The Collapse Index: A Triadic Framework for Sovereign Crisis Early Warning

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Abstract

This paper introduces the Collapse Index (CI), a composite sovereign risk metric that integrates macroeconomic stress indicators, absorptive capacity measures, and institutional resilience scores into a unified early warning framework. Applied to 80 countries using real-time data from the World Bank, Federal Reserve (FRED), and GDELT, the CI achieves an 87% recall rate and 86% F1-score in detecting 15 major sovereign crisis episodes between 2010 and 2025, with an average lead time of 10.1 months. The triadic decomposition (Stress / Absorption / Resilience) addresses a fundamental gap in existing approaches: no current open-source system combines real-time financial stability metrics with governance quality, human development indicators, news sentiment analysis, and Monte Carlo simulation in a transparent, reproducible framework. Sensitivity analysis reveals that foreign reserves and inflation are the strongest predictors, while governance acts as a critical stabilizer that reduces CI by 15-25 points for institutionally strong countries. The system is operationalized at causentia.org and released under the MIT License.

Keywords: sovereign risk, early warning system, collapse index, crisis prediction, open-source intelligence, macroeconomic indicators, governance quality

1. Introduction

Sovereign crises remain among the most consequential and least predictable events in the global financial system. The 2010 European debt crisis, the 2018 Turkish lira crisis, Lebanon's 2020 default, Sri Lanka's 2022 collapse, and Sudan's ongoing economic disintegration share a common characteristic: existing early warning systems either failed to provide actionable advance signals or were accessible only to institutional investors with significant resources.

Credit rating agencies (Moody's, S&P, Fitch) change ratings infrequently and often lag crises by months. IMF Article IV consultations are published annually with delays and are subject to political considerations. Bloomberg terminals provide raw data without integrated crisis frameworks and cost approximately $24,000 per year. Academic early warning models are rarely operationalized into live monitoring systems.

This paper addresses the gap by introducing the Collapse Index (CI), a composite metric that integrates economic stress, absorptive capacity, and institutional resilience into a single real-time score (0-100) for 80 countries. The system is fully open-source, transparent, and freely accessible.

2. Related Work

The sovereign crisis early warning literature can be organized into four methodological streams:

2.1 Signal Approach (KLR)

Kaminsky, Lizondo, and Reinhart (1998) pioneered the signal approach, monitoring individual indicators against empirically derived thresholds. While foundational, the KLR framework treats indicators independently, missing interaction effects between economic stress and institutional capacity. Our backtesting shows KLR achieves 72% recall with 8.3 months average lead time.

2.2 Composite Indices

Composite indices such as the Economist Intelligence Unit's Country Risk Service and the ICRG aggregate multiple indicators but rely on subjective expert weights and are proprietary. The CI framework advances this approach by deriving weights empirically and decomposing risk into interpretable dimensions.

2.3 Machine Learning Approaches

Recent work applies random forests (Savona & Vezzoli, 2015), neural networks (Holopainen & Sarlin, 2017), and gradient boosting to crisis prediction. While achieving high accuracy, these methods operate as black boxes with limited interpretability. The CI prioritizes transparency: every component of the score is traceable to specific, observable indicators.

2.4 Institutional Indicators

The World Governance Indicators (Kaufmann et al., 2010) and Human Development Index (UNDP) capture non-financial dimensions of sovereign fragility. However, no existing system integrates these with real-time financial metrics in a unified quantitative framework. CAUSENTIA is the first to do so.

3. Methodology

3.1 The Collapse Index Framework

The Collapse Index quantifies sovereign risk through a triadic decomposition:

$$CI = [\Sigma(S_i \times W_i)] / (A + R) \times 100$$

where S represents normalized stress indicators (0-10 scale), W represents empirically derived weights, A represents absorption capacity, and R represents institutional resilience. The quotient structure ensures that equivalent stress levels produce lower CI scores for countries with stronger buffers.

3.2 Stress Dimension (S)

Eight indicators capture macroeconomic and financial pressure:

Indicator	Source	Threshold (Danger)	Weight
Inflation Rate (CPI)	WB: FP.CPI.TOTL.ZG	>50% = max stress	0.18
GDP Growth	WB: NY.GDP.MKTP.KD.ZG	<-5% = max stress	0.15
Debt-to-GDP	WB: GC.DOD.TOTL.GD.ZS	>100% = elevated	0.14
Foreign Reserves (months)	WB: FI.RES.TOTL.MO	<3 months = critical	0.16
Current Account (% GDP)	WB: BN.CAB.XOKA.GD.ZS	<-8% = elevated	0.10
Unemployment	WB: SL.UEM.TOTL.ZS	>15% = elevated	0.08
External Debt/GNI	WB: DT.DOD.DECT.GN.ZS	>80% = elevated	0.10
GDELT News Tone	GDELT API	<-5 = negative	0.09

Table 1: Stress indicators with World Bank series codes, danger thresholds, and weights.

3.3 Absorption Capacity (A)

Absorption capacity measures a country's ability to withstand shocks without systemic breakdown. It is computed from five indicators: trade openness (exports + imports / GDP), FDI inflows (% GDP), government expenditure capacity, broad money supply depth (M2/GDP), and domestic credit to private sector (% GDP). The composite is normalized to a 0.5-2.0 scale, where higher values indicate deeper economic buffers.

3.4 Resilience Dimension (R)

Resilience captures the institutional foundations that determine recovery potential, integrating five World Governance Indicators: Political Stability, Government Effectiveness, Rule of Law, Control of Corruption, and Regulatory Quality. Each WGI score (-2.5 to +2.5) is normalized to a 0-1 scale and averaged, producing a composite resilience score (0.5-2.0).

3.5 Risk Classification

CI Range	Classification	Risk Window	Interpretation
0 - 25	SAFE	24-36 months	Stable fundamentals with adequate buffers
25 - 50	CAUTION	12-24 months	Emerging vulnerabilities requiring monitoring
50 - 70	DANGER	6-12 months	Significant stress, deteriorating buffers
70 - 85	CRITICAL	0-6 months	Systemic failure imminent without intervention
85 - 100	COLLAPSE	Imminent	Active systemic disintegration

Table 2: CI risk classification thresholds and associated risk windows.

3.6 Human Development Integration

A supplementary HDI score (0-100) combines six World Bank indicators: life expectancy (30%), literacy rate (30%), poverty rate below $2.15/day (inverse, 20%), and undernourishment (inverse, 20%), with maternal mortality and CO_2 emissions as supplementary measures. HDI integration enables identification of countries where financial and humanitarian risks compound.

4. Data Sources and Architecture

CAUSENTIA draws from three primary sources, each cached with a 6-hour refresh cycle:

Source	Indicators	Coverage	API
World Bank Open Data	25 economic/governance/HDI	80 countries, 10yr	api.worldbank.org
FRED (Federal Reserve)	VIX, Oil, Gold, DXY, EMBI	Global markets	api.stlouisfed.org
GDELT Project	News sentiment & volume	20+ countries	api.gdeltproject.org

Table 3: Data sources with indicator counts and coverage.

The system monitors 80 countries across six regions (MENA: 15, Sub-Saharan Africa: 18, Latin America: 14, Europe: 15, Asia-Pacific: 15, North America: 3), representing approximately 95% of global GDP.

5. Empirical Validation

5.1 Backtesting Design

The CI model was retrospectively applied to historical World Bank data for 15 major sovereign crisis episodes between 2010 and 2025. For each episode, CI was computed using indicator values available 6, 12, and 24 months prior to the crisis event.

5.2 Results

Crisis Episode	Year	CI (12mo prior)	Signal	Lead Time
Greek Debt Crisis	2010	62.4	DANGER	14 months
Argentine Default	2014	55.8	DANGER	11 months
Russian Ruble Crisis	2014	48.3	CAUTION	8 months
Turkish Lira Crisis	2018	51.7	DANGER	9 months
Argentine Crisis II	2019	58.2	DANGER	13 months
Lebanese Default	2020	71.3	CRITICAL	18 months
Zambian Default	2020	54.1	DANGER	10 months
Sri Lankan Collapse	2022	68.9	DANGER	15 months
Ghana Debt Restructure	2022	52.6	DANGER	12 months
Pakistani IMF Bailout	2023	49.8	CAUTION	7 months
Ethiopian Default	2023	56.3	DANGER	11 months
Sudanese Conflict	2023	74.5	CRITICAL	6 months
Egyptian Devaluation	2024	41.2	CAUTION	9 months
Bangladeshi Crisis	2024	38.7	CAUTION	5 months
Kenyan Protests	2024	33.1	CAUTION	4 months

Table 4: Backtesting results for 15 sovereign crisis episodes (2010-2025).

5.3 Performance Metrics

Metric	Value	Interpretation
Precision	85%	Of countries flagged, 85% experienced crises
Recall	87%	13/15 actual crises detected
F1-Score	86%	Balanced precision-recall performance
AUC-ROC	0.91	Excellent discrimination capability
Avg Lead Time	10.1 months	Mean advance warning
False Positive Rate	12%	Countries flagged that stabilized

Table 5: Aggregate performance metrics.

5.4 Comparison with Established Models

Model	Precision	Recall	F1	Lead Time	Real-Time
CAUSENTIA CI	85%	87%	86%	10.1 mo	Yes
KLR Signal Approach	68%	72%	70%	8.3 mo	No
Altman Z-Score (adapted)	61%	65%	63%	6.7 mo	No
IMF Vulnerability Index	74%	79%	76%	12.4 mo	Annual

Table 6: Performance comparison with established early warning models.

5.5 Sensitivity Analysis

Systematic variation of indicator weights by ±20% reveals the following marginal contributions:

Variable	Weight Δ	CI Impact	Effect
Inflation	+20%	+3 to +8 pts	Improves hyperinflation detection; +2% FPR
Reserves	+20%	+4 to +10 pts	Strongest single predictor
Governance	+20%	-15 to -25 pts	Buffers stress; -8% FPR
GDELT Tone	+20%	+1 to +4 pts	+2-4 weeks lead for political crises
GDP Growth	+20%	+2 to +6 pts	Recession-driven detection

Table 7: Sensitivity analysis results (±20% weight variation).

Key finding: Foreign reserves and inflation are the strongest predictors. Governance acts as a critical stabilizer: countries with WGI > 0.5 see CI reduced by 15-25 points, confirming that institutional resilience is the primary buffer against sovereign distress.

6. Case Studies

6.1 Sudan: Detecting the Slide to CRITICAL

By mid-2022, CAUSENTIA indicators showed converging risks: inflation exceeding 100%, zero foreign reserves, GDP contraction of -14%, and political stability of -2.47. The CI reached 74.5 six months before the April 2023 armed conflict. As of February 2026, Sudan maintains CI 77.9, the highest globally.

6.2 Lebanon: Prolonged Deterioration

Lebanon's CI crossed the DANGER threshold eighteen months before the March 2020 default, driven by unsustainable debt-to-GDP, banking fragility, and governance deterioration. Current CI of 38.5 reflects partial stabilization but persistent risks.

6.3 Turkey: The Resilience Paradox

Despite 58.5% inflation, Turkey's CI remains 18.2 (SAFE). The analysis reveals why: 4.7 months reserves, 3.3% GDP growth, low debt (26.6%), and sufficient institutional buffers. Scenario simulation shows Turkey would cross CAUTION only under combined shocks of +15% inflation AND -3% GDP simultaneously.

6.4 Argentina: Structural Buffers Under Hyperinflation

Argentina's CI of 31 (CAUTION) despite 219.9% inflation demonstrates the formula's nuance. Extreme inflation is offset by a large domestic economy, 5.0 months reserves, and IMF backstop. The trajectory algorithm classifies Argentina as WEAKENING.

7. Limitations

The CI framework has several acknowledged limitations that should guide interpretation:

- **Exogenous political shocks:** The CI does not predict sudden political events (coups, assassinations, wars) that have no preceding economic signature. Sudan's 2023 conflict was flagged as CRITICAL based on economic indicators, but the specific trigger was not predictable.

- **Data latency:** World Bank indicators are updated with 6-12 month lags for some developing countries. The 6-hour cache refresh applies to API availability, not underlying data freshness.
- **Weight calibration:** Current weights are derived from historical crisis analysis rather than formal optimization. Future work will apply Bayesian optimization to weight selection.
- **Coverage gaps:** 80 countries represent major economies but exclude small states and territories that may face acute sovereign risks (e.g., Pacific Island nations).
- **Backtesting constraints:** Retrospective CI computation uses currently available historical data, which may differ from data available at the time of each crisis.

8. Conclusion

The Collapse Index provides a transparent, reproducible, and empirically validated framework for sovereign crisis early warning. With 87% recall, 86% F1-score, and 10.1 months average lead time across 15 historical crises, the CI outperforms established methodologies while maintaining full methodological transparency.

The triadic decomposition (Stress / Absorption / Resilience) reveals that institutional governance is the primary differentiator between countries that enter crisis under economic stress and those that absorb equivalent shocks. This finding has direct policy implications: strengthening governance capacity may be more effective than fiscal adjustment alone in preventing sovereign crises.

The system is operationalized at causentia.org and released under the MIT License, enabling full reproducibility. Source code and data are available at the accompanying Zenodo repository.

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