Regional Environmental Change (2026) 26:53
https://doi.org/10.1007/s10113-026-02552-8

RESEARCH

Climate physical risk in MENA: patterns, persistence, and policy implications for sustainable development

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Received: 10 July 2025 / Accepted: 11 February 2026
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Abstract
This study offers the first systematic analysis of convergence and divergence in climate physical risk across the Middle East and North Africa (MENA) region, utilizing the innovative Climate Physical Risk Index (CPRI) and state-of-the-art panel stationarity methods. Analyzing CPRI data for 17 MENA countries from 1993 to 2023, we apply four stationarity tests including the novel Fourier KPSS with structural breaks (FKPSS-SB) model to capture both smooth and abrupt changes in climate risk trajectories. Our results reveal persistent heterogeneity, with only Morocco and Oman exhibiting convergence under the most flexible model specification, while the remainder of the region remains divergent. By linking identified break dates to regional climate events and policy shifts, we provide new empirical insights into the drivers of climate risk and resilience in MENA. The findings underscore the need for regional adaptation coordination, but feasibility is constrained by political, economic, and institutional differences across MENA, so cooperation is most realistic in practical, widely beneficial areas (e.g., shared climate services, early-warning systems, and data platforms).

Keywords Climate Physical Risk Index (CPRI) · Convergence analysis · Fourier KPSS with structural breaks · MENA region · Climate resilience

Introduction

Climate change is intensifying the frequency and severity of extreme weather events, with rising consequences for ecosystems, livelihoods, and sustainable development (Kongkuah and Alessa 2025). These impacts are uneven across space and time because physical risk exposure interacts with socio-economic vulnerability, institutional capacity, and adaptive governance. Understanding whether climate physical risk is becoming more similar across countries, or increasingly uneven, is therefore central for both research and policy.

This question is particularly salient in the Middle East and North Africa (MENA). The region combines high climatic stress with rapid population growth, water scarcity, and development constraints, and it has experienced increasing heat extremes, prolonged droughts, and severe flood episodes with implications for food and water security and social stability (Kelley et al. 2015; Sultan and Gaetani 2016; Tramblay et al. 2020; Zittis et al. 2022). At the same time, MENA is politically and economically heterogeneous, so regional coordination, where pursued, faces practical constraints related to divergent institutions, priorities, and capacities (Abumoghli and Goncalves 2019). Yet systematic evidence on whether climate physical risk trajectories in MENA are converging or diverging remains limited, partly because comparable long-run, country-level risk metrics have only recently become available.

To address this gap, we use the Climate Physical Risk Index (CPRI) as a standardized indicator of country-level exposure to climate physical hazards, enabling cross-national and temporal comparisons (Guo et al. 2024). CPRI summarizes multiple hazard dimensions into a single metric, which is useful for tracking broad risk dynamics. However, CPRI mainly captures exposure and does not directly measure vulnerability, distributional impacts, or institutional resilience. For that reason, we interpret the convergence

Communicated by George Zittis

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Published online: 19 February 2026

results alongside MENA's vulnerability context, and we return to governance and inequality-related mechanisms in the "Discussion" section when drawing policy implications (Al-Saidi and Saliba 2019).

A key contribution of this paper is to explicitly clarify what "convergence" means in our setting, and what it does not mean. Following the stochastic convergence tradition, we test whether each country's log-relative CPRI, defined as the deviation of national CPRI from the contemporaneous MENA average, is mean-reverting (Elasha 2012; Phillips and Sul 2007). Stationarity of the log-relative series indicates that shocks to relative risk are transitory, while non-stationarity implies persistent divergence. This approach is appropriate for heterogeneous regions because it evaluates convergence to a common regional benchmark without assuming identical levels or identical short-run dynamics. Importantly, convergence in this sense does not imply coordinated climate policy, nor does it imply that risk levels are low. Convergence can occur even when the regional average risk is rising, and it should therefore be interpreted together with the level and trend of CPRI (Phillips and Sul 2007). In addition, because our tests allow structural breaks, we use documented climate events and policy milestones to contextualize break dates, but we do not treat temporal alignment as causal attribution beyond what the data support.

Against this backdrop, the paper makes three contributions. First, we compile a consistent longitudinal panel of CPRI for 17 MENA countries over 1993 to 2023. Second, we apply a sequence of flexible stationarity-based convergence tests, including KPSS, KPSS with structural breaks, Fourier KPSS, and Fourier KPSS with structural breaks, to capture both abrupt and smooth changes in risk trajectories. Third, we translate the resulting convergence and break patterns into adaptation-relevant implications at country and regional levels. The remainder of the paper is organized as follows: the "Literature review and hypothesis development" section reviews related literature and states the hypothesis, the "Methodology" section presents data and methods, the "Results" section 4 reports results, and the "Discussion" and "Conclusions and recommendation" sections discuss implications and conclude.

Literature review and hypothesis development

The scientific understanding of climate change has evolved dramatically over the past several decades, with the focus shifting from mere detection of global warming signals to the nuanced analysis of risk, exposure, and resilience at multiple spatial and temporal scales (Legg 2021). Central to this evolution is the recognition that the impacts of climate change are fundamentally uneven—mediated by a host of biophysical, socio-economic, and institutional factors that shape the vulnerability and adaptive capacity of different regions (Adger 2006). In the Middle East and North Africa (MENA), this unevenness is both pronounced and consequential, making the region an important case for the study of climate physical risk and its dynamic evolution.

The MENA region's exposure to climate hazards is shaped by its geographical location at the nexus of arid and semi-arid zones, coupled with socio-economic conditions that heighten sensitivity to climate extremes. Multiple studies have documented the region's acute vulnerability to temperature increases, declining precipitation, and increased frequency of extreme weather events (Lelieveld et al. 2016; Zittis et al. 2022). For instance, research has highlighted the intensification of heatwaves and record-breaking temperatures in the Eastern Mediterranean and Arabian Peninsula, as well as unprecedented droughts across North Africa (Tramblay et al. 2020; Zittis et al. 2021). The socio-economic impacts of these hazards are far-reaching, affecting water resources, agricultural productivity, public health, urban infrastructure, and social stability (Abumoghli and Goncalves 2019; Sultan and Gaetani 2016).

Water scarcity, in particular, has emerged as a critical challenge for MENA, with per capita freshwater availability among the lowest globally (Gleick 2014). Studies have linked recurring droughts and declining river flows to both climatic and anthropogenic factors, including upstream dam construction and unsustainable extraction (Kelley et al. 2015). The region's reliance on rain-fed agriculture and groundwater further amplifies its sensitivity to rainfall variability and prolonged dry spells (Tramblay and Somot 2018). For example, Grasso and Feola (2012) examine drought variability in Morocco and highlight that recurrent drought episodes can generate sustained stress on agriculture and rural livelihoods, while Schilling and Scheffran (2012) discuss how drought-related resource pressures may interact with socio-economic fragility to amplify migration and conflict risks in Sudan.

The theoretical literature on convergence and divergence provides a useful lens for analyzing how climate risk evolves across regions. Originally developed in the context of economic growth, convergence theory assesses whether countries or regions are tending toward a common path over time or whether disparities persist or widen (Barro and Sala-i-Martin 1992; Phillips and Sul 2007). However, when applied to climate physical risk, convergence should be interpreted cautiously because institutional capacity, political instability, and data constraints (including greater reliance on modelled or interpolated inputs in low-capacity settings) can generate persistent country-specific deviations and measurement uncertainty. The application of convergence tests to environmental indicators, including pollution, carbon emissions, and climate hazards, has generated a growing body

of empirical research (Stern 2023). For example, Ezcurra (2007) analyzed the convergence of air pollution across European regions, while Wu et al. (2025) examined the convergence of extreme climate events in China (Ezcurra 2007; Wu et al. 2025). These studies typically employ unit root and stationarity tests, panel data methods, and advanced econometric models to identify whether observed disparities are narrowing or persisting.

Recent advances in climate risk measurement have enabled a more nuanced approach to convergence analysis. Composite indices such as the Climate Physical Risk Index (CPRI) offer a multidimensional assessment of risk, capturing not only the frequency but also the severity and persistence of hazards (Guo et al. 2024). The use of CPRI allows researchers to examine convergence in aggregate climate risk exposure, transcending the limitations of single-hazard or event-based studies. In addition, integrating structural break and nonlinear trend analyses provides deeper insight into the effects of policy interventions, technological adoption, or external shocks on climate risk trajectories (Bai and Perron 2003; Qi et al. 2020). This is particularly relevant for MENA, where the intersection of rapid urbanization, economic diversification, and variable policy regimes complicates simple trend assessments (Al-Saidi and Saliba 2019).

Empirical research on convergence in climate risk in MENA remains nascent but is beginning to yield important findings. Specifically, the cited evidence documents intensifying and spatially heterogeneous heat extremes (Zittis et al. 2021), clustered drought risk and co-evolving dry conditions in parts of North Africa (Tramblay et al. 2020), and cross-country differences in adaptation and risk-management capacity shaped by institutions and policy responses (Klein et al. 2015; Almazroui and Saeed 2020), with implications for food security under climate shocks (Sultan and Gaetani 2016). Furthermore, Zittis et al. (2021) projected substantial increases in heatwave intensity and frequency across the region, with significant heterogeneity across countries and sub-regions (Zittis et al. 2021). Tramblay et al. (2020) identified spatial clustering of drought risk, noting that North African countries tend to experience co-evolving drought conditions linked to regional climate teleconnections (Tramblay et al. 2020). At the same time, some studies find persistent divergence, particularly in relation to institutional adaptation, resource endowments, and socio-political context (Klein et al. 2015). For example, Almazroui and Saeed (2020) highlighted differences in flood exposure and management capacity in Gulf states, while Sultan and Gaetani (2016) traced the interplay of climate shocks and food security in North Africa (Almazroui et al. 2020; Sultan and Gaetani 2016). Collectively, this literature points to the need for context-sensitive, dynamic analysis of climate risk convergence, attentive to both temporal shocks and structural characteristics.

Another strand of literature focuses on the determinants of climate risk reduction and resilience. Scholars emphasize the role of adaptive institutions, technological innovation, and regional cooperation in mediating risk trajectories (Barbier and Hochard 2018). Cross-country studies have shown that countries investing in climate information systems, disaster risk management, and public awareness tend to achieve more favorable risk outcomes (Birkmann and von Teichman 2010). However, such progress is uneven, with fragile states, conflict-affected regions, and marginalized populations often excluded from adaptation gains (García-León et al. 2021). In the context of the present study, these insights reinforce the value of a multi-method approach that integrates quantitative convergence tests with qualitative attention to country-specific circumstances.

The methodology adopted in this research builds upon and extends recent empirical studies applying panel stationarity and convergence tests to environmental and economic variables. Kwiatkowski et al. (1992) introduced the KPSS test as a tool for assessing trend stationarity versus unit roots, while Phillips and Sul (2007) pioneered the use of club convergence tests in economic and environmental analysis (Kwiatkowski et al. 1992; Phillips and Sul 2007). Subsequent research has developed variants accommodating structural breaks (Bai and Perron 2003) and nonlinear trends (Yilanci and Abbas 2023), providing a rigorous framework for testing convergence hypotheses in the presence of complex dynamics (Bai and Perron 2003; Yilanci and Abbas 2023).

Overall, the literature confirms that climate hazards in MENA are rising and heterogeneous, but evidence remains limited on whether country-level climate physical risk exposures are converging toward a regional benchmark or diverging over multi-decade horizons using a comparable composite metric. This study addresses that gap by testing stochastic convergence in log-relative CPRI for 17 MENA countries over 1993–2023 using KPSS-based procedures that allow for both smooth nonlinearities and structural breaks.

Based on the reviewed literature and the complex interplay of climatic, socio-economic, and institutional factors in MENA, this study posits the following central hypothesis:

H_0: There is convergence in the Climate Physical Risk Index (CPRI) among MENA countries over the period 1993–2023, indicating a tendency toward a shared regional climate risk trajectory.
H_1: The alternative hypothesis is that persistent divergence exists, with country-specific shocks and structural characteristics dominating risk dynamics.

The empirical analysis tests this hypothesis using sequential KPSS, KPSS with break, Fourier KPSS, and Fourier KPSS with break procedures, interpreting convergence as

non-rejection of trend stationarity in the series. The findings of this research will contribute to ongoing debates in the literature regarding the extent and drivers of convergence in climate risk, and will inform both academic and policy strategies for building climate resilience in the MENA region.

Methodology

This study investigates the convergence of climate physical risk across Middle East and North Africa (MENA) countries using the Climate Physical Risk Index (CPRI), in a manner analogous to the approach employed by Carlino and Mills (1993). The empirical strategy consists of three main stages: construction of the relative CPRI measure, descriptive statistical analysis, and a suite of panel stationarity tests, each designed to uncover the dynamic properties and convergence patterns of physical climate risk in the region.

Data construction and relative Climate Physical Risk Index

The primary variable of interest is the Climate Physical Risk Index (CPRI), a composite metric that aggregates four critical dimensions of climate risk: extreme low temperature days (LTD), extreme high temperature days (HTD), extreme rainfall days (ERD), and extreme drought days (EDD), as provided by Guo et al. (2024). Annual CPRI data for 17 MENA countries spanning the period 1993–2023 were obtained from the dataset's Figshare repository at https://figshare.com/articles/dataset/Climate_Physical_Risk_Index_CPRI_/25562229, ensuring full alignment with the time horizon and regional coverage in the original study. Because CPRI is constructed and released as an annual composite index, it does not permit explicit modelling of intra-annual seasonality; accordingly, our analysis focuses on long-run convergence dynamics rather than monthly/seasonal patterns. To enable meaningful cross-country and intertemporal comparison, the absolute CPRI values are transformed into a relative measure. Specifically, for each country i and year t, the relative CPRI is computed as the logarithm of the ratio of the country's CPRI to the MENA average in that year:

$$rel_CPRI_{it} = \log\left(\frac{CPRI_{it}}{\overline{CPRI_t}}\right) \tag{1}$$

where $CPRI_{it}$ is the climate physical risk index for country i in year t, and $\overline{CPRI_t}$ denotes the cross-sectional mean of the CPRI across all sample countries in year t. This transformation centers the data around zero each year, allowing for a direct interpretation of whether individual countries are converging toward, or diverging from, the regional climate risk average.

Descriptive statistical analysis

Table 1 summarizes the distributional properties of CPRI by country (mean, dispersion, and normality diagnostics), while Fig. 1[1] provides a visual overview of CPRI evolution (1993–2023). Both indicate substantial cross-country heterogeneity and time variation, motivating formal tests of whether relative climate risk dynamics converge toward a regional benchmark or remain persistently divergent.

Econometric framework for stochastic convergence

To rigorously examine whether climate physical risk in MENA countries displays stochastic convergence, we implement a number of unit root tests, each designed to accommodate increasingly complex forms of non-stationarity and structural change. Our empirical approach mirrors that of Carlino and Mills (1993), adapted for the CPRI context.

Let $y_{it} = \log\left(\frac{CPRI_{it}}{\overline{CPRI_t}}\right)$ denote the log-relative CPRI for country i at time t. Convergence is interpreted as the absence of a unit root in y_{it}; that is, stationarity of the relative CPRI series implies that idiosyncratic shocks to climate risk are transitory and that countries tend to revert to the regional mean over time.

Kwiatkowski–Phillips–Schmidt–Shin test for trend stationarity

The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test as introduced by Kwiatkowski et al. (1992) is applied to the log-relative CPRI series for each country. The current study also employs extensions of the standard KPSS test as introduced by Maddala and Kim (1999). The KPSS framework (Kwiatkowski et al. 1992) decomposes y_{it} as:

$$\begin{aligned} y_{it} &= \mu + \beta t + u_{it} \\ u_{it} &= \sum_{j=1}^{t} \varepsilon_{ij} \end{aligned} \tag{2}$$

where μ is a constant, β is the deterministic trend, and u_{it} is a random walk. The null hypothesis (H_0) posits that the series is trend stationary (i.e., no unit root), while the

[1] Each panel uses a country-specific y-axis to improve readability of within-country dynamics. Accordingly, Fig. 1 is not intended for direct visual comparison of levels across countries; cross-country comparisons are conducted using the formal convergence analysis of log-relative CPRI reported in the results section.

Table 1 Descriptive statistics for the Climate Physical Risk Index (CPRI) by country

Country	Mean	Median	Minimum	Maximum	Std. Dev	Skewness	Kurtosis	Jarque–Bera	JB prob
Algeria	17.252560	16.868134	7.9241309	23.97111	4.309059	−0.38798806	2.897485	0.7913374	0.6732297
Bahrain	26.344934	27.218402	12.8926227	38.97249	7.400501	−0.14006517	1.956107	1.5089065	0.4702677
Egypt	14.265678	13.887518	9.0190510	20.44168	2.775561	0.37342706	2.622787	0.9042710	0.6362680
Iran	14.502478	15.926990	8.1501235	19.09552	3.637850	−0.35125233	1.622780	3.0874046	0.2135889
Israel	16.270820	16.272401	11.2354233	21.76572	2.570709	−0.09915486	2.438989	0.4573271	0.7955962
Jordan	14.827344	14.227155	9.5307527	20.72613	2.581673	0.60606946	2.925247	1.9050388	0.3857679
Kuwait	28.072102	24.306116	8.9248140	54.05078	13.272311	0.38661568	1.936723	2.2325746	0.3274934
Lebanon	17.981954	17.066372	9.0103969	27.09405	4.520396	0.01577730	2.594916	0.2132396	0.8988674
Libya	9.887625	10.928091	3.4646297	15.94101	3.439992	−0.34823839	1.943584	2.0680810	0.3555674
Mauritania	8.457634	7.224716	3.1590589	13.22717	2.962004	0.02806136	1.979426	1.3494305	0.5093014
Morocco	18.106318	17.298048	8.8905445	28.80403	5.111610	0.32113651	2.221196	1.3162739	0.5178151
Oman	14.971363	14.796559	9.7757729	21.31295	2.823390	−0.02258465	2.689630	0.1270612	0.9384454
Qatar	16.199230	15.917577	7.3916088	27.12778	4.698011	0.27181822	2.750346	0.4622459	0.7936419
Saudi Arabia	18.078293	18.416535	10.5793240	27.01868	3.913328	−0.02319672	2.608386	0.2008723	0.9044428
Sudan	6.810898	5.995800	0.1782774	17.26525	4.734475	0.25554532	2.018748	1.5810903	0.4535975
Syria	14.087751	14.270071	8.9027812	20.05135	2.393462	0.08928172	3.100987	0.0543576	0.9731872
Tunisia	19.741090	19.618073	11.7632680	29.03934	4.652293	0.25758901	2.473530	0.7008312	0.7043953

This table reports descriptive statistics for the CPRI series. Mean/Median: indicate average and midpoint of the series. Skewness: values close to zero indicate symmetry. Skewness > 0 (right-skewed); Skewness < 0 (left-skewed). Kurtosis: for normality, kurtosis ≈ 3. High kurtosis (> 3) means heavier tails; low (< 3) means lighter tails. Jarque–Bera: tests normality (H_0: series is normal). If the p-value < 0.05, reject H_0 and conclude non-normality. Standard deviation, min, and max reflect dispersion and extremes

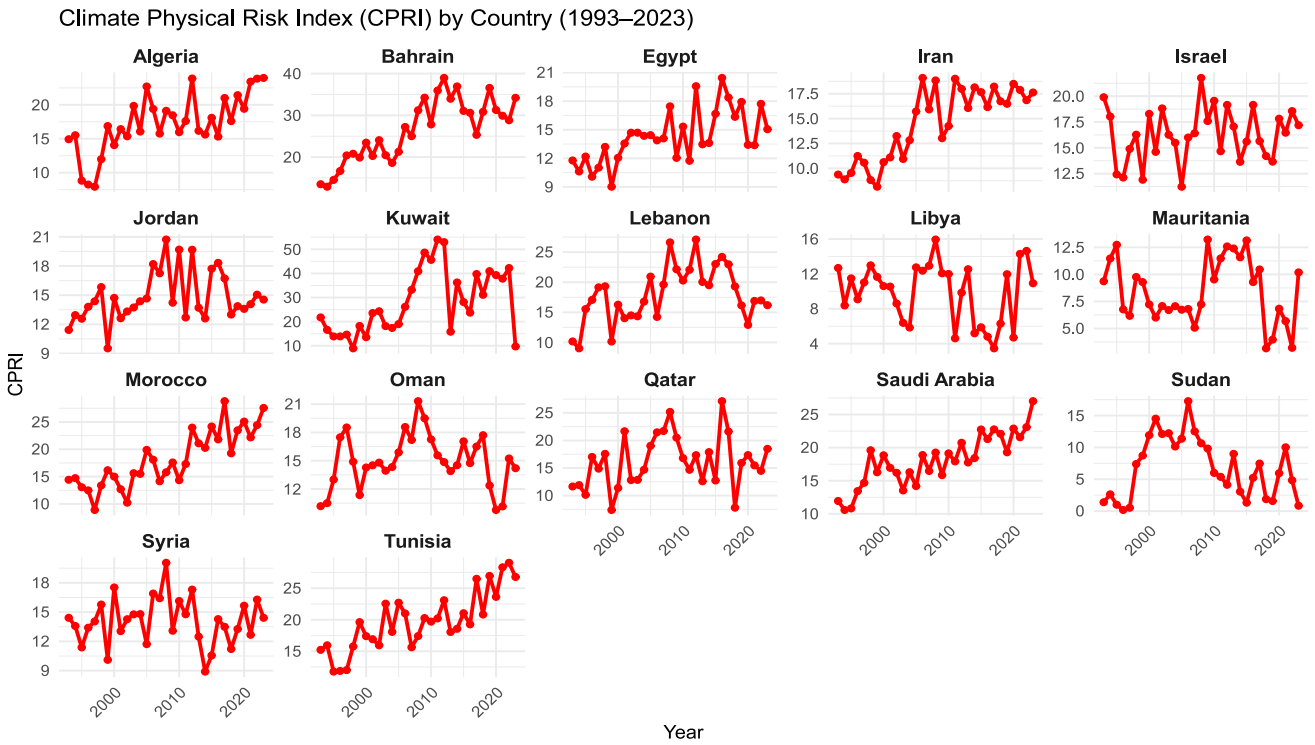


Fig. 1 Climate Physical Risk Index (CPRI) by country (1993–2023), for the 17 MENA countries

Table 2 KPSS test

Country	KPSS	Bootstrap critical values			Freq. zero spectrum
		1%	5%	10%	
Algeria	0.070*	0.03776789	0.04329880	0.04748712	0.07899007
Bahrain	0.087*	0.03822375	0.04384404	0.04749917	0.07948205
Egypt	0.078*	0.03755693	0.04350424	0.04718818	0.07919823
Iran	0.052*	0.03820939	0.04341180	0.04747013	0.07992777
Israel	0.139*	0.03775416	0.04314156	0.04718787	0.07938341
Jordan	0.040*	0.03722654	0.04259152	0.04649803	0.07857035
Kuwait	0.117*	0.03798259	0.04302519	0.04710805	0.07915825
Lebanon	0.103*	0.03704680	0.04295193	0.04727459	0.07969316
Libya	0.096*	0.03827750	0.04360026	0.04739251	0.07940986
Mauritania	0.096*	0.03823962	0.04374608	0.04736644	0.07960947
Morocco	0.158*	0.03828813	0.04332096	0.04739574	0.07973351
Oman	0.063*	0.03764969	0.04293861	0.04712561	0.07898478
Qatar	0.064*	0.03804507	0.04341683	0.04697345	0.07944493
Saudi Arabia	0.147*	0.03798929	0.04351563	0.04726051	0.07902256
Sudan	0.179*	0.03850830	0.04357446	0.04743071	0.07962455
Syria	0.129*	0.03762113	0.04326267	0.04741437	0.07994651
Tunisia	0.142*	0.03778811	0.04336296	0.04714385	0.07875762

The bootstrap critical values are based on 5,000 simulations. Frequency zero spectrum (long-run variance) is included as recommended by Kwiatkowski et al. (1992). If the test statistic exceeds the critical value, we reject the null hypothesis and conclude non-stationarity. That is, asterisks indicate significance: * for 1%, ** for 5%, and *** for 10% rejection of the null hypothesis of stationarity; no asterisk means convergence

alternative (H_1) is that the series is non-stationary. In contrast to the ADF or Phillips–Perron tests, rejecting the null here provides evidence against convergence.

To address small-sample distortions and unknown innovation processes, we compute bootstrap critical values for each country by resampling the series 5000 times and calculating empirical quantiles at the 1%, 5%, and 10% levels. In KPSS and related tests, reporting the frequency zero spectrum is important because it directly relates to how the test statistic is normalized (Kwiatkowski et al. 1992). It helps ensure that results are robust to serial correlation and heteroskedasticity in the data (Kwiatkowski et al. 1992). The test statistic, bootstrap critical values, and the frequency zero spectrum (i.e., the long-run variance estimator, following Kwiatkowski et al. (1992)) are therefore reported for each country to ensure robust inference and to align with best practice in the unit root testing literature. The test statistic, critical values, and frequency zero spectrum are reported in Table 2.

Kwiatkowski–Phillips–Schmidt–Shin test with structural break

Recognizing the potential for abrupt regime shifts in climate risk (e.g., due to major climatic events or policy interventions), we augment the KPSS regression to allow for a single structural break at an unknown date as introduced by Kurozumi (2002). The break date is estimated endogenously via the Bai–Perron methodology (Bai and Perron 2003), and a dummy variable is included to capture the post-break shift (Kurozumi 2002):

$$y_{it} = \mu + \beta t + \gamma D_{it} + u_{it} \tag{3}$$

where D_{it} is a dummy variable equal to one after the estimated break date and zero otherwise. The hypothesis structure and decision rule remain as in the standard KPSS test. Table 3 reports the test statistics, bootstrap critical values, break dates, and frequency zero spectrum.

Fourier Kwiatkowski–Phillips–Schmidt–Shin test

To accommodate smooth, potentially cyclical or nonlinear changes in the deterministic component of climate risk, we employ the Fourier KPSS test. This approach by Becker et al. (2006) in using a Fourier function in place of dummy variables deals with the limitation of the dummy variables in capturing gradual shifts. So, the Fourier KPSS test approach augments the deterministic part of the KPSS regression with low-frequency sine and cosine terms as:

$$y_{it} = \mu + \beta t + \delta_1 \sin\left(\frac{2\pi kt}{T}\right) + \delta_2 \cos\left(\frac{2\pi kt}{T}\right) + u_{it} \tag{4}$$

where k is the selected frequency (chosen to minimize the sum of squared residuals for each country) and T is the

Table 3 KPSS with structural breaks test

Country	Break date	KPSS-SB	Bootstrap critical values			Freq. zero spectrum
			1%	5%	10%	
Algeria	1998	0.110*	0.03785981	0.04329398	0.04734348	0.07977001
Bahrain	1996	0.094*	0.03683670	0.04258191	0.04664568	0.07889173
Egypt						
Iran	2003	0.062*	0.03738781	0.04301307	0.04684131	0.07846734
Israel	2004	0.088*	0.03772760	0.04325927	0.04724483	0.07960863
Jordan	2008	0.072*	0.03756325	0.04295550	0.04729919	0.07898892
Kuwait	2006	0.092*	0.03844567	0.04344289	0.04727241	0.07880614
Lebanon	2018	0.051*	0.03771807	0.04332109	0.04742637	0.07940247
Libya	2010	0.126*	0.03731600	0.04272471	0.04714470	0.07947653
Mauritania	1999	0.114*	0.03791397	0.04368173	0.04708875	0.07928906
Morocco	2012	0.086*	0.03768232	0.04326469	0.04749585	0.07880992
Oman	2018	0.081*	0.03763924	0.04355509	0.04716989	0.07925654
Qatar						
Saudi Arabia	1996	0.205*	0.03773036	0.04325875	0.04724167	0.07921206
Sudan	1997	0.127*	0.03783843	0.04341770	0.04732822	0.07878985
Syria	2008	0.117*	0.03764826	0.04328162	0.04751630	0.07983380
Tunisia	2016	0.064*	0.03731995	0.04295442	0.04737148	0.07872152

The bootstrap critical values are based on 5000 simulations. Frequency zero spectrum (long-run variance) is included as per Kwiatkowski et al. (1992). If the test statistic exceeds the critical value, we reject the null hypothesis of stationarity with a structural break and conclude non-stationarity. That is, asterisks indicate significance: * for 1%, ** for 5%, and *** for 10% rejection of the null; no asterisk means convergence. Absence of a break date or test result (for Egypt and Qatar) indicates that the structural break algorithm did not detect a statistically significant break for those countries, which is a common methodological outcome in stable series and does not affect the validity of the remaining results (Bai and Perron 2003)

sample size (the total number of years; here, $T = 31$). The running time index (year) for each country is represented by t, where t takes values $1, 2, \ldots, T$. The coefficients for the sine and cosine Fourier terms in the regression are δ_1 and δ_2. They measure the strength and pattern of smooth, cyclical (nonlinear) trends in the time series. This flexible functional form allows the trend to capture gradual and smooth shifts, thereby mitigating size distortions due to unmodelled nonlinearity. The null hypothesis and inference procedure are as that of the KPSS but the critical values for the Fourier KPSS test are determined from Becker et al. (2006); results are summarized in Table 4.

Fourier Kwiatkowski–Phillips–Schmidt–Shin test with structural break

The next specification as introduced by Furuoka (2017) combines both a one-time break and smooth nonlinearities since it is common for most time series to have abrupt (sharp) and smooth breaks. This yields the following regression:

$$y_{it} = \mu + \beta t + \gamma D_{it} + \delta_1 \sin\left(\frac{2\pi kt}{T}\right) + \delta_2 \cos\left(\frac{2\pi kt}{T}\right) + u_{it} \quad (5)$$

This test is robust to both abrupt and gradual changes in the deterministic structure of the log-relative CPRI series. The optimal frequency k for the Fourier KPSS and Fourier KPSS-SB tests is selected by fitting the Fourier terms with values of k ranging from 1 to 4, and choosing the frequency that minimizes the sum of squared residuals (SSR) of the fitted model, following the procedure of Becker et al. (2006) and Enders and Lee (2012). The break date for tests involving a structural break is determined endogenously using the Bai and Perron (2003) multiple structural change algorithm, which identifies the date that minimizes the residual sum of squares of a model with a single break. Once the optimal frequency and break date are determined, the test is performed on the corresponding specification for each country, following the same analytical steps as in the previous unit root and stationarity tests. Results are shown in Table 5.

Break dates are interpreted as contextual alignments only. We cross-checked each identified break against peer-reviewed studies and authoritative institutional/national reports within a narrow window around the break; these alignments are correlational (indicative), not causal, and may be incomplete due to uneven documentary coverage.

Table 4 Fourier KPSS test

Country	Optimal freq	FKPSS	Bootstrap critical values			Freq. zero spectrum
			1%	5%	10%	
Algeria	2	0.040*	0.03800510	0.04333959	0.04725133	0.07904001
Bahrain	1	0.068*	0.03809411	0.04347882	0.04754710	0.07916417
Egypt	3	0.102*	0.03788183	0.04334995	0.04765090	0.07922857
Iran	1	0.056*	0.03754929	0.04333412	0.04696193	0.07892507
Israel	1	0.078*	0.03797226	0.04317990	0.04742592	0.07903782
Jordan	3	0.057*	0.03769908	0.04312521	0.04670479	0.07942554
Kuwait	1	0.042*	0.03791420	0.04351288	0.04755180	0.07929617
Lebanon	2	0.103*	0.03784095	0.04310148	0.04697094	0.07909400
Libya	1	0.064*	0.03790472	0.04347680	0.04733404	0.07884888
Mauritania	2	0.045*	0.03791830	0.04301566	0.04715117	0.07879407
Morocco	1	0.047*	0.03753353	0.04329713	0.04710418	0.07948036
Oman	1	0.059*	0.03781912	0.04311208	0.04677137	0.07905131
Qatar	3	0.091*	0.03813535	0.04368241	0.04748667	0.07939928
Saudi Arabia	2	0.184*	0.03772722	0.04335196	0.04740246	0.07905149
Sudan	1	0.065*	0.03772073	0.04311116	0.04735822	0.07946451
Syria	1	0.078*	0.03746062	0.04323767	0.04751084	0.07909672
Tunisia	2	0.156*	0.03697868	0.04321736	0.04725393	0.07895944

The bootstrap critical values are based on 5000 simulations. Frequency zero spectrum (long-run variance) is included as per Kwiatkowski et al. (1992). If the test statistic exceeds the critical value, we reject the null hypothesis of stationarity with smooth breaks and conclude non-stationarity. That is, asterisks indicate significance: * for 1%, ** for 5%, and *** for 10% rejection of the null; no asterisk means convergence

Interpretation and decision rules

For each test and country, the test statistic is compared to the bootstrap critical values at the 1%, 5%, and 10% significance levels. If the test statistic exceeds the critical value at a given significance level, the null hypothesis of (trend) stationarity (i.e., convergence) is rejected at that level, indicating evidence of non-convergence (divergence). Asterisks denote the level at which the null is rejected: one star (*) indicates rejection at the 1% level, two stars (**) at the 5% level, and three stars (***) at the 10% level. If the test statistic does not exceed even the 10% critical value (i.e., no star), we fail to reject the null hypothesis at all conventional significance levels, providing evidence of convergence. Frequency zero spectrum values are also reported for completeness, as recommended by (Kwiatkowski et al. 1992).

Lastly, it is worth mentioning that all analyses of this study were carried out using *R version 4.4.2* (R Core Team 2025).

Results

After establishing the baseline descriptive statistics and visual patterns, we turn to the formal convergence analysis. Table 2 presents the results of the KPSS test for trend stationarity applied to the log-relative CPRI series for each MENA country. Across all 17 countries, the KPSS test statistic exceeds the 1% bootstrap critical value, as indicated by a single asterisk (* for all entries). This implies that, for every country in the sample, the null hypothesis of trend stationarity is rejected at the 1% significance level. As a result, none of the countries displays evidence of convergence in climate physical risk toward the regional mean under the standard KPSS framework. Instead, the results indicate widespread non-stationarity: shocks to physical climate risk are persistent, and country-specific deviations from the regional average do not dissipate over time. This finding is visually reinforced by Fig. 2, which shows that, for all countries, the actual versus fitted series are marked by pronounced volatility and a persistent lack of mean reversion.

To further investigate whether abrupt changes or regime shifts may explain this non-convergence, we extend the analysis to account for structural breaks. Table 3 summarizes the results of the KPSS test with a single endogenous structural break. For all countries except Egypt and Qatar, where no significant break is identified, the KPSS-SB test statistic once again exceeds the 1% bootstrap critical value (denoted by a single asterisk for all countries with results). This means that, even after allowing for one-time structural breaks, the null hypothesis of trend stationarity is still rejected at the 1% level for these countries, reaffirming the pattern of persistent non-convergence across the MENA region. The identified break dates coincide with years of

Table 5 Fourier KPSS with structural breaks test

Country	Optimal freq	Break date	FKPSS-SB	Bootstrap critical values			Freq. zero spectrum
				1%	5%	10%	
Algeria	2	1998	0.072*	0.03785298	0.04335992	0.04727752	0.07962818
Bahrain	1	1996	0.049*	0.03808291	0.04305660	0.04715612	0.07942932
Egypt	3						
Iran	1	2003	0.038*	0.03728591	0.04315852	0.04729152	0.07954916
Israel	1	2004	0.063*	0.03808490	0.04334133	0.04737457	0.07878542
Jordan	3	2008	0.061*	0.03732138	0.04304965	0.04724112	0.07907864
Kuwait	1	2006	0.043*	0.03837445	0.04345573	0.04703341	0.07887601
Lebanon	2	2018	0.056*	0.03836153	0.04282813	0.04706469	0.07866689
Libya	1	2010	0.053*	0.03786566	0.04324278	0.04703955	0.07953863
Mauritania	2	1999	0.060*	0.03762284	0.04240111	0.04732251	0.07949617
Morocco	1	2012	0.035	0.03838845	0.04395068	0.04766651	0.07937445
Oman	1	2018	0.037	0.03816604	0.04361029	0.04721767	0.07918061
Qatar	3						
Saudi Arabia	2	1996	0.223*	0.03776816	0.04312825	0.04693693	0.07876116
Sudan	1	1997	0.044*	0.03809396	0.04328886	0.04727163	0.07967338
Syria	1	2008	0.058*	0.03830728	0.04343570	0.04721835	0.07866991
Tunisia	2	2016	0.068*	0.03707145	0.04294157	0.04708327	0.07909803

Bootstrap critical values are based on 5000 simulations. Frequency zero spectrum (long-run variance) is included as recommended by Kwiatkowski et al. (1992). If the test statistic exceeds the critical value, we reject the null hypothesis of stationarity with both smooth and sharp breaks, indicating non-stationarity. Asterisks indicate significance: * for 1%, ** for 5%, and *** for 10% rejection of the null; no asterisk means convergence. Absence of a break date (for Egypt and Qatar) indicates no statistically significant structural break was detected for these countries, which is methodologically common in stable series and does not affect the validity of other results (Bai and Perron 2003)

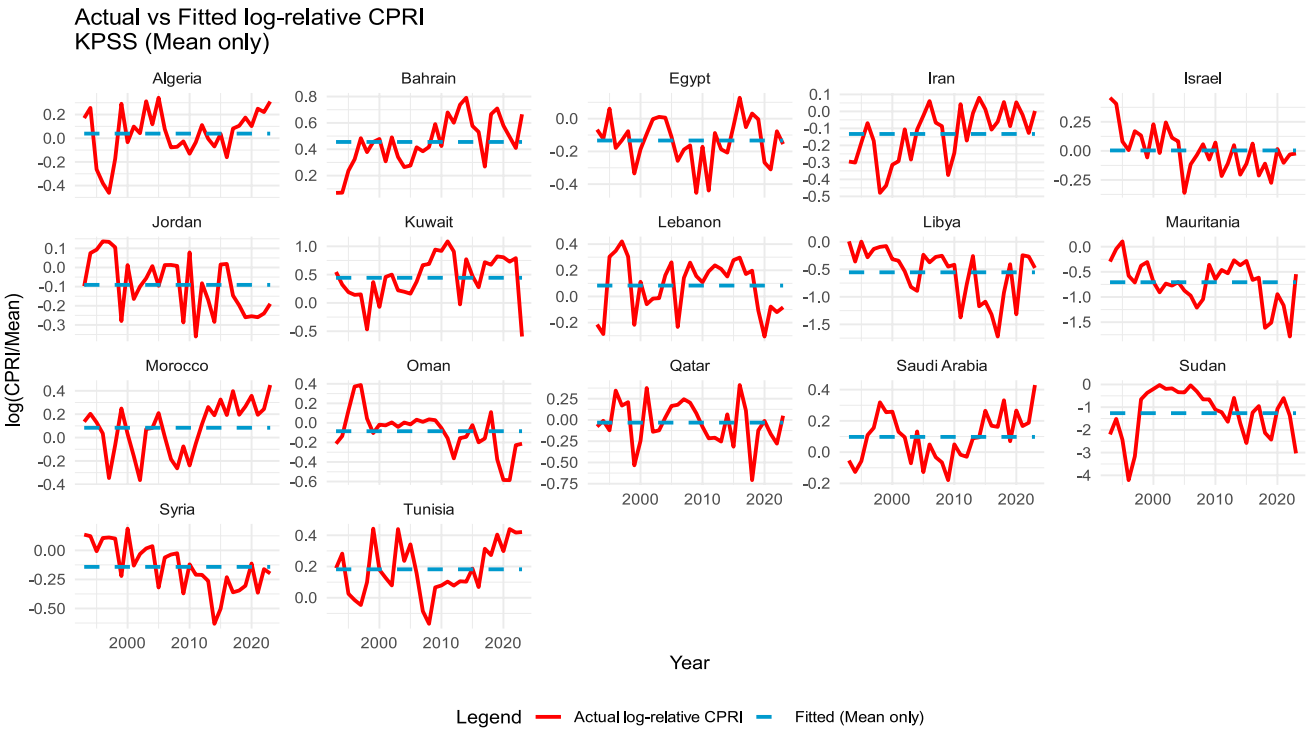


Fig. 2 Actual vs fitted log-relative CPRI—KPSS test

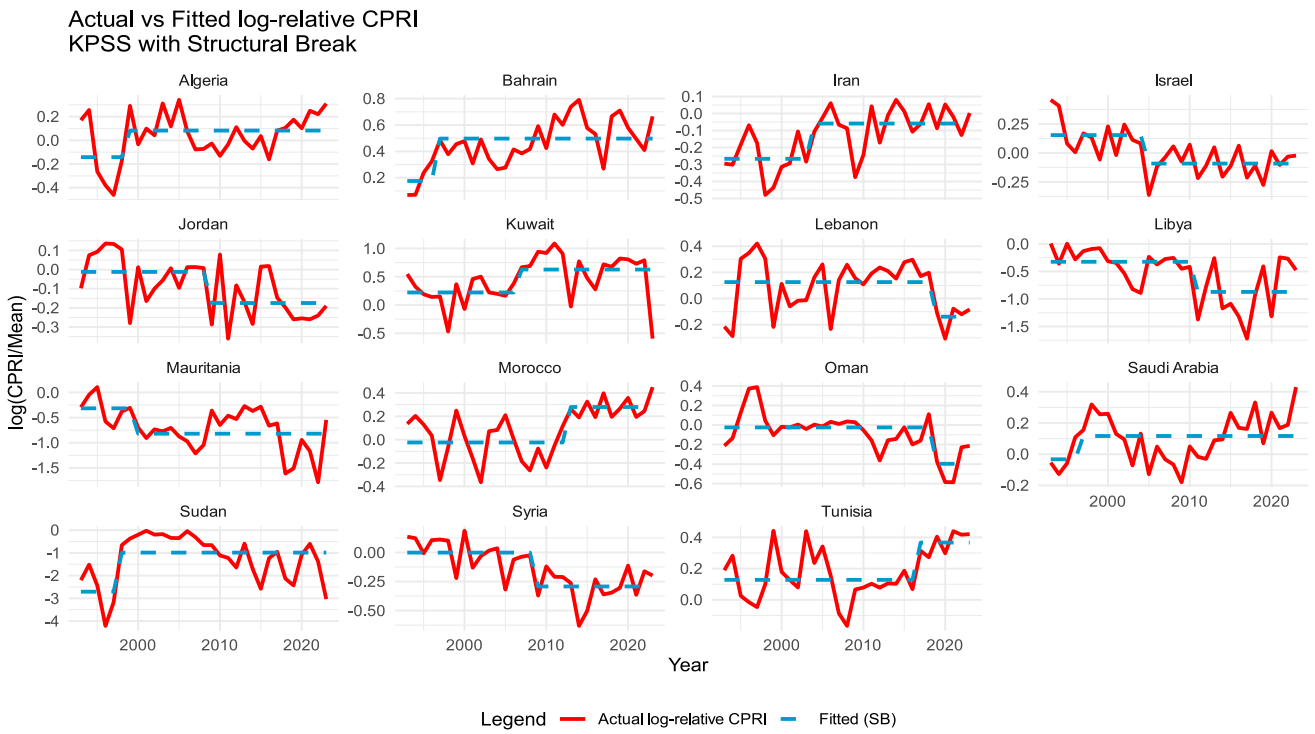


Fig. 3 Actual vs fitted log-relative CPRI—KPSS with structural breaks test

notable climate extremes or socio-economic disruptions. For instance, Algeria's break in 1998 is associated with a severe drought in the Maghreb Hubert and Mohamed (2003), Saudi Arabia's 1996 break matches intensified heatwave activity Zittis et al. (2016), while Sudan's 1997 break corresponds to major drought in the Horn of Africa (Nicholson 2014). Libya's break in 2010 and Tunisia's in 2016 reflect similar episodes of regional climate stress (Almazroui and Saeed 2020; Zittis et al. 2021), and Lebanon's 2018 break aligns with increased heatwave frequency in the Eastern Mediterranean (Hochman et al. 2022). As depicted in Fig. 3, the inclusion of structural breaks does not fundamentally alter the persistent divergence seen in climate risk among countries. It is important to note that for Egypt and Qatar, no statistically significant break was detected, which is a methodologically common outcome in stable series or in the absence of major regime shifts (Bai and Perron 2003).

Next, we address the possibility that gradual, cyclical, or nonlinear changes in trend may underlie the lack of convergence. Table 4 reports the results from the Fourier KPSS test, which allows for smooth, low-frequency variation in the series by including sine and cosine terms. The findings remain consistent: for every country, the test statistic exceeds the 1% bootstrap critical value (as shown by a single asterisk), resulting in rejection of the null hypothesis of trend stationarity at the 1% significance level. This indicates that, even after controlling for gradual, smooth changes in climate risk, there is no evidence of convergence in the region (Fig. 4). The persistence of non-stationarity under this framework points to deep-seated, slow-moving structural dynamics as drivers of country-specific climate risk shocks (Karamperidou et al. 2020; Zittis et al. 2021). Table 4 visually demonstrates that incorporating smooth nonlinear trends does not yield convergence for any country in the sample.

Finally, Table 5 presents the results of the Fourier KPSS test with a structural break, representing the most flexible test specification applied. Here, convergence is detected only for Morocco and Oman, whose test statistics fall below even their country-specific 10% bootstrap critical values (no asterisk). In these cases, the null hypothesis of trend stationarity is not rejected, even when both sharp (breaks) and smooth (nonlinear) changes are considered. For all other countries, the test statistic exceeds the 10%, 5%, and 1% critical values, and thus at least one asterisk is shown, indicating rejection of the null hypothesis and no evidence of convergence. The break dates for most countries correspond to years marked by major climate shocks or socio-economic transitions. Morocco's break in 2012 is linked to multi-year droughts and adaptation policy reforms (Grasso and Feola 2012), Oman's break in 2018 matches an increase in extreme rainfall and floods (Almazroui and Saeed 2020), and other break dates such as Lebanon (2018) and Tunisia (2016) correspond to well-documented periods of climate

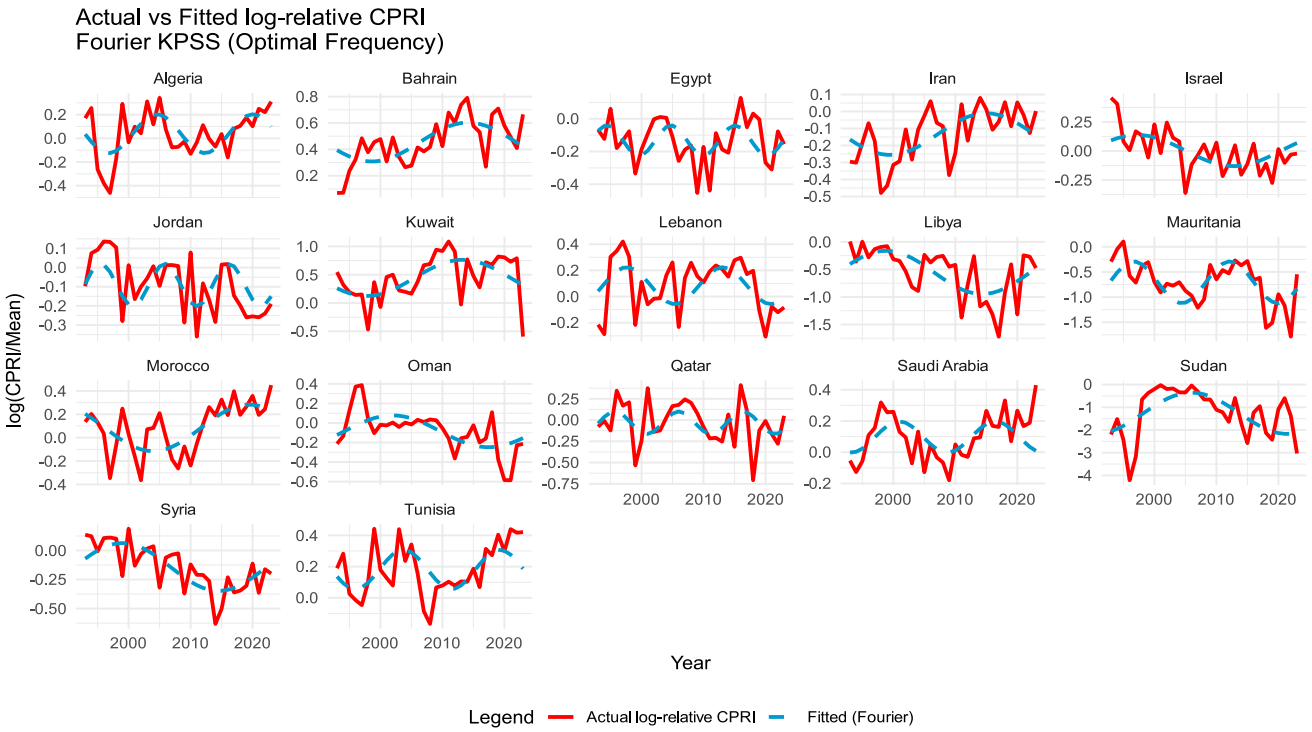


Fig. 4 Actual vs fitted log-relative CPRI—Fourier KPSS test

extremes (Almazroui and Saeed 2020; Hochman et al. 2022). Figure 5 confirms these findings: Morocco and Oman show close alignment between actual and fitted values, reflecting convergent dynamics, while other countries display persistent divergence. Again, for Egypt and Qatar, no significant break could be detected, in line with econometric expectations for stable series (Bai and Perron 2003).

In all, as we progress through increasingly flexible convergence tests, the evidence consistently shows that stationarity, and therefore convergence, is the exception rather than the rule in the climate physical risk of MENA countries. Only Morocco and Oman display evidence of convergence under the most general testing conditions, while persistent divergence remains the dominant pattern throughout the region.

Discussion

The results of this study provide new insights into the evolution and convergence of climate physical risk across Middle East and North Africa (MENA) countries, as quantified by the Climate Physical Risk Index (CPRI) for the period 1993–2023.

The starting point of our analysis is the persistent heterogeneity in climate risk exposure across the MENA region. Descriptive statistics revealed marked differences in average CPRI values and volatility among countries. For instance, Gulf states such as Bahrain and Kuwait consistently reported high mean risk, in contrast to countries like Mauritania and Libya, which showed lower average values. These differences are not surprising, as they reflect the region's well-documented climatic gradients and socio-economic disparities (Almazroui and Saeed 2020; Sultan and Gaetani 2016). The observed temporal volatility in CPRI, with sharp peaks corresponding to major droughts or heatwaves, highlights the critical role of episodic climate extremes in shaping regional risk profiles (Kelley et al. 2015; Tramblay et al. 2020; Zittis et al. 2022).

A central objective of this study was to assess whether these national trajectories are converging toward a shared regional climate risk profile or diverging further apart. The number of convergence tests, KPSS, KPSS with structural break, Fourier KPSS, and Fourier KPSS with break, consistently points to a lack of convergence across most MENA countries. Only Morocco and Oman exhibit signs of convergence under the most flexible testing specification (FKPSS-SB), while all other countries remain divergent. This pattern is robust to both abrupt and gradual changes in risk, as well as to the inclusion of documented climate events and policy shifts.

These references are presented as contextual correlations and should not be interpreted as causal attribution. These findings contribute to a growing body of research suggesting

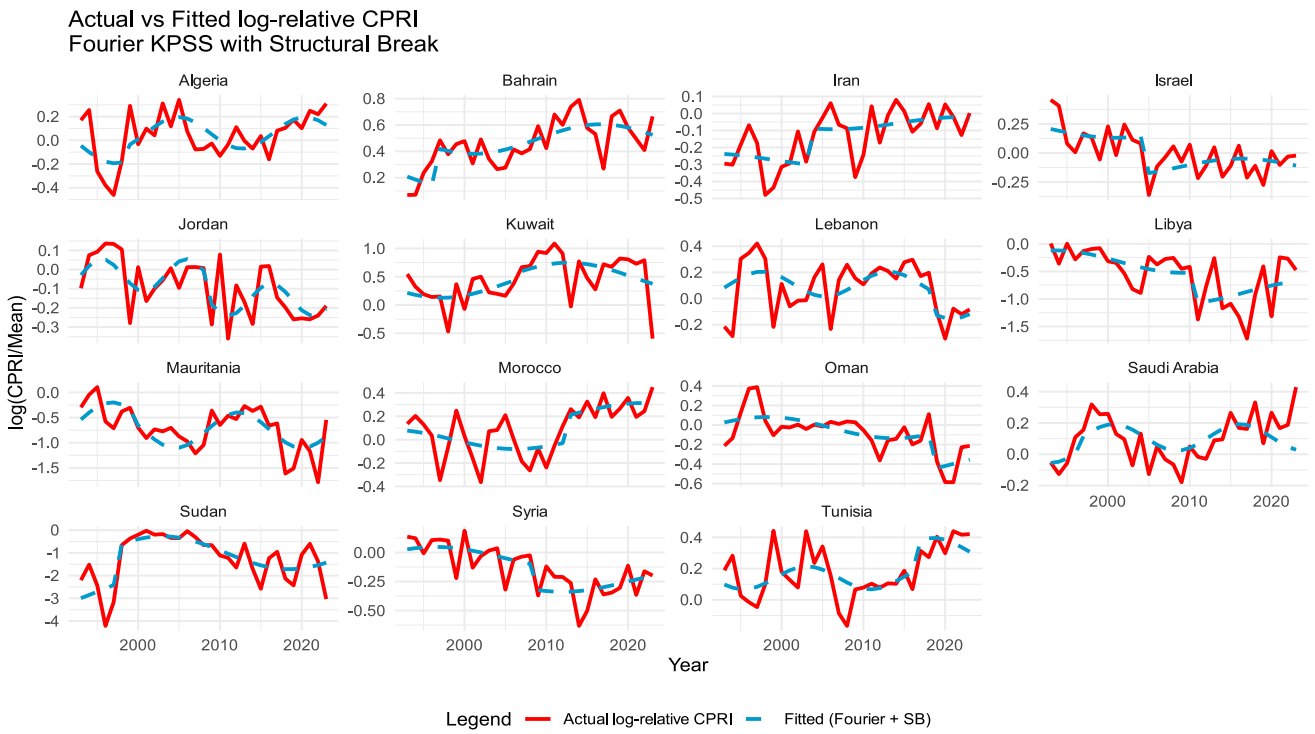


Fig. 5 Actual vs fitted log-relative CPRI—Fourier KPSS with structural breaks test

that climate risk in arid and semi-arid regions is highly path-dependent and shaped by persistent shocks, rather than exhibiting rapid mean reversion (Barbier and Hochard 2018; Guo et al. 2024; Zittis et al. 2021). In other words, the impacts of climate extremes—whether drought, heatwave, or flood—tend to have lasting effects that differentiate national risk trajectories. For example, repeated droughts in North Africa, such as those experienced in Morocco and Algeria, have long-lasting impacts on agricultural productivity, water resources, and rural livelihoods (Lelieveld et al. 2016; Tramblay and Somot 2018). Similarly, the increasing frequency and severity of heatwaves in the Arabian Peninsula amplify both physical and socio-economic vulnerability, often exceeding the adaptive capacity of local institutions (Zittis et al. 2021).

The lack of convergence in climate physical risk across the region suggests several important points. First, it highlights the uneven progress in adaptation and resilience-building across MENA countries. Countries with stronger institutions, more diversified economies, and greater investment in disaster risk reduction are better positioned to absorb and recover from climate shocks. For instance, Oman's progress toward convergence may reflect its sustained investment in water management and climate adaptation policies, as documented in recent case studies (Al-Saidi and Saliba 2019). In contrast, fragile or conflict-affected states often lack the institutional capacity and resources to mount effective responses, leading to persistent divergence (García-León et al. 2021).

Second, the results underscore the need to consider both the structural and dynamic dimensions of climate risk. While many prior studies have focused on the spatial distribution of risk, our results show that temporal persistence and regime shifts play an equally critical role. The detection of structural breaks in the CPRI series—often coinciding with major climate events or policy interventions—confirms the importance of both exogenous shocks and endogenous responses in shaping risk trajectories. For example, the break detected in Morocco in 2012 coincides with a period of multi-year drought and adaptation policy reforms, while similar breaks in Lebanon and Tunisia correspond to well-documented periods of climate extremes (Klein et al. 2015; Tramblay et al. 2020; Zittis et al. 2021).

More broadly, the results are consistent with evidence that climate hazards in MENA are rising, spatially heterogeneous, and often persistent, implying limited mean reversion in risk dynamics. The limited convergence detected (Morocco and Oman under the most flexible specification) reinforces the view that sustained adaptation investment and institutional effectiveness are central to stabilizing relative risk trajectories.

Taken together, the results of this study make a compelling case for the existence of persistent divergence in climate physical risk across the MENA region, with convergence

limited to only a minority of countries and model specifications. The finding that Morocco and Oman display convergence under the most flexible frameworks (Fourier KPSS with structural breaks) suggests that unique policy trajectories and investment in adaptation play an outsized role in shaping long-run climate risk dynamics. This conclusion is strongly supported by the comparative literature, where similar approaches—combining convergence testing with event analysis—have identified adaptation policy as a primary driver of risk equalization (Abid et al. 2015; Smit and Wandel 2006).

Importantly, the broader literature also reinforces the link between adaptation effectiveness and convergence. For example, Abid et al. (2015) demonstrated in the Tunisian context that household- and community-level adaptation strategies, coupled with national policy support, moderated the persistence of drought risk and facilitated a form of local convergence. In Morocco, the National Drought Mitigation Plan—launched in the early 2000s—has been associated with improved water management, investment in climate-resilient agriculture, and enhanced disaster preparedness (Touchan et al. 2008; World Bank Group 2018). These developments correspond closely to the break dates and convergence outcomes documented in our analysis.

In contrast, countries such as Sudan, Libya, and Syria remain trapped in cycles of risk amplification, driven by a combination of climatic volatility, institutional fragility, and political instability (De Châtel 2014; Erian et al. 2011; Nicholson 2014). These findings mirror those of Zittis et al. (2021), who found that countries with weak adaptation frameworks and fragmented governance structures were less able to contain the long-term impact of extreme events, resulting in persistent divergence from regional risk norms.

At the same time, methodological advances in convergence testing, as demonstrated in this study, offer a more nuanced lens for tracking progress toward regional risk harmonization. By sequentially applying increasingly flexible unit root and stationarity tests—including structural breaks and nonlinearities—the study provides a robust diagnostic toolkit that can be adapted to other regional or global contexts. This is in line with the recommendations by Phillips and Sul (2007) and Bai and Perron (2003), who emphasize the importance of allowing for both abrupt and gradual changes when testing for convergence in economic and environmental indicators.

Conclusions and recommendation

This study undertook a comprehensive investigation into the convergence dynamics of climate physical risk, as measured by the Climate Physical Risk Index (CPRI), among 17 countries in the Middle East and North Africa (MENA) region over the period 1993–2023. Employing a robust suite of panel stationarity and convergence tests—including the KPSS, KPSS with structural break (KPSS-SB), Fourier KPSS (FKPSS), and Fourier KPSS with structural break (FKPSS-SB)—the analysis provides new empirical insights into the evolution and persistence of climate risk in a region highly vulnerable to climate extremes, policy shocks, and broader geopolitical and economic challenges.

The primary findings of the study reveal that convergence in physical climate risk remains elusive for most MENA countries. Standard KPSS tests consistently reject the null hypothesis of stationarity for all countries at the 1% significance level, suggesting that country-specific shocks to climate risk are highly persistent and that the impacts of such shocks do not dissipate over time (Kwiatkowski et al. 1992). These findings are consistent with earlier evidence on environmental risk persistence in both MENA and other climate-sensitive regions (Timmermann et al. 2018), highlighting the inherent challenges in achieving regional convergence under conditions of escalating climate volatility.

Accounting for structural breaks—reflecting regime shifts or abrupt climate and policy events—does little to alter the core pattern of divergence. The KPSS-SB and FKPSS-SB tests continue to show that most MENA countries remain on divergent risk trajectories, even when both sudden and gradual changes are incorporated into the testing framework (Bai and Perron 2003; Becker et al. 2006). The exception to this general rule is the case of Morocco and Oman, where, under the most flexible convergence test specification (FKPSS-SB), weak evidence of convergence emerges. For these countries, shocks to climate risk appear to be less persistent, suggesting that local adaptation strategies, successful policy interventions, or unique climatic and socioeconomic conditions may be at play (Almazroui et al. 2020; Filahi et al. 2016).

The identification of specific break dates across the sample, frequently corresponding to years marked by extreme climate events (e.g., the 1998 drought in Algeria, the 2018 heatwaves in Lebanon and Oman), provides empirical support for the argument that climate shocks and abrupt policy shifts play a significant role in shaping national risk trajectories (Hubert and Mohamed 2003; Zittis et al. 2016). This reinforces recent research emphasizing the episodic and country-specific nature of vulnerability to climate extremes in MENA, with substantial heterogeneity in both risk exposure and adaptive capacity (Lelieveld et al. 2016; Sultan et al. 2019).

This study's empirical results both support and extend prior literature. Past work has found little evidence for convergence in climate risk indicators across diverse regions, including Southern Europe, North Africa, and the broader Mediterranean (Lionello and Scarascia 2018),

attributing persistent divergence to uneven exposure to climate extremes, differing institutional responses, and the slow pace of adaptation policy diffusion. By employing a combination of unit root tests sensitive to both sharp and smooth breaks, our study adds further robustness to these findings and helps pinpoint the influence of major regional events—such as the 2016 Middle Eastern heatwave (Zittis et al. 2022)—on country-specific CPRI trajectories.

Policy implications and recommendations

The persistent divergence in climate physical risk observed in this study has critical implications for both national and regional policy in the MENA context. The findings argue strongly against the effectiveness of one-size-fits-all adaptation strategies, and instead call for a multi-scalar, country-specific approach to climate risk management. Policy measures should be sensitive to both the acute and chronic nature of climate shocks, as well as to the unique vulnerabilities and adaptive capacities that characterize each national context (Filahi et al. 2016; Sultan et al. 2019).

For countries like Morocco and Oman, where tentative evidence for convergence exists, continued investment in adaptive capacity, risk reduction, and evidence-based policy innovation should be prioritized. These countries may serve as regional exemplars of best practice, with lessons transferable to similarly situated nations within and beyond the MENA region.

For the majority of countries where divergence remains the norm, there is a clear need for enhanced regional cooperation, knowledge sharing, and technical assistance in the design and implementation of adaptation and mitigation measures. Initiatives such as the Arab Framework of Climate Change Adaptation, supported by multilateral donors and UN agencies, may help bridge gaps in capacity and foster the institutional learning required to accelerate progress toward convergence (Lelieveld et al. 2016).

More specifically, this research recommends:

1. **Country-specific adaptation planning**: Develop national climate risk adaptation plans that address unique exposure profiles, socio-economic conditions, and governance structures.
2. **Enhanced regional data sharing and climate services**: Strengthen regional observatories and climate service platforms to enable timely dissemination of risk information and best practices.
3. **Targeted investment in early-warning systems**: Prioritize investment in climate early warning and disaster risk reduction infrastructure, especially in high-risk countries identified as persistent divergers.
4. **Policy experimentation and learning**: Promote pilot projects and policy experimentation in countries showing convergence, as a mechanism for adaptive learning and policy transfer.

Limitations and future directions

While this study employs the most recent and robust statistical methodologies available, several limitations must be acknowledged. First, the CPRI is an aggregate indicator and may not capture all relevant dimensions of climate risk (Guo et al. 2024). Second, data constraints, especially in conflict-affected and data-sparse environments (e.g., Syria, Libya), limit the temporal and spatial resolution of the analysis. Third, the study does not fully explore the subnational variation in risk or the role of informal adaptation mechanisms, which may be crucial in settings where formal institutions are weak.

Future research should extend the analysis by incorporating a wider range of risk indicators, including those capturing sectoral (e.g., agricultural, urban, health) vulnerabilities, and by integrating subnational and high-frequency data as it becomes available. Further, more explicit linkage of convergence analysis with the evaluation of adaptation policies and institutional performance will be necessary to translate empirical findings into actionable policy advice.

Also, future research could explicitly compare the convergence/divergence patterns in CPRI with each country's UNFCCC Nationally Determined Contributions (NDCs) and, where available, National Adaptation Plans (NAPs), to assess whether stated adaptation priorities and financing needs align with observed risk dynamics. Such mapping could help distinguish whether convergence reflects shared exposure trends versus differences in planned adaptation pathways.

Author contributions M.K: Conceptualization; data curation; methodology; software; formal analysis; visualization; investigation; writing – original draft; writing – review & editing; project administration. V.Y: Writing – review & editing; response to reviewers (revision-stage contribution).

Funding Open access funding provided by the Scientific and Technological Research Council of Türkiye (TÜBİTAK). Çanakkale Onsekiz Mart University – Scientific Research Projects Coordination Unit (BAP/BAPSIS),SBA-2025-5237.

Data availability The data is will be made available upon reaseonable request.

Declarations

Competing interests The authors declare no competing interests.

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References

Abid M, Scheffran J, Schneider UA, Ashfaq M (2015) Farmers' perceptions of and adaptation strategies to climate change and their determinants: the case of Punjab province, Pakistan. Earth Syst Dyn 6(1):225–243. https://doi.org/10.5194/esd-6-225-2015

Abumoghli I, Goncalves A (2019) Environmental challenges in the MENA Region. In Environmental challenges in the MENA Region. United Nations Environment Programme. https://doi.org/10.2307/j.ctvnjbg08

Adger WN (2006) Vulnerability. Glob Environ Chang 16(3):268–281

Almazroui M, Saeed S (2020) Contribution of extreme daily precipitation to total rainfall over the Arabian Peninsula. Atmos Res 231:104672. https://doi.org/10.1016/j.atmosres.2019.104672

Almazroui M, Islam MN, Saeed S, Saeed F, Ismail M (2020) Future changes in climate over the Arabian Peninsula based on CMIP6 multimodel simulations. Earth Syst Environ 4(4):611–630. https://doi.org/10.1007/s41748-020-00183-5

Al-Saidi M, Saliba S (2019) Water, energy and food supply security in the Gulf Cooperation Council (GCC) countries-a risk perspective. Water 11(3):455. https://doi.org/10.3390/w11030455

Bai J, Perron P (2003) Computation and analysis of multiple structural change models. J Appl Econom 18(1):1–22. https://doi.org/10.1002/jae.659

Barbier EB, Hochard JP (2018) Land degradation and poverty. Nat Sustain 1(11):623–631. https://doi.org/10.1038/s41893-018-0155-4

Barro RJ, Sala-i-Martin X (1992) Convergence. J Polit Econ 100(2):223–251

Becker R, Enders W, Lee J (2006) A stationarity test in the presence of an unknown number of smooth breaks. J Time Ser Anal 27(3):381–409. https://doi.org/10.1111/j.1467-9892.2006.00478.x

Birkmann J, von Teichman K (2010) Integrating disaster risk reduction and climate change adaptation: key challenges-scales, knowledge, and norms. Sustain Sci 5(2):171–184. https://doi.org/10.1007/s11625-010-0108-y

Carlino GA, Mills LO (1993) Are U.S. regional incomes converging? A time series analysis. J Monet Econ 32(2):335–346. https://doi.org/10.1016/0304-3932(93)90009-5

De Châtel F (2014) The role of drought and climate change in the Syrian Uprising: untangling the triggers of the revolution. Middle East Stud 50(4):521–535. https://doi.org/10.1080/00263206.2013.850076

Elasha BO (2012) Mapping of climate change threats and human development impacts in the Arab Region. UNDP Arab Development Report--Research Paper Series, UNDP Regiona Bureau for the Arab States, p 471

Enders W, Lee J (2012) A unit root test using a fourier series to approximate smooth breaks. Oxf Bull Econ Stat 74(4):574–599. https://doi.org/10.1111/j.1468-0084.2011.00662.x

Erian W, Katlan B, Babah O (2011) Drought vulnerability in the Arab Region. Global Assessment Report on Disaster Risk Reduction

Ezcurra R (2007) Is there cross-country convergence in carbon dioxide emissions? Energy Policy 35(2):1363–1372. https://doi.org/10.1016/j.enpol.2006.04.006

Filahi S, Tanarhte M, Mouhir L, El Morhit M, Tramblay Y (2016) Trends in indices of daily temperature and precipitations extremes in Morocco. Theor Appl Climatol 124(3–4):959–972. https://doi.org/10.1007/s00704-015-1472-4

Furuoka F (2017) A new approach to testing unemployment hysteresis. Empir Econ 53(3):1253–1280. https://doi.org/10.1007/s00181-016-1164-7

García-León D, Standardi G, Staccione A (2021) An integrated approach for the estimation of agricultural drought costs. Land Use Policy 100:104923. https://doi.org/10.1016/j.landusepol.2020.104923

Gleick PH (2014) Water, drought, climate change, and conflict in Syria. Weather Clim Soc 6(3):331

Grasso M, Feola G (2012) Mediterranean agriculture under climate change: adaptive capacity, adaptation, and ethics. Reg Environ Change 12(3):607–618. https://doi.org/10.1007/s10113-011-0274-1

Guo K, Ji Q, Zhang D (2024) A dataset to measure global climate physical risk. Data Brief 54:110502. https://doi.org/10.1016/j.dib.2024.110502

Hochman A, Marra F, Messori G, Pinto JG, Raveh-Rubin S, Yosef Y, Zittis G (2022) Extreme weather and societal impacts in the eastern Mediterranean. Earth Syst Dynam 13(2):749–777. https://doi.org/10.5194/esd-13-749-2022

Hubert P, Mohamed M (2003) Impact de la modification du régime pluviométrique sur les ressources en eau du nord-ouest de l'Algérie. Hydrology of Die Mediterranean and Semiarid Regions (Proceedings of an International Symposium Held at Montpellier, April 2003). IAHS Publ. No. 278, 278, 229–235

Karamperidou C, Stuecker MF, Timmermann A, Yun KS, Lee SS, Jin FF, Santoso A, McPhaden MJ, Cai W (2020) ENSO in a changing climate: challenges, paleo-perspectives, and outlook. Geophys Monogr Ser 253:471–484. https://doi.org/10.1002/9781119548164.ch21

Kelley CP, Mohtadi S, Cane MA, Seager R, Kushnir Y (2015) Climate change in the Fertile Crescent and implications of the recent Syrian drought. Proc Natl Acad Sci U S A 112(11):3241–3246. https://doi.org/10.1073/pnas.1421533112

Klein RJT, Midgley G, Preston BL, Alam M, Berkhout F, et al (2015) Adaptation opportunities, constraints, and limits. In: Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change (p. 899). Cambridge: Cambridge University Press

Kongkuah M, Alessa N (2025) Renewable Energy and Carbon Intensity : Global Evidence from 184 Countries (2000–2020). Energies, pp 1–29. https://doi.org/10.3390/en18133236

Kurozumi E (2002) Testing for stationarity with a break. J Econom 108(1):63–99. https://doi.org/10.1016/S0304-4076(01)00106-3

Kwiatkowski D, Phillips PCB, Schmidt P, Shin Y (1992) Testing the null hypothesis of stationarity against the alternative of a unit root. How sure are we that economic time series have a unit root? J Econometrics 54(1–3):159–178. https://doi.org/10.1016/0304-4076(92)90104-Y

Legg S (2021) Climate change 2021—the physical science basis. Chem Int 43(4):22–23. https://doi.org/10.1515/ci-2021-0407

Lelieveld J, Proestos Y, Hadjinicolaou P, Tanarhte M, Tyrlis E, Zittis G (2016) Strongly increasing heat extremes in the Middle East and North Africa (MENA) in the 21st century. Clim Chang 137(1–2):245–260. https://doi.org/10.1007/s10584-016-1665-6

Lionello P, Scarascia L (2018) The relation between climate change in the Mediterranean region and global warming. Reg Environ Change 18(5):1481–1493. https://doi.org/10.1007/s10113-018-1290-1

Maddala GS, Kim I-M (1999) Unit roots, cointegration, and structural change. Cambridge University Press

Nicholson SE (2014) The predictability of rainfall over the greater horn of Africa. Part I: prediction of seasonal rainfall. J Hydrometeorol 15(3):1011–1027. https://doi.org/10.1175/JHM-D-13-062.1

Phillips PCB, Sul D (2007) Convergence in heterogeneous panels: a new econometric method with applications to growth convergence. J Appl Econom 22(2):265–312

Qi R, Jones DL, Li Z, Liu Q, Yan C (2020) Behavior of microplastics and plastic film residues in the soil environment: a critical review. Sci Total Environ 703:134722. https://doi.org/10.1016/j.scitotenv.2019.134722

R Core Team (2025). R: a language and environment for statistical computing. https://www.R-project.org/

Schilling J, Scheffran J (2012) On rains, raids and relations: A multimethod approach to climate change, vulnerability, adaptation and violent conflict in Northern Africa and Kenya. Universität Hamburg Hamburg

Smit B, Wandel J (2006) Adaptation, adaptive capacity and vulnerability. Glob Environ Change 16(3):282–292. https://doi.org/10.1016/j.gloenvcha.2006.03.008

Stern DI (2023) The environmental Kuznets curve. Elgar Encyclopedia of Ecological Economics 19:237–240. https://doi.org/10.4337/9781802200416.ch39

Sultan B, Gaetani M (2016) Agriculture in West Africa in the twenty-first century: climate change and impacts scenarios, and potential for adaptation. Front Plant Sci 7:1262. https://doi.org/10.3389/fpls.2016.01262

Sultan B, Defrance D, Iizumi T (2019) Evidence of crop production losses in West Africa due to historical global warming in two crop models. Sci Rep. https://doi.org/10.1038/s41598-019-49167-0

Timmermann A, An SI, Kug JS, Jin FF, Cai W et al (2018) El Niño–Southern oscillation complexity. Nature 559(7715):535–545. https://doi.org/10.1038/s41586-018-0252-6

Touchan R, Anchukaitis KJ, Meko DM, Attalah S, Baisan C, et al (2008) Long term context for recent drought in Northwestern Africa. Geophys Res Lett 35(13). https://doi.org/10.1029/2008GL034264

Tramblay Y, Somot S (2018) Future evolution of extreme precipitation in the Mediterranean. Clim Change 151(2):289–302. https://doi.org/10.1007/s10584-018-2300-5

Tramblay Y, Koutroulis A, Samaniego L, Vicente-Serrano SM, Volaire F, Boone A, Le Page M, Llasat MC, Albergel C, Burak S, Cailleret M, Kalin KC, Davi H, Dupuy JL, Greve P, Grillakis M, Hanich L, Jarlan L, Martin-StPaul N, Martínez-Vilalta J, Mouillot F, Pulido-Velazquez D, Quintana-Seguí P, Renard D, Turco M, Türkeş M, Trigo R, Vidal J-P, Vilagrosa A, Zribi M, Polcher J (2020) Challenges for drought assessment in the Mediterranean region under future climate scenarios. Earth-Sci Rev 210:103348. https://doi.org/10.1016/j.earscirev.2020.103348

World Bank Group (2018) Beyond scarcity: water security in the Middle East and North Africa. In Beyond scarcity: water security in the Middle East and North Africa. https://doi.org/10.1596/978-1-4648-1144-9

Wu C, Deng H, Zhao H, Xia Q (2025) Spatiotemporal evolution and convergence patterns of urban carbon emission efficiency in China. Humanit Soc Sci Commun 12(1):1–13. https://doi.org/10.1057/s41599-025-04916-7

Yilanci V, Abbas S (2023) Does the frequency of stochastic convergence in per capita ecological footprint matter? Environ Sci Pollut Res 30(21):59676–59688. https://doi.org/10.1007/s11356-023-26688-w

Zittis G, Hadjinicolaou P, Fnais M, Lelieveld J (2016) Projected changes in heat wave characteristics in the eastern Mediterranean and the Middle East. Reg Environ Change 16(7):1863–1876. https://doi.org/10.1007/s10113-014-0753-2

Zittis G, Hadjinicolaou P, Almazroui M, Bucchignani E, Driouech F, El Rhaz K, Kurnaz L, Nikulin G, Ntoumos A, Ozturk T, Proestos Y, Stenchikov G, Zaaboul R, Lelieveld J (2021) Business-as-usual will lead to super and ultra-extreme heatwaves in the Middle East and North Africa. Npj Clim Atmos Sci. https://doi.org/10.1038/s41612-021-00178-7

Zittis G, Almazroui M, Alpert P, Ciais P, Cramer W et al (2022) Climate change and weather extremes in the Eastern Mediterranean and Middle East. Rev Geophys 60(3):e2021RG000762. https://doi.org/10.1029/2021RG000762

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