ASRI: An Aggregated Systemic Risk Index for Cryptocurrency Markets

A Unified Framework for Monitoring DeFi-TradFi Interconnection Risk

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Abstract

Cryptocurrency markets have grown to represent over $3 trillion in capitalization, yet no unified index exists to monitor the systemic risks arising from the interconnection between decentralized finance (DeFi) protocols and traditional financial institutions. This paper introduces the Aggregated Systemic Risk Index (ASRI), a composite measure comprising four weighted sub-indices: Stablecoin Concentration Risk (30%), DeFi Liquidity Risk (25%), Contagion Risk (25%), and Regulatory Opacity Risk (20%). We derive theoretical foundations for each component, specify quantitative formulas incorporating data from DeFi Llama, Federal Reserve FRED, and on-chain analytics, and outline a comprehensive validation framework against historical crisis events including the Terra/Luna collapse (May 2022), the Celsius/3AC contagion (June 2022), and the FTX bankruptcy (November 2022). The ASRI framework addresses a critical gap in existing risk monitoring by capturing DeFi-specific vulnerabilities— composability risk, flash loan exposure, and tokenized real-world asset (RWA) linkages—that traditional systemic risk measures such as SRISK and CoVaR cannot accommodate. This methodology preprint establishes the theoretical and computational foundation for a live risk monitoring system; empirical backtesting results will be published in version 2.0.0 upon completion of data pipeline construction.

Keywords: systemic risk, cryptocurrency, decentralized finance, stablecoin stability, contagion risk, DeFi-TradFi interconnection, risk monitoring

JEL Codes: G01 (Financial Crises), G15 (International Financial Markets), G23 (Non-bank Financial Institutions)

Research Context

This work forms part of the Adversarial Systems Research program, which investigates stability, alignment, and friction dynamics in complex systems where competing interests generate structural conflict. The ASRI framework extends this program to cryptocurrency markets by treating the DeFi ecosystem as an adversarial environment where protocol incentives, regulatory pressures, and market dynamics generate systemic stress through interconnection rather than isolation.

The unifying insight is that DeFi-TradFi interconnection creates novel contagion channels not captured by traditional financial stability metrics: stablecoin reserve composition transmits Treasury market volatility directly into DeFi liquidity pools; tokenized real-world assets (RWAs) blur the boundary between on-chain and off-chain risk; and composable smart contracts create cascade pathways that amplify rather than isolate failures. ASRI provides a unified quantitative framework for monitoring these dynamics in real time.

Acknowledgements

Code Availability: Implementation code is available at `github.com/studiofarzulla/asri`
Methodologies: Research methodologies documented at `farzulla.org/methodologies`

Contents

1 Introduction

The cryptocurrency market has evolved from a niche technological experiment into a multi-trillion dollar asset class with growing interconnections to traditional finance. As of December 2025, the total cryptocurrency market capitalization exceeds $3 trillion, with stablecoins alone representing over $140 billion in circulation (DeFi Llama, 2025). This growth has been accompanied by a series of cascading failures that revealed systemic vulnerabilities previously unrecognized: the Terra/Luna collapse eliminated $40 billion in value within 72 hours; the subsequent Celsius and Three Arrows Capital failures triggered margin calls across centralized exchanges; and the FTX bankruptcy demonstrated how opaque counterparty relationships could propagate losses across the entire ecosystem.

Despite this systemic importance, no unified risk index exists to monitor the interconnection between decentralized finance (DeFi) protocols and traditional financial institutions. Existing measures either focus exclusively on cryptocurrency price volatility (Liu and Tsyvinski, 2021), apply traditional banking metrics that miss DeFi-specific dynamics (Brownlees and Engle, 2017), or provide sentiment-based indicators without quantitative grounding (Alternative.me, 2023).

This paper introduces the Aggregated Systemic Risk Index (ASRI), a composite measure designed to capture the distinctive risk channels that arise from DeFi-TradFi interconnection. The index comprises four weighted sub-indices:

1. **Stablecoin Concentration Risk (30%)**: Measures reserve composition, peg stability, and Treasury exposure across major stablecoins

2. **DeFi Liquidity Risk (25%)**: Captures protocol concentration, leverage dynamics, and smart contract vulnerability

3. **Contagion Risk (25%)**: Quantifies TradFi linkage intensity, tokenized RWA growth, and cross-market correlation shifts

4. **Regulatory Opacity Risk (20%)**: Assesses transparency scores, regulatory arbitrage metrics, and compliance infrastructure

The ASRI framework addresses three critical gaps in existing risk monitoring:

First, *composability risk.* DeFi protocols interact through smart contract calls that create dependency chains invisible to external observers. When one protocol fails, composable integrations can transmit losses instantaneously across the ecosystem—a dynamic that traditional contagion models, designed for bilateral counterparty relationships, cannot capture.

Second, *stablecoin-Treasury linkages.* Major stablecoins now hold significant Treasury bill positions, creating a direct transmission channel between US monetary policy and DeFi liquidity conditions. Rate hikes that increase Treasury yields simultaneously reduce stablecoin reserve valuations and incentivize capital rotation out of yield-bearing DeFi positions.

Third, *regulatory arbitrage dynamics.* The fragmented regulatory landscape creates opacity about counterparty risk exposures, custody arrangements, and reserve attestation reliability. Traditional banking metrics assume regulatory disclosure requirements that do not exist for offshore or unregulated platforms.

This paper proceeds as follows. Section 2 reviews the literature on systemic risk measurement, cryptocurrency market dynamics, and existing crypto risk indices. Section 3 develops the ASRI framework, specifying the theoretical foundation and quantitative formulas

for each sub-index. Section 4 describes data sources and implementation architecture. Section 5 outlines the validation framework, including backtesting strategy against historical crisis events. Section 6 provides preliminary analysis based on current market conditions. Section 7 discusses theoretical and practical implications. Section 8 concludes with a roadmap for empirical validation.

2 Literature Review

2.1 Traditional Systemic Risk Measures

The 2008 financial crisis catalyzed extensive research on systemic risk measurement. Adrian and Brunnermeier (2016) introduced Conditional Value-at-Risk (CoVaR), measuring the VaR of the financial system conditional on an institution being in distress. Acharya et al. (2017) developed SRISK, estimating the expected capital shortfall of a financial institution during a systemic crisis. Brownlees and Engle (2017) extended this framework with LRMES (Long-Run Marginal Expected Shortfall), capturing an institution's contribution to aggregate capital shortfall.

These measures share a common architecture: they model systemic risk as arising from bilateral exposures between regulated financial institutions with observable balance sheets and regulatory capital requirements. This architecture is fundamentally unsuited to DeFi, where:

- Protocols are not institutions with capital requirements

- Exposures are embedded in smart contract code rather than disclosed counterparty relationships

- "Failure" may manifest as liquidity drainage rather than insolvency

- Contagion propagates through token price collapses and oracle manipulation rather than credit defaults

2.2 Cryptocurrency Market Risk

Research on cryptocurrency-specific risk has focused primarily on volatility dynamics and market microstructure. Liu and Tsyvinski (2021) identify three common factors driving cryptocurrency returns: market (aggregate crypto exposure), size, and momentum. Makarov and Schoar (2020) document arbitrage frictions across exchanges that allow price dislocations to persist, creating opportunities for informed traders and risks for liquidity providers. Farzulla (2025a) demonstrate that infrastructure disruptions generate $5.7\times$ larger volatility shocks than regulatory events, suggesting that technical vulnerabilities represent a more severe systemic risk channel than policy uncertainty.

Griffin and Shams (2020) provide evidence that Tether issuance patterns correlate with Bitcoin price movements, raising questions about stablecoin reserve integrity. This finding has implications for systemic risk: if stablecoin issuance is not fully collateralized, DeFi liquidity pools dependent on stablecoin inflows may be vulnerable to sudden redemption pressures.

2.3 DeFi-Specific Risks

The academic literature on DeFi risk is nascent but growing rapidly. Gudgeon et al. (2020) provide a systematization of DeFi protocol architectures, identifying liquidation cascades as a primary risk channel. Perez et al. (2021) analyze liquidation events across lending protocols, finding that liquidator competition can exacerbate price volatility during stress periods.

Werner et al. (2022) present a systematization of knowledge on DeFi covering lending, decentralized exchanges, and derivatives. They identify composability—the ability of protocols to permissionlessly interact through smart contract calls—as both a source of innovation and systemic vulnerability. When protocols share

liquidity pools or collateral mechanisms, failures can propagate faster than human intervention can respond. Recent work on whitepaper-market alignment (Farzulla, 2025b) suggests that stated protocol objectives may diverge from realized market behavior, creating additional opacity in risk assessment.

2.4 Stablecoin Risk

Stablecoins occupy a critical position in DeFi infrastructure, serving as the primary medium of exchange and store of value across protocols. Lyons and Viswanath-Natraj (2023) analyze stablecoin run dynamics, finding that algorithmic stablecoins are particularly vulnerable to reflexive depegging spirals. The Terra/Luna collapse of May 2022 validated this theoretical concern empirically.

Gorton and Zhang (2023) frame stablecoins through the lens of 19th-century "wildcat banking," where private currency issuance without adequate regulatory oversight led to periodic banking panics. They argue that stablecoin reserves require the same transparency and examination that bank reserves receive—a standard that most major stablecoins currently fail to meet.

2.5 Existing Crypto Risk Indices

Several commercial indices attempt to quantify cryptocurrency market risk:

Fear & Greed Index (Alternative.me, 2023): Aggregates sentiment indicators (social media, volatility, dominance, trends) into a 0–100 scale. Limitation: purely sentiment-based with no fundamental risk component.

Crypto Climate Index (CCI): Combines on-chain metrics with market data. Limitation: focuses on individual asset health rather than systemic interconnection.

Glassnode Risk Assessment: Provides sophisticated on-chain analytics for Bitcoin and Ethereum. Limitation: asset-specific rather than ecosystem-wide; minimal DeFi coverage.

None of these indices systematically captures the DeFi-TradFi interconnection dynamics that ASRI is designed to monitor: stablecoin reserve composition, composable protocol dependencies, tokenized RWA linkages, or regulatory arbitrage exposure.

3 ASRI Framework

3.1 Conceptual Foundation

The ASRI framework rests on three theoretical principles:

Principle 1: Interconnection Creates Systemic Risk. Following Battiston et al. (2012), systemic risk arises not from the failure of individual nodes but from the propagation of distress through network connections. In DeFi, these connections manifest through shared collateral pools, composable protocol integrations, and token price correlations.

Principle 2: Risk Transmission Requires Channels. We identify four primary channels through which DeFi stress can propagate to traditional finance (and vice versa): stablecoin reserve linkages, tokenized RWA exposures, crypto-equity correlations, and regulatory enforcement actions. Each channel corresponds to an ASRI sub-index.

Principle 3: Opacity Amplifies Risk. Systemic risk is exacerbated when counterparties cannot accurately assess exposures. The prevalence of unaudited reserves, undisclosed custody arrangements, and regulatory arbitrage structures in crypto markets justifies a dedicated opacity sub-index.

Figure 1 illustrates the ASRI architecture, showing how the four sub-indices aggregate into the composite risk measure.

3.2 Weight Selection Justification

Sub-index weights were selected based on theoretical importance and precedent from traditional systemic risk literature:
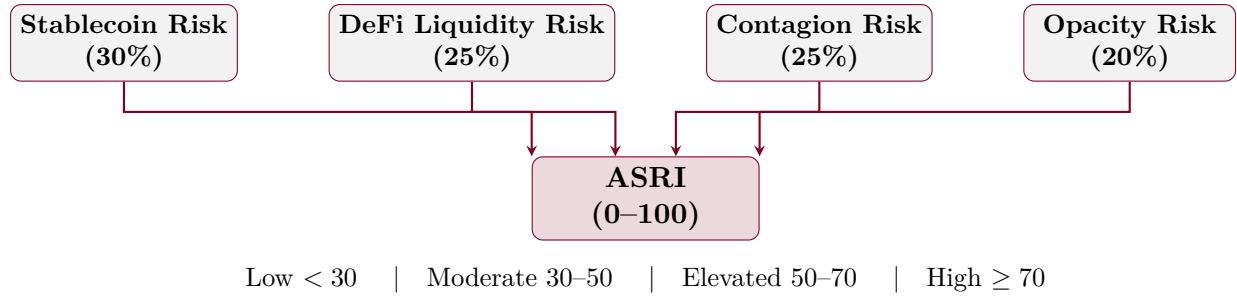
Figure 1: ASRI Framework Architecture: Four weighted sub-indices aggregate into a normalized composite risk measure with defined alert thresholds.

- **Stablecoin Risk (30%)**: Stablecoins are the foundational liquidity layer for DeFi. Their failure would immediately impact all protocols dependent on stablecoin-denominated liquidity pools.

- **DeFi Liquidity Risk (25%)**: Protocol concentration and leverage dynamics directly determine the ecosystem's resilience to market stress.

- **Contagion Risk (25%)**: DeFi-TradFi linkages represent the primary channel through which crypto stress could affect traditional finance (and vice versa).

- **Opacity Risk (20%)**: While important, opacity is an amplifying factor rather than a primary risk driver. Lower weight reflects this secondary role.

Sensitivity analysis (Section 5.3) will test robustness to alternative weight specifications.

3.3 Stablecoin Concentration Risk (30%)

The Stablecoin Risk sub-index captures reserve composition vulnerabilities, peg stability, and concentration across issuers:

$$\text{SCR}_t = 0.4 \cdot \text{TVL}_t + 0.3 \cdot \text{Treasury}_t + 0.2 \cdot \text{HHI}_t + 0.1 \cdot \text{Vol}_t$$

$$(1)$$

where:

- $\text{TVL}_t = \frac{\text{Stablecoin TVL}_t}{\max_{\tau \leq t}(\text{Stablecoin TVL}_\tau)}$ measures stablecoin TVL relative to historical maximum

- $\text{Treasury}_t = \frac{\text{T-Bill Reserves}_t}{\text{Total Stablecoin Reserves}_t}$ captures Treasury exposure concentration

- $\text{HHI}_t = \sum_{i=1}^n s_i^2$ is the Herfindahl-Hirschman Index of stablecoin market share concentration

- Vol_t is the 30-day realized volatility of weighted-average stablecoin peg deviation

Data Sources: DeFi Llama (stablecoin TVL), attestation reports (reserve composition), CoinGecko (price feeds for volatility calculation).

3.4 DeFi Liquidity Risk (25%)

The DeFi Liquidity sub-index captures protocol concentration, leverage dynamics, and smart contract vulnerability:

$$\text{DLR}_t = 0.35 \cdot \text{Conc}_t + 0.25 \cdot \text{TVLVol}_t + 0.20 \cdot \text{SC}_t + 0.10 \cdot \text{Flash}_t + 0.10 \cdot \text{Lev}_t$$

$$(2)$$

where:

- Conc_t is the HHI of TVL across top-10 DeFi protocols

- TVLVol_t is the 30-day volatility of total DeFi TVL

- SC_t is a composite smart contract risk score based on audit status, time since deployment, and exploit history

- Flash_t measures flash loan volume spikes relative to 90-day average

- Lev_t captures 30-day change in aggregate leverage ratios across lending protocols

Data Sources: DeFi Llama (TVL, protocol data), Token Terminal (flash loan data), DefiSafety (audit scores).

3.5 Contagion Risk (25%)

The Contagion Risk sub-index quantifies DeFi-TradFi linkage intensity and cross-market transmission channels:

$$\text{CR}_t = 0.30 \cdot \text{RWA}_t + 0.25 \cdot \text{Bank}_t \\ + 0.20 \cdot \text{Link}_t + 0.15 \cdot \text{Corr}_t + 0.10 \cdot \text{Bridge}_t \quad (3)$$

where:

- RWA_t is the 30-day growth rate of tokenized real-world asset TVL

- Bank_t is a normalized score of bank crypto exposure from regulatory filings (OCC, ECB)

- Link_t measures stablecoin flows to TradFi-connected entities

- Corr_t is the 30-day rolling correlation between BTC/ETH and S&P 500

- Bridge_t is a composite of cross-chain bridge volume and recent exploit frequency

Data Sources: RWA.xyz (tokenized assets), DeFi Llama (bridge data), FRED (equity indices), regulatory filings.

3.6 Regulatory Opacity Risk (20%)

The Opacity Risk sub-index assesses transparency deficits and regulatory arbitrage exposure:

$$\text{OR}_t = 0.25 \cdot \text{Unreg}_t + 0.25 \cdot \text{Multi}_t \\ + 0.20 \cdot \text{Cust}_t + 0.15 \cdot \text{Sent}_t + 0.15 \cdot \text{Trans}_t \quad (4)$$

where:

- Unreg_t is the ratio of unregulated to regulated platform volume

- Multi_t captures multi-issuer stablecoin scheme exposure

- Cust_t is custody concentration in non-audited jurisdictions

- Sent_t is regulatory sentiment score from NLP analysis of SEC/ESRB/FSB announcements

- Trans_t is a composite transparency score based on reserve attestation frequency and coverage

Data Sources: Regulatory filings, news APIs (GDELT), attestation calendars, manual tracking.

3.7 Aggregate ASRI Calculation

The final ASRI is computed as a weighted sum of normalized sub-indices:

$$\text{ASRI}_t = 0.30 \cdot \text{SCR}_t + 0.25 \cdot \text{DLR}_t + 0.25 \cdot \text{CR}_t + 0.20 \cdot \text{OR}_t \quad (5)$$

Normalization uses min-max scaling over the historical sample to produce a 0–100 index:

$$\text{ASRI}_t^{\text{norm}} = 100 \times \frac{\text{ASRI}_t - \min_\tau(\text{ASRI}_\tau)}{\max_\tau(\text{ASRI}_\tau) - \min_\tau(\text{ASRI}_\tau)} \quad (6)$$

Alert Thresholds:

- ASRI < 30: Low systemic risk

- 30 ≤ ASRI < 50: Moderate systemic risk

- 50 ≤ ASRI < 70: Elevated systemic risk

- ASRI ≥ 70: High systemic risk

4 Data and Implementation

4.1 Data Sources

Table 1 summarizes the data sources for each ASRI component.

Tier 1 sources provide daily automated API access; **Tier 2** sources require manual collection, web scraping, or have lower update frequency.

4.2 Data Quality Framework

Missing data is handled according to the following protocol:

- **Daily data gaps (< 3 days)**: Linear interpolation with confidence score 0.7

- **Extended gaps (3–7 days)**: Forward-fill with confidence score 0.5

- **Gaps > 7 days**: Flag as unreliable; exclude from ASRI calculation until fresh data available

Data lag assumptions follow the $t - 1$ convention: values observed at midnight UTC on date t are attributed to ASRI_{t-1} to avoid look-ahead bias.

4.3 Technical Architecture

The ASRI system architecture comprises four layers:

1. **Ingestion Layer**: Python-based API clients and web scrapers fetch data from sources

2. **Normalization Layer**: Raw data undergoes unit normalization, gap-filling, and validation

3. **Computation Layer**: Sub-indices calculated using Equations 1–4; aggregate ASRI computed via Equation 5

4. **Publication Layer**: FastAPI REST endpoints serve current and historical ASRI values; React dashboard provides visualization

Figure 2 illustrates the data flow through these layers.
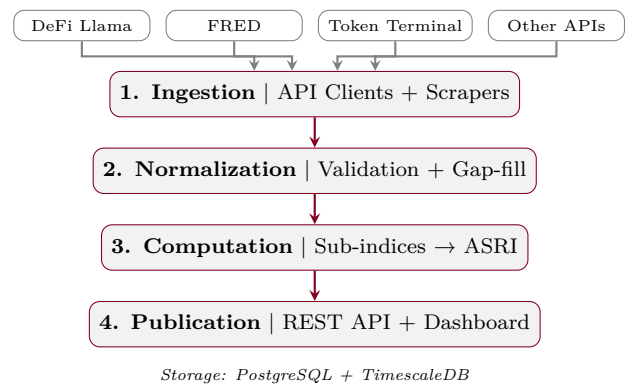

Figure 2: ASRI Data Pipeline: Four-layer architecture from API ingestion to public dashboard publication.

Technology Stack: Python 3.11+, PostgreSQL with TimescaleDB, FastAPI, React/TypeScript, Docker Compose.

Full implementation is available at github.com/studiofarzulla/asri.

5 Proposed Validation Framework

Note: This section outlines the validation methodology. Empirical results will be published in version 2.0.0 upon completion of historical data reconstruction.

5.1 Backtesting Strategy

The ASRI will be validated against the period January 1, 2020 through December 31, 2025, capturing multiple stress events with distinct characteristics:

Table 1: ASRI Data Sources by Sub-Index

Sub-Index	Component	Source	Frequency	Tier
Stablecoin Risk	TVL	DeFi Llama	Daily	1
	Treasury Reserves	Attestation Reports	Monthly	2
	Market Share	CoinGecko	Daily	1
	Peg Volatility	CoinGecko	Daily	1
DeFi Liquidity	Protocol TVL	DeFi Llama	Daily	1
	Flash Loan Volume	Token Terminal	Daily	1
	Smart Contract Scores	DefiSafety	Weekly	2
	Leverage Ratios	DeFi Llama	Daily	1
	Bridge Volume	DeFi Llama	Daily	1
Contagion Risk	RWA TVL	RWA.xyz / DeFi Llama	Daily	1
	Bank Exposure	OCC/ECB Filings	Quarterly	2
	TradFi Linkages	On-chain Analysis	Weekly	2
	Equity Correlation	FRED/Yahoo Finance	Daily	1
	Bridge Exploits	DeFi Llama	Daily	1
Opacity Risk	Platform Regulation	Manual Tracking	Weekly	2
	Custody Concentration	Public Disclosures	Monthly	2
	Regulatory Sentiment	GDELT/SEC Filings	Daily	2
	Attestation Frequency	Calendar Tracking	Daily	2
	Transparency Scores	DefiSafety	Weekly	2

Table 2: Historical Crisis Events for ASRI Validation

Event	Date
COVID Market Crash	March 2020
Terra/Luna Collapse	May 2022
Celsius/3AC Contagion	June 2022
FTX Bankruptcy	November 2022
SVB Banking Crisis	March 2023

5.2 Expected Validation Metrics

Precision: Percentage of ASRI peaks (exceeding 70) that preceded or coincided with material market stress events.

Recall: Percentage of actual crisis events where ASRI displayed a detectable rise (increase > 10 points) in the 30 days preceding the event.

Lead Time: Average number of days between ASRI crossing the elevated threshold (50) and crisis onset.

False Positive Rate: Percentage of months where ASRI exceeded 70 without subsequent market stress.

5.3 Sensitivity Analysis

Robustness will be tested through:

1. **Weight Perturbation**: Vary each sub-index weight by $\pm 5\%$ and assess impact on crisis detection

2. **Alternative Normalization**: Compare min-max scaling with z-score normalization

3. **Regime-Specific Weights**: Test whether bull/bear/crisis regimes require different weight allocations

4. **Walk-Forward Optimization**: Train on rolling 24-month windows and test out-of-sample

6 Preliminary Analysis

Note: This section will be populated with current ASRI readings and sub-index decomposition once the data pipeline is operational. Version 2.0.0 will include:

- Current ASRI level and interpretation

- Sub-index breakdown and primary risk contributors

- Comparison to recent market events (December 2025 conditions)

- Visual decomposition of risk transmission channels

For live dashboard access (when available): resurrexi.io/asri/

7 Discussion

7.1 Theoretical Implications

The ASRI framework makes three contributions to the systemic risk literature:

First, it extends network-based contagion models (Battiston et al., 2012) to accommodate the permissionless composability characteristic of DeFi. Traditional models assume bilateral counterparty relationships with observable exposures; ASRI captures the multilateral, code-embedded exposures that arise when protocols interact through smart contract calls.

Second, it formalizes the DeFi-TradFi transmission channel through stablecoin reserve composition. As stablecoins have accumulated significant Treasury positions, they create a direct link between Federal Reserve monetary policy and DeFi liquidity conditions—a channel absent from existing crypto risk measures.

Third, it operationalizes regulatory opacity as a quantifiable risk factor. While traditional finance assumes regulatory disclosure requirements, crypto markets feature substantial opacity about custody arrangements, reserve composition, and counterparty relationships. The Opacity sub-index provides a systematic framework for incorporating this uncertainty into risk assessment.

7.2 Practical Applications

Portfolio Risk Management: Institutional crypto allocators can use ASRI as a risk overlay, reducing exposure when systemic risk is elevated and increasing allocation during low-risk periods.

Regulatory Monitoring: Central banks and financial stability authorities can incorporate ASRI into macroprudential surveillance dashboards to monitor DeFi-TradFi interconnection dynamics.

Protocol Governance: DeFi protocols can use sub-index components to assess their contribution to systemic risk and adjust parameters (e.g., collateral ratios, withdrawal limits) accordingly.

Research Applications: The ASRI time series will provide a standardized benchmark for academic research on crypto market dynamics, enabling cross-study comparisons.

7.3 Limitations

Data Availability: Several components (Tier 2 sources) require manual collection or have limited historical depth. Enterprise APIs (TRM Labs, Chainalysis) that would improve coverage are cost-prohibitive for academic research.

Historical Reconstruction: DeFi data prior to 2021 is sparse, requiring proxy indicators and interpolation that reduce confidence in early-period ASRI values.

Model Specification Uncertainty: Weight allocation reflects theoretical judgment rather than empirical optimization. Walk-forward analysis (Section 5.3) will assess whether data-driven weights outperform.

Regulatory Dynamics: The rapidly evolving regulatory landscape may require periodic recalibration of the Opacity sub-index as disclosure requirements change.

8 Conclusion

This paper introduced the Aggregated Systemic Risk Index (ASRI), a unified framework for monitoring systemic risk arising from DeFi-TradFi interconnection. The index comprises

four weighted sub-indices—Stablecoin Risk, DeFi Liquidity Risk, Contagion Risk, and Regulatory Opacity Risk—designed to capture risk transmission channels absent from traditional systemic risk measures.

The methodology presented here establishes the theoretical and computational foundation for a live risk monitoring system. Version 2.0.0 will extend this work with:

1. Backtesting results against 2020–2025 historical data

2. Validation metrics for crisis detection performance

3. Sensitivity analysis of weight specifications

4. Comparative analysis against existing risk indices

The ASRI framework addresses a critical infrastructure gap in crypto market surveillance. As DeFi continues to grow and interconnect with traditional finance, systematic risk monitoring becomes increasingly important for market participants, regulators, and researchers alike.

Live Dashboard: resurrexi.io/asri/

Code Repository: github.com/studiofarzulla/asri

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A API Documentation Summary

Table 3 provides endpoint documentation for primary data sources.

Table 3: Primary API Endpoints

Source	Endpoint	Rate Limit	Authentication
DeFi Llama	`api.llama.fi/v2/tvl`	300/5min	None
DeFi Llama	`stablecoins.llama.fi/stablecoins`	300/5min	None
FRED	`api.stlouisfed.org/fred/series`	None	API Key
CoinGecko	`api.coingecko.com/api/v3`	10-50/min	API Key (Pro)
Token Terminal	`api.tokenterminal.com/v2`	Varies	API Key

B Sub-Index Calculation Code

Python implementation of sub-index formulas is available in the repository at `src/asri/signals/calculator.py`. Key functions:

```python
def calculate_stablecoin_risk(
    tvl_ratio: float,
    treasury_weight: float,
    hhi_concentration: float,
    peg_volatility: float
) -> float:
    return (
        0.4 * tvl_ratio +
        0.3 * treasury_weight +
        0.2 * hhi_concentration +
        0.1 * peg_volatility
    )
```

Full implementation: github.com/studiofarzulla/asri

C Historical Crisis Event Details

Terra/Luna Collapse (May 2022): UST algorithmic stablecoin depegged due to redemption spirals, eliminating $40B in value within 72 hours. LUNA dropped from $80 to near-zero.

Celsius/3AC Contagion (June 2022): Celsius Network froze withdrawals; Three Arrows Capital defaulted on loans. Combined losses exceeded $10B, triggering margin calls across crypto lending platforms.

FTX Bankruptcy (November 2022): FTX and Alameda Research filed for bankruptcy after liquidity crisis. Opaque counterparty relationships propagated losses across the ecosystem.