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Women's empowerment and climate resilience: global evidence

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Despite sustained global economic growth, climate change remains a critical challenge. As global energy demand is projected to rise by about 43% between 2020 and 2035, the question of how to reduce climate vulnerability and strengthen climate readiness remains urgent. Thus, the question, of how to mitigate the adverse climate impacts is of paramount importance. This study investigates whether empowering women can reduce climate vulnerability, and enhance nations' resilience, readiness and adaptability to climate change. Using panel data from 185 countries (1995–2022), we measure climate vulnerability and readiness through the ND-GAIN vulnerability and readiness indices and capture women's empowerment via three core indicators: women's labour force participation, the "Women, Business and the Law" index, and the women's political empowerment index. A series of advanced estimation techniques provide consistent evidence of a positive link between women's empowerment and climate outcomes. Specifically, a 1% rise in women's labour force share is associated with up to a 0.11% reduction in climate vulnerability, while enhancing resilience by 0.08–0.35%. Improvement in the "Women, Business and the Law" indicator reduces vulnerability by up to 0.17% and increases readiness by 0.05 to 0.2 %. Notably, women's political empowerment is found to have the strongest effect, decreasing vulnerability by 0.02–0.2% and boosting readiness by up to 41% across specifications. The relationships are statistically significant at 1–10% levels. Local Projections confirm that these impacts persist in both the short and long run. We further develop a theoretical framework (and empirically test it) that systematically links women's empowerment to climate resilience through well-defined mechanisms and sub-mechanisms, for enhanced understanding of the subject.

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Introduction

"Climate change is a man-made problem with a feminist solution."

- Mary Robinson

(Former President of Ireland and UN High Commissioner for Human Rights)

Climate change presents mounting threats to societies worldwide (Sachan and SenGupta 2026; Fankhauser and Tol 2005; SenGupta and Atal 2026, 2024; Steininger et al. 2015; Tol 2009), with both the frequency of extreme events and average temperatures rising sharply (Figs. 1 and 2). While women experience these impacts more acutely, owing to social roles, resource constraints and governance gaps (Fig. 3), their potential as agents of resilience remains under-utilised. In particular, empowering women economically and politically can unlock three key mechanisms for climate resilience: inclusive governance that amplifies diverse perspectives, equitable resource allocation that targets the most vulnerable, and socially responsive policy-making that embeds gender-sensitive adaptation measures (Alston 2013; Gaard 2015; Pearse 2017).

Against this backdrop, we ask: *Does multidimensional women's empowerment—labour force participation (WLFP), entrepreneurial opportunity (WBUS) and political representation (WPOL)—reduce national climate vulnerability and enhance readiness?* To answer this, we construct a global panel of up to 185 countries over 1995–2022, using the NDGAIN Vulnerability (VUL) and Readiness (READ) indices as our outcomes. We apply Fully Modified OLS and Panel DOLS to capture long-run equilibria, while Driscoll–Kraay, PCSE, FGLS, and panel quantile regressions address cross-sectional dependence, heteroskedasticity, and serial correlation. We further deploy a two-step System GMM to guard against endogeneity and local projections to illustrate impulse responses.

We find that all three dimensions of empowerment are associated with lower vulnerability and higher readiness, with political empowerment exhibiting the largest effect. These results hold across estimators and error-correction schemes, indicating that the findings are not an artefact of any single modelling choice. Our study goes beyond prior work that focuses narrowly on emissions or specific regions by using the ND-GAIN indices to capture both environmental exposure and socio-economic capacity, thereby offering a more complete view of climate resilience across 185 countries (Table A2.1 in the Appendix) from 1995 to 2022.

In this broader context, our study complements earlier cross-country evidence, including Asongu et al. (2022), while extending it in scope and method. We analyse both ND-GAIN Vulnerability and Readiness, cover a longer period and a larger sample, and broaden empowerment beyond politics to include labour-force participation and the Women, Business and the Law index. Methodologically, we account for cross-sectional dependence and outliers, estimate long-run cointegrating relationships with FMOLS and PDOLS, address dynamic endogeneity with two-step System GMM, and trace the evolution of effects using local projections. Another important contribution is the integrated theoretical framework that we developed to link empowerment mechanisms to climate outcomes. This framework, together with the accompanying empirical analysis, structures and guides the empirical investigation.

The remainder of the paper is organised as follows. Section "An overview of the global climate scenario" presents stylised climate facts; Section "Literature review" reviews theoretical and empirical antecedents; Section "Empirical framework" describes our data and econometric strategy; and Section "Conclusion" discusses implications and avenues for future research.

An overview of the global climate scenario

This section offers a concise examination of the current global climate situation by looking at greenhouse gas (GHG) and carbon emissions, temperature trends, policy targets, and energy patterns. Figure 4 shows that total global GHG and carbon dioxide emissions, as well as per capita emissions, have risen markedly over the past few decades. Overall emissions have grown in tandem with industrial activities and increasing energy consumption. Per capita carbon emissions have similarly increased, whereas per capita GHG emissions appear to have levelled off at a high baseline that still contributes significantly to global warming.

Figure 5 illustrates how temperatures have evolved globally from 1850 to 2024, alongside more detailed data on global surface temperatures from the 1940s to the 2020s. These long-term records emphasise a pronounced warming trend, particularly accelerating in the latter half of the twentieth century. Figure 6 provides a monthly perspective on temperature anomalies from 1940 to 2024, indicating that, in recent years, virtually every month has registered above-average temperatures.

Turning to policy measures, Fig. 7 portrays the status of net-zero carbon emissions targets across the world as of 2022. Only a minority of countries have achieved or legally enshrined such goals, while most nations remain at the proposal or policy-document stage. This distribution shows that global commitments to cutting emissions vary considerably, highlighting the need for more robust and enforceable strategies that drive meaningful emissions reductions.

We further project that global energy demand will reach around 0.565 million Petajoules by 2035 (see Fig. 8), which is a 43% increase approximately from 2020[1]. Growing populations and economic expansion in developing regions are key drivers of this trend. Since electricity demand constitutes one of the major components of overall energy demand, Fig. 9 presents data on the global electricity market from 1990 to 2022. Electricity consumption has climbed consistently, outpacing the growth rate of renewable energy's share in power generation (Fig. 9a, b). Although the contribution of renewable sources to electricity production has increased from 26.39% in 2019 to 29.83% in 2022, fossil-based energy continues to dominate the electricity mix (Fig. 9c). Finally, Fig. 10 depicts the composition of the global energy market. Despite incremental gains in renewable energy production capacity, consumption has historically lagged behind, with non-renewable sources still dominating overall energy use. This

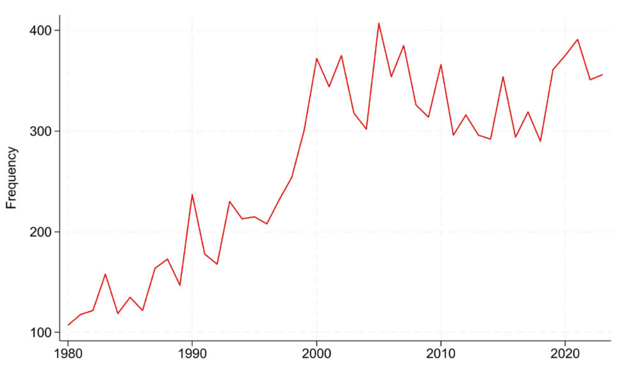

Fig. 1 Global climate-related disasters frequency, 1980–2023. Source: EM-DAT, CRED, UCLouvain. Disasters include drought, extreme temperature, flood, landslide, storm and wildfire.

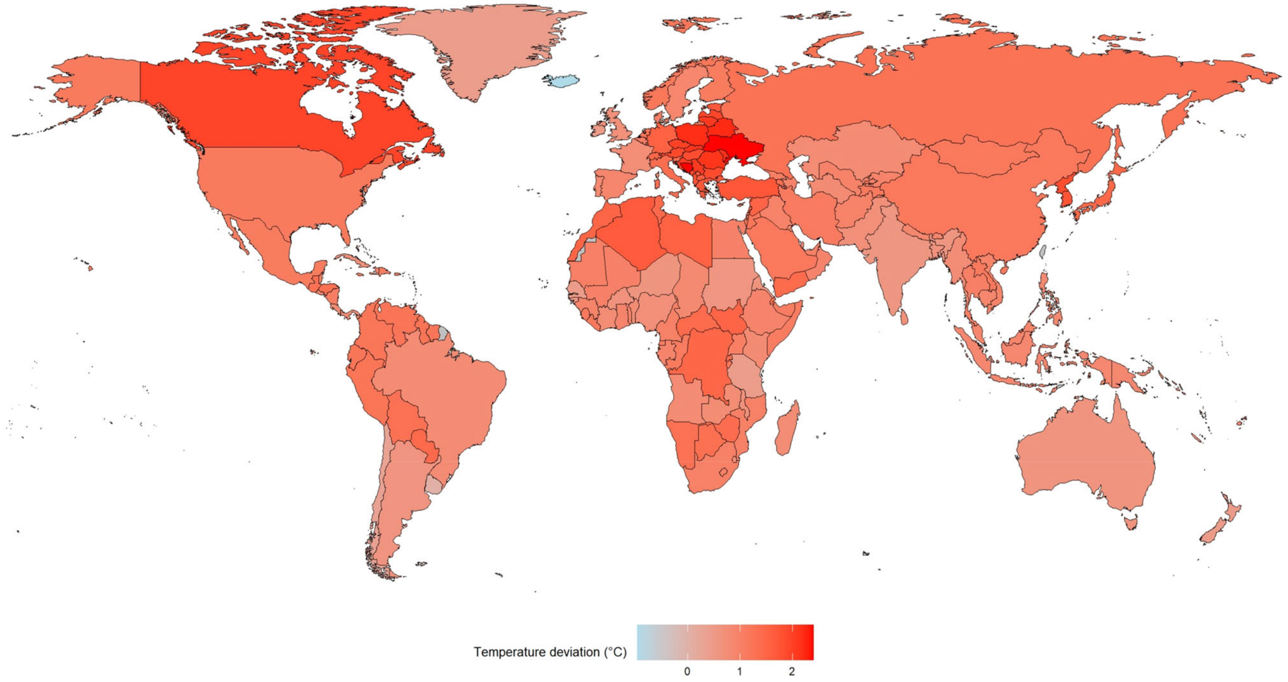

Fig. 2 Annual temperature anomalies, 2024. Source: Copernicus Climate Change Service; Our World in Data. Deviation of each year's surface temperature from the 1991–2020 mean.

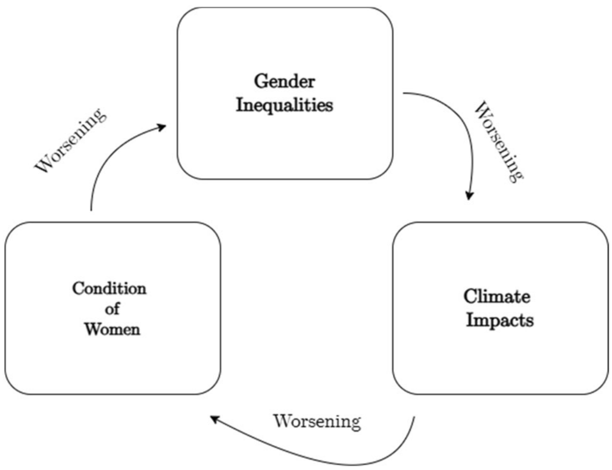

Fig. 3 Mechanisms linking women's empowerment to climate resilience. The diagram shows a reinforcing cycle in which poorer conditions for women increase gender inequalities, which can worsen climate impacts; these impacts can in turn further weaken women's conditions and deepen existing inequalities.

highlights the significant scope for improvement, which could greatly contribute to environmental sustainability.

These findings, considered together, point to the urgency of bridging the gap between emission-reduction goals and actual energy trends. The next sections will link these patterns to the concept of women's empowerment, illustrating how inclusive strategies can help tackle climate challenges effectively.

Literature review

Theoretical review. Ecofeminism theory highlights a connection between the oppression of women and the exploitation of natural resources. It suggests that patriarchal values and norms, which have shaped civilisations, have also influenced how humans interact with the environment (Murphy 2022). Women, particularly in developing countries, are often the first to identify and report environmental issues, given their frequent interaction with the ecosystem for resource collection. This further emphasises the status of women as more capable environmental stewards (Currea and Huus-Hansen, 2018; Zanotti and Suiseeya 2020). Ecofeminism also provides a unique viewpoint on the intersection of women's rights and environmental degradation, asserting that women have a distinctive ability to address and combat environmental challenges (Barthold et al. 2022; Haas 2010).

Literature indicates that gender influences perceptions and behaviours regarding environmental issues, with women generally showing greater environmental awareness and a higher likelihood of engaging in pro-environmental actions compared to men (Berger and Wyss 2021; Blankenberg and Alhusen 2019; Echavarren 2023; Hailemariam et al. 2023; Zelezny et al. 2000). Two primary hypotheses explain this pattern:

The *gender socialisation hypothesis* suggests that women are conditioned to be more nurturing, cooperative, and caring than men, leading them to display altruistic behaviours toward both people and the environment (Arnocky and Stroink 2010; Chodorow 1978; Gilligan 1993; Liu et al. 2019; Stern et al. 1993; Stern and Dietz 1994). It assumes a broadly uniform norm of female caregiving across cultures, though in practice this socialisation may vary with local customs, economic necessity and changing social roles. Tisserand et al. (2022) further claim that these traits enable women to perceive the environment differently than men (Fortnam et al. 2019) and lead them to contribute more frequently to sustainable resource use.

The *safety concern hypothesis* highlights gender differences in perceptions of safety, risk and health (Brown et al. 2021; Dietz et al. 2002; Hitchcock 2001; Xiao and McCright 2012). Women, often socialised to prioritise caregiving roles, tend to place greater importance on the health and safety of their families and communities (Blocker and Eckberg 1997; Davidson and Freudenburg 1996; Freudenburg and Davidson 2007; Guberman et al. 1992; Ruiz and Nicola´s 2018; WHO 2010). This hypothesis presumes that women's risk aversion is principally shaped by

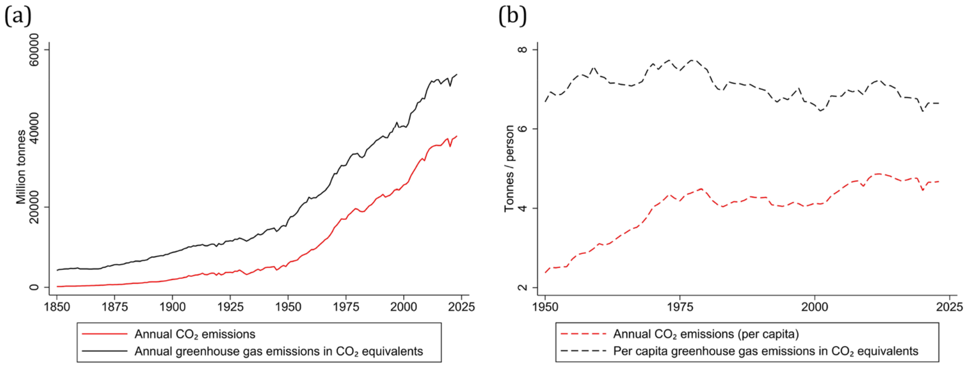

Fig. 4 Global greenhouse gas and carbon emissions. a Annual global CO_2 and greenhouse gas emissions, 1850–2023, measured in million tonnes. **b** Per capita CO_2 and greenhouse gas emissions, 1950–2023, measured in tonnes per person. Red lines indicate CO_2 emissions; black lines indicate greenhouse gas emissions in CO_2 equivalents. Source: Global Carbon Budget; Jones et al. (2023); Our World in Data.

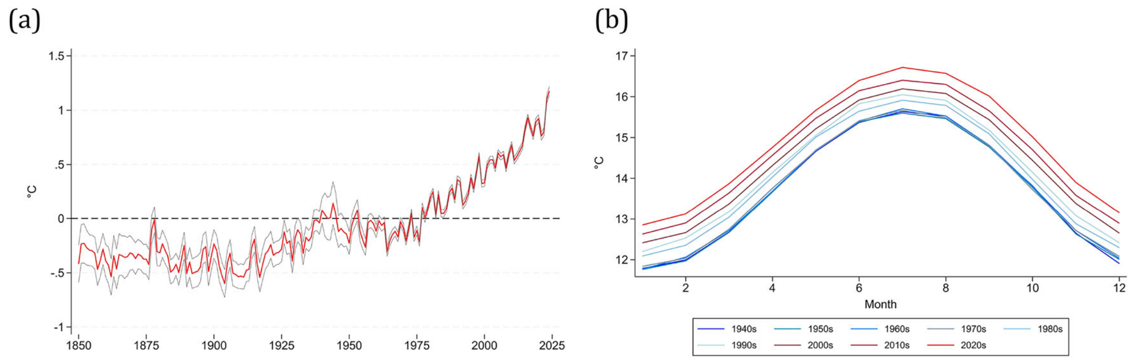

Fig. 5 Global temperature evolution. a Yearly global land-sea temperature anomalies, 1850–2024, relative to the 1961–1990 baseline; grey lines show the 95% confidence interval. **b** Monthly global surface temperature by decade, from the 1940s to the 2020s. Source: Met Office Hadley Centre; Copernicus Climate Change Service; Our World in Data.

Fig. 6 Global temperature anomalies, 1940–2024. Source: Copernicus Climate Change Service; Our World in Data. The deviation in a specific month's average surface temperature from the mean temperature of the same month during the period 1991–2020.

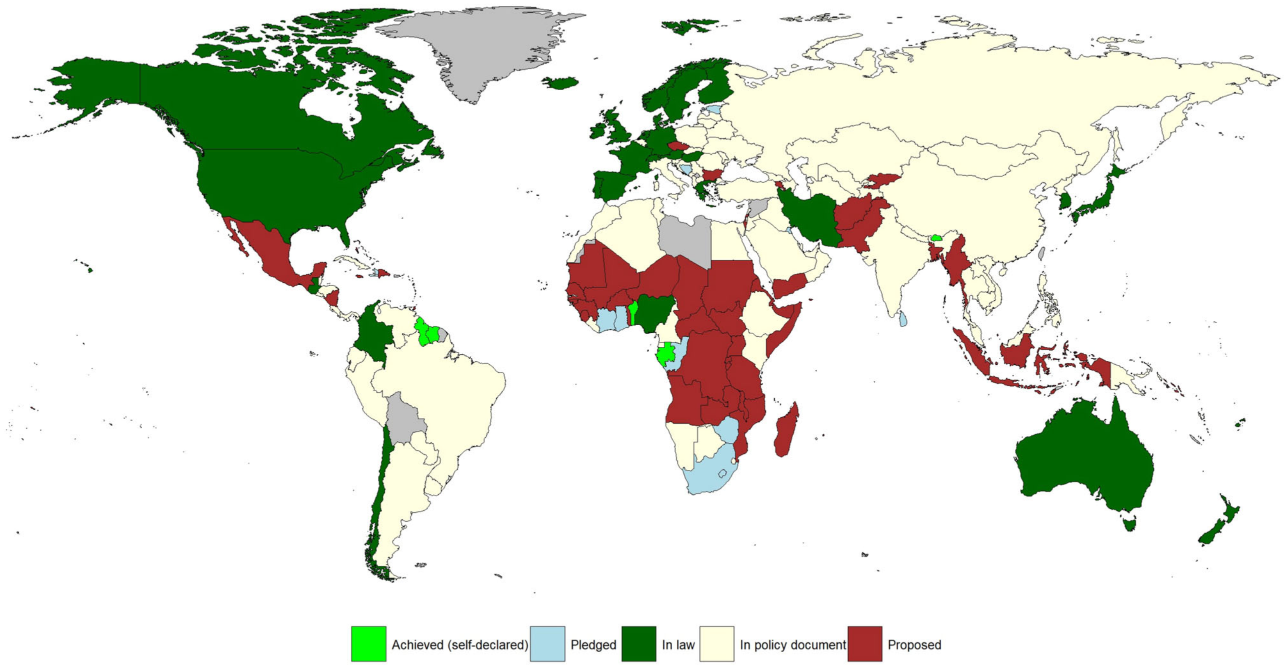

Fig. 7 Status of net-zero carbon emissions target, 2022. Source: Energy and Climate Intelligence Unit, Data-Driven EnviroLab, New Climate Institute, Oxford Net Zero - Net Zero Tracker.

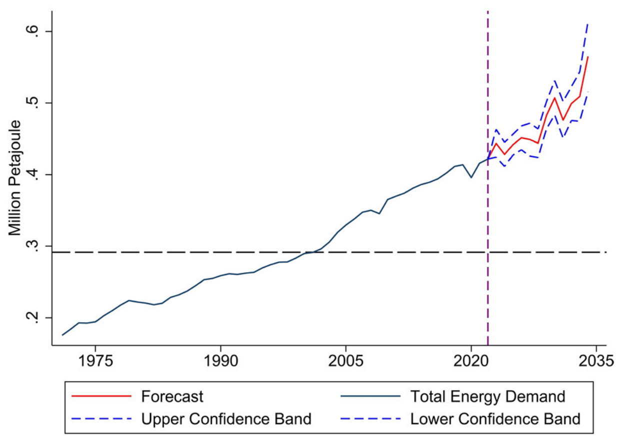

Fig. 8 Global energy demand forecast, 1971–2035. Source: International Energy Agency (IEA)—World Energy Balances; authors' calculations. The horizontal dashed line is the average energy demand (approximately 0.2913 million PJ) from 1971 to 2022.

these roles, but institutional contexts and socioeconomic status can moderate their concerns. Greenbaum (1995) and Khramtsova et al. (2019) show that such socialisation heightens women's attention to long-term health and safety, driving stronger engagement with environmental protection.

It is therefore evident that women, by virtue of these socialised traits and societal constructs, are positioned as vital agents in addressing environmental crises. Integrating empowerment into this equation serves as a powerful catalyst, harnessing and optimising their potential to drive sustainable solutions. To operationalise these ideas, we adopt the framework of Sundstro¨m et al. (2017), who capture the three most prominent strands of empowerment—*choice*, *agency* and *participation*:

(1) Choice: the capacity of individuals to make meaningful decisions in crucial areas of their lives.
(2) Agency: the autonomy and power an individual has to shape their own life, decisions and actions.
(3) Participation: active involvement in formal and informal structures where women can voice concerns, contribute ideas and influence outcomes.

Developing the framework. Building on the theoretical frameworks, we explore how women's empowerment impacts climate change outcomes by focusing on key indicators: women's labour force participation, political empowerment, and the 'Women, Business and Law' index. These carefully selected indicators, each aligning with the three dimensions of empowerment, offer a concrete way to assess how women's involvement in the socio-economic and political spheres influences environmental action.

Let's first discuss how each of our selected indicators captures the three elements of empowerment. (1) Women's labour force participation not only reflects *choice* in terms of the freedom to enter the workforce and autonomy in terms of making socio-economic decisions, but it also demonstrates *agency* by enabling women to shape their own economic roles. Concurrently, it embodies *participation* by acknowledging women's inclusion in broader societal and economic structures. (2) Political empowerment connects with *agency* as it provides women with the autonomy to influence policy decisions, including those related to climate change. It supports *participation* by ensuring women's active involvement in governance and decision-making. It also ties to *choice* by giving women the opportunity to choose leaders and policies that reflect their values and concerns. (3) The Women, Business, and Law Index was selected because it systematically measures the extent to which legal frameworks support or hinder women's economic opportunities, thus simultaneously capturing all three strands of empowerment. This index specifically examines legal constraints and rights that affect women's capacity to make independent economic decisions in business and workplace (*choice*), their ability to exercise power over personal and professional life choices (*agency*), and their entitlement to participate equally in market and civic domains

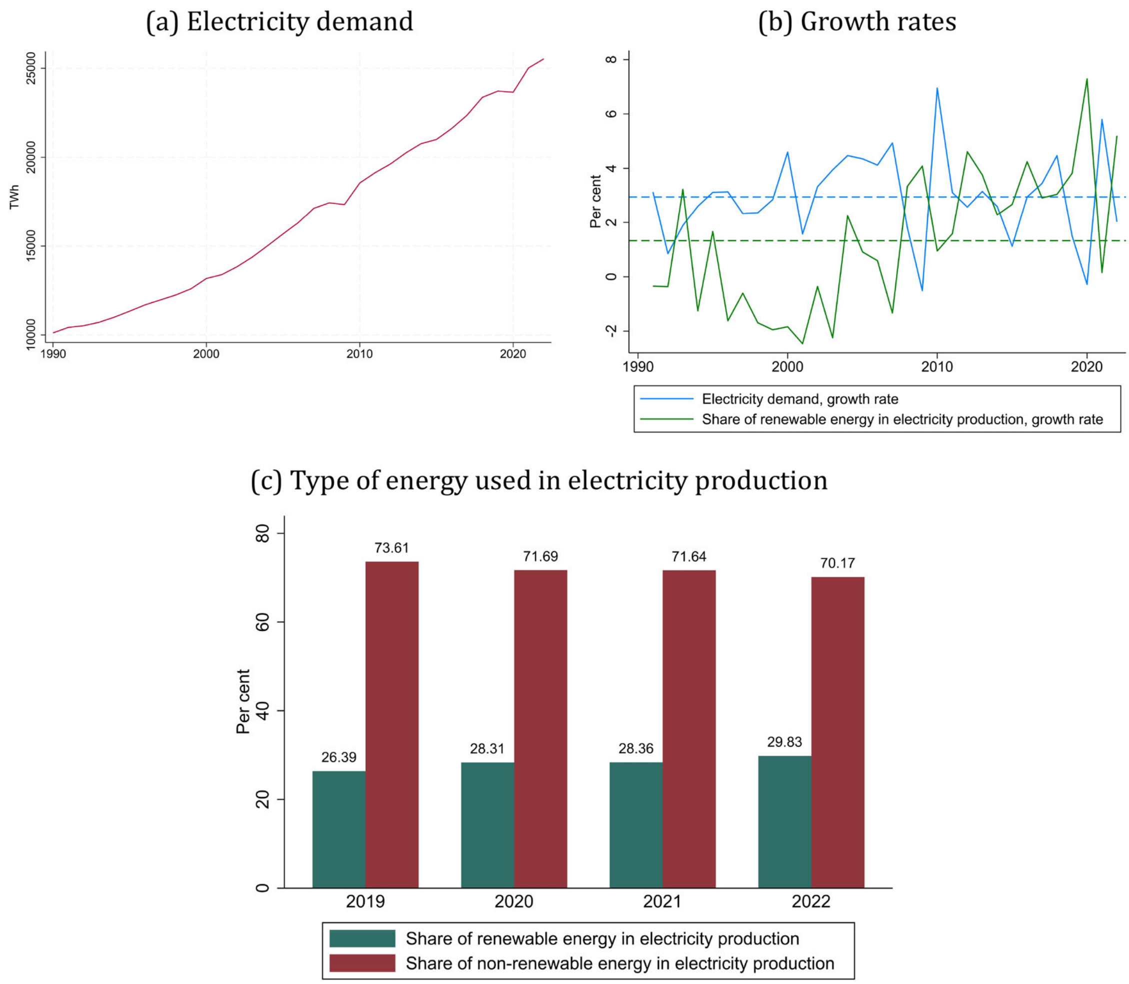

Fig. 9 Global electricity market, 1990–2022. a Global electricity demand, measured in TWh. **b** Growth rates of electricity demand and the renewable share in electricity production; horizontal dashed lines show the observed averages of the corresponding series. **c** Renewable and non-renewable shares in electricity production, 2019–2022. Source: Enerdata; authors' calculations.

(*participation*). Given that legal empowerment is essential for translating broader social, economic, and political gains into tangible outcomes, this particular index aligns especially well with the multidimensional view of empowerment presented here.

Summarising the diverse literature, we identify three primary mechanisms—*economic freedom*, *institutional integrity*, and *care and empathy orientations*—and four sub-mechanisms through which women's empowerment reduces climate vulnerability and enhances readiness (see Fig. 11).

The first primary mechanism, *economic freedom*, arises when women's greater labour market engagement and supportive legal frameworks enable independent socioeconomic decisions. This, in turn, leads to *better wealth management*—women allocate resources toward sustainable investments and technologies (Pan et al. 2020).

The second mechanism, *institutional integrity*, merges safety and security priorities with reduction in corruption into a unified concept reflecting robust rule-of-law and transparent governance[2]. Women's safety concerns—rooted in socialisation that primes them to prioritise family and community welfare—translate into greater advocacy for public spending on education and health, investments that indirectly bolster climate resilience by strengthening human capital and adaptive capacity (Dahlum et al. 2022; Rustagi and Akter 2022; Tadadjeu et al. 2021; Bitoto and Ongo 2024; Halim et al. 2016).

At the same time, empirical evidence indicates that women's heightened risk aversion and ethical governance preferences lead to reductions in corrupt practices, ensuring that climate finance and disaster-response resources are allocated transparently and equitably (Dollar et al. 2001; Esarey and Schwindt-Bayer 2018; Rios et al. 2023). The combined effect of these safety-driven investments and improved accountability yields greener choices, as empowered women champion stricter environmental protections and resource-efficient policies (Blankenberg and Alhusen 2019; Buenstorf and Cordes 2008), and drives the adoption of more effective climate legislation and disaster-preparedness measures, thus markedly reducing vulnerability and enhancing readiness (Mavisakalyan and Tarverdi 2019).

The third mechanism, *care and empathy orientations*, reflects women's socialised focus on collective well-being. This drives both *greener choices* and *increased education and health spending*, while also underpinning *improved governance and climate policies* through socially conscious decision-making that emphasises long-term outcomes.

The theoretical framework has been empirically tested in Appendix A1 (Tables A1.1–A1.5).

Empirical literature review. A few empirical analyses exist that complement the theoretical understanding. The empirical literature on women's empowerment and climate change relationship

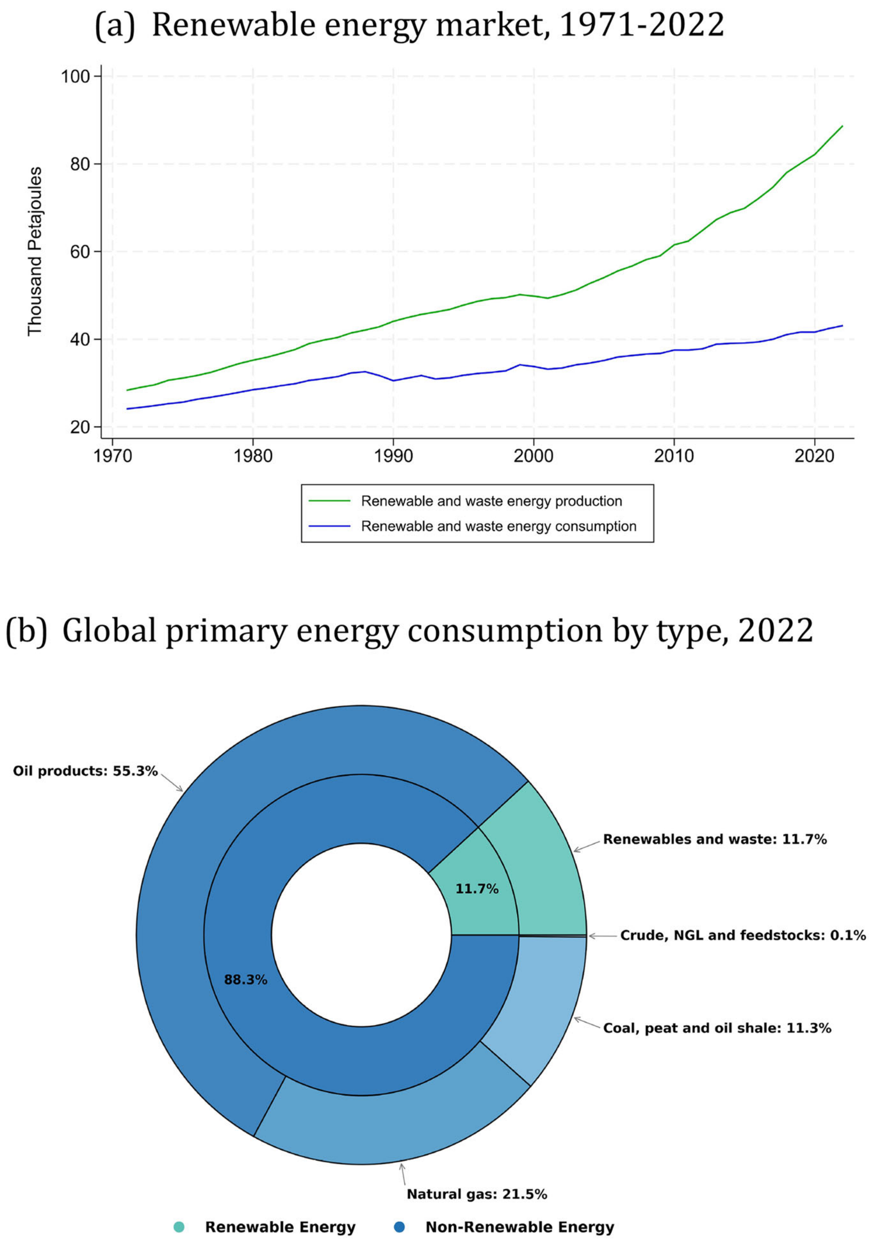

Fig. 10 Global energy market by type. a Global renewable and waste energy production and consumption, 1971–2022, measured in thousand petajoules. **b** Global primary energy consumption by type in 2022, showing renewable and non-renewable energy shares. Source: International Energy Agency (IEA).

can be divided into two classifications based on the context of analysis: (1) corporate environmental quality and (2) general climate change. The former category includes studies that specifically analyse the role of women's empowerment in influencing corporate-level environmental practices and outcomes. These studies focus on how empowered women in leadership, decision-making, or as stakeholders impact corporate environmental policies, sustainability initiatives, and resource management. The latter includes studies that examine the broader relationship between women's empowerment and climate change outcomes without narrowing on corporate contexts. These might involve topics like women's roles in community-based climate adaptation, household-level decision-making, or participation in policy-making to address climate change.

Li et al. (2024) examine 74 nations using threshold regression analyses and find that women's empowerment significantly improves corporate environmental quality, reducing greenhouse gas (GHG) emissions. Liu (2018), applying Tobit regressions on a dataset of S&P 1500 US firms (2011–2015), finds that firms with larger board gender diversity are less often sued for environmental infringements. Similar conclusions are drawn in a study on 383 A-listed Chinese firms over 2011–2015. It is found that the proportion and age of female directors have a positive influence on the overall corporate environmental performance. Altunbas et al. (2022) match firm-corporate governance characteristics with firm-level CO_2 emissions over 2009–2019 to analyse the relationship between gender diversity in the workplace and firm carbon emissions for 1951 listed firms in 24 industrialised companies. Using panel-fixed effects methodology, they find that a 1 percentage point increase in the percentage of female managers within the firm causes a 0.5% decrease in CO_2 emissions. Several other empirical studies attest to the improvement of corporate environmental quality (via enhancement in CSR activities) due to increased participation of women in decision-making positions (for e.g., Burkhardt et al. 2020; Xie et al. 2020).

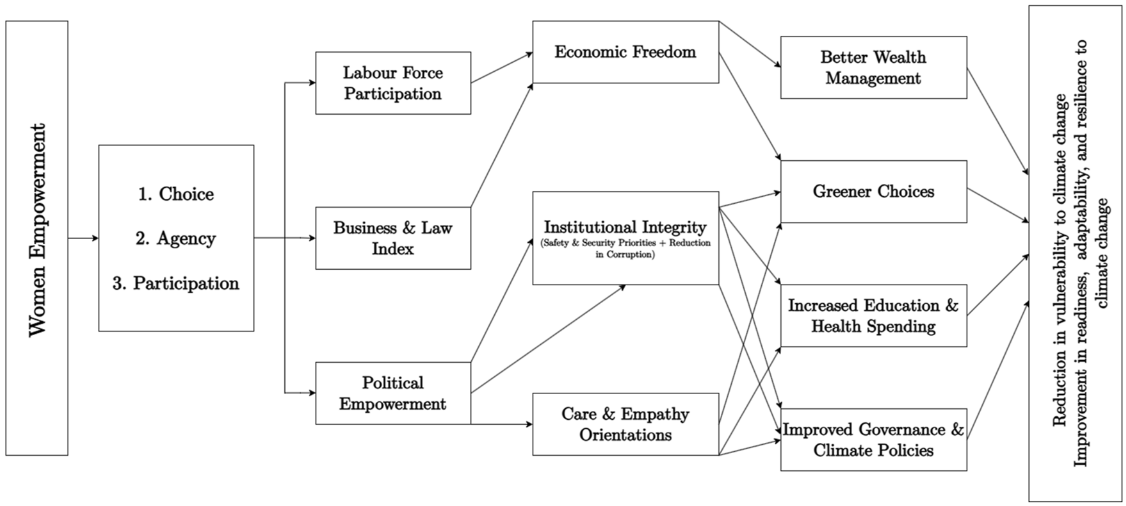

Fig. 11 Conceptual framework on the gender-climate nexus. The framework links women's empowerment, through choice, agency and participation, to labour force participation, legal and business rights, and political empowerment. These channels may affect economic freedom, institutional integrity, care-oriented preferences, greener choices, public spending, governance and climate policy, leading to lower climate vulnerability and greater readiness, adaptability and resilience to climate change.

We now focus on the studies that analyse the relationship in a broader and more generalised context. Employing instrumental variables and partial identification methods, Rios et al. (2024) find that female political empowerment is consistently linked with improved air quality across 230 European regions. Sahoo et al. (2023) use cointegration and causality analysis examine the impact of gender equality in CO_2 emissions for a panel of six emerging market economies over the period of 1990–2019 and find that gender equality reduces carbon emissions. Sharma et al. (2024), applying multiple linear regressions, find that more female seats in the national parliaments reduce carbon emissions in India.

Henceforth, summarising the review, we form the following hypotheses:

H_1 (Economic freedom): greater women's labour force participation, by expanding economic freedoms, reduces national climate vulnerability and enhances climate readiness.

H_2 (Institutional integrity and care): increased women's political empowerment—by reinforcing institutional integrity and care-driven governance—reduces national climate vulnerability and enhances climate readiness.

H_3 (Legal empowerment): stronger legal rights for women, as measured by the Women, Business and Law index, reduce national climate vulnerability and enhance climate readiness by expanding women's economic agency and contractual security.

Contribution to literature. The empirical literature linking women's empowerment to climate outcomes is growing but remains fragmented. Much of it concentrates on corporate environmental sustainability using firm-level data, which limits external validity for national resilience. Studies that investigate broader relationships often rely on small or region-specific samples and proxy climate degradation with greenhouse-gas or carbon emissions, thereby capturing contributions to climate change rather than a country's exposure, sensitivity and adaptive capacity.

This study advances the literature in three ways. First, it evaluates climate resilience using the ND-GAIN Vulnerability and Readiness indices, which jointly reflect exposure to hazards, sensitivity, and socio-economic and institutional capacity. This provides a more holistic measure than emissions alone and allows us to assess how empowerment relates to both reduced vulnerability and enhanced preparedness. Second, it treats empowerment as multidimensional by combining women's labour-force participation, the Women, Business and the Law index, and political representation. This captures participation, rights and voice across economic and political spheres, rather than focusing solely on leadership roles. Third, it employs a comprehensive empirical design. Long-run estimators identify equilibrium relationships; Driscoll–Kraay, PCSE and FGLS address cross-sectional dependence and heteroskedasticity; panel quantile regressions reduce sensitivity to non-normality and outliers; two-step System GMM tackles endogeneity; and local projections trace the dynamic path of effects. The analysis spans up to 185 countries over 1995–2022, enabling robust inference over time and space[3].

Relative to the closest antecedent, Asongu et al. (2022), our contribution is both conceptual and methodological. Their study focuses on political empowerment and vulnerability; we analyse both vulnerability and readiness, extend the period and coverage, incorporate labour-force participation and legal-economic opportunity, and explicitly address cross-sectional dependence, long-run cointegration and dynamic endogeneity. We also develop a structured framework (Section "Developing the framework") that links primary empowerment mechanisms to specific pathways through which resilience can improve, thereby offering a replicable lens for future empirical work.

Empirical framework

Model specifications and variable descriptions. To explore the empirical relationship between climate change and women's multidimensional empowerment, we employ separate linear regressions for each dimension of women's empowerment. Specifically, we analyse how each independent empowerment variable (WLFP, WBUS, and WPOL) individually influences two aspects of climate change, readiness, and vulnerability, using the ND-GAIN Readiness Index (READ) and the ND-GAIN Vulnerability Index (VUL). We further select a set of control variables, including per capita GDP (PCGDP), greenhouse gas emissions (GHGEM), and urban population (URBPOP), to capture economic, environmental, and demographic influences on the dependent variables. Henceforth, our baseline specification is as follows:

$$Climate_{it} = f(Empowerment_{it}, PCGDP_{it}, GHGEM_{it}, URB_{it}) \quad (1)$$

Specifically, we model the baseline specification as:

$$Climate_{it} = Empowerment_{it}^{\theta} \cdot PCGDP_{it}{}^{\kappa} \cdot GHGEM_{it}{}^{\lambda} \cdot URB_{it}{}^{\xi} \quad (2)$$

Log-linearising and converting it into a stochastic model:

$$\begin{aligned} \ln Climate_{it} = \theta \ln Empowerment_{it} + \kappa \ln PCGDP_{it} \\ + \lambda \ln GHGEM_{it} + \xi \ln URB_{it} + \upsilon_{it} \end{aligned} \quad (3)$$

where Climate and Empowerment refer to the two climate outcomes and the three women's empowerment indices[4], respectively; i is country, t is year and υ is the error term[5].

The ND-GAIN Country Indices serve as a robust proxy for assessing climate change impacts because they offer a comprehensive and multidimensional approach to evaluating countries' vulnerabilities and readiness capacities. By breaking vulnerability into exposure, sensitivity, and adaptive capacity, the framework provides nuanced insights into how climate disruptions affect nations differently. Simultaneously, its focus on readiness, divided into economic, governance, and social components, highlights countries' ability to mobilise resources for readiness. ND-GAIN Score calculates the values for vulnerability and readiness indicators on a scale from 0–1. When determining the vulnerability score, a lower score indicates better performance, while for the readiness score, a higher score signifies better performance.

We further select a set of control variables to account for economic, environmental, and demographic factors. First, PCGDP encapsulates the differences between countries' financial resources, which play a critical role in strengthening readiness capacity and reducing exposure to vulnerability (Bowen et al. 2012). Developed countries, as shown by the higher levels in per capita GDP, are better equipped to allocate fiscal resources to implement climate mitigation and readiness strategies and to innovate resilient infrastructure, early warning systems, advanced green technologies, and improve the production of renewable energy, resulting in better climate change outcomes (Milindi and Inglesi-Lotz 2022; Trinh et al. 2023). They have better governance structures to implement and enforce climate policies, along with robust research and development (R&D) sectors essential for innovating and deploying climate-resilient technologies (Jiang et al. 2024). They tend to have more diversified economies, reducing reliance on climate-sensitive sectors such as agriculture and fisheries. Economic diversification mitigates climate-related risks by allowing losses in one sector to be offset by gains in others (Bowen et al. 2012; UNFCCC 2025; Dar 2012). Higher per capita GDP levels also facilitate access to financial markets, enabling individuals, businesses, and governments to utilise insurance and credit to hedge against climate risks and enhance disaster recovery. Greater integration into global trade networks in wealthier nations further supports readiness capacity by providing access to resources, advanced technologies, and specialised knowledge.

Second, GHGEM increase vulnerability by disrupting the Earth's atmospheric balance, leading to rising surface temperatures and intensifying climate hazards (IPCC 2023; Darby et al. 2024; Hammond 2024). These hazards severely impact food systems by reducing agricultural yields and food quality. Extreme weather events cause direct losses and disrupt crop production, as seen in 1998 when Hurricane Mitch destroyed 35% of bean production in Honduras and floods in Vietnam wiped out 7600 hectares of farmland (Mainville 2003; Chau et al. 2013). Additionally, increased emissions contribute to economic losses, affecting labour productivity, employment, and revenue generation (Mora et al. 2018; Chavaillaz et al. 2019; Miti´c et al. 2023). The financial burden of climate-related disasters extends beyond immediate property damage to indirect costs, such as reduced workforce capacity and business disruptions. The intensification of climate hazards due to rising GHG emissions deepens socioeconomic vulnerabilities, disproportionately affecting those with limited resources for readiness.

Lastly, urbanisation, captured by URBPOP can have mixed impacts. Urban areas experience higher temperatures than rural regions, a phenomenon known as the urban heat island (UHI) (United States Environmental Protection Agency (EPA) 2025). Reduced green space and increased impervious surfaces limit evapotranspiration, directing more energy into sensible heat (Oke 1982; Grimmond and Oke 1991). Anthropogenic heat from vehicles, air-conditioning units, buildings, and industrial facilities intensifies UHI effects, as urban areas generate more heat than rural ones. Rapid urbanisation, poor climate planning, and intensifying climate hazards increase urban vulnerability, especially for marginalised populations and key infrastructure. Urban vulnerability is rising fastest in unplanned settlements and smaller urban centres in low- and middle-income nations with limited readiness capacity (Chapman et al. 2019; IPCC 2023). On the other end, urbanisation can reduce vulnerability and enhance resilience to climate change by concentrating economic activities and resources within cities, thereby enabling economies of scale in infrastructure and service provision. Chai et al. (2022) find that the impact of climate change decreases with increasing urbanisation and they speculate that this might be due to complete and robust infrastructures in the urban areas. Additionally, urban areas typically offer better access to specialised services, education, and information, which improves the population's capacity to prepare for and respond to climate-related challenges. Investment in robust urban infrastructure, such as efficient public transport, flood defense, and sustainable energy systems, further mitigates the impacts of extreme weather events. The details of the variables are summarised in Table 1.

We do not include further commonly incorporated controls in the climate change literature, like technology level, industrialisation level, and energy consumption, because our core controls correlate with technology, industrialisation, and energy use at up to 0.90, so including them separately would introduce multicollinearity. Moreover, key dimensions of technological capacity, sectoral structure, and energy resilience are already captured in our ND-GAIN outcome measures; adding them as regressors risks circularity and doublecounting. Lastly, we chose those control variables that would keep missing observations to the minimum.

The following are the series of techniques that we follow to shed light on our research questions:

Multicollinearity test. To determine whether multicollinearity exists among the variables in the study, we perform a Variance Inflation Factor (VIF) test. Neglecting multicollinearity can lead to inflated standard errors, unreliable statistical interpretations, and potentially misleading regression results. The VIF measures the extent to which the variance of a regression coefficient increases due to correlation among the predictors in the model. Based on prior research, a VIF exceeding 10 or a 1/VIF value below 0.10 is typically considered indicative of multicollinearity problems (see, for example, Jijian et al. 2021).

Causality tests. To analyse causality and the potential bi-directional causality as hypothesised in the literature, we apply

Table 1 Summary of study variables.

Variable name	Variable acronym	Measurement	Expected impact	Source
		Climate outcome variables (dependent variables)		
ND-GAIN Readiness Index	READ	log of ND-GAIN Readiness Index	-	Notre Dame Global Adaptation Initiative
ND-GAIN Vulnerability Index	VUL	log of ND-GAIN Vulnerability Index	-	Notre Dame Global Adaptation Initiative
		Empowerment variables		
Women Labour Force Participation	WLFP	log of Women labour force participation to total labour force	Positive	WDI
Women Entrepreneurship Indicator Score	WBUS	log of Women, Business and the Law Index (The index measures how laws and regulations affect women's economic opportunity on a scale from 0 to 100, where 100 means equal legal rights for men and women. It is the average score of eight categories: mobility, workplace, pay, marriage, parenthood, entrepreneurship, assets and pension.)	Positive	WDI
Women Political Empowerment Index	WPOL	log of Women political empowerment index	Positive	V-Dem
		Control variables		
Per Capita GDP	PCGDP	log of per capita GDP	Positive	WDI
Green House Gas Emissions	GHGEM	log of GHG emissions	Negative	Climate Watch
Urban Population	URBPOP	log of Urban population	Mixed	WDI

the Dumitrescu and Hurlin (2012) panel Granger non-causality test. This test evaluates causal relationships across multiple cross-sectional units simultaneously. This approach accommodates heterogeneous causal relationships, allowing the direction and existence of causality to vary between different panels. This flexibility makes the test suitable for datasets with diverse entities, where uniform causal patterns are unlikely. The methodology involves estimating individual Granger causality tests for each cross-sectional unit and then aggregating the results to determine overall significance using bootstrap techniques. This ensures robustness even when the number of time periods is relatively small compared to the number of cross-sectional units. Additionally, this test accounts for potential cross-sectional dependence, enhancing its applicability in environments where units may influence each other.

Cross-sectional dependence analysis. Cross-sectional dependence (hereafter CD) is a common phenomenon in macro panel data. This type of correlation can arise due to global shocks that affect countries differently, such as the oil crises of the 1970s or the global financial crisis that began in 2007. It may also stem from local spillover effects among countries or regions.

To analyse CD, we use the Pesaran (2004) CD test, which relies on the correlation coefficients between the time series of each panel member. The Pesaran CD test statistic is calculated as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{4}$$

Here, T represents the time dimension, N is the number of cross-sectional units, and $\hat{\rho}_{ij}$ denotes the sample estimate of the pairwise correlation of the residuals.

Unit root tests. We conduct both the first-generation Maddala and Wu (1999) and the second-generation Pesaran (2007) panel unit root tests. The Maddala and Wu test accommodates heterogeneity in the autoregressive coefficient of the Dickey-Fuller regression while assuming no cross-sectional dependence in the data. Grounded in the Fisher principle, it computes a chi-squared statistic by converting the p values from individual (A)DF tests for each panel member into logarithms and summing them. This sum, multiplied by -2, follows a chi-squared distribution with 2N degrees of freedom under the null hypothesis that all panel members or series are nonstationary.

The Pesaran CIPS test, on the other hand, accounts for heterogeneity in the autoregressive coefficient while incorporating a single unobserved common factor with heterogeneous factor loadings. The test statistic is derived from individual (A)DF regressions that include the cross-sectional averages of both the dependent and independent variables, alongside lagged differences to control for serial correlation. These regressions are referred to as CADF models. The group-specific results are then averaged following the methodology of the Im et al. (2003) test. Under the null hypothesis of nonstationarity, the resulting test statistic exhibits a non-standard distribution.

Cointegration tests. We employ three different cointegration tests—to override drawbacks and produce reliable results—to test for cointegrating relationships.

Kao (1999) cointegration test is a residual-based test specifically designed for panel data analysis. This test assesses whether a long-term equilibrium relationship exists among multiple time series across different cross-sectional units. Kao's approach assumes homogeneity in the cointegration vectors, meaning that the long-term relationships are identical across all cross-sections. The methodology involves estimating a pooled regression model and then testing the residuals for stationarity using conventional unit root tests. If the residuals are stationary, it indicates the presence of cointegration. This test is favoured for its simplicity and computational efficiency, making it suitable for large panel datasets. However, its assumption of homogeneous cointegration vectors may limit its applicability in cases where different units exhibit distinct long-term relationships.

Pedroni's (1999) panel cointegration test is a comprehensive test set that accommodates heterogeneity across cross-sectional units. Unlike Kao's approach, Pedroni's tests allow for variations in both the cointegration vectors and the error variances among different panels. This flexibility makes Pedroni's methodology more robust in diverse economic settings where individual units may follow distinct long-term dynamics. The framework includes several test statistics that capture different aspects of cointegration, such as within-group and between-group variations. Additionally, Pedroni's tests account for within-group serial correlation and cross-sectional dependence, enhancing their reliability in practical applications. This adaptability has made Pedroni's cointegration tests widely adopted in empirical research, particularly in studies involving diverse countries or regions with varying economic structures.

Westerlund (2008) proposes an advanced panel cointegration test that builds upon error correction models to detect long-term relationships among variables. This test is designed to handle more general forms of non-stationarity and allows for cross-sectional dependence, which is common in large panel datasets. Westerlund's approach involves testing for error correction mechanisms that indicate whether deviations from the long-term equilibrium are corrected over time. The methodology includes both group-mean and panel-based test statistics, providing comprehensive insights into the presence of cointegration. One of the key strengths of Westerlund's test is its ability to accommodate complex error structures and dynamic interactions across panels, making it highly suitable for modern econometric analyses. Consequently, this test offers a robust alternative for researchers seeking to identify stable long-term relationships in the presence of heterogeneous and interdependent panel data.

Cointegrating regressions. When sufficient evidence of cointegration is established, the analysis proceeds using Dynamic OLS (DOLS) and Fully Modified OLS (FMOLS) estimation methods. The FMOLS estimator, developed by Phillips and Hansen (1990), is designed to address endogeneity and serial correlation issues in cointegrated time series data through targeted adjustments. It operates within a cointegration framework by using residuals from the long-run relationship to correct for endogeneity, ensuring unbiased and consistent coefficient estimates. Additionally, FMOLS adjusts the asymptotic variance-covariance matrix to account for serial correlation in error terms, thereby providing reliable standard errors and improving inference. These properties make FMOLS a robust tool for estimating long-run relationships in econometric models (SenGupta and Mihalache 2021).

The DOLS estimator, introduced by Saikkonen (1991) and Stock and Watson (1993), addresses endogeneity in panel data by incorporating lead and lagged values of the regressors. This inclusion captures dynamics and reduces potential biases arising from correlated regressors. Furthermore, DOLS applies adjustments to handle serial correlation in the error terms, enhancing the reliability of standard error estimates and hypothesis testing. These features make DOLS a powerful method for estimating long-run relationships in panel data models, particularly when dealing with endogeneity and serial correlation, ensuring consistent and robust results (Sengupta 2022).

Robustness checks. To ensure the consistency of our main findings, we conduct several additional estimation techniques. We start with System GMM estimation, which is robust in the presence of different endogeneities. The System GMM (SGMM) panel estimation method is designed for dynamic models with a small-time dimension and a large panel population, particularly when individual fixed effects are unobserved. This technique assumes a linear functional relationship and recognises that regressors may not be strictly exogenous. SGMM tackles endogeneity by using instrumental variables, often relying on lagged values of the dependent variable. It also accounts for heteroscedasticity and autocorrelation. The core of the dynamic panel SGMM approach lies in utilising lagged values of the dependent variable, specifically incorporating its own past realisations. We apply the two-step SGMM method introduced by Arellano and Bover (1995) and Blundell and Bond (1998), which is known for its efficiency and robustness, particularly in small time periods. This method corrects endogeneity by introducing additional instruments, which substantially enhance efficiency, and transforming the instruments to ensure they are uncorrelated with the fixed effects (SenGupta et al. 2025). To validate the model specification, we perform two diagnostic tests:

(1) Hansen *J* test of over-identifying restrictions: these tests evaluate the null hypothesis that the instruments used are valid overall. Insignificant test statistics suggest the instruments are appropriate.
(2) Test for autocorrelation in the error term: this tests the null hypothesis that the differenced error term is serially uncorrelated at first- and second-order. Failing to reject the null hypothesis implies that the original error term is serially uncorrelated and the moment conditions are correctly specified ($\text{AR}(2) > 0.10$).

We then move on to the Driscoll and Kraay (1998) (DK) method. This approach computes heteroskedasticity and autocorrelation consistent (HAC) estimators by averaging the products of independent variables and residuals, which serve as weights. The DK method also accounts for cross-sectional and temporal dependencies, producing robust results (Vogelsang 2012; Le and Tran-Nam 2018). Key attributes of the DK method include: (1) its ability to provide reliable estimators under spatial dependence and heteroskedasticity, (2) suitability for both short and long time series, (3) improvement of the covariance matrix through a large constant, and (4) compatibility with missing data and both balanced and unbalanced panel datasets (Hoechle 2007). Overall, the DK method effectively addresses heteroskedasticity, serial correlation, and cross-sectional dependence.

Next, we utilise the panel-corrected standard error (PCSE) technique, which adjusts for correlations in residuals across cross-sectional units and corrects for variability that could distort regression results. This method is particularly robust in managing cross-sectional dependence (CD), heteroskedasticity, and serial correlation (Tawiah et al. 2024b; Zhu et al. 2024).

We also implement the feasible generalised least squares (FGLS) method, chosen for its capacity to handle autocorrelation within panels, cross-sectional dependence, and heteroskedasticity across panels. This ensures the reliability and efficiency of the estimates (Saeed et al. 2024; Tawiah et al. 2024a).

Finally, we employ the Powell (2022) panel quantile regression approach to further confirm robustness. Building on the quantile regression framework by Koenker and Bassett Jr (1978) and its extension to panel data by Koenker (2004), this method estimates the effects of covariates across quantiles while incorporating unobserved fixed effects as parameters. Unlike other panel quantile regression models, the Powell (2022) approach allows parameter variation based on observation-specific error components and an unknown function of the fixed effect. This method examines covariate impacts across the entire distribution of the dependent variable, offering robustness against non-linear distributions and outliers.

The Powell (2022) model is expressed as:

$$V_{it} = \sum_{i=1}^{N} P'_{it}\delta_j \iota_{it} \tag{5}$$

where, V_{it} represents Climate, P'_{it} is the vector of independent variables, δ_j are the coefficients, and ι_{it} denotes the random disturbance term, which may vary across time and include fixed effects. The estimated coefficients are linear, and $P_{it}{}' \ \delta(\psi)$ is increasing at ψ. The quantile regression model depends on the conditional restriction for the ψ^{th} quantile of V_{it}:

$$C\left(V_{it} \leq P'_{it}\delta(\psi)|P_i\right) = \psi \tag{6}$$

This implies that the quantile function exceeds the probability of the outcome variable, remains consistent across all P_{it} and equals ψ. The Powell (2022) estimator accommodates variations in the outcome variable's probability across cross-sectional units, provided these variations are orthogonal to the instruments. The estimator relies on both unconditional and conditional restrictions, allowing for:

$$C\left(V_{it} \leq P'_{it}\delta(\psi)|P_i\right) = C\left(V_{it} \leq P'_{it}\delta(\psi)|P_i\right) \tag{7}$$

This method enables non-parametric variation in the conditional probability by including a term dependent on unobserved and non-additive fixed effects. The primary objective of QRPD is to accurately estimate this heterogeneity while avoiding arbitrary relationships between treatment variables and individual effects.

Local projections. We employ the Local Projections (LP) method introduced by Jorda' (2005) to investigate both the short- and long-term dynamics of the relationships under study. The LP methodology involves estimating a sequence of regressions for the dependent variable at various future time horizons rather than relying on a single set of initial estimated coefficients. This feature allows the method to avoid imposing a rigid structure on the Impulse Response Functions (IRFs), making it less susceptible to errors stemming from model misspecification when compared to conventional VAR models (Auerbach and Gorodnichenko 2013; Jorda' 2005). In addition to being more robust to misspecification than a VAR, LP has three key advantages for our setting. First, they estimate each h-step-ahead response directly, so we never have to commit to the lag structure of every variable in a large system, avoiding the companion-matrix errors that can plague short panels or highly persistent data. Second, LPs accommodate additional controls (and fixed effects) with ease, letting us partial out confounders at each horizon rather than shoe-horning them into a single reduced-form VAR. Third, standard errors in LP can be made robust to both serial and cross-sectional dependence, which is essential for our global panel. By contrast, simply adding lags of the dependent variable to a regression would capture only an "average" dynamic multiplier and still leave us vulnerable to omitted-variable bias and system-wide mis-specification.

To implement this, we define a straightforward baseline panel specification for different horizons $h = (0,1,\ldots,10)$ years, as follows:

$$\begin{aligned} Climate_{t+h,i} - Climate_{t-1,i} &= \alpha_i + \tau_t \\ +\beta_h Empowerment_{i,t} &+ \gamma_h Z_{i,t} + \mu_{i,t+h} \end{aligned} \tag{8}$$

Here, α_i represents country fixed effects, τ_t captures time fixed effects, and β_h reflects the cumulative responses of the climate variables at each h-year horizon following shocks in the respective regressors of interest. Additionally, $Z_{i,t}$ denotes the vector of control variables, including up to three lags, as previously discussed.

Estimation and analysis. We start with a preliminary analysis in the form of a visual aid (see Fig. 12). We find that the three empowerment indices are negatively and positively correlated with VUL and READ, respectively. As expected, we find that the low-income developing economies are the most vulnerable to climate change in general, followed by the emerging and advanced economies. The order is exactly reversed for readiness.

From Table 2, we see that all the VIF values are less than the threshold of 10, and the mean VIF values are lower than 2. Hence, we conclude no multicollinearity issues in our chosen specifications.

Following theories of climate and gender outcomes affecting each other, we report the results of Dumitrescu and Hurlin (2012) panel Granger non-causality test in Table 3. All the test statistics are highly significant at the 1% level, and thus we reject the null hypothesis of non-causality across all the specifications. This also implies the need to handle endogeneity issues like reverse causation and simultaneity biases while estimating the relationships.

In Table 4, the test statistics of all the series are highly significant at 1% level. Hence, we reject the null hypothesis of cross-sectional independence. We then check the existence of unit roots in the series. From Table 5, we find that WPOL, PCGDP, GHGEM, and URBPOP are not I(1) series across both the lags, as per the Maddala and Wu (1999) test. However, since we confirm the existence of CD, we go with the second-generation CIPS test that produces insignificant test statistics for all the series across both lags. Hence, we fail to reject the null hypothesis of I(1) series. Consequently, we perform cointegration tests to test the presence of cointegration among the I(1) series (Table 6). We find that the majority of the test statistics are statistically significant (ranging from 1–10% levels). Hence, we safely reject the null hypothesis of no cointegration across all the specifications.

Given the proof of cointegration, it is appropriate to estimate cointegrating regressions. Table 7 presents the PDOLS estimates. We find that a 1% increase in WLFP, WBUS and WPOL leads to 0.28%, 0.2% and 0.3% increase in READ, respectively. The coefficients are statistically significant at 1% level. Similarly, consistent with expectations, we find that VUL is reduced by 0.06%, 0.04% and 0.22% due to a 1% increase in WLFP, WBUS and WPOL, respectively. The coefficients are highly significant at 1% level, except for the WBUS coefficient, which is significant at the 5% level. We find qualitatively similar results in the case of FMOLS estimates (Table 8). We find that a 1% increase in WLFP leads to 0.13% increase in READ and 0.05% decrease in VUL with a 1% significance level. Similarly, a per cent increase in WBUS leads to a 0.13% increase in READ and a 0.03% decrease in VUL with a 5% significance level. Lastly, READ is enhanced by 0.02% and VUL diminishes by 16% due to a 1% improvement in WPOL. High R^2 and adjusted R^2 values indicate robust models with strong explanatory power. For brevity, we skip interpreting the estimates of the control variables.

We further check the robustness of our previous findings by employing Driscoll Kraay, PCSE, FGLS, quantile regressions, and 2-SGMM techniques to estimate the relationships (see Tables 9–11). The robustness regressions produce identical results, both qualitatively and quantitatively. Let us first discuss the DK, PCSE and FGLS estimations. In the DK regressions, the coefficients for WLFP, WBUS, and WPOL with READ as the regressand (cols. 1–3) are positive and statistically significant, indicating that a 1% increase in WLFP is associated with a 0.083% increase in READ, while a similar increase in WBUS results in a

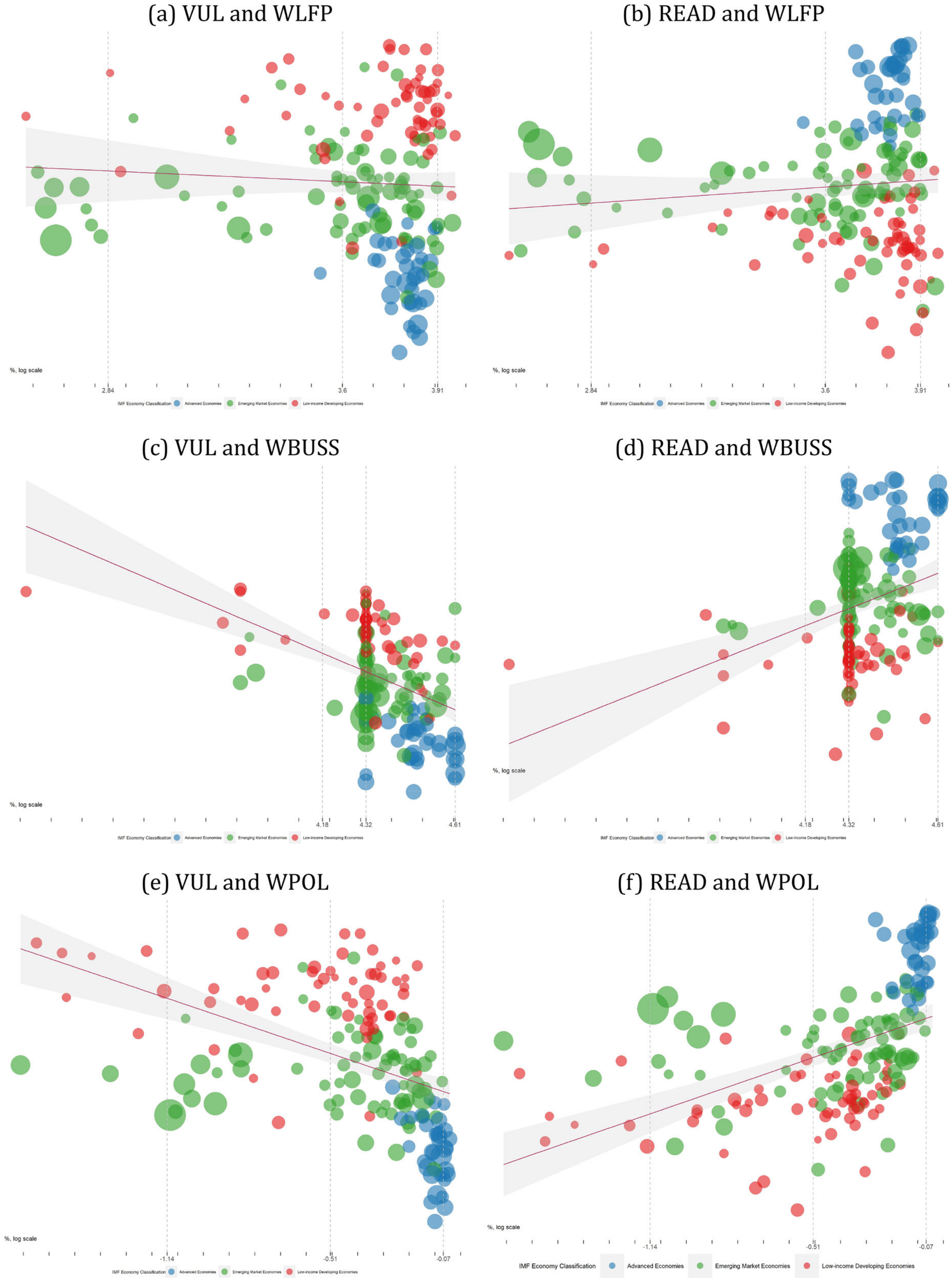

Fig. 12 Climate outcomes, women's empowerment and GHG emissions per capita. a ND-GAIN vulnerability and women's labour force participation. **b** ND-GAIN readiness and women's labour force participation. **c** ND-GAIN vulnerability and the Women, Business and the Law index. **d** ND-GAIN readiness and the Women, Business and the Law index. **e** ND-GAIN vulnerability and women's political empowerment. **f** ND-GAIN readiness and women's political empowerment. Country averages are calculated over 1995–2022. Bubble size indicates GHG emissions per capita; vertical lines show the 5th, 25th and 95th percentiles. Source: WDI, ND-GAIN, V-Dem; authors' calculations.

0.048% rise in READ. The WPOL coefficient is notably larger at 41%, suggesting a substantial positive impact on READ. Conversely, in the specifications with VUL as the dependent variable (cols. 4–6), all three variables exhibit negative and significant coefficients, with a 1% increase in WLFP leading to a 0.025% reduction in VUL, WBUS contributing to a 0.008% decrease, and WPOL associated with a 21% decline in VUL. The PCSE results further support these findings, showing positive coefficients of 0.105%, 0.112%, and 0.17% for WLFP, WBUS, and WPOL in the READ specifications, respectively, all highly significant at 1–5% levels. For VUL, the coefficients indicate reductions of 0.058%, 0.014%, and 0.054% corresponding to WLFP, WBUS, and WPOL, respectively, all highly significant at the 1% level. The FGLS regressions provide the most robust estimates, with WLFP, WBUS, and WPOL positively influencing READ by 0.129%, 0.112%, and 0.15%, respectively, and reducing VUL by 0.090%, 0.173%, and 0.2%, respectively, each significant at the 1% level.

All the series exhibit significant Jarque-Bera test statistics, as presented in Table A2.2, indicating deviation from normality in the residual distributions. This non-normality is often attributable to the presence of outliers or skewed data, which can distort the results of traditional mean regression techniques. Consequently, employing Quantile Regressions for Panel Data (QRPD) becomes both relevant and necessary, as QRPD allows for a more comprehensive analysis by examining the effects of the independent variables at various quantiles of the dependent variable distribution. Table 10 displays the results of the quantile regressions for both READ and VUL across the 10th, 25th, 50th, 75th, and 90th percentiles. For READ, the coefficients of WLFP are positive and significant across all quantiles, with the most substantial impact observed at the 25th percentile (0.352) and the 75th percentile (0.186). This suggests that increases in WLFP consistently enhance READ, with varying magnitudes depending on the position within the distribution. Similarly, WBUS shows positive and significant effects on READ at the lower (q10: 0.061) and middle quantiles (q25: 0.166 and q50: 0.075), though the effect diminishes slightly at higher quantiles (q75: 0.086 and q90: 0.013). WPOL exhibits a strong positive association with READ across all quantiles, peaking at the 25th (0.502) and 90th (0.299) percentiles, indicating that political factors play a crucial role in enhancing READ throughout the distribution. In contrast, the coefficients for VUL are consistently negative and significant across all quantiles for WLFP, WBUS, and WPOL. Specifically, WLFP reduces VUL by between 0.058 and 0.11%, with the largest impact at the 75th percentile. WBUS decreases VUL most significantly at the 10th percentile (−0.159) and maintains substantial negative effects across other quantiles, although the impact at the 50th percentile (−0.050) is not statistically significant. WPOL shows a strong negative relationship with VUL, particularly at the lower quantiles (q10: −0.133 and q25: −0.199), and remains significant though slightly less pronounced at higher quantiles. The results can be better visualised in Fig. A2.1.

Given the established endogeneity in the climate outcomes and women's empowerment relationship, particularly as evidenced by the bidirectional relationship confirmed in Table 3, it is imperative to address potential endogeneities to obtain unbiased and consistent estimates. To this end, we employ the two-step System

Generalised Method of Moments (2-SGMM) approach, which effectively mitigates issues related to endogeneity, simultaneity, and unobserved heterogeneity. Table 11 presents the results of the 2-SGMM regressions for both READ and VUL. Focusing first on

Table 2 Multicollinearity test.

	READ			VUL		
	(1)	(2)	(3)	(4)	(5)	(6)
WLFP	1.03			1.03		
WBUS		1.13			1.13	
WPOL			1.26			1.26
PCGDP	2.18	2.21	2.58	2.18	2.21	2.58
GHGEM	1.10	1.08	1.09	1.10	1.08	1.09
URBPOP	2.33	2.16	2.35	2.33	2.16	2.35
Mean VIF	1.66	1.64	1.82	1.66	1.64	1.82

Table 4 Pesaran (2004) cross-sectional dependence test.

	Test statistic
VUL	332.7***
READ	81.7***
WLFP	95.2***
WBUS	75.1***
WPOL	237.1***
PCGDP	390.0***
GHGEM	119.2***
URBPOP	385.1***

***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Table 3 Dumitrescu and Hurlin (2012) Panel Granger non-causality test.

Null hypothesis	*W*-stats	*Z*-stats	*Z*-bar stats	Remarks
WLFP does not Granger cause READ	2.63	14.68***	11.73***	WLFP ↔ READ
READ does not Granger cause WLFP	4.96	35.71***	29.57***	
WBUSS does not Granger cause READ	3.57	28.21**	25.98**	WBUSS ↔ READ
READ does not Granger cause WBUSS	2.86	23.39***	21.11**	
WPOL does not Granger cause READ	2.15	10.41***	8.11***	WPOL ↔ READ
READ does not Granger cause WPOL	2.18	10.64***	8.30***	
WLFP does not Granger cause VUL	3.39	21.61***	17.61***	WLFP ↔ VUL
VUL does not Granger cause WLFP	6.41	48.82***	40.70***	
WBUSS does not Granger cause VUL	5.70	19.66***	15.29**	WBUSS ↔ VUL
VUL does not Granger cause WBUSS	6.49	27.84*	22.73**	
WPOL does not Granger cause VUL	2.65	14.91***	11.92***	WPOL ↔ VUL
VUL does not Granger cause WPOL	1.88	7.93***	6.00***	

***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Table 5 Unit root tests.

H0: I(1) series

lags	READ	VUL	WLFP	WBUS	WPOL	PCGDP	GHGEM	URBPOP
		Maddala and Wu (1999) Panel unit root test						
0	231.83	352.22	367.52	79.11	466.11***	458.16***	511.10***	1600.58***
1	265.64	254.54	358.99	76.83	503.16***	389.31***	368.73	932.14***
		Pesaran (2007) Panel unit root test (CIPS)						
0	12.193	−0.73	6.54	31.24	1.16	5.15	1.57	15.53
1	10.04	1.61	2.86	31.88	−0.25	−0.042	5.40	3.90

***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Table 6 Cointegration tests.

	Kao (1999) cointegration test					
	VUL			READ		
	WLFP	WBUS	WPOL	WLFP	WBUS	WPOL
Modified Dickey-Fuller	2.41***	1.95**	2.90***	−0.82	−0.61	−1.75**
Dickey-Fuller	2.67***	2.42***	3.24***	−1.86**	−1.66**	−2.67***
Augmented Dickey-Fuller	4.73***	5.35***	5.50***	−4.60***	−3.37***	−4.06***
Unadjusted modified Dickey-Fuller	−1.46*	−2.42***	−0.57	−1.12	−1.04	−1.39*
Unadjusted Dickey-Fuller	−0.41	−0.92	0.35	−2.06**	−1.96**	−2.44***
	Pedroni (1999) cointegration test					
Modified variance ratio	−3.93***	−0.13	—	−5.62***	−5.05***	−7.78***
Modified Phillips-Perron	4.04***	5.66***	4.76***	6.89***	5.80***	5.41***
Phillips-Perron	−8.50***	−4.33***	−7.71***	−2.95***	−4.94***	−5.05***
Augmented Dickey-Fuller	−11.73***	−5.47***	−7.62***	−4.68***	−5.66***	−5.52***
	Westerlund (2008) cointegration test					
Variance ratio	−2.92***	−2.79***	−4.74***	−3.78***	−3.31***	−3.03***

***, *, and * represent 1%, 5%, and 10% significance levels, respectively. H₀: No cointegration.

Table 7 PDOLS regressions.

	READ			VUL		
	(1)	(2)	(3)	(4)	(5)	(6)
WLFP	0.276***			−0.058***		
	(0.030)			(0.011)		
WBUS		0.201***			−0.037**	
		(0.050)			(0.015)	
WPOL			0.297***			−0.215***
			(0.071)			(0.020)
PCGDP	0.169***	0.116***	0.119***	−0.055***	−0.053***	−0.071***
	(0.011)	(0.030)	(0.013)	(0.003)	(0.009)	(0.004)
GHGEM	0.040***	0.019	0.009	−0.005*	0.012**	−0.010***
	(0.006)	(0.020)	(0.008)	(0.003)	(0.006)	(0.002)
URBPOP	−0.073**	−0.157	−0.531***	−0.085***	−0.183***	−0.024***
	(0.024)	(0.106)	(0.026)	(0.009)	(0.032)	(0.007)
Observations	3824	1380	3934	4102	1380	3939
No of groups	167	60	164	169	60	164
R^2	0.993	0.995	0.844	0.998	0.999	0.969
Adj. R^2	0.974	0.981	0.735	0.996	0.995	0.947

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Robust standard errors are presented in the parentheses.

READ as regressands (cols. 1–3), the lagged dependent variable READ (−1) exhibits a strong and highly significant positive relationship, with coefficients ranging from 0.856 to 0.979. This indicates a high degree of persistence in READ over time. The coefficient for WLFP is positive and statistically significant in column (1) at the 10% level, suggesting a marginal positive impact of women's labour force participation on READ. WBUS shows a positive and statistically significant effect (at 5%) in column (2), implying that increased WBUS has an enlarging effect on READ in this context. WPOL also exhibits a positive and highly significant coefficient at 1% level, reinforcing the positive influence of political factors on READ. Turning to VUL (cols. 4–6), the lagged dependent variable VUL also displays a strong and highly significant positive relationship, with

Table 8 FMOLS regressions.

	READ			VUL		
	(1)	(2)	(3)	(4)	(5)	(6)
WLFP	0.130***			−0.052***		
	(0.003)			(0.008)		
WBUS		0.134**			−0.028**	
		(0.043)			(0.009)	
WPOL			0.020*			−0.155***
			(0.046)			(0.016)
PCGDP	0.161***	0.143***	0.178***	−0.057***	−0.062***	−0.088***
	(0.002)	(0.027)	(0.012)	(0.003)	(0.006)	(0.003)
GHGEM	−0.037***	0.008	−0.004	−0.005***	−0.008**	−0.020***
	(0.004)	(0.016)	(0.009)	(0.002)	(0.003)	(0.002)
URBPOP	−0.139***	−0.146*	−0.155***	−0.084***	−0.100***	0.015**
	(0.0001)	(0.089)	(0.033)	(0.007)	(0.020)	(0.006)
Observations	4419	2028	4223	4419	2028	4223
No of groups	173	81	167	173	81	167
R^2	0.923	0.933	0.927	0.992	0.990	0.720
Adj. R^2	0.920	0.927	0.924	0.991	0.989	0.720

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Robust standard errors are presented in the parentheses.

Table 9 DK, PCSE and FGLS regressions.

	Driscoll and Kraay (1998) regressions with fixed effects					
	READ			VUL		
	(1)	(2)	(3)	(4)	(5)	(6)
WLFP	0.083**			−0.025***		
	(0.033)			(0.005)		
WBUS		0.048**			−0.008**	
		(0.023)			(0.003)	
WPOL			0.410***			−0.021***
			(0.009)			(0.005)
Observations	4623	4655	4423	4623	4655	4423
No. of groups	174	178	168	174	178	168
R^2	0.173	0.191	0.172	0.554	0.574	0.484
Controls	✓	✓	✓	✓	✓	✓
		PCSE regressions				
WLFP	0.105**			−0.058***		
	(0.021)			(0.007)		
WBUS		0.112***			−0.014***	
		(0.016)			(0.004)	
WPOL			0.167***			−0.054***
			(0.031)			(0.008)
Observations	4623	4655	4423	4623	4655	4423
No. of groups	174	178	168	174	178	168
R^2	0.630	0.677	0.648	0.903	0.896	0.910
Controls	✓	✓	✓	✓	✓	✓
		FGLS regressions				
WLFP	0.129***			−0.090***		
	(0.009)			(0.005)		
WBUS		0.112***			−0.173***	
		(0.015)			(0.009)	
WPOL			0.153***			−0.203***
			(0.030)			(0.009)
Observations	4623	4655	4423	4623	4655	4423
No. of groups	174	178	168	174	178	168
Controls	✓	✓	✓	✓	✓	✓

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Standard errors are presented in the parentheses.

Table 10 Quantile regressions for panel data.

	READ					VUL				
	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
WLFP	0.141***	0.352***	0.128***	0.186***	0.130***	−0.060***	−0.058***	−0.083***	−0.110***	−0.095***
	(0.053)	(0.026)	(0.027)	(0.009)	(0.002)	(0.008)	(0.009)	(0.001)	(0.004)	(0.001)
WBUS	0.061**	0.166***	0.075***	0.086***	0.013***	−0.159***	−0.086***	−0.050	−0.085***	−0.094***
	(0.028)	(0.008)	(0.012)	(0.003)	(0.003)	(0.005)	(0.033)	(0.013)	(0.006)	(0.006)
WPOL	0.350***	0.521***	0.285***	0.476*	0.292***	−0.133***	−0.199***	−0.172***	−0.110***	−0.071***
	(0.059)	(0.001)	(0.026)	(0.010)	(0.002)	(0.004)	(0.002)	(0.002)	(0.015)	(0.009)
Observations (WLFP)	4623	4623	4623	4623	4623	4623	4623	4623	4623	4623
No. of groups (WLFP)	174	174	174	174	174	174	174	174	174	174
Observations (WBUS)	4655	4655	4655	4655	4655	4655	4655	4655	4655	4655
No. of groups (WBUS)	178	178	178	178	178	178	178	178	178	178
Observations (WPOL)	4423	4423	4423	4423	4423	4423	4423	4423	4423	4423
No. of groups (WPOL)	168	168	168	168	168	168	168	168	168	168
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Robust standard errors are presented in the parentheses.

Table 11 Two-steps SGMM regressions.

	READ			VUL		
	(1)	(2)	(3)	(4)	(5)	(6)
READ (−1)	0.956***	0.856***	0.979***			
	(0.011)	(0.015)	(0.008)			
VUL (−1)				0.979***	0.984***	0.981***
				(0.009)	(0.006)	(0.010)
WLFP	0.005*			−0.002**		
	(0.003)			(0.001)		
WBUS		0.023**			−0.005***	
		(0.012)			(0.002)	
WPOL			0.028***			−0.006***
			(0.008)			(0.002)
Observations	4455	4490	4092	4455	4490	4264
No. of groups	174	178	164	174	178	168
No. of instruments	162	81	74	78	162	78
Arellano-Bond test for AR (2) statistic	−0.91	−1.09	−0.98	1.69	1.91	1.57
Hansen test statistic	143.81	62.93	25.62	44.90	130.46	52.90
Controls	✓	✓	✓	✓	✓	✓

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Robust standard errors are presented in the parentheses.

coefficients close to 0.98 across all specifications, underscoring the persistence of vulnerability over time. The coefficient for WLFP is negative and significant in column (4), indicating that higher women's labour force participation contributes to a reduction in vulnerability. Similarly, WBUS has a negative and highly significant effect in column (5), suggesting that increased business activities are associated with lower vulnerability levels. WPOL maintains a negative and highly significant coefficient in column (6), highlighting the role of political factors in mitigating vulnerability. The diagnostic tests further validate the robustness of the 2-SGMM estimates. The Arellano-Bond test for second-order autocorrelation (AR(2)) does not indicate significant autocorrelation in the residuals, as evidenced by the non-significant test statistics across all models. Additionally, the Hansen test statistics are sufficiently high, implying that the instruments used are valid and not overidentified.

Finally, Fig. 13 presents the IRFs of the LP estimates. We begin with the responses to a shock in WLFP. In panel 13a, VUL starts slightly below zero and declines steadily over time. By around year 10, VUL is reduced by 0.18%, suggesting that a positive WLFP shock is associated with a persistent decrease in VUL. In panel 13b, READ remains steady in the positive zone at around 0.16%, indicating that the effect of WLFP remains positive throughout. Next, we turn to the responses of climate outcomes to a shock in WOMBUSS. Panel 13c suggests that the effect on VUL is mildly negative and stable near 0 till the 4th year and then becomes increasingly negative, reaching around −0.2% in year 10. The overall negative trajectory points to a reducing effect of the WOMBUSS shock on VUL over the long run. In contrast, in panel 13d, READ is increased by approximately 0.02% in the first year and this increasing effect reaches the peak at 0.05% at the 6th year, and then settles slightly lower but still above zero by the end of the horizon. Lastly, we analyse the climate responses to a shock in WPOL. We observe in panel 13e that VUL experiences some early fluctuations in the negative zone, and the downward tendency becomes more pronounced over time. By year 10, the estimated effect is −0.025%, suggesting that an increase in WPOL shock correlates with lower VUL in the long run. In panel 13f, READ begins slightly above zero, then sharply increases year 2 onwards, showing that WPOL shocks contribute to higher READ.

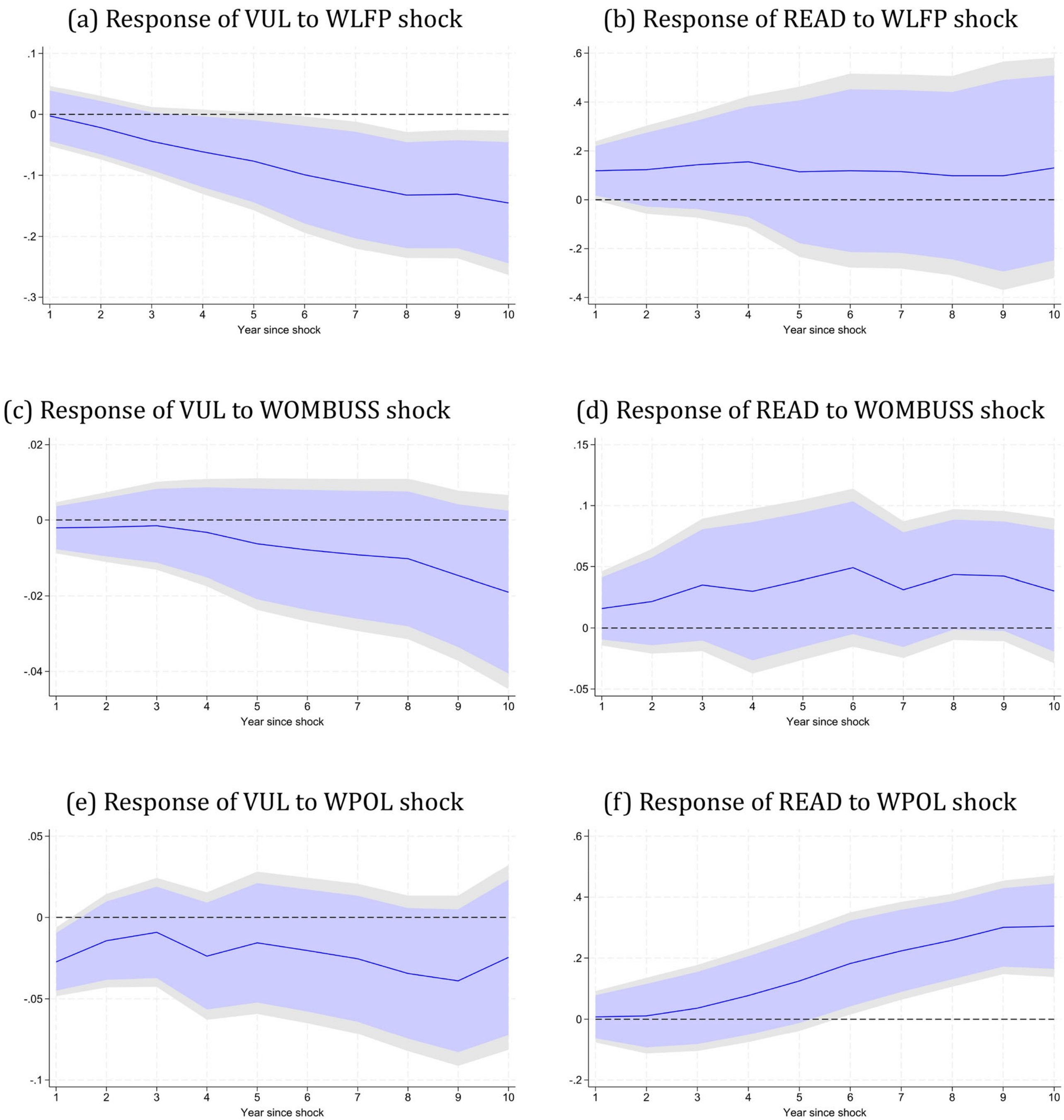

Fig. 13 Local projection estimates. a Response of ND-GAIN vulnerability to a women's labour force participation shock. **b** Response of ND-GAIN readiness to a women's labour force participation shock. **c** Response of ND-GAIN vulnerability to a Women, Business and the Law index shock. **d** Response of ND-GAIN readiness to a Women, Business and the Law index shock. **e** Response of ND-GAIN vulnerability to a women's political empowerment shock. **f** Response of ND-GAIN readiness to a women's political empowerment shock. Shocks are 1 pp and identified using Cholesky decomposition. Shaded regions show the 90% and 95% confidence intervals. Source: Authors' calculations.

In summary, our extensive analysis across various regression methodologies consistently reveals that enhancements in women's labour force participation, economic activities facilitated by legal frameworks, and political empowerment significantly contribute to increasing READ while concurrently reducing vulnerability (VUL). These positive and negative relationships persist across Driscoll-Kraay, PCSE, FGLS, quantile regressions, and two-step System GMM estimations, highlighting the robustness of our findings despite potential endogeneities, heteroskedasticity, non-normality and CD. Furthermore, the Local Projection estimates demonstrate that shocks to WLFP, WBUS, and WPOL lead to sustained improvements in READ and enduring decreases in VUL over the long term. Collectively, these results highlight the crucial role of women's empowerment and economic engagement in enhancing resilience and mitigating vulnerability within the studied framework.

We recognise that broad structural transformations, such as industrialisation, globalisation, and institutional reform, and episodic shocks (e.g. financial crises or regime changes) may influence both women's empowerment and national climate resilience. A full mediation or moderation analysis of each shock lies beyond our current scope, but our core specification already addresses many of these concerns. First, country and year fixed effects, together with regional time-trend controls, absorb unobserved heterogeneity stemming from long-run structural shifts and regionally synchronised shocks. Second, we include annual GDP per capita growth to proxy for ongoing economic transformation. Nevertheless, explicitly modelling crisis dummies or polity-change indicators represents a promising avenue for future work on targeted mediation and moderation tests.

Conclusion

Despite growing global efforts, climate resilience remains uneven, and identifying the social drivers of improved outcomes is imperative. In this paper, we show that multidimensional women's empowerment, measured by labour-force participation, the Women, Business and the Law index, and political representation, significantly reduces vulnerability and enhances readiness capacity across 185 countries (1995–2022). Political empowerment exerts the strongest effect, and our results hold across a suite of robust estimators (Driscoll–Kraay, PCSE, FGLS, FMOLS, PDOLS, System-GMM and Local Projections), addressing concerns over cross-sectional dependence, heteroskedasticity, serial correlation and endogeneity. Specifically, a 1% rise in women's labour force share is associated with up to a 0.11% reduction in climate vulnerability, while enhancing resilience by 0.08–0.35%. Improvement in the "Women, Business and the Law" indicator reduces vulnerability by up to 0.17% and increases readiness by 0.05 to 0.2%. Notably, women's political empowerment is found to have the strongest effect, decreasing vulnerability by 0.02–0.20% and boosting readiness by up to 0.41% across specifications. The relationships are statistically significant at 1–10% levels.

Future research could classify countries by income, development or fragility to reveal heterogeneity and inform targeted interventions. Intersectional analyses (race, class) and qualitative case studies would add contextual depth, while sector-specific work (e.g. agriculture, energy) and mediation analyses of education, technology and incentives could clarify causal pathways. Evaluating gender-responsive policies and global governance frameworks, alongside machine-learning techniques for large-scale pattern detection, would modernise empirical approaches. Finally, exploring behavioural drivers and transboundary dynamics will help design more inclusive climate strategies.

These findings highlight that enhancing women's voice in government is both a fundamental right and a powerful mechanism for climate action. To translate these insights into practice, we recommend that national and local legislatures adopt binding gender quotas and establish clear enforcement mechanisms and regular progress reporting. Equally, expanding opportunities for women in green sectors—through STEM training, mentorship schemes and preferential access to low-interest loans or grants for renewable-energy and sustainable-agriculture ventures—will broaden the talent pool and accelerate the transition to a greener economy. Finally, climate finance must become gender-sensitive: all projects should include gender-disaggregated impact assessments, prioritise initiatives that demonstrably advance women's resilience, and be subject to independent oversight, civil-society engagement and transparent compliance reports. By embedding gender inclusion at every stage, from quota systems and education programmes to finance and oversight, policymakers can activate a virtuous cycle of fairer governance, more effective legislation and broader economic participation. In so doing, women's empowerment becomes not only an end in itself but also a practical driver of adaptive capacity, social justice and sustainable development.

Data availability

The authors compile data from publicly available sources that are outlined in detail in the article. The compiled datasets and codes are available on reasonable request.

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Notes

1 We calculate the projections using a Vector Autoregressive model of lag order 25, specified as $\text{Demand}_t = \Phi_1\text{Demand}_{t-1} + \Phi_2\text{Demand}_{t-2} + \cdots + \Phi_{25}\text{Demand}_{t-25} + \xi_t$. This model calculates projections by leveraging the historical patterns and temporal dependencies present in the energy consumption data. The model uses multiple lagged values of energy demand—up to 25 past periods—to capture the dynamic relationships and long-term trends influencing current and future energy usage. By estimating the coefficients that quantify each lagged period's impact, it constructs a system of equations where each equation predicts the current energy demand based on its own past values. When generating forecasts, the model applies these estimated coefficients to the most recent observed data, iteratively projecting energy demand forward till 2035. This iterative process ensures that each new forecasted value incorporates the influence of previously forecasted values, thereby maintaining consistency with the established historical patterns. Our projections are comparable to projection reports by different institutions that estimate around a 40–50% increase (e.g., Global Energy Perspective 2024 2024; NESO 2024).

2 https://static.heritage.org/index/pdf/2024/2024_indexofeconomicfreedom_twelvefreedoms.pdf.

3 We must mention that Asongu et al. (2022) study the relationship between climate vulnerability and different aspects of women's political empowerment, but using a dataset of 169 countries for the period 1995–2017. However, they do not analyse the impacts on readiness to climate shocks. They also do not examine the dynamic relationship as well as account for cross-sectional dependence, outliers, non-normality, and a non-linear relationship.

4 We present the three empowerment indices separately rather than jointly in each model. Presenting each dimension of women's empowerment on its own not only aligns with the potentially distinct theoretical pathways through which they operate but also preserves estimation precision: when all three variables are entered simultaneously, standard errors inflate modestly, and the narrative around each channel becomes harder to communicate. To reassure that this approach does not obscure interdependencies, we add joint regression specifications, focussing on the two-way fixed effects model with Driscoll-Kraay standard errors, PCSE and FGLS techniques (discussed in later sections), in Table A2.3. Despite some higher correlation coefficients (Table A2.4), VIF factors remain well below conventional thresholds (Table A2.5) and the main coefficients retain their original signs and significance. This confirms that our separate specifications simply highlight each empowerment dimension without introducing bias.

5 Note that we suitably augment the model with fixed effects, instruments, and lags wherever necessary.

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