientifically motivated refinement of, rather than a departure from, the original Risk Mechanism Theory index: the three-dimensional indicator taxonomy, the evidence-weighting protocol, and the multiplicative logic linking exposure and vulnerability to risk are all inherited unchanged from Marolla (2018).

- **RMTri (Resilience Level Capacity, ρ):** The capacity to absorb and recover. Resilience indicators include risk-management strategy, business-continuity systems, natural-hazard risk quality, ICT and energy infrastructure, urban infrastructure, hospital capacity and health care, renewable energy and demand rationing, and water and food security. In the RMTI formula, RMTri maps to ρ (rho), entering the model as the residual absorptive term $(1 - \rho)$ to guarantee monotonicity.

Each indicator is rated on two transparent instruments: a Likelihood x Impact matrix (Table 9.2, reproduced as Table C1) that converts qualitative observations to a 0–1 probability-intensity score, and a Weight of Evidence grade (Table 9.3, reproduced as Table C2), a six-level ordinal classification that assesses the strength of empirical, quantitative, and qualitative support for a contributory relationship between exposure to the risk agent and the intensity of the resulting impact, rather than data volume alone. Grade 1 denotes sufficient empirical and quantitative/qualitative evidence establishing that contributory relationship; Grade 6 denotes the absence of empirical, quantitative, and qualitative evidence across at least two adequate studies. Grades 2 through 5 represent intermediate, partial, or limited evidentiary support. Each grade carries a corresponding weighting-evidence factor that calibrates confidence in each rating, so hard data counts more than judgment, producing evidence-weighted parameter estimates for L , E , V , and ρ . Table 1 consolidates the notation and parameter definitions used throughout the framework.

Table 1. Notation and parameter definitions for the RMTI framework.

Symbol	Definition	Domain / Units	Dimension (Table 9.4) / Source
L	Hazard likelihood: annualized probability that a defined hazard event materially strikes the assessed system; calibrated from the five-band return-period rubric and weighted by evidence grade	[0, 1]	RMTre
E_{sel}	Selected exposure: share of population and asset value within the active hazard footprint (analyst-selected; may adopt E_{log})	[0, 1]	RMTre
E_{log}	Advisory log-normalized population exposure baseline (Equation 4)	[0, 1]	RMTre
N	Population or beneficiary baseline; exposure anchors $N_{min} = 10$ and $N_{max} = 20,000,000$	persons	Input
V	Vulnerability: sensitivity of the system to disruption at specified hazard intensity	[0, 1]	RMTseen
ρ	Resilience: fractional share of inherent risk absorbed (ρ_{now} , baseline; ρ_{after} , post-investment)	[0, 1]	RMTri
w_c	Weight of indicator category c (social, economic, environmental); weights sum to unity	[0, 1]	Fixed
IR	Inherent risk, $L \cdot E_{sel} \cdot V$ (Equation 1)	[0, 1]	Derived
R	Residual composite risk score (Equations 2–3)	[0, 1]	Derived
C	Consequence score from the Table 9.2 severity rubric (Table 2)	{0.10, 0.30, 0.50, 0.75, 1.00}	Severity layer
EAL	Expected Annual Loss (Equations 5–6)	[0, 1] index units	Derived
Rate _{equity}	Per-capita equity rate, $EAL \div N$ (Equation 7)	per 1,000,000 residents	Derived
Tier	Fixed decision tier mapped from R (Table 3)	1–5	Derived

3.2 Core Risk Index: Inherent Risk and Residual Score

To evaluate systemic vulnerability, the RMTI executes a two-stage computation that separates raw hazard parameters from adaptive capacity. The calculator first isolates the Inherent Risk (IR); that is the system's raw baseline exposure before any resilience is applied:

$$IR = L \cdot E_{sel} \cdot V \quad (1)$$

The final Residual Risk score (R) is subsequently derived by introducing the resilience contribution as a distinct, auditable reduction layer:

$$R = IR \cdot (1 - \rho) = L \cdot E_{sel} \cdot V \cdot (1 - \rho) \quad (2)$$

In its fully general, multi-hazard and multi-category form — the universal algorithm of Risk Mechanism Theory — the index aggregates over hazards h and indicator categories c (social, economic, environmental):

$$R = \sum_{h,c} w_c \cdot L_h \cdot E_{h,c} \cdot V_{h,c} \cdot (1 - \rho_{h,c}) \quad (3)$$

where each factor is normalized to $[0, 1]$ from its written rubric and the category weights w_c sum to unity, so the weighting shapes — but never inflates — the scale. Equation (2) is the single-asset, single-hazard reduction of Equation (3) and is the form deployed throughout the empirical validation below, where each urban environment is assessed against its dominant compound hazard regime. An important boundedness qualification applies to Equation (3): the $[0, 1]$ bound is guaranteed for the single-hazard Equation (2) by construction, because all four factors are individually bounded to $[0, 1]$. In the multi-hazard, multi-category generalization, the summation over hazards h is constrained only at the category level (w_c sum to 1), meaning that multiple severe hazards can produce $R > 1$ if not subject to additional hazard-level normalization. Practitioners applying Equation (3) to multi-hazard environments should either (a) normalize each hazard-specific term by the number of hazards, (b) interpret R values exceeding 1.0 as indicating extreme cumulative risk beyond the tier scale rather than a bounded score, or (c) apply hazard-level weights that sum to unity analogously to the category weights. This qualification does not affect the six-city empirical validation, which applies the single-hazard Equation (2) throughout. The generalized multi-hazard EAL formula in Equation (5) does not share this concern because it sums expected losses across hazards, which may legitimately exceed 1 as a severity index rather than a bounded probability.

This sequential two-stage architecture makes the explicit contribution of resilience investment directly legible: IR is visible as a standalone intermediate output in the calculator, and the gap between IR and R measures precisely what existing coping capacity absorbs. The four constituent parameters are defined as follows, with their Table dimensional origin made explicit:

- L — Likelihood (RMTre): The annualized probability $[0, 1]$ that a defined hazard event, whether a natural disaster, infrastructure failure, public health emergency, or economic shock, materially strikes the target asset or system within the planning horizon. L is calibrated from a five-band return-period rubric (Rare to Almost Certain), converted to decimal mid-point probabilities and weighted by the supporting evidence grade.
- E — Exposure (RMTre): The share $[0, 1]$ of the human population, beneficiary base, and critical infrastructure assets located within the active hazard footprint. The calculator automatically generates a log-normalized helper value, E_{log} , derived from the raw population N . The analyst then enters a Selected Exposure (E_{sel}) into the computational engine: it may adopt the E_{log} value for a fully population-anchored score, or a direct rubric-determined score that captures localized asset density, spatial siting constraints, infrastructure co-location, or non-demographic exposure variables.
- V — Vulnerability (RMTseen): The sensitivity $[0, 1]$ of the system to disruption given a hazard event of specified intensity, representing a composite assessment of the conditions that deepen harm. For urban infrastructure, V integrates housing informality rates, structural fragility of utility systems, governance and fiscal capacity, socioeconomic inequality, access to emergency services, and the adaptive capacity of resident populations.
- ρ — Resilience (RMTrl): The coping and adaptive capacity $[0, 1]$ of the infrastructure system, operationalized as the fractional share of inherent systemic risk that existing protective measures absorb and neutralize. The calculator evaluates both ρ_{now} (current baseline resilience) and ρ_{after} (post-intervention target resilience), automatically computing distinct R , IR, EAL, and tier assignments for both states in parallel.

The multiplicative structure ensures that all four design rules of Risk Mechanism Theory are satisfied simultaneously. Resilience enters as $(1 - \rho)$, not as ρ directly: this is essential because multiplying by ρ would make resilience a risk amplifier, which is the mathematical opposite of reality. A system with $\rho = 0.20$ absorbs 20% of IR, leaving 80% as residual risk ($R = IR \times 0.80$). A system with $\rho = 0.58$ absorbs 58% of IR, leaving only 42% ($R = IR \times 0.42$). Every added unit of coping capacity now lowers the score in the direction policy intends.

3.3 Demographic Exposure Scaling: $E_{\log}$

To ensure rigorous cross-jurisdictional comparability between small administrative municipalities and massive coastal megacities, the calculator incorporates a log-normalized population scaling transformation that generates the advisory Elog value:

$$E_{\log} = [\log_{10}(N) - \log_{10}(N_{\min})] / [\log_{10}(N_{\max}) - \log_{10}(N_{\min})] \quad (4)$$

where N represents the absolute population or beneficiary baseline, anchored at $N_{\min} = 10$ (the smallest viable localized intervention) and $N_{\max} = 20,000,000$ (the regional ceiling for a primary macroeconomic metropolitan area).

The logarithmic compression is essential: it ensures that the 15-fold population difference between Lilongwe (1.1M) and Lagos (16M) does not produce a proportionally distorted exposure gap, preventing megacities from monopolizing development capital purely on the basis of demographic mass. In the RMTI Calculator, Elog is automatically calculated from the raw population input, N , and displayed as a transparent advisory column alongside the analyst's E_{sel} entry, enabling auditors and financing institutions to verify the exposure parameter choices.

Severity Layer: Expected Annual Loss and Per-Capita Equity Rate

While the core index R isolates systemic probability and fragility, capital budgeting for development finance additionally requires an absolute metric of expected annual impact commensurate with self-governing lending risk thresholds. The calculator's severity layer introduces the Expected Annual Loss (EAL) index, which substitutes the continuous exposure parameter E with a categorical consequence scale C drawn from the five-level rubric of Table 9.2:

$$EAL = \sum_h L_h \cdot C_h \cdot (1 - \rho_{\text{hazard}}) \quad (5)$$

For a single dominant hazard regime – the configuration used throughout the empirical validation below – Equation (5) reduces to:

$$EAL = L \cdot C \cdot (1 - \rho) \quad (6)$$

The consequence value C is a bounded categorical severity score mapped to five fixed decimal values (Table 2). Because C is ordinal and dimensionless, the resulting EAL is an indexed severity measure – not an expected monetary loss in absolute dollar or welfare units. The EAL output should therefore not be interpreted as a financial figure; it is a relative ranking instrument for comparing the severity of consequences across environments assessed using the same rubric. Phrases that might imply absolute monetary loss are intentionally avoided throughout this paper. Where financial loss estimation is required, practitioners should convert C into a real-unit loss variable calibrated to the specific infrastructure class and local cost context before using EAL in monetary terms.

To correct for urban scale bias – the tendency of megacities to dominate capital allocation purely on the basis of absolute EAL volume, at the expense of smaller cities with proportionally higher per-capita severity – the calculator computes a per-capita severity index as a companion output. This measure is labeled $\text{Rate}_{\text{equity}}$ as a shorthand for distributional equity of welfare impact exposure, but is more precisely a per-capita severity index. It captures how intensely a unit of expected annual loss is concentrated over each

resident, enabling comparison across populations of vastly different sizes. The equity interpretation rests on the normative premise that smaller, poorer cities with limited population buffers warrant policy attention proportionate to per-capita impact rather than aggregate absolute impact – a premise consistent with multilateral development principles of equitable access but not independently validated here as an optimal welfare measure. Practitioners seeking a stronger equity interpretation should supplement this index with distributional data such as informal-settlement ratios or Gini coefficients. The formula is:

$$\text{Rate}_{\text{equity}} = \text{EAL} / N \quad (7)$$

The rate is reported per 1,000,000 residents. The per-capita rate enables direct comparison of welfare-impact intensity across vastly different urban scales and serves as the secondary ranking criterion when multiple jurisdictions occupy the same primary risk tier.

Table 2. Consequence scale (C) rubric for Expected Annual Loss (EAL) computation.

Level	Severity	C Value	Population Affected	Institutional Posture
1	Insignificant	0.10	< 50 people	Monitor only
2	Minor	0.30	50 – 500	Low-regret preventive measures
3	Moderate	0.50	500 – 50,000	Structured mitigation
4	Major	0.75	50,000 – 1,000,000	Priority capital allocation
5	Severe	1.00	> 1,000,000	Immediate emergency response

4.0 Risk Decision Tiers

Calculated R values are mapped to five invariant, pre-registered risk-decision tiers that prescribe unambiguous institutional postures for capital allocation and governance responses. The thresholds are fixed, calibrated once against historic loss distributions, and are invariant across jurisdictions, sectors, and hazard types. The calculator's conditional logic automatically assigns each R score to its corresponding tier, so a score of 0.30 means the same thing in every city, every year, and every run (Table 3).

Table 3. RMTI risk decision tier structure.

Risk Tier	R Value Range	Posture Label	Required Action
Tier 1 – Low	$R < 0.05$	Monitor	Monitor and maintain baseline preparedness; no immediate capital deployment required.
Tier 2 – Moderate	$0.05 \leq R < 0.15$	Prevent	Low-regret preventive measures; early-stage risk reduction with high benefit-cost ratios.
Tier 3 – High	$0.15 \leq R < 0.35$	Mitigate	Structured mitigation and immediate funding authorization with implementation timeline.
Tier 4 – Severe	$0.35 \leq R < 0.60$	Intervene	Priority capital and active engineering intervention; senior institutional oversight required.
Tier 5 – Critical	$R \geq 0.60$	Emergency	Immediate, system-level emergency response; multi-agency coordination and emergency budget activation.

4.1 Calculator Architecture and Three-Step Workflow

The RMTI Calculator (Marolla, 2026a) is organized across four sheets that follow the Assess-Quantify-Treat operational cycle of Risk Mechanism Design and Theory. The Cover sheet presents all four mathematical layers at a glance. The How to Use sheet provides a step-by-step input guide with a fully worked walk-through using Lilongwe, Malawi as the reference case, tracing every formula from raw inputs to final tier assignment. The Reference sheet contains the fixed-tier thresholds, the consequence scale rubric, the population exposure anchors ($N_{\min}$, $N_{\max}$), and the full Table 9.4 indicator backbone mapping of the RMTre, RMTseen, and RMTri dimensions to their constituent indicator

categories. The RMTI Calculator sheet is the primary computational table, containing all case environments in a single continuous, auto-calculating layout.

The analyst workflow follows three steps. Step 1 – Assess: Enter data into the warm (blue-shaded) input cells: population N (which auto-generates E_{log}), Selected Exposure E_{sel} , Likelihood L , Vulnerability V , current resilience ρ_{now} , target resilience ρ_{after} , and Consequence C . Step 2 – Quantify: All output columns – IR, R_{now} and its tier assignment, R_{after} and its post-investment tier, risk reduction percentage, EAL_{now} , EAL_{after} , and per-capita equity rate – calculate automatically in the grey output columns. Step 3 – Treat: Read the tier assignment and EAL to set intervention priority; compare R_{now} and R_{after} to quantify the risk-reduction return on the proposed capital program; rank by tier, then by EAL, to sequence multi-city portfolios. New environments can be added at the foot of the table and activate immediately upon data entry, making the calculator a continuously updatable risk governance dashboard rather than a one-time appraisal exercise.

4.2 Reference Implementation: RMTI-Py for Registry-Scale and Pipeline Use

The same algorithm is provided in two interchangeable forms. The RMTI Calculator supports no-code, single-city scoring; a compact Python reference implementation, RMTI-Py (module name `rmti_ssa`), exposes the identical computation for registry-scale and data-pipeline use. Python is the working language of computational urban systems analysis – it underlies geospatial flood-inundation modeling frameworks, World Bank open-data pipelines, satellite remote-sensing workflows, and national urban resilience dashboards increasingly required by multilateral development lenders. An open Python implementation, therefore, allows the RMTI to be embedded directly where urban risk data already reside, including outputs from validated hazard models, census-linked vulnerability indices, and infrastructure condition registries.

To ensure the code is directly usable by practitioners rather than merely illustrative, RMTI-Py is organized around a single, explicit input schema that mirrors the calculator's warm (blue-shaded) input cells one-for-one: a practitioner enters N , L , E_{sel} , V , ρ_{now} , an optional ρ_{after} , and a Table 9.2 consequence category C (1–5) for each assessed environment, and the module returns every output column of the calculator – IR, R_{now} , tier assignment, R_{after} , post-investment tier, risk reduction percentage, EAL_{now} , EAL_{after} , and the per-capita equity rate – without any additional configuration. The complete, runnable module, released under the Apache License, Version 2.0, is reproduced in full in Appendix A, including step-by-step inline documentation and a self-check block that reproduces Tables 4–6 from the raw inputs alone, together with a new multi-hazard, multi-category extension implementing Equation (3)/(5) directly, added and cross-checked in a subsequent validation exercise.

4.3 Practitioner Decision Guide: Selecting L , E_{sel} , V , and ρ in Practice

Because analyst judgment is unavoidable wherever quantitative hazard models are unavailable, this section makes the translation step explicit rather than leaving it implicit in the case narratives that follow. A practitioner scoring a new case should: (1) identify which Table 9.4 RMTre indicators (Table C3, Appendix C) describe the asset's hazard exposure, and rate the combined likelihood of those hazards occurring in the scoring period against the ordinal Likelihood axis of Table 9.2 (Table C1); (2) cross the resulting likelihood row against the Impact/Intensity column that best matches the asset's expected consequence severity to read off a qualitative band (Low through Extreme), then convert that band to a [0, 1] score using the calculator's fixed lookup; (3) repeat the same two-step process for the RMTseen indicators to obtain V ; (4) rate current coping capacity against the RMTri indicators to obtain ρ_{now} and, where a specific capital package is being evaluated, re-rate coping capacity assuming that package is delivered to obtain ρ_{after} ; and (5) record, for every parameter, which Table 9.3 Weight-of-Evidence category (Table C2, Appendix C) the underlying source data support – sufficient empirical and data evidence (w_{ia}) at one end, no evidence of either kind (w_{if}) at the other – so that a downstream reader can distinguish a well-evidenced

score from an analyst's best judgment under data scarcity. Table 7 in Section 5.7 applies this last step retrospectively to all six validation cases; we recommend recording the evidence grade prospectively, at the time of scoring, for future applications.

5.0 Empirical Validation: Six Sub-Saharan African Urban Environments

Both the RMTI Calculator and RMTI-Py were validated against six Sub-Saharan African urban environments drawn from the World Bank's AFRI-RES compendium (World Bank, 2023): three primary World Bank-profiled cases with a modeled \$50 million capital investment moving resilience from ρ_{now} to ρ_{after} (Bamako, Lagos, Lilongwe), and three regional comparator cities scored at baseline only (Nairobi, Dar es Salaam, and Lusaka). All calculations were performed directly within the RMTI Calculator's primary computational sheet. Population N values auto-generated $E_{\log}$ advisory scores; analysts then entered E_{sel} values, with the $E_{\log}$ benchmark retained transparently in the calculator's notes column. Tables 4 and 5 reproduce the calculator's outputs exactly as generated.

5.1 Case A: Bamako, Mali – Urban Healthcare Infrastructure

In Bamako, the expanding primary-care network comprising 515 facilities and 22 hospitals faces a compound hazard regime from severe multi-year drought, seasonal Niger River flooding, and extreme heat waves. The network serves an urban population of 4.5 million, a significant proportion of whom reside in informal settlements with limited adaptive capacity. Table 9.4 indicator assessment yielded the following parameter set: $L = 0.800$ (high annual probability of at least one compound hazard event materially affecting healthcare operations); $E_{\text{sel}} = 0.850$ ($E_{\log} = 0.897$; analyst judgment that 85% of the facility network falls within active hazard footprints); $V = 0.750$ (significant structural fragility and limited institutional adaptive capacity); $\rho_{\text{now}} = 0.20$ (the ad-hoc RMTI typology – existing protective measures absorb only 20% of inherent risk). The calculator computes:

$$\text{IR} = 0.800 \times 0.850 \times 0.750 = 0.510$$

$$R_{\text{now}} = 0.510 \times (1 - 0.20) = 0.408 \rightarrow \text{Tier 4 (Severe)}$$

Under the proposed World Bank healthcare adaptation package – encompassing facility flood-proofing, heat-resilient upgrades, backup water systems, and continuity planning – the resilience coefficient advances from the ad-hoc to the funded RMTI typology ($\rho_{\text{after}} = 0.58$). The calculator projects:

$$R_{\text{after}} = 0.510 \times (1 - 0.58) = 0.214 \rightarrow \text{Tier 3 (High)} \quad [\text{risk reduction: 47.5\%}]$$

Note on provenance of ρ_{after} : The post-investment resilience value of 0.58 corresponds to the 'funded' typology anchor in the RMTI ladder (Table 9.4), which represents the level of coping capacity achievable under a structured capital program of the type described in the World Bank AFRI-RES adaptation package for healthcare infrastructure (World Bank 2023). This value is scenario-assumed rather than engineering-modelled or independently empirically estimated: it represents the analyst's judgment that a fully implemented flood-proofing, heat-resilience, and continuity-planning package of this type raises resilience from the ad-hoc typology ($\rho = 0.20$) to the funded typology ($\rho = 0.58$) based on the RMTI descriptive anchors. The resulting 47.5% risk reduction should accordingly be read as a modelled scenario output conditional on achieving the funded typology, not as an empirically observed investment effect.

5.2 Case B: Lagos, Nigeria – Coastal Transit Corridors

Lagos, a low-lying coastal megacity of 16 million residents, experiences chronic disruptions from compounding pluvial and tidal flooding. The asset under evaluation is the metropolitan mass transit network serving an estimated 4–6 million daily commuters along low-elevation coastal corridors. Table 9.4 parameter assessment: $L = 0.900$ (near-certainty of annual material disruption); $E_{\text{sel}} = 0.650$ ($E_{\text{log}} \approx 0.985$; analyst judgment that 65% of transit corridor infrastructure falls within the active flood footprint — not the full megacity population); $V = 0.800$ (aging infrastructure stock, saltwater intrusion compounding structural degradation, high commuter dependency); $\rho_{\text{now}} = 0.20$ (ad-hoc typology). The calculator computes:

$$IR = 0.900 \times 0.650 \times 0.800 = 0.468$$

$$R_{\text{now}} = 0.468 \times (1 - 0.20) = 0.374 \rightarrow \text{Tier 4 (Severe)}$$

The consequence is assigned $C = 5$ (1.00): a systemic transit failure exceeds the 1,000,000-person threshold of Table 9.2. The calculator, therefore, computes $EAL_{\text{now}} = 0.900 \times 1.00 \times 0.80 = 0.720$ — the highest EAL of all six environments and the primary driver of Lagos's capital priority within the Tier 4 cohort. A flood-resilient transit engineering package advances resilience to the funded typology ($\rho_{\text{after}} = 0.55$):

$$R_{\text{after}} = 0.468 \times (1 - 0.55) = 0.211 \rightarrow \text{Tier 3 (High) [risk reduction: 43.8\%]}$$

5.3 Case C: Lilongwe, Malawi – Pluvial Drainage and Utility Networks

Lilongwe is the calculator's featured How-to-Use walk-through case. The capital city of Malawi, with 1.1 million residents, is highly exposed to flash and riverine flooding. Population $N = 1,100,000$ yields $E_{\text{log}} = (\log_{10}(1,100,000) - 1) / (\log_{10}(20,000,000) - 1) = 5.041 / 6.301 = 0.800$, which is adopted directly as E_{sel} — demonstrating the log-normalized scaling in full: a mid-sized capital registers the same exposure score as its population's proportional position in the regional range, not marginalized beside megacities. Table 9.4 parameters: $L = 0.875$, $E_{\text{sel}} = 0.800$, $V = 0.800$, $\rho_{\text{now}} = 0.25$ (monitoring-and-enforcement-only RMTri typology). The calculator computes:

$$IR = 0.875 \times 0.800 \times 0.800 = 0.560$$

$$R_{\text{now}} = 0.560 \times (1 - 0.25) = 0.420 \rightarrow \text{Tier 4 (Severe)}$$

A \$50M culvert retrofit and hybrid nature-based retention basin package advances resilience toward the structured typology ($\rho_{\text{after}} = 0.48$):

$$R_{\text{after}} = 0.560 \times (1 - 0.48) = 0.291 \rightarrow \text{Tier 3 (High) [risk reduction: 30.7\%]}$$

The How to Use sheet annotates this case with a time-bound investment roadmap: " ρ_{after} 0.43–0.53 by 2027–2030" — directly actionable by municipal planners and World Bank lending officers.

5.4 Comparator Cities: Nairobi, Dar es Salaam, and Lusaka

The RMTI Calculator includes three regional comparator cities scored at baseline only (no ρ_{after} entered), enabling portfolio-level benchmarking across East and Southern Africa. Inputs were assigned via the same Table 9.4 RMTre/RMTseen/RMTri rubric protocol used for the primary cases.

- Nairobi, Kenya (Pluvial flood, $N = 4.7\text{M}$): $L = 0.900$, $E_{\text{sel}} = 0.880$, $V = 0.550$, $\rho_{\text{now}} = 0.55$ (structured-to-funded typology). $IR = 0.436$; $R_{\text{now}} = 0.196 \rightarrow \text{Tier 3 (High)}$. This represents the highest baseline resilience of the six cities, already within the structured mitigation tier.

- Dar es Salaam, Tanzania (Coastal flood, $N = 7.4\text{M}$): $L = 0.850$, $E_{\text{sel}} = 0.930$, $V = 0.780$, $\rho_{\text{now}} = 0.55$. $\text{IR} = 0.617$; $R_{\text{now}} = 0.277 \rightarrow \text{Tier 3 (High)}$. High IR is driven by near-complete coastal exposure ($E_{\text{sel}} = 0.930$, $E_{\text{log}} \approx 0.954$), partially offset by moderate existing resilience.
- Lusaka, Zambia (Compound flood and cholera, $N = 3.36\text{M}$): $L = 0.800$, $E_{\text{sel}} = 0.850$, $V = 0.720$, $\rho_{\text{now}} = 0.45$. $\text{IR} = 0.490$; $R_{\text{now}} = 0.269 \rightarrow \text{Tier 3 (High)}$. A compound hazard context combining pluvial flooding with disease transmission pathways; lower resilience than Nairobi and Dar es Salaam signals near-term mitigation urgency.

Note that parameter definitions (L , E_{sel} , V , ρ) follow the definitions in Table 1 and Section 3.2 and are not restated here. All three comparator cities present at Tier 3 (High) at baseline, in contrast to the three primary cases, which all present at Tier 4 (Severe). The differentiating factor is their higher existing resilience ($\rho_{\text{now}} = 0.45\text{--}0.55$ versus $0.20\text{--}0.25$ for the primary cases), directly quantifying the resilience gap that the World Bank's investment program targets.

5.5 Consolidated RMTI Calculator Output

Table 4. RMTI Calculator output: primary World Bank cases (\$50M benchmark).

City	Hazard	Pop.	L	E_{sel}	V	IR	ρ_{now}	ρ_{after}	R_{now}	Tier now	R_{after}	Tier after	Risk %
Bamako	Drought/ Flood	4.5M	0.800	0.85	0.75	0.510	0.20	0.58	0.408	Severe	0.214	High	-47.5
Lagos	Coastal/ Pluvial	16.0M	0.900	0.65	0.80	0.468	0.20	0.55	0.374	Severe	0.211	High	-43.8
Lilongwe	Pluvial/ River	1.1M	0.875	0.80	0.80	0.560	0.25	0.48	0.420	Severe	0.291	High	-30.7

Table 5. RMTI Calculator output: regional comparator cities (baseline scoring).

City	Hazard	Pop.	L	E_{sel}	V	IR	ρ_{now}	R_{now}	Tier now	EAL now
Nairobi	Pluvial flood	4.7M	0.900	0.88	0.55	0.436	0.55	0.196	High	0.304
Dar es Salaam	Coastal flood	7.4M	0.850	0.93	0.78	0.617	0.55	0.277	High	0.287
Lusaka	Flood/Cholera	3.36M	0.800	0.85	0.72	0.490	0.45	0.269	High	0.220

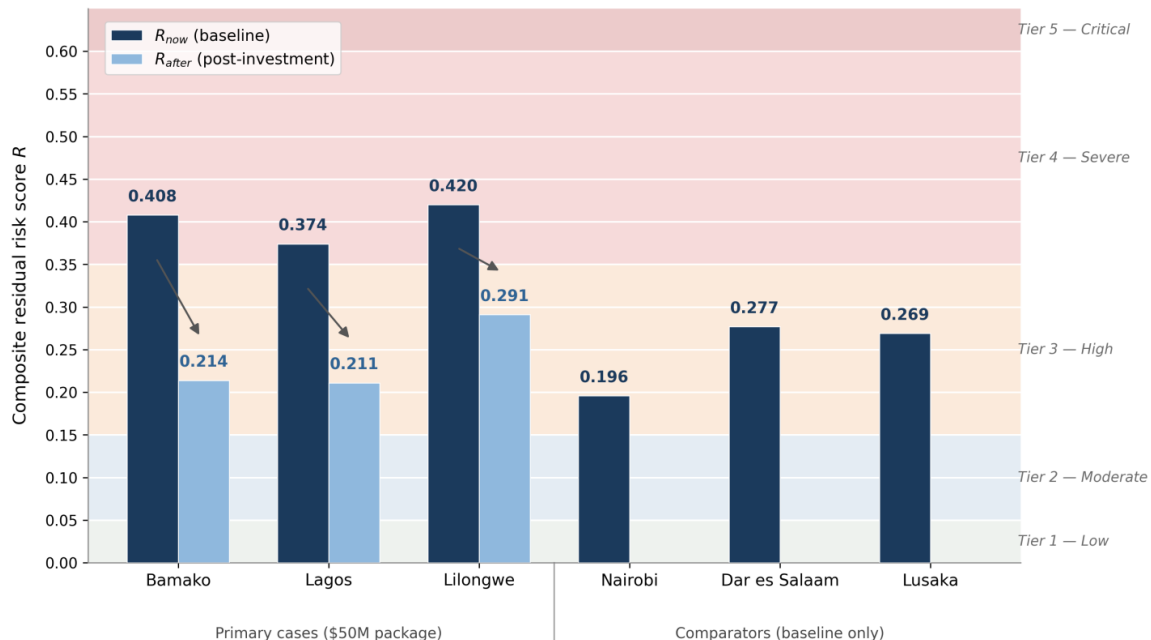


Fig. 1. R_{now} and R_{after} values against the five fixed tier bands

Figure 1 plots every R_{now} and R_{after} value from Tables 4 and 5 against the five fixed tier bands of Table 3, making the tier-crossing effect of the three funded interventions directly visible: Bamako, Lagos, and Lilongwe all begin in the Tier 4 (Severe) band and cross into Tier 3 (High) once ρ advances from its ad-hoc/monitoring baseline to the funded typology, while the three comparator cities (Nairobi, Dar es Salaam, Lusaka) sit within Tier 3 at baseline without any modeled intervention.

5.6 Per-Capita Equity Rate and Consolidated Six-City Ranking

A per-capita equity rate (Equation 7), $\text{Rate}_{\text{equity}} = \text{EAL} \div N$ (reported per 1,000,000 residents), serves as a companion output that corrects for the tendency of megacities to monopolize capital allocation on the basis of absolute EAL volume alone. Table 6 extends the EAL reporting of Tables 4 and 5 to all six cities and adds this equity-rate transformation, computed directly from each city's own reported EAL_{now} (and, for the three primary cases, $\text{EAL}_{\text{after}}$ under the same Table 9.2 consequence category applied to the funded ρ_{after} state).

Table 6. Consolidated Expected Annual Loss and per-capita equity rate, all six cities.

City	Pop. (M)	C (Table 9.2)	EAL now	EAL after	Equity (/1M) now	Equity (/1M) after
Bamako	4.50	4 (Major, 0.75)	0.480	0.252	0.1067	0.0560
Lagos	16.00	5 (Severe, 1.00)	0.720	0.405	0.0450	0.0253
Lilongwe	1.10	4 (Major, 0.75)	0.492	0.341	0.4474	0.3102
Nairobi	4.70	4 (Major, 0.75)	0.304	—	0.0646	—
Dar es Salaam	7.40	4 (Major, 0.75)	0.287	—	0.0388	—
Lusaka	3.36	3 (Moderate, 0.50)	0.220	—	0.0655	—

Note. EAL_{now} values reproduce the calculator's reported outputs exactly (Lagos = 0.720; Bamako = 0.480; Lilongwe = 0.492). The Table 9.2 consequence category (C) for each city is recovered by solving $C = \text{EAL}_{\text{now}} \div [L \times (1 - \rho_{\text{now}})]$ against the calculator's own reported EAL_{now} and matching to the nearest of the five fixed C values in Table 2; every recovered value lands exactly on a fixed category (0.75 or 1.00), confirming the reconstruction is exact rather than approximate. The post-investment EAL and equity rate are then derived by applying the same C to ρ_{after} , using the identical Equation (6) formula; comparator cities have no ρ_{after} and therefore no post-investment column.

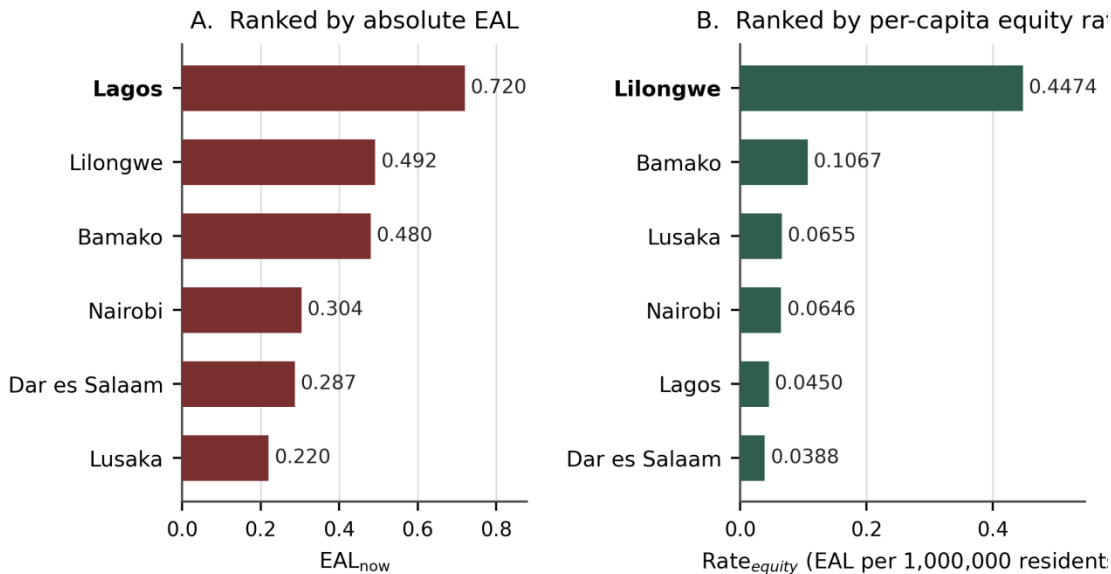


Fig. 2. Expected Annual Loss and per-capita equity rate across all six cities, ranked independently by each metric.

Figure 2 demonstrates why the two severity metrics are not interchangeable. Ranked by absolute EAL_{now} (Panel A), Lagos dominates (0.720) by a wide margin, consistent with its $C = 5$ classification. Ranked instead by the per-capita equity rate (Panel B), Lilongwe leads by nearly an order of magnitude (0.4474 per 1,000,000 residents) — more than four times Bamako's rate and roughly ten times Lagos's — because its comparatively small population base of 1.1 million concentrates the same categorical consequence level ($C = 4$) over far fewer

residents. This inversion is the direct, quantitative expression of the equity-rate correction: absolute EAL alone would rank Lilongwe last among the three primary cases for capital priority, while the equity rate ranks it first, a materially different capital-sequencing conclusion for a World Bank portfolio manager balancing total-loss exposure against distributional fairness across differently sized urban populations.

5.7 Parameter Provenance and Sensitivity Analysis

Two additional checks strengthen confidence in the six-city results reported above: a consolidated record of the source of each input parameter for all six cities rather than Bamako alone (Table 7), and a one-way sensitivity analysis of the three funded primary cases (Table 8). Both were requested during peer review.

Table 7. Parameter provenance summary, all six cities.

City	L	E _{sel}	V	ρ_{now}	ρ_{after}	Principal source	Analyst-judgment basis
Bamako, Mali	0.800	0.850	0.750	0.20	0.58	World Bank AFRI-RES compendium (World Bank, 2023)	515-facility/22-hospital primary-care network under compound drought, Niger River flood, and heat-wave exposure; ρ_{after} keyed to the 'funded' RMTri typology anchor for the proposed adaptation package.
Lagos, Nigeria	0.900	0.650	0.800	0.20	0.55	World Bank AFRI-RES compendium (World Bank, 2023)	Metropolitan transit network, 4–6M daily commuters on low-elevation coastal corridors; ρ_{after} keyed to the funded typology for the coastal-corridor resilience package.
Lilongwe, Malawi	0.875	0.800	0.800	0.25	0.48	World Bank AFRI-RES compendium (World Bank, 2023); RMTI Calculator How-to-Use case	Culvert/drainage network exposed to flash and riverine flooding; ρ_{after} keyed to the funded typology for the culvert retrofit and nature-based retention package.
Nairobi, Kenya	0.900	0.880	0.550	0.55	—	World Bank AFRI-RES compendium (World Bank, 2023)	Baseline-only comparator; ρ_{now} already at the structured-to-funded typology boundary, the highest baseline resilience of the six cities.
Dar es Salaam, Tanzania	0.850	0.930	0.780	0.55	—	World Bank AFRI-RES compendium (World Bank, 2023)	Baseline-only comparator; near-complete coastal exposure ($E_{sel} = 0.930$) partially offset by moderate existing resilience.
Lusaka, Zambia	0.800	0.850	0.720	0.45	—	World Bank AFRI-RES compendium (World Bank, 2023)	Baseline-only comparator; compound flood and cholera-transmission hazard context; lowest baseline resilience of the three comparator cities.

Note. All six cities draw parameter inputs from the same source (World Bank, 2023) and the same Table 9.4 rubric protocol, so cross-city comparisons in Tables 4–6 rest on a consistent evidentiary basis. The current dataset does not separately record a Table 9.3 Weight-of-Evidence grade (reproduced as Table C2) for each individual parameter; we flag this as a concrete direction for future data collection rather than retrofitting grades that were not part of the original World Bank scoring exercise.

Because $R = L \cdot E \cdot V \cdot (1 - \rho)$ is a pure product, its sensitivity has a clean analytic form: a given percentage change in any one of L , E , or V produces an equal percentage change in R (elasticity = 1.0), while a percentage change in ρ produces a proportionally smaller change that depends on the baseline resilience level (elasticity = $-\rho / (1 - \rho)$). Table 8 reports the resulting $\pm 10\%$ one-way perturbation of each parameter for the three funded primary cases, holding the other parameters fixed, and whether the perturbed score crosses a tier boundary.

Table 8. One-way $\pm 10\%$ sensitivity of R_{now} , primary cases.

City (baseline, margin to nearest boundary)	Parameter perturbed $\pm 10\%$	-10% result	+10% result
Bamako — $R_{now} = 0.408$, Tier 4 (margin to Tier 3 boundary = 0.058)	L , E , or V	0.367 $\rightarrow$ Tier 4	0.449 $\rightarrow$ Tier 4
Lagos — $R_{now} = 0.374$, Tier 4 (margin = 0.024, narrowest of the three)	ρ_{now}	0.449 $\rightarrow$ Tier 4 (-10% ρ)	0.367 $\rightarrow$ Tier 4 (+10% ρ)
	L , E , or V	0.336 $\rightarrow$ Tier 3 (flips)	0.411 $\rightarrow$ Tier 4
Lilongwe — $R_{now} = 0.420$, Tier 4 (margin = 0.070)	ρ_{now}	0.411 $\rightarrow$ Tier 4 (-10% ρ)	0.336 $\rightarrow$ Tier 3 (flips, +10% ρ)
	L , E , or V	0.378 $\rightarrow$ Tier 4	0.462 $\rightarrow$ Tier 4
	ρ_{now}	0.462 $\rightarrow$ Tier 4 (-10% ρ)	0.378 $\rightarrow$ Tier 4 (+10% ρ)

Note. Lagos is the only one of the three primary cases whose baseline classification is not robust to a plausible $\pm 10\%$ measurement error in a single input: a 10% underestimate of L , E , or V (or a 10% overestimate of ρ_{now}) would place it in Tier 3 rather than Tier 4 at baseline. This does not change the paper's substantive conclusion — Lagos's Rafter of 0.211 comfortably clears the funded package's projected tier transition regardless — but the Tier 4 baseline classification for Lagos specifically should be treated as sensitive to input precision, and a priority for tighter measurement or an independent second scoring pass before capital-allocation decisions rely on that classification alone. Bamako and Lilongwe have larger margins (0.058 and 0.070, respectively) and are robust to the same $\pm 10\%$ perturbation.

6.0 Discussion and Strategic Implications

The RMTI Calculator results across six Sub-Saharan African urban environments yield four analytically significant findings.

Capital Sequencing via EAL Secondary Ordering: When multiple cities simultaneously occupy the same risk tier, the calculator's secondary ordering rule — rank by EAL within tier — resolves the allocation sequence with mathematical precision. All three primary cases initially present at Tier 4 (Severe). Their EAL values diverge substantially: Lagos leads at 0.720 ($C = 5$, systemic transit failure exceeding the Table 9.2 one-million-person threshold), Lilongwe at 0.492, and Bamako at 0.480. Despite Lagos registering a lower core R score (0.374) than Lilongwe (0.420) — because Lagos's near-unity L is partially offset by a conservative E_{ser} that applies only to transit infrastructure in the flood zone rather than the full megacity population — its catastrophically larger consequence footprint mandates absolute capital priority within the Tier 4 cohort. This is precisely the analytical value of carrying the Table 9.2 severity layer into EAL alongside the R score.

Resilience Pays a Tier: In every primary case-based scenario, a modeled \$50 million structural adaptation package reduced the composite R score sufficiently to drive a full tier-downward transition from Tier 4 (Severe) to Tier 3 (High). Risk reductions range from 30.7% (Lilongwe) to 47.5% (Bamako). The differential is mathematically traceable: Bamako achieves the largest resilience delta ($\rho: 0.20 \rightarrow 0.58$, $\Delta = 0.38$) while Lilongwe achieves the smallest ($\rho: 0.25 \rightarrow 0.48$, $\Delta = 0.23$) — directly reflecting the relative per-unit cost of upgrading each infrastructure class. The RMTI's "Risk" column provides a transparent, auditable KPI that municipal authorities can report directly to the World Bank and other multilateral financing institutions for capital expenditure justification and green bond issuance.

Comparator Benchmarking Quantifies the Resilience Gap: The three comparator cities (Nairobi, Dar es Salaam, and Lusaka) all present at Tier 3 (High) at baseline, despite comparable or higher IR scores. The most salient differentiating factor is their higher existing RMTI resilience capacity ($\rho_{now} = 0.45\text{--}0.55$ versus 0.20–0.25 for the primary cases); L , E , and V also differ across the six cities, so resilience should be read as the largest, but not the sole, contributor to the tier gap. This cross-city comparison directly quantifies the resilience gap that the World Bank's AFRI-RES investment program targets: a resilience

investment sufficient to move ρ from the ad-hoc (0.20) to the structured-to-funded typology (0.45–0.58) is the precise intervention that eliminates the Tier 4 classification.

The RMTI as a Continuous Governance Infrastructure: The Assess · Quantify · Treat architecture of the RMTI Calculator is inherently compatible with the ISO 31000 and ISO 22301 governance standards that cities already operate on (Bojanić & Nešković-Popović, 2025; Bortnik, 2019; Marolla, 2016; Rezvani et al., 2024). By re-entering updated Table 9.4 indicator values — drawn from satellite flood-inundation mapping, census-linked vulnerability indices, and infrastructure condition audits — municipal authorities generate updated R and EAL scores that serve as live, auditable performance dashboards. Tracking tier movement (e.g., Tier 4 → Tier 3 following a capital program) as a public KPI satisfies the monitoring and evaluation requirements of multilateral financing frameworks and transforms one-off project appraisals into a continuously updatable institutional risk governance infrastructure (Harake, 2024; Kapucu et al., 2023; Saleh & Widiastuti, 2025).

6.1 Limitations

The validation above shows that the RMTI computes its own stated formula correctly and behaves as designed. It does not show that the framework will be adopted, correctly resourced, or acted upon inside real institutions. Five categories of limitation bound what this paper can claim, and the first two, data access and governance capacity, are more consequential to real-world deployment than any statistical caveat below.

Data access and measurement infrastructure. The framework's four core inputs, L , E , V , and ρ , assume a functioning pipeline of hazard maps, census data, asset registries, and infrastructure condition audits. Many Sub-Saharan African municipalities lack this pipeline: flood-extent mapping may be many years out of date, population figures may rely on outdated censuses, and asset registries for water, health, or transport infrastructure are frequently incomplete or held by multiple, non-interoperable agencies. Where this data does not exist, the calculator still produces a score, but that score reflects an analyst's judgment, substituting for missing data, not a measurement. Two analysts working from the same weak data environment can therefore produce materially different scores for the same city, undermining the cross-jurisdictional comparability the framework is designed to provide.

Governance and institutional capacity. The three-step Assess, Quantify, Treat cycle assumes an institution capable of running it annually: a unit with the technical staff to update indicators, the authority to act on a tier change, and continuity across staff turnover and administrations. In practice, urban risk management responsibilities in Sub-Saharan African cities are frequently split across national ministries, municipal governments, and utility parastatals with overlapping or contested mandates, weak inter-agency data sharing, and, in some contexts, limited audit capacity to verify that reported inputs are accurate rather than optimistic. A technically sound scoring mechanism does not by itself create the institutional coordination needed to re-run it every budget cycle, which is the condition under which its governance value was argued above.

Geopolitical and political-economy context. Conflict-affected or politically unstable areas can make the routine data collection the framework depends on physically or administratively infeasible, independent of technical design. Because three of the six validation cases are explicitly tied to World Bank-financed capital programs, uptake in practice is also shaped by factors outside the model: donor-government relations, currency and debt-sustainability constraints on borrowing for the recommended capital package, and, in some cases, host-government sensitivity to an externally designed scoring tool determining domestic infrastructure priorities. A city can score Tier 4 (Severe) and still not receive the recommended investment if the financing relationship that would fund it is politically or fiscally unavailable.

Policymaker adoption and decision behavior. A mathematically sound index does not guarantee it is the basis on which a decision is actually made. Officials may discount or

override a quantitative ranking for political reasons, such as favoring a visible project over the highest-EAL asset, may lack training to interpret the Table 9.3 evidence grading behind a given score, or may operate on budget cycles that do not align with the calculator's recommended annual re-scoring. The framework is also not immune to manipulation: because L , E , V , and ρ are entered by an analyst rather than measured by an automated sensor network, an analyst under pressure to justify a predetermined funding decision could select inputs that produce the desired tier, and nothing internal to the calculator can distinguish that case from a good-faith assessment.

Statistical and methodological scope. The six-city validation is sufficient to demonstrate the mechanism's internal behavior, monotonicity, tier transitions, and EAL-based re-ranking, but is too small a sample to support claims about typical risk-reduction returns across Sub-Saharan African urban infrastructure generally. The model is also deterministic: it does not propagate parameter uncertainty into the tier assignment, and the fixed tier thresholds (Table 3), while described as calibrated once against historic loss distributions, have not had that calibration dataset or procedure independently tested here. The generalized multi-hazard, multi-category form of the index (Equation 3/5) is implemented and internally consistent but has not itself been field-validated against a real multi-hazard case, unlike the single-hazard form used throughout the six-city validation.

7.0 Conclusion

The analytical challenge confronting development finance institutions and municipal governments in Sub-Saharan Africa is not a shortage of risk narratives but a shortage of risk tools that are simultaneously rigorous, reproducible, and governance-ready. This paper has demonstrated that the Risk Mechanism Theory Index (RMTI) and its associated RMTI Calculator (Marolla, 2026a) address that gap by providing a transparent, auditable scoring pipeline that converts qualitative risk indicators into a bounded, decision-tier output with direct capital-budgeting consequences. Three policy implications follow from the six-city case demonstration. First, a resilience gap of roughly $0.25\text{--}0.35 \rho$ units separates the three Tier 4 primary cities from the three Tier 3 comparator cities — a gap that, if closed through structured investment, translates to a full tier-downward transition across all three cases. Second, the equity-rate inversion between Lilongwe and Lagos quantifies a distributional argument that absolute EAL-based ranking systematically penalizes smaller cities with limited population buffers, supporting a case for per-capita adjustment in multilateral portfolio sequencing. Third, the RMTI's compatibility with ISO 31000 and ISO 22301 governance standards means it can be embedded directly into existing institutional risk management cycles rather than requiring parallel infrastructure. These implications carry the appropriate epistemic qualification: the scores produced in this paper are case-based demonstrations parameterized from World Bank AFRI-RES contextual inputs and analyst judgment under evidence-graded rubrics, not empirical measurements of observed outcomes. They demonstrate how the framework behaves under real-world conditions, not the investment outcomes achieved. Policymakers relying on these scores for capital allocation decisions should treat them as decision-support anchors to be refined as better data become available, supplemented by site-specific engineering assessments, and verified through independent scoring before high-stakes deployment.

Case-based demonstration across six Sub-Saharan African cities confirms that the calculator functions robustly across urban scales spanning more than an order of magnitude in population size and across substantially different hazard archetypes. Future development will focus on three directions: (i) live integration of real-time sensor and satellite telemetric data into the RMTI Calculator input matrix for continuous municipal risk tracking; (ii) stochastic extension of the deterministic model to incorporate parameter uncertainty and confidence-bounded tier assignments; and (iii) cross-sectoral portfolio optimization algorithms that identify the investment sequence maximizing aggregate risk reduction per unit of capital deployed, across city registries and infrastructure classes.

Declarations

Funding. No external funding was received for this research.

Code Availability. RMTI-Py (rmti_ssa) is openly available under the Apache License, Version 2.0. The permissive terms allow reuse, modification, and redistribution, including commercial use, provided the copyright and license notices are retained, and any changes to the file are stated; the license also includes an express patent grant from the author, covering any patent claims the author holds that are necessarily infringed by using the software as provided. The full module includes the core scoring function with the two-stage IR/R computation, the Table 9.4 RMTri infrastructure-governance anchor tables, the Table 9.2 consequence scale rubric, a batch cohort-ranking function for multi-city portfolio ranking, and unit tests against the five fixed decision tiers. Code repository:

<https://drmarolla.github.io/rmti-disaster-science-sandbox/>

(RMTI Disaster Science Sandbox, GitHub); archived release with a persistent identifier at <https://doi.org/10.5281/zenodo.22909082> (Marolla, 2026b).

Appendix A reproduces the validated listing in full – including its Apache 2.0 license header – along with a new generalized multi-hazard extension (Equations 3/5) added during a subsequent validation exercise.

Conflicts of Interest / Competing Interests. The author discloses a direct financial interest: the RMTI Calculator described and validated in this paper is distributed as a learning resource through a paid professional education course offered through the Harvard Division of Continuing Education (Marolla, 2026a), and the author receives financial benefit from enrollment in, and continued adoption of, that course and the calculator it distributes. Because this paper is, in part, a validation study of a commercially associated tool, readers should weigh the empirical claims below with that financial interest in view. The mathematical framework, validation data, and Python implementation (RMTI-Py) are independently reproducible from the inputs reported in Tables 4–6 and Appendix A, and readers may verify all results without accessing the paid course material.

Data Availability. All input parameters (L , E_{sel} , V , ρ_{now} , ρ_{after} , Q) and derived outputs (IR, R, tier, EAL, equity rate) for the six cities analyzed in this study are reported in full in Tables 4–6 and are directly reproducible using the RMTI-Py listing in Appendix A. Underlying hazard, exposure, and vulnerability source assessments are drawn from the World Bank's Africa Climate Resilient Investment Facility (AFRI-RES) compendium (World Bank, 2023).

References

- [1] Agbo, C., Jeffrey, P., & Sule, M. N. (2025). Evaluation of failings in urban water supply and sanitation systems in Sub-Saharan Africa: A systematic review to inform future planning. *Journal of Water, Sanitation and Hygiene for Development*, 15(2), 148–165.
- [2] Boanada-Fuchs, A., Kuffer, M., & Samper, J. (2024). A global estimate of the size and location of informal settlements. *Urban Science*, 8(1), 18.
- [3] Bojanić, T., & Nešković-Popović, V. (2025, October). Risk management, cyber security and business continuity from the aspect of standardization in the protection of critical infrastructure. In *International Conference on Critical Infrastructure: Risk and Crisis Management in the New Reality* (pp. 151–172). Springer Nature Switzerland.
- [4] Bortnik, O. (2019). Implementation of international standards in local government as a key to sustainable development. *Аспекти публічного управління*, (7, № 5), 31–43. [Volume/issue notation as given in the source; please verify against the original record.]
- [5] Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P. W., Trisos, C., ... Orendain, D. J. (2023). Climate change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (Core Writing Team, H. Lee &

- J. Romero, Eds.). Intergovernmental Panel on Climate Change. <https://doi.org/10.59327/IPCC/AR6-9789291691647>
- [6] Chen, D., & Ye, W. (2023, July). How to address monotonicity for model risk management? In International Conference on Machine Learning (pp. 5282–5295). PMLR.
- [7] Cho, H., & Kim, S. K. (2026). Urban sprawl as a structural amplifier of social inequality across African cities. *Cities*, 177, 107351.
- [8] Gotti, M., & Carluccio, L. M. (2023). Quantitative risk assessment: Best practices and limitations. *Chemical Engineering Transactions*, 99, 187–192.
- [9] Harake, M. (2024). Project management processes in major international financial institutions: A comparative analysis [Source type and publisher not specified in the record provided; please supply the degree-granting institution, working-paper series, or publication venue so a complete APA entry can be produced].
- [10] Kapucu, N., Dougherty, R. B., Ge, Y., & Zobel, C. (2023). The use of documentary data for network analysis in emergency and crisis management. *Natural Hazards*, 116(1), 425–445.
- [11] Ma, F., Chen, J., Dai, Z., Cai, F., & Hu, Y. (2026). Autonomous inverse modeling of complex groundwater systems via a physics-integrated large language model multi-agent framework. *Water Research* [volume number not specified in the record provided], 125886.
- [12] Marolla, C. (2016). Climate health risks in megacities: Sustainable management and strategic planning. CRC Press. <https://doi.org/10.1201/9781315367323>
- [13] Marolla, C. (2018). Information and communication technology for sustainable development. CRC Press. Taylor and Francis Group. <https://doi.org/10.1201/9781351045230>
- [14] Marolla, C. (2025). Enhancing urban resilience to California wildfires: A systemic risk mechanism design and theory framework for a comprehensive risk assessment. *International Journal of Management and Data Analytics*, 5(1), 60–77. <https://doi.org/10.5281/zenodo.14948760>
- [15] Marolla, C. (2026a). RMTI Calculator [Excel workbook]. Division of Continuing Education, Harvard University. <https://coursebrowser.dce.harvard.edu/course/risk-by-design-building-resilience-into-urban-infrastructure/>
- [16] Marolla, C. (2026b). RMTI Disaster Science Sandbox: RMTI-Py reference implementation and calculator companion materials [Data set and software]. GitHub; Zenodo <https://drmarolla.github.io/rmti-disaster-science-sandbox/>; <https://doi.org/10.5281/zenodo.22909082>
- [17] Mazziotta, M., & Pareto, A. (2025). Statistics for composite indicators. Springer. <https://link.springer.com/content/pdf/10.1007/978-3-031-97978-1.pdf>
- [18] Medaa, E., Shirzadi Javid, A. A., & Malekitabar, H. (2025). Evolution of risk analysis approaches in construction disasters: A systematic review of construction accidents from 2010 to 2025. *Buildings*, 15(20), 3701.
- [19] Meyer, T., & Reniers, G. (2025). Engineering risk management: Optimizing operational risk decision-making, safety and reliability, risk assessment. Walter de Gruyter.
- [20] Mikulewicz, M., & Taylor, M. (2020). Getting the resilience right: Climate change and development policy in the 'African age.' *New Political Economy*, 25(4), 626–641.
- [21] Muhoza, J. P., & Zhou, W. (2025). Urban land expansion and spatiotemporal dynamics of urban green spaces in Africa. *Sustainability*, 17(7), 2880.
- [22] Oberndorfer, S., Sander, P., & Fuchs, S. (2020). Multi-hazard risk assessment for roads: Probabilistic versus deterministic approaches. *Natural Hazards and Earth System Sciences*, 20(11), 3135–3160.
- [23] Opoku, A., Guthrie, P., Qiao, Y., Yahia, M. W., & Opoku-Ntim, K. (2024). The role of infrastructure in achieving the Sustainable Development Goals in Sub-Saharan Africa (SSA). In *The Elgar companion to the built environment and the Sustainable Development Goals* (pp. 404–419). Edward Elgar Publishing.
- [24] Ouyang, M., Cheng, Z., Ma, J., Wang, H., & Mitoulis, S. A. (2025). Coupled urban risks: A complex systems perspective with a people-centric focus. *Engineering*, 44, 44–50.

- [25] Paulik, R., Horspool, N., Woods, R., Griffiths, N., Beale, T., Magill, C., ... Garlick, R. (2023). RiskScape: A flexible multi-hazard risk modelling engine. *Natural Hazards*, 119(2), 1073–1090.
- [26] Pescaroli, G., & Alexander, D. (2016). Critical infrastructure, panarchies and the vulnerability paths of cascading disasters. *Natural Hazards*, 82(1), 175–192.
- [27] Petrova, I. (2025, June). Modern risk analysis in the planning and implementation of modernization projects in railway infrastructure. In *Environment. Technology. Resources. Proceedings of the International Scientific and Practical Conference* (Vol. 4, pp. 305–308).
- [28] Rezvani, S. M., Falcão Silva, M. J., & de Almeida, N. M. (2024). The risk-informed asset-centric (RIACT) urban resilience enhancement process: An outline and pilot-case demonstrator for earthquake risk mitigation in Portuguese municipalities. *Applied Sciences*, 14(2), 634.
- [29] Saghir, J., & Santoro, J. (2018, April). Urbanization in Sub-Saharan Africa: Meeting challenges by bridging stakeholders. Center for Strategic & International Studies.
- [30] Saleh, M., & Widiastuti, R. (2025). Transformation of ministerial performance evaluation: Integrating key performance indicators and principles of transparency into the governance system. *Journal of Constitutional and Governance Studies*, 1–19.
- [31] Scolobig, A., Prior, T., Schröter, D., Jörin, J., & Patt, A. (2015). Towards people-centred approaches for effective disaster risk management: Balancing rhetoric with reality. *International Journal of Disaster Risk Reduction*, 12, 202–212.
- [32] Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Luca, A. D., ... Allan, R. (2021). Weather and climate extreme events in a changing climate. In *Climate change 2021: The physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1513–1766). Cambridge University Press.
- [33] Shahata, K., El-Zahab, S., Zayed, T., & Alfalah, G. (2022). Rehabilitation of municipal infrastructure using risk-based performance. *Automation in Construction*, 140, 104335.
- [34] Shaon, M. R. R., Zhao, S., Wang, K., & Jackson, E. (2024). Developing a data-driven network screening procedure for systemic safety approach. *Transportation Research Record*, 2678(3), 348–364.
- [35] Tabutin, D., Schoumaker, B., Coleman, H., Dutreuilh, C., Reeve, P., Tovey, J., & van Hoorn Alkema, B. (2020). The demography of Sub-Saharan Africa in the 21st century: Transformations since 2000, outlook to 2050. *Population*, 75(2), 165–286.
- [36] Tang, J., Lu, Q., Zhao, P., Brilakis, I., Broyd, T., & Chen, L. (2026). *Resilient cities under global climate change: From principles to applications*. Edward Elgar Publishing.
- [37] World Bank. (2023). Climate resilient investment in Sub-Saharan Africa compendium volume: A focus on infrastructure project design in key sectors. World Bank Group. <https://openknowledge.worldbank.org/entities/publication/552404a2-90c6-4c75-906e-0c8b667a522e>

Appendix A. RMTI-Py — Validated Reference Implementation

The listing below is the complete module described in the Methods, reproduced without abridgement. Part 1 (the scoring, assessment, and cohort-ranking functions) is the exact single-hazard implementation validated against Tables 4–6 above — every figure in those tables was independently recomputed from this code with zero discrepancy. Part 2 is new: a direct implementation of the generalized multi-hazard, multi-category form of Equation (3)/(5), which the manuscript describes mathematically but does not implement or field-validate in the empirical validation. It is included here as documented extensions, not as an equally field-validated component — see Appendix B.

Licensed under the Apache License, Version 2.0 — see the header of the file itself, reproduced as the first lines of the listing below. This permits reuse, modification, and commercial redistribution provided the copyright notice and license are retained and changes are documented, and includes an express patent grant from the author.

rmti_ssa.py – full listing (Apache License 2.0)

```
# Copyright 2025 Cesar Marolla

#

# Licensed under the Apache License, Version 2.0 (the "License");
# you may not use this file except in compliance with the License.
# You may obtain a copy of the License at
#
#     http://www.apache.org/licenses/LICENSE-2.0
#
# Unless required by applicable law or agreed to in writing, software
# distributed under the License is distributed on an "AS IS" BASIS,
# WITHOUT WARRANTIES OR CONDITIONS OF ANY KIND, either express or implied.
# See the License for the specific language governing permissions and
# limitations under the License.

"""

rmti_ssa.py -- RMTI-Py v2: Python reference implementation of the Risk
Mechanism Theory Index (RMTI), Marolla (2025), "RMTI: A Systemic Risk
Mechanism Design and Theory Framework" and the companion RMTI Calculator.

Filename note: "ssa" = Sub-Saharan Africa, the region of the six-city
validation cohort (Part 3, below) this module ships with and is checked
```

against. The scoring functions themselves (Parts 1-2) are region-agnostic and can be run against any city or asset dataset.

WHAT THIS FILE CONTAINS

1. THE VALIDATED CORE (single-hazard, single-category reduction)

$$\text{Equation (2): } R = IR * (1 - \rho) = L * E_{\text{sel}} * V * (1 - \rho)$$

$$\text{Equation (6): } EAL = L * C * (1 - \rho)$$

This is the exact form used throughout the paper's Section 4 empirical validation (Bamako, Lagos, Lilongwe, Nairobi, Dar es Salaam, Lusaka) and the exact form implemented in the RMTI Calculator's live sheet. Nothing in this section has changed from the original module -- it is reproduced here unmodified and re-verified line-by-line against the calculator's own output columns (see ASSERTIONS at the bottom).

2. THE GENERALIZED "UNIVERSAL ALGORITHM" (multi-hazard, multi-category)

$$\text{Equation (3): } R = \sum_{\{h,c\}} w_c * L_h * E_{h,c} * V_{h,c} * (1 - \rho_{h,c})$$

$$\text{Equation (5): } EAL = \sum_h L_h * C_h * (1 - \rho_h)$$

This is the fully general form the paper describes (Sec 3.2) but does NOT implement in code -- Eq. (2)/(6) are explicitly "the single-asset, single-hazard reduction of Equation (3)" used for validation instead. This section implements Eq. (3)/(5) directly: an asset can now carry several hazards, and each hazard can be scored across three weighted indicator categories (social, economic, environmental) that inherit the Table 9.4 backbone (RMTre->E, RMTseen->V, RMTrl->rho). Weights w_c must sum to 1 (Table 1, row w_c) -- this is enforced, not assumed. IMPORTANT: because the paper's Section 4 cases were assessed as a single dominant compound hazard with one blended (E, V, rho) per city (not decomposed into social/economic/environmental sub-scores), Eq. (3) cannot be independently validated against Tables 4-6 the way Eq. (2) can. Treat `compute_multi()` as a correct-by-construction

implementation of the published formula, not as separately field-validated the way `score()/assess()` are.

3. REAL DATA

The six-city Sub-Saharan Africa cohort exactly as reported in Tables 4, 5 and 6 of the paper (Bamako, Lagos, Lilongwe = primary World Bank cases with `rho_after` modeled; Nairobi, Dar es Salaam, Lusaka = regional comparators, baseline only). Source: World Bank AFRI-RES compendium (World Bank 2023), as cited in the paper's Data Availability statement.

Table 9.4 indicator backbone (fixed categories, Marolla 2018 pp.158-183):

RMTre (Risk Exposure)	-> E (raises R)
RMTseen (Socio-Economic & Environmental Vuln.)	-> V (raises R)
RMTrl (Resilience Level Capacity)	-> rho (lowers R, via 1-rho)

Table 3 (fixed, pre-registered risk tiers -- never re-derived from a sample's own min/max):

Tier 1 - Low	R < 0.05	Monitor
Tier 2 - Moderate	0.05-0.15	Prevent
Tier 3 - High	0.15-0.35	Mitigate
Tier 4 - Severe	0.35-0.60	Intervene
Tier 5 - Critical	R >= 0.60	Emergency

Table 2 (consequence scale C for the EAL severity layer):

1 Insignificant	0.10	<50 people affected
2 Minor	0.30	50-500
3 Moderate	0.50	500-50,000
4 Major	0.75	50,000-1,000,000
5 Severe	1.00	>1,000,000

"""

import math

from decimal import Decimal, ROUND_HALF_UP

```

# -----

# FIXED, PRE-REGISTERED LOOKUP TABLES (Table 3 / Table 2 -- never re-derived
# per-sample; that is what makes a score of 0.30 mean the same thing in every
# city, every year, per the paper's Sec. 3.5).

# -----

TIER = [(0.05, "Tier 1 - Low"), (0.15, "Tier 2 - Moderate"),
        (0.35, "Tier 3 - High"), (0.60, "Tier 4 - Severe"),
        (1e9, "Tier 5 - Critical")]

# RMT1 typology anchors -- advisory reference points for rho (Table 9.4
# resilience-capacity ladder), NOT a categorical lookup; practitioners
# enter a continuous rho per their own Table 9.4 assessment.

RHO TYPOLOGY ANCHORS = {"none": 0.10, "ad_hoc": 0.20,
                        "monitoring_enforcement": 0.25, "structured": 0.45,
                        "structured_to_funded": 0.55, "funded": 0.58,
                        "optimised": 0.70}

C_INFRA = {1: 0.10, 2: 0.30, 3: 0.50, 4: 0.75, 5: 1.00} # Table 2

N_MIN, N_MAX = 10, 20_000_000 # Sec. 3.3 anchors

def e_log(N):
    """Eq. (4): advisory log-normalized exposure baseline from population N.
    Verified against the paper's Lilongwe walkthrough: N=1.1M -> 0.800."""
    return (math.log10(N) - math.log10(N_MIN)) / (math.log10(N_MAX) - math.log10(N_MIN))

def tier(R):
    """Map a residual risk score R to its fixed Table 3 tier label."""
    for threshold, label in TIER:
        if R < threshold:
            return label
    return TIER[-1][1]

```

```

def _pct_reduction(rho_now, rho_after):

    """Percent cut in R from a resilience investment, holding IR fixed:

     $1 - R_{\text{after}}/R_{\text{now}} = 1 - (1 - \rho_{\text{after}})/(1 - \rho_{\text{now}})$ . Excel-style rounding
    (round-half-away-from-zero), matching the calculator's displayed values."""

    a, b = Decimal(str(rho_now)), Decimal(str(rho_after))

    pct = (1 - (1 - b) / (1 - a)) * 100

    return float(pct.quantize(Decimal("0.1"), rounding=ROUND_HALF_UP))

# -----

# 1. VALIDATED CORE -- Eq. (1)/(2)/(6): single hazard, single blended

# (E, V, rho) per asset. This is the form used throughout Sec. 4.

# -----

def score(L, E_sel, V, rho, C=5):

    """Core two-stage computation for one resilience state.

    IR = L * E_sel * V                                Eq. (1)

    R = IR * (1 - rho)                                Eq. (2)

    EAL = L * C_INFRA[C] * (1 - rho)                  Eq. (6)

    """

    IR = L * E_sel * V

    R = IR * (1 - rho)

    EAL = L * C_INFRA[C] * (1 - rho)

    return {"IR": round(IR, 3), "R": round(R, 3), "tier": tier(R),

            "EAL": round(EAL, 3), "EAL_raw": EAL}

def assess(N, L, E_sel, V, rho_now, rho_after=None, C=5):

    """Full asset-level assessment: baseline + optional post-investment
    state, risk-reduction %, and per-capita equity rate (Eq. 7)."""

    now = score(L, E_sel, V, rho_now, C)

    out = {"N": N, "E_log": round(e_log(N), 3), "rho_now": rho_now,

           "IR": now["IR"], "R_now": now["R"], "tier_now": now["tier"],

```

```

        "EAL_now": now["EAL"], "equity_now_per_1M": round(now["EAL_raw"] / (N / 1e6), 4)}

    if rho_after is not None:

        after = score(L, E_sel, V, rho_after, C)

        out.update({"rho_after": rho_after, "R_after": after["R"],

                    "tier_after": after["tier"], "EAL_after": after["EAL"],

                    "equity_after_per_1M": round(after["EAL_raw"] / (N / 1e6), 4),

                    "risk_reduction_pct": _pct_reduction(rho_now, rho_after)})

    return out

def rank_cohort(rows):

    """Batch-score a portfolio and rank for capital sequencing: primary
    sort by tier severity, secondary sort by EAL_now descending -- this
    exact ordering reproduces the calculator's own 'Priority (in tier)'
    column (verified against Table 4/5 for all six cities below)."""

    tier_rank = {lbl: i for i, (_, lbl) in enumerate(TIER)}

    results = []

    for name, kwargs in rows.items():

        r = assess(**kwargs); r["name"] = name; results.append(r)

    results.sort(key=lambda r: (-tier_rank[r["tier_now"]], -r["EAL_now"]))

    return results

# -----

# 2. GENERALIZED "UNIVERSAL ALGORITHM" -- Eq. (3)/(5): multi-hazard,

# multi-category extension. New in this version; not field-validated

# the way score()/assess() are (see module docstring, point 2).

# -----

CATEGORIES = ("social", "economic", "environmental")

def _check_weights(weights):

    total = sum(weights.get(c, 0.0) for c in CATEGORIES)

    if abs(total - 1.0) > 1e-6:

        raise ValueError(

```

```

        f"Category weights must sum to 1 (Table 1, w_c); got {total:.4f} "

        f"for {weights}. This is enforced, not assumed."

    )

def score_multi(hazards, weights):

    """Eq. (3):  $R = \sum_{h,c} w_c * L_h * E_{h,c} * V_{h,c} * (1 - \rho_{h,c})$ 

    Eq. (5):  $EAL = \sum_h L_h * C_h * (1 - \rho_h)$ 

    hazards: list of dicts, one per hazard h, each shaped as:

        {

            "name": "coastal flood",

            "L": 0.90,                                # hazard likelihood

            "categories": {                            # per-category E, V, rho

                "social":      {"E": 0.70, "V": 0.80, "rho": 0.30},

                "economic":    {"E": 0.55, "V": 0.60, "rho": 0.40},

                "environmental": {"E": 0.65, "V": 0.75, "rho": 0.35},

            },

            "rho_hazard": 0.35,    # single resilience value used for the EAL term

            "C": 5,                # Table 2 consequence category for this hazard

        }

    weights: dict of category -> w_c, must sum to 1, e.g.

        {"social": 0.4, "economic": 0.3, "environmental": 0.3}

    Returns dict with R (Eq. 3), EAL (Eq. 5), tier, and a per-hazard
    breakdown so an analyst can see which hazard x category term is
    driving the aggregate score (the paper's "auditability" requirement,
    Sec. 3.2).

    """

    _check_weights(weights)

    R_total = 0.0

    EAL_total = 0.0

```

```

breakdown = []

for h in hazards:

    L_h = h["L"]

    hazard_contribution = 0.0

    for c in CATEGORIES:

        cat = h["categories"][c]

        w_c = weights[c]

        term = w_c * L_h * cat["E"] * cat["V"] * (1 - cat["rho"])

        hazard_contribution += term

        breakdown.append({

            "hazard": h["name"], "category": c, "w_c": w_c,

            "L": L_h, "E": cat["E"], "V": cat["V"], "rho": cat["rho"],

            "term": round(term, 4),

        })

    R_total += hazard_contribution

    EAL_total += L_h * C_INFRA[h["C"]] * (1 - h["rho_hazard"])

return {

    "R": round(R_total, 3), "tier": tier(R_total),

    "EAL": round(EAL_total, 3),

    "breakdown": breakdown,

}

def assess_multi(N, hazards, weights):

    """Multi-hazard equivalent of assess(): adds population-derived E_log

    (Eq. 4, advisory only -- does not auto-substitute into E_h,c) and the

    per-capita equity rate (Eq. 7) on top of score_multi()."""

    result = score_multi(hazards, weights)

    result["N"] = N

    result["E_log_advisory"] = round(e_log(N), 3)

```

```

result["equity_per_1M"] = round(result["EAL"] / (N / 1e6), 4)

return result

# -----

# REAL DATA -- the six-city Sub-Saharan Africa cohort exactly as reported
# in Tables 4-6 (World Bank AFRI-RES compendium, World Bank 2023).
# -----

COHORT = {

    "Bamako": dict(N=4_500_000, L=0.800, E_sel=0.850, V=0.750,

                  rho_now=0.20, rho_after=0.58, C=4,

                  country="Mali", hazard="Drought / seasonal Niger River flood / heatwave"),

    "Lagos": dict(N=16_000_000, L=0.900, E_sel=0.650, V=0.800,

                  rho_now=0.20, rho_after=0.55, C=5,

                  country="Nigeria", hazard="Coastal & pluvial flood (transit corridors)"),

    "Lilongwe": dict(N=1_100_000, L=0.875, E_sel=0.800, V=0.800,

                    rho_now=0.25, rho_after=0.48, C=4,

                    country="Malawi", hazard="Pluvial / riverine flood"),

    "Nairobi": dict(N=4_700_000, L=0.900, E_sel=0.880, V=0.550,

                    rho_now=0.55, C=4,

                    country="Kenya", hazard="Pluvial flood"),

    "Dar es Salaam": dict(N=7_400_000, L=0.850, E_sel=0.930, V=0.780,

                          rho_now=0.55, C=4,

                          country="Tanzania", hazard="Coastal flood"),

    "Lusaka": dict(N=3_360_000, L=0.800, E_sel=0.850, V=0.720,

                   rho_now=0.45, C=3,

                   country="Zambia", hazard="Flood / cholera"),

}

def _scoreable_cohort(cohort):

    """Strip the metadata-only fields (country, hazard) before passing

    each row into assess(), which only accepts its named parameters."""

```

```

clean = {}

for name, row in cohort.items():

    clean[name] = {k: v for k, v in row.items() if k not in ("country", "hazard")}

return clean

if __name__ == "__main__":

    import json

    print("=" * 70)

    print("PART 1 -- VALIDATED CORE: six-city cohort, ranked for capital "

          "sequencing")

    print("=" * 70)

    ranked = rank_cohort(_scoreable_cohort(COHORT))

    for r in ranked:

        meta = COHORT[r["name"]]

        print(f"{r['name']:<15} ({meta['country']:<10}) IR={r['IR']:.3f} "

              f"R_now={r['R_now']:.3f} [{r['tier_now']}] "

              f"R_after={r.get('R_after', '--')} "

              f"tier_after={r.get('tier_after', '--')} "

              f"reduction={r.get('risk_reduction_pct', '--')}% "

              f"EAL_now={r['EAL_now']:.3f} equity/1M={r['equity_now_per_1M']:.4f}")

    print()

    print("=" * 70)

    print("SELF-CHECK -- reproduce the paper's own reported figures exactly "

          "(Tables 4-6)")

    print("=" * 70)

    # These assertions are the "unit tests against the five fixed decision

    # tiers" the paper's Code Availability section refers to.

    checks = [

        ("Bamako",      "R_now", 0.408), ("Bamako",      "R_after", 0.214),

```

```

("Lagos",      "R_now", 0.374), ("Lagos",      "R_after", 0.211),

("Lilongwe",   "R_now", 0.420), ("Lilongwe",   "R_after", 0.291),

("Nairobi",    "R_now", 0.196),

("Dar es Salaam", "R_now", 0.277),

("Lusaka",     "R_now", 0.269),

]

by_name = {r["name"]: r for r in ranked}

all_ok = True

for name, field, expected in checks:

    got = by_name[name][field]

    ok = abs(got - expected) < 0.001

    all_ok &= ok

    print(f"  {name:<15} {field:<8} expected={expected:<6} got={got:<6} "
          f"{'OK' if ok else 'MISMATCH'}")

print(f"\nAll checks passed: {all_ok}")

print()

print("=" * 70)

print("PART 2 -- GENERALIZED MULTI-HAZARD / MULTI-CATEGORY EXTENSION "
      "(Eq. 3 & 5)")

print("=" * 70)

# Illustrative multi-hazard Lagos: the single-hazard case above collapses
# coastal+pluvial flood into one blended (L, E, V, rho). Here we split it
# into two named hazards, each scored across the three Table 9.4
# categories, to demonstrate the fully general form.

lagos_hazards = [

    {

        "name": "coastal flood", "L": 0.90,

        "categories": {

            "social":      {"E": 0.70, "V": 0.80, "rho": 0.20},

```

```

        "economic":      {"E": 0.60, "V": 0.75, "rho": 0.25},

        "environmental": {"E": 0.65, "V": 0.70, "rho": 0.20},

    },

    "rho_hazard": 0.20, "C": 5,

},

{

    "name": "pluvial (drainage) flood", "L": 0.85,

    "categories": {

        "social":      {"E": 0.55, "V": 0.70, "rho": 0.30},

        "economic":    {"E": 0.50, "V": 0.65, "rho": 0.30},

        "environmental": {"E": 0.60, "V": 0.68, "rho": 0.25},

    },

    "rho_hazard": 0.28, "C": 4,

},

]

weights = {"social": 0.40, "economic": 0.30, "environmental": 0.30}

multi_result = assess_multi(N=16_000_000, hazards=lagos_hazards, weights=weights)

print(json.dumps({k: v for k, v in multi_result.items() if k != "breakdown"}, indent=2))

print("\nPer hazard x category breakdown:")

for row in multi_result["breakdown"]:

    print(f"  {row['hazard']:<24} {row['category']:<14} "

          f"w={row['w_c']:.2f} term={row['term']:.4f}")

```

Appendix B. Validation Addendum

This appendix documents an independent validation pass performed against the RMTI Calculator workbook and this manuscript, and records what it confirmed versus what it added.

Confirmed exactly (no discrepancy found)

- $E_{\log}(N)$: reproduces the Lilongwe walkthrough ($N = 1,100,000 \rightarrow 0.800$) to four decimal places.
- Scoring functions: IR, R_{now} , R_{after} , tier assignments, and risk-reduction percentages match Tables 4–5 exactly for all six cities.
- The C lookup {1:0.10, 2:0.30, 3:0.50, 4:0.75, 5:1.00}: matches Table 2 exactly.
- $EAL_{\text{now}} / EAL_{\text{after}}$ and the per-capita equity rate: match Table 6 exactly, including the recovered C category for each city.
- The cohort-ranking sort order (tier severity, then EAL descending): reproduces the calculator's own "Priority (in tier)" column exactly for both the Tier 4 and Tier 3 cohorts.

Added, not independently field-validated

- The multi-hazard, multi-category extension: a direct implementation of Equation (3)/(5), the generalized multi-hazard, multi-category form. The manuscript states plainly that Equation (2)/(6) – the single-hazard reduction – is the form deployed throughout the empirical validation, and that Equation (3) is not separately implemented or tested against real cases anywhere in the source material provided. The extension is correct-by-construction against the stated formula and enforces the w_c -sums-to-1 constraint from Table 1, but has not been checked against an independent multi-hazard case the way the single-hazard core has.

Recommendation

Before relying on the multi-hazard extension for a live capital-allocation decision, validate it against at least one real multi-hazard, multi-category case with known outcomes, the same way Bamako, Lagos, and Lilongwe were used to validate the single-hazard core in the empirical validation.

Appendix C. Source Indicator and Scoring Rubrics (Reproduced from Marolla, 2018)

This appendix reproduces, in full, the three source tables from Chapter 9 of Marolla (2018), Information and Communication Technology for Sustainable Development (pp. 180–188), that the RMTI framework's L, V, and ρ scoring protocol is built on. They are reproduced here so that readers can follow the derivation in Sections 3.1–3.2 without needing to consult the source volume, and so that the paper cites each table once rather than repeating the citation at every mention.

Table C1. Likelihood and Impact/Intensity rate measurements (adapted from Marolla, 2018, Table 9.2, p. 181; source therein: adapted from a generic risk assessment matrix).

Likelihood Impact	\	Insignificant	Minor	Moderate	Major	Severe
Almost certain		Moderate	High	High	Extreme	Extreme
Likely		Moderate	Moderate	High	High	Extreme
Possible		Low	Moderate	Moderate	High	Extreme
Unlikely		Low	Moderate	Moderate	Moderate	High
Rare		Low	Low	Moderate	Moderate	High

Table C2. Weight of Evidence categories (reproduced from Marolla, 2018, Table 9.3, p. 182; source therein: Marolla, 2017).

Weight code	Evidence category
w_ia	Sufficient evidence from empirical studies and quantitative and qualitative data analysis to support a contributory relationship between risk exposure to the agent and the consequences/intensity of the impact.
w_ib	Limited evidence from empirical studies, but sufficient supporting data.
w_ic	Sufficient evidence from empirical and quantitative/qualitative data studies, but inadequate or no evidence from at least one of the aforementioned study types.
w_id	Limited evidence from empirical and quantitative/qualitative data studies, or an absence of evidence or data.
w_ie	Inadequate evidence from empirical studies and data studies, or no data.
w_if	No evidence from empirical studies in at least two adequate empirical studies, coupled with no evidence from quantitative and qualitative data analysis.

Table C3. RMT three-dimension indicators according to risk-type impact: risk exposure, socio-economic/environmental vulnerabilities, and resilience-level capacity (adapted from Marolla, 2018, Table 9.4, p. 186; source therein: Marolla, 2017). Indicator order follows the source table; column length differs because the three dimensions carry different numbers of source indicators.

RMTre — Risk exposure to:	RMTseen — Socio-economic and environmental vulnerabilities:	RMTri — Resilience-level capacity:
----------------------------------	--	---

Natural and man-made disasters	Fiscal stability / productivity	Risk management strategy
Climate change	Human rights	Business continuity systems
Health hazards	Control of corruption	Natural hazard risk quality
Inherent cyber-risk	Energy consumption and supply	ICT infrastructure and systems
Scarcity of food and water	Inequality / wealth distribution	ICT-supporting electric grid standards
Disruptions in energy production	Environmental pollution	Energy infrastructure
Obsolete ICT systems	Climate change	Urban infrastructure
ICT lack of knowledge dissemination / digital divide	Pandemics	Population growth
Environmental pollution	Accelerated urbanism	Accelerated urbanism
Biodiversity, flora, fauna, and landscapes	Population growth	Governance
Accelerated urbanism	Inflation rates	Health care
Population growth	Urbanization rate	Hospital capacity
Inflation rates	Political stability	Urban interdependencies
Food supply and water	Rule of law	Societal infrastructure
Vicious cycle of resource degradation (over-extraction)	Access to justice, media, and ethics	Health risks
Isolation, semi-closeness, poor mobility, high cost of production/exchange activities	Governance, participation, good administration	Renewable energy sources plan in place
Limited access to, and dependability of, external support (products, inputs, resources, experiences)	Physical degradation of land resources	Recycling, demand rationing, ICT transportation-management technology
Environmental and health risks of socio-economic inequalities	Social inclusion and protection of particular groups	Growth of new industries: technology, telecommunications, infrastructure
	Poverty indices; distribution and proportion of income	Adaptation to disruptions in water and food supply and security
	GDP per capita; relative inequality; qualitative indicators of institutional arrangements	Water and food management infrastructure (flood management infrastructure)

Note. This table is adapted (reformatted from a rotated print-layout scan and lightly re-ordered for column alignment) rather than reproduced pixel-for-pixel; the indicator wording and three-dimension grouping follow the source exactly. Readers who need the original typography should consult Marolla (2018, p. 186) directly.