



Impacts of renewable energy on climate vulnerability: A global perspective for energy transition in a climate adaptation framework

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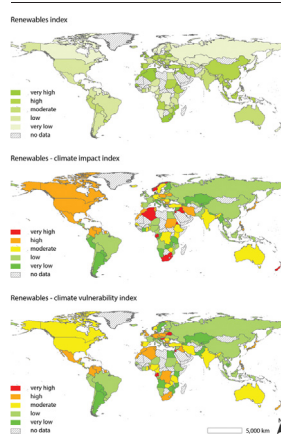
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HIGHLIGHTS

- A comprehensive climate vulnerability dimension is incorporated into the assessment of renewable energy policies.
- Existing renewable energy policies have been aligned with socioeconomic status, rather than considering climate vulnerability.
- Technological advancement in renewable energy has exacerbated climate inequality.
- Considering adaptive capacity is essential for improving the efficiency of the renewable energy transition on climate change.
- We provide empirical evidence that existing renewable energy implementation fails to adequately promote climate change adaptation.

GRAPHICAL ABSTRACT



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ABSTRACT

The transition to renewable energy can disproportionately impact the effectiveness of climate change adaptation, due to regional heterogeneity. Many countries attempt to promote renewable energy to reduce the impact of climate change, but the impacts of national energy policy in the climate vulnerability framework remain little understood. Here, we exploit variations in renewable energy uses to test the effectiveness of climate adaptation policy across the dimensions of climate impact and vulnerability. Using the Fuzzy Analytic Hierarchy Process and panel data regression, we analyze the spatiotemporal correlation between renewable energy transition and climate vulnerability across the world. We find that while renewable energy increases proportionally with climate exposure and sensitivity, many countries exhibit discrepancies between the variation in renewable energy transition and climate vulnerability. The promotion of renewable energy funnels into nations with a higher level of adaptive capacity while bypassing more vulnerable countries. The results signify that existing renewable energy policies can exacerbate climate inequality and undermine the benefits of the transition to renewable energy by neglecting the spatial heterogeneity in climate vulnerability. Our findings provide empirical evidence for the ways in which renewable energy policy can generate spatial inequalities in climate adaptation.

1. Introduction

Renewable energy has been promoted globally as one of the primary strategies for both climate change mitigation and adaptation (Suman, 2021). Renewable energy helps reduce greenhouse gas emissions, and

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thus has been used as an effective tool to fight against climate change (Long and Steinberger, 2016). In the adaptation perspective, renewable energy infrastructure, such as solar and wind plants, functions as green infrastructure, lowering utility costs, enhancing ecosystem services, and increasing resilience to the exacerbated disasters caused by climate change (Flores and Peralta, 2020; Semeraro et al., 2018). Accordingly, the transition to renewable energy from fossil fuels has been increasingly adopted, especially in countries with high climate risk, so that 123 countries having been producing renewable energy since 2000 (Chan et al., 2022; Sovacool et al., 2020).

Despite the remarkable relationship between renewable energy and pro-environmental behavior, numerous studies have attributed variations in national renewable energy investments to different factors. Renewable energy deployment can be affected by technological innovation (Johnstone et al., 2010; Popp et al., 2011), energy security (Chien and Hu, 2008; Gan et al., 2007), electricity prices (Gelabert et al., 2011; Würzburg et al., 2013), fossil fuel-based economies (Carley, 2009), environmental concerns (Chan and Tam, 2021; Eom et al., 2016), and social dominance orientation (Milfont et al., 2018). Similarly, Marques et al. (2010) argue that political factors (e.g., feed-in tariffs or investment in research and development), socioeconomic factors (e.g., income and energy consumption), and country-specific drivers (e.g., renewable energy potential) influence the determinants of renewable energy deployment.

In this context, the magnitude and speed of renewable energy deployment are variable across countries due to varying economic interests and renewable technological capacity (Sovacool et al., 2020). Considering the unequal pace of development, developing countries pay more attention to climate change adaptation, rather than carbon mitigation, creating a gap in renewable energy investment between developed and developing countries (Venema and Rehman, 2007). In addition to this disparity in climate change and associated renewable energy policy directions, the impact and vulnerability of climate change vary according to socioeconomic status (Kim et al., 2021; Noy, 2016). For example, low-income countries are more vulnerable to the impact of climate change because of their limited capacity to deal with climate extremes and natural resource dependency (Abeygunawardena et al., 2003; Venema and Rehman, 2007).

In other words, since climate change affects countries and regions disproportionately according to socioeconomic capacity, the impact of climate change is spatially heterogeneous (Fattouh et al., 2019; Islam and Winkel, 2017; Kim et al., 2021). Thus, effective renewable energy strategy requires the adequate integration of local, unique climate vulnerability dimensions. This is because the rapidly accelerating renewable energy transition that prioritizes climate mitigation may actually increase regional inequities in climate change vulnerability, therefore weakening the positive function of renewables on climate adaptation (Banhamli-Zakar et al., 2016).

Despite the importance of the determinants of impact and vulnerability in climate change research, there is dearth of studies that integrate climate adaptation parameters into the effect of renewable energy transition on climate change. In addition, a large strand of the relevant literature is broadly related to the components of adaptive capacity, which refers to adjustments in social, economic, and ecological systems in response to climatic stimuli and impacts (Smit et al., 2000). However, this notion has yet to be sufficiently realized in the study of the climate-energy nexus on a global scale (Ruffato-Ferreira et al., 2017). Since functions of climate vulnerability—which consist of climate exposure, sensitivity, and adaptive capacity—are interrelated, omitting one of these dimensions can produce misleading results, and therefore ineffective policy.

Addressing this gap, this study offers a comprehensive comparison of the effects of climate adaptation between climate impact and climate vulnerability on renewables deployments across 121 countries. We used panel data analysis to interrogate consistent global datasets extending over the last three decades. To select relevant indicators covering the full range of climate adaptation dimensions, we adopted the Intergovernmental Panel on Climate Change's (IPCC) climate vulnerability framework.

Our novel approach incorporates the climate adaptation and vulnerability components into renewable energy transition and provides

comprehensive and in-depth insights for a sustainable and effective renewable energy transition in the era of climate change.

The remaining sections of this paper are composed as follows. Section 2 discusses relevant literature, including a brief overview of the determinants of renewable energy growth in climate vulnerability dimensions. Section 3 explains our data, indicator selection, and analytical approaches. Section 4 presents our empirical results and discusses key findings. Section 5 concludes with policy recommendations for future renewable strategies to ensure effective climate change adaptation.

2. Implication of renewable energy transition in climate change

Renewable energy has been emphasized as a vital tool for climate change mitigation across the world (Carley and Konisky, 2020). A substantial body of literature supports the fact that renewables not only help climate mitigation due to their carbon reduction effect but also promote climate adaptation, contributing to building the capacity to address climate change (Flores and Peralta, 2020; Long and Steinberger, 2016; Semeraro et al., 2018; Suman, 2021). For example, Kusumadewi et al. (2017) demonstrated that renewable energy transition in Thailand could achieve a carbon emission reduction >41 % by comparing a 100 % renewable energy option with their business-as-usual scenario. Mostafaiepour et al. (2022) estimate that the use of renewable electricity can reduce carbon emissions by 7–41 % in Iran. Similarly, several studies indicate that increasing renewable energy consumption supports carbon emission reduction in the U.S. (Jaforullah and King, 2015), China (Liu et al., 2015), 25 selected African countries (Zoundi, 2017), 17 OECD countries (Bilgili et al., 2016), Brazil, Russia, India, China, and South Africa (Hassan et al., 2020), and 30 selected countries globally (Jin and Kim, 2018).

The impact of renewable energy on carbon emissions also substantially influences climate adaptation (Venema and Rehman, 2007). The IPCC has indicated that global warming caused by climate change can significantly increase climate impact, especially through the acceleration of the frequency and intensity of extreme climate events (Adger et al., 2007). Unlike other conventional thermoelectric electricity generation systems, renewables are not sensitive to water resources for purposes of cooling, contributing to the improved sustainability of aquatic ecosystems and water resources (Jin et al., 2019; van Vliet et al., 2012). A decentralized energy generation system for renewables reduces the probability of overall failure in energy supply caused by extreme events, compared to a centralized energy production system (Eitan, 2021; Venema and Rehman, 2007). Furthermore, renewables can help reduce heat-related mortality in vulnerable populations by contributing to lowering maximum temperatures and associated heat island effects (Sims, 2004).

These advantages offered by renewables in coping with climate change drive the promotion of renewable energy transition globally. According to the International Energy Agency (IEA), renewables supplied nearly 27 % of global electricity in 2019 and could become the primary electricity source by 2030, providing 40 % of the world's electricity supply (IEA, 2020).

Over the past decades, the growth of renewables at the global level can be roughly categorized into three phases, with opportunities in terms of energy security, socioeconomic development, energy access, and climate change mitigation (Sen and Ganguly, 2017). The first phase of renewable growth was catalyzed by the petroleum price increase triggered by geographically decreased petroleum supply, especially during the 1973 oil crisis and after the Gulf War in 1991 (Sen et al., 2016). Since renewables help reduce the dependency on fossil fuels, it diversifies local energy supply options, enhancing energy security (Sen and Ganguly, 2017). The second phase began with efforts toward sustainable socioeconomic development and expanding energy access along with the Millennium Development Goals, which called for increases in reliable and clean energy (Kaygusuz, 2007). Since renewables are more decentralized, they can play a significant role in reducing extreme poverty and economic development, especially in developing countries (Sen and Ganguly, 2017). In the third phase, the use

of renewable energy has received growing attention along with global climate change mitigation and adaptation efforts, because decarbonization through renewables can positively influence sensitivity and vulnerability to climate risks and impacts by enhancing social and economic operating capability (Sarma and Zabaniotou, 2021).

Meanwhile, the conceptual framework of vulnerability to climate change has evolved over the past decade by progressively including non-climatic determinants such as adaptive capacity (Füssel and Klein, 2006). However, a large portion of existing climate vulnerability research prioritizes climate factors over socioeconomic contexts, while climate vulnerability is dynamic due to its close relationship to social systems and spatiotemporal scales (Ford et al., 2018). In this study, therefore, we primarily focus on literature that considers the evolved concept of climate vulnerability in line with the IPCC's vulnerability assessment (2nd generation), which clarifies that climate impacts and vulnerability can be directly influenced by non-climatic factors.

As IPCC defines climate vulnerability as a function of climate exposure, sensitivity, and adaptive capacity, many studies identify factors that are associated with each function (Füssel and Klein, 2006; Schmidt-Thomé and Greiving, 2013). Climate change exposure is defined as “the nature and degree to which a system is exposed to climatic variations,” and this parameter frequently involves extreme weather events such as tropical cyclones, extreme temperature, and unusual precipitation in the relevant studies (Schmidt-Thomé and Greiving, 2013). Sensitivity, which refers to the degree to which a system is influenced by climate stimuli, is typically represented by physical and social characteristics such as coastal proximity, elevation above sea level, urban density, and marginalized populations (Cardona et al., 2012; Ludena et al., 2015; Miola et al., 2015; Zhang and Chen, 2019). Adaptive capacity, which is defined as the ability of a society to deal with the negative consequences of climate change, consists of determinants that reflect economic, social, institutional, and infrastructural capacities (Juhola and Kruse, 2015; Ludena et al., 2015; McIntosh and Becker, 2020; Schmidt-Thomé and Greiving, 2013). GDP per capita, research and development, road accessibility, level of education, and number of medical institutions or hospital beds are widely used to assess this parameter (Ludena et al., 2015; McIntosh and Becker, 2020; Miola et al., 2015; Shepard et al., 2012; Zhang and Chen, 2019). According to the IPCC's conceptual framework, the combination of exposure and sensitivity results in the impact of climate change, while a system's vulnerability is based not only on climate change impact (exposure and sensitivity) but also adaptive capacity (Füssel and Klein, 2006).

3. Institutional setting and empirical approach

We combine global renewable electricity production data and climate change vulnerability assessments with the Fuzzy Analytic Hierarchy Process (F-AHP) to investigate the impact of renewable energy transition on climate impact and vulnerability.

Since climate change impact is ubiquitous and occurs over a long-term period, we examine 121 countries that produced renewable electricity over the last three decades (Chapagain et al., 2009; Hendrix and Glaser, 2007; Sovacool et al., 2020). To obtain a robust global trend of renewable energy deployment on climate change adaptation, we include all countries that use renewables at different stages. Among them, 115 countries have used renewables throughout the study period. The other six countries adopted renewables at different years within the specified period. Average years of use of renewables within these six countries (Benin, Cyprus, Eritrea, Estonia, Niger, and Trinidad and Tobago) are 12 years. Using panel data regression, we identify the spatial disparity of renewable transitions between climate impact and vulnerability.

3.1. Selection of climate change indicators and data

To quantify the impacts of climate change globally, we utilize the IPCC's vulnerability framework, which consists of climate exposure, sensitivity, and adaptive capacity (Füssel and Klein, 2006; Schmidt-Thomé and Greiving, 2013). Based on previous literature assessing climate vulnerability (Table 1) and a selection process via expert survey (Supplementary Table 1), we finally select globally essential indicators for each of the three functions (exposure, sensitivity, and adaptive capacity) within the conceptual framework of climate vulnerability. Due to the subjective nature of the indicator selection and its relative importance between compared indicators, we use expert surveys as follows: first, we select 18 climate vulnerability indicators by expert judgements among 21 most common indicators from relevant studies (Supplementary Tables 1 and 2). Second, we weight the different contributing indicators based on expert judgement using AHP method. Third, we further apply fuzzy membership function to mitigate concerns of using subjective human judgement on AHP weight (Chang, 1996).

To avoid the occurrence of bias due to different development statuses among the 121 countries (particularly between developed and developing countries), we adopt the UN's Human Development Index (HDI) method, with their suggested threshold of 0.8, rather than including binary variables

Table 1
Climate change indicators.

Aspect	Indicator	Literature
Exposure	Storm frequency	(Kim et al., 2021; Ludena et al., 2015; McIntosh and Becker, 2020; Miola et al., 2015; Yusuf and Francisco, 2009; Zhang and Chen, 2019)
	Natural disaster casualty	(Muttarak et al., 2015; Zagheni et al., 2015; Zhao et al., 2015)
	Precipitation	(Binita et al., 2015; Kim et al., 2021; Ludena et al., 2015; McIntosh and Becker, 2020; Schmidt-Thomé and Greiving, 2013; Zhang and Chen, 2019)
Sensitivity	Temperature anomaly	(Binita et al., 2015; Schmidt-Thomé and Greiving, 2013)
	Sea level rise	(Brenkert and Malone, 2005; Ludena et al., 2015; McIntosh and Becker, 2020; Miola et al., 2015; Yusuf and Francisco, 2009)
	Coastal proximity	(Bagheri et al., 2021; Kim et al., 2021; Ludena et al., 2015; Milfont et al., 2014)
	Elevation	(Bagheri et al., 2021; Kim et al., 2021; Miola et al., 2015; Zhang and Chen, 2019)
	Population density	(Brenkert and Malone, 2005; Kim et al., 2021; McIntosh and Becker, 2020; Miola et al., 2015; Shepard et al., 2012; Yusuf and Francisco, 2009; Zhang and Chen, 2019)
	Urbanization density	(Kim et al., 2021; Zhang and Chen, 2019)
Adaptive Capacity	Vulnerable population	(Binita et al., 2015; Cardona et al., 2012; Kim et al., 2021; Ludena et al., 2015; Shepard et al., 2012)
	Gender	(Ampaire et al., 2020; Eastin, 2018; Shepard et al., 2012)
	Economy	(Binita et al., 2015; Brenkert and Malone, 2005; Kim et al., 2021; Ludena et al., 2015; Miola et al., 2015; Zhang and Chen, 2019)
	Government effectiveness	(Craft and Fisher, 2016; Ludena et al., 2015)
	Mobile subscribers	(Miola et al., 2015; Yusuf and Francisco, 2009)
	Access to electricity	(Perera et al., 2015; Sun et al., 2021; Yusuf and Francisco, 2009)
	Insurance	(Lucas and Booth, 2020; Mills, 2005; Surminski et al., 2016)
	R&D	(Craft and Fisher, 2016; Li et al., 2021)
	Human development index	(Yusuf and Francisco, 2009; Zagheni et al., 2015)
	Road accessibility	(Kim et al., 2021; Shepard et al., 2012; Yusuf and Francisco, 2009; Zhang and Chen, 2019)
	Education attainment	(Binita et al., 2015; Brenkert and Malone, 2005; Kim et al., 2021; Shepard et al., 2012; Yusuf and Francisco, 2009)
	Health service capacity	(Kim et al., 2021; Miola et al., 2015; Shepard et al., 2012; Zhang and Chen, 2019)

to indicate a nation's development status (UNDP, 2022). Since we assess long-term data over the past three decades, the status of a nation's development is likely to have changed over that time. Thus, using yearly economic and development status data makes the results more accurate and allowed us to avoid multicollinearity. However, some developing countries such as China and India have begun deploying a large-scale renewable energy during the most recent decade, so analysis results could be biased with a binary categorization between developed and developing status. Therefore, we add one additional category representing a middle-income country (HDI between 0.7 and 0.8) as a robustness check (UNDP, 2022).

Although our dataset includes eight small island developing states (i.e., Cuba, Dominican Republic, Haiti, Jamaica, Mauritius, Singapore, Suriname, and Trinidad and Tobago), we systematically capture their unique geographical characteristics by including physical geographic sensitivity variables (i.e., sea level rise, coastal proximity, and elevation).

We use data from multiple sources in our analysis. Renewable electricity capacity and generation data from 1992 to 2019 were obtained from the World Bank and the Global Economy. To identify the impacted countries of each tropical cyclone, we use the U.S. National Oceanic and Atmospheric Administration's (NOAA) International Best Track Archive for Climate Stewardship data (Knapp et al., 2018). Given the classification of tropical cyclones defined by World Meteorological Organization, we use storms that exceed a maximum sustained surface wind speed of 34 knots (WMO, 2022). All other data in climate exposure, sensitivity, and adaptive capacity is aggregated from other open-source databases or commercial data providers such as the National Aeronautics and Space Administration, Our World Data, Trading Economics, the Global Economy, and World Bank (Supplementary Table 3). Since information on vulnerable populations was missing in the database, we combine the percentage of the population below the age of 14 and the population aged 65 years old and over (Miola et al., 2015).

3.2. Assessment of climate change indicators

To assess the spatial correlation between renewable energy transition and climate change indicators across the climate vulnerability dimensions, we develop unique climate impact and vulnerability indices. Since each defined indicator has different orders of magnitude, it is necessary to uniformize the values and to define a comprehensive weight in each factor (Kim et al., 2021; Schmidt-Thomé and Greiving, 2013; Zhang and Chen, 2019). Accordingly, we perform the linear Min-Max method and F-AHP with the following equations.

$$Y_{ijt} = \frac{\chi_{ijt} - \rho_{ijt}}{\varphi_{ijt} - \rho_{ijt}} \quad (1)$$

where Y_{ijt} is a normalized value between 0 and 1 for the climate indicator i in country j in year t ; χ is an original indicator value; ρ is the minimum value; and φ is the maximum value.

In order to assess the aggregate climate impact and vulnerability values, we conduct the F-AHP method. This method, which has been widely used in climate vulnerability assessment, is based on pair-wise comparisons to weigh the normalized aggregate values (Saaty, 1977; Yang et al., 2013; Zhang and Chen, 2019).

Since each climate change indicator has a different relative importance, it is necessary to identify appropriate weight values within and across climate vulnerability dimensions (climate exposure, sensitivity, and adaptive capacity). For example, storm frequency and temperature anomaly may not have equal importance, and may be subjective based on individual experience. Likewise, climate exposure may not have the same impact as adaptive capacity. To obtain the comprehensive and robust weight values, we administered a questionnaire survey via email to 37 experts from international government (i.e., the United Nations Committee of Experts on Public Administration), research institutes, and educational sectors between April 4 and April 29, 2022. To ensure the validity of the respondents' judgement, we invited experts who have been broadly recognized

(e.g., appointed to an expert position by renowned institutes) with sufficient experience (e.g., over 20 years' field experience) in the subject fields of climate change, disaster management, public administration, and resilience policies.

Using a binary questionnaire (i.e., 1 if agreed, 0 otherwise), respondents screened the initially selected climate change indicators based on relevant literature at the global scale. Through this screening process, three variables (gender, mobile subscribers, and insurance) were excluded in the analyses as those variables did not achieve 50 % consensus (Supplementary Table 1).

On the finalized indicator set from the expert screening processes, we obtain the weights of indicators for climate vulnerability criteria from 14 experts (due to 23 invited experts being unresponsive). We adopt a nine-point comparative scale that used Saaty's original Analytic Hierarchy Process (AHP). A value of "1" is assigned if two comparing indicators are equally important, while "9" is inputted if one indicator is far more important than the other. The full set of experts' AHP weights are presented in Supplementary Table 4.

Although all the AHP matrix's consistency ratio values are <0.1, indicating that the expert judgements for their AHP weights are consistent (Zhang and Chen, 2019), the limitation remains due to human judgement still being subjective. To overcome the subjectivity issue, we additionally employ Chang (1996)'s F-AHP method, which uses a linguistic scale based on a triangular membership function (Demirel et al., 2008; Tam et al., 2019). The corresponding fuzzy triangular scale to Saaty's linguistic terms is shown in Supplementary Table 5 (Ayhan, 2013). We obtain the F-AHP matrix with Eqs. 2 and 3.

$$\tilde{A}_i = \sum_{j=1}^n (l_{ij}, m_{ij}, u_{ij}) \left[\sum_{i=1}^n \sum_{j=1}^n (l_{ij}, m_{ij}, u_{ij}) \right]^{-1} \quad (2)$$

where $\tilde{A}_i$ is the value of fuzzy synthetic extent; i and $j = 1, 2, \dots, n$; and $i \neq j$.

$$\zeta_i = \frac{\min_j (\tilde{A}_i \geq \tilde{A}_j)}{\sum_{k=1}^n \min_j (\tilde{A}_k \geq \tilde{A}_j)} \quad (3)$$

where ζ_i is the F-AHP weight value in indicator i ; the probability degree, $\eta(\tilde{A}_i \geq \tilde{A}_j) = (u_i - l_j) / [(u_i - m_i) + (m_j - l_j)]$; i and $j = 1, 2, \dots, n$; $i \neq j$; $j \neq k$; m_i and m_j represent the ordinates of the highest intersection point in triangular membership function. However, $\eta(\tilde{A}_i \geq \tilde{A}_j)$ equals to 1 if m_i is greater than or equal to m_j and is valued zero if u_i is smaller than l_j . The full sets of AHP and F-AHP matrixes are presented in Supplementary Tables 6 and 7. Finally, we calculate a comprehensive F-AHP weights using the following equation:

$$W_t = \left(\sum_{f=1}^n \omega_{e,t} \times \zeta_{f,t} \right) + \left(\sum_{g=1}^n \omega_{s,t} \times \zeta_{g,t} \right) - \left(\sum_{h=1}^n \omega_{c,t} \times \zeta_{h,t} \right) \quad (4)$$

where W_t is a comprehensive F-AHP weighted value in country t ; ω_e , ω_s , and ω_c are the sectional weights of exposure, sensitivity, and adaptive capacity, respectively; ζ_f is a weight of f^{th} indicator in climate exposure; ζ_g is a weight of g^{th} indicator in climate sensitivity; and ζ_h is a weight of h^{th} indicator in adaptive capacity. The final AHP and F-AHP weights are shown in Supplementary Tables 8 and 9, respectively.

3.3. Impact of renewable energy transition on climate vulnerability

Using the defined indicators of four climate exposure, six sensitivity, and eight adaptive capacity variables with the F-AHP weights, we use a panel data regression to estimate the effects of renewable energy transition on climate vulnerability dimensions with the following equation.

$$\ln Y_{it} = \alpha_0 + \alpha_1 E_{it} + \alpha_2 S_{it} + \alpha_3 X_{it} + c_i + \varepsilon_{it} \quad (5)$$

where $\ln Y_{it}$ is the percentage changes of renewable electricity production and renewable energy capacity in country i in year t ; E_{it} , S_{it} , and X_{it} are vectors of climate exposure, climate sensitivity, and adaptive capacity, respectively; and c_t represents the recession dummy variable. ε_{it} is the error term. In all models overall and in different time periods, Prob>chi2 is higher than 0.05 in the Hausman specification test and thus we use a random effect model, rather than a fixed effect model.

4. Results and discussion

We find that most of the indicators associated with adaptive capacity are sensitive to national renewable energy policy throughout the study periods (Table 2). Gross Domestic Product per capita (GDPPC), government effectiveness (Gov. effect), access to electricity (Elec. access), research and development (R&D), and human development index (HDI) have a positive impact on renewable energy transition. By contrast, education and hospitals are statistically insignificant at the 5 % significance level on renewable electricity generation (columns 1–3). Among the climate impact (exposure and sensitivity) indicators, precipitation, temperature anomaly, sea level rise, urban density, and vulnerable populations are associated with an increase in renewable energy generation and capacity. After 2005, variables in climate impact parameters are broadly consistent with the results of the period between 1992 and 2005, while the coefficients of adaptive capacity indicators are higher in the last 14 years (2006–2019) than the period before 2006 (Fig. 1).

The positive results on most of the adaptive capacity variables indicate that renewables have been promoted in the countries where the adaptive capacity is higher than in low-income countries that may have less capacity to adapt climate change. More robust results in the more recent timeframe (2006–2019) signify that recent renewable technology development may promote spatial inequality of renewable energy in climate change by exacerbating the phenomena of wealthier countries promoting more renewable energy while developing countries have less deployed renewable energy.

This phenomenon can become more pronounced in combination with other endogenous factors, including economic and political factors. One plausible example is that low-income countries are more reliant on fossil fuels and traditional biomass for heating and cooking in rural areas where

renewable alternatives are not affordable or not yet available (Daiglou et al., 2012). Another factor may be a lack of available capital for investment in renewables and infrastructural maintenance (Cantarero, 2020). Lastly, insufficient social awareness of clean energy-related issues and a predominantly top-down approach in the decision-making process without reaching social consensus may also be a cause (Brown and McGranahan, 2016; Devine-Wright, 2012). All of these, among others, may contribute to spatial inequality in renewable energy investment in developing countries.

To further investigate the spatial inequality of renewable energy deployment across climate change impact and vulnerability dimensions, we normalized an original value of each indicator and then reclassified them into a 5-point scale, with 1 being least change in renewables and 5 being the most (Supplementary Fig. 1). This clustering process allows us to create two unique index maps: a renewables-climate impact index and a renewables-climate vulnerability index (Supplementary Fig. 2).

Since our preliminary regression results in Fig. 1 show that climate vulnerability indicators are broadly more associated with renewable energy variation, we adopt the renewables-climate vulnerability index. To validate the hypothesis that renewables yield spatial inequality due to asymmetrical provision between climate impact and vulnerability dimensions, we estimate the F-AHP weighted renewables-climate vulnerability index as our main dependent variable.

Here, we reveal that the majority of adaptive capacity variables are negatively associated with the discrepancy between an increase in renewable electricity generation and climate vulnerability (Table 3). This result implies that the gap between renewables and climate vulnerability is higher in low-income developing countries, while wealthier countries have less of a gap. To test the effect associated with middle-income countries such as China and India that have deployed for large scale renewables over the last decade, we estimate high-income, middle-income, and low-income countries separately as a robustness check. The results show that all the coefficients in adaptive capacity variables are negative in low-income countries, further confirming our main results (Supplementary Table 12). By contrast, most variables in climate exposure and sensitivity have a positive impact on the discrepancy between renewables and climate vulnerability. The impact of climate change indicators on the discrepancy are more

Table 2
Regression results.

		(1)	(2)	(3)	(4)	(5)	(6)
		lnRPG 1992–2019	lnRPG 1992–2005	lnRPG 2006–2019	lnRPC 1992–2019	lnRPC 1992–2005	lnRPC 2006–2019
Exposure	Storm	0.004	0.001	0.005	0.007	0.003	0.009
	Casualty	−0.001	−0.001	0.001	−0.001	0.002	−0.004
	Precipitation	0.283***	0.214**	0.290***	0.234***	0.196**	0.213***
	Temperature	−0.004	0.010**	0.012*	0.020***	−0.021***	0.023***
Sensitivity	Sea level rise	0.337***	0.334***	0.218*	0.241**	0.227*	0.189
	Coastal prox.	−0.078	−0.032	−0.326***	−0.224**	−0.155	−0.363***
	Elevation	−0.030	−0.029	−0.039	−0.094	−0.159*	−0.027
	Pop density	−0.055**	0.019	0.033	−0.004	−0.010	0.074
Adaptive capacity	Urban density	0.046	0.083	0.100	0.073**	0.109*	0.152**
	Vulnerable	0.103***	0.096***	0.166***	0.071***	0.114***	0.141***
	GDPPC	0.065***	0.023	0.079***	0.152***	0.106***	0.091***
	Gov effect	0.080***	0.102***	0.043	0.073***	−0.010	0.047
	Elec access	0.129***	0.126***	0.281***	0.144***	0.094*	0.257***
	R&D	0.212***	0.020	0.256***	0.266***	0.113***	0.262***
	HDI	0.545***	0.421***	0.368***	0.348***	0.270***	0.376***
	Road	0.032***	−0.023	0.079***	0.014	−0.044**	0.063***
	Education	−0.013	−0.004	0.038*	0.072***	0.044**	0.093***
	Hospital	−0.003	0.003	−0.024	−0.009	0.003	−0.039*
	Recess	0.004	−0.006	−0.002	0.010**	0.005	0.003
	Observation	3296	1635	1661	3294	1617	1677
R^2		0.468	0.254	0.346	0.461	0.267	0.377

Notes: Dependent variables are logged renewable power generation (columns 1–3) and logged renewable power capacity (columns 4–6). The main entries in each column report the standardized beta coefficients estimated by random effect model.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

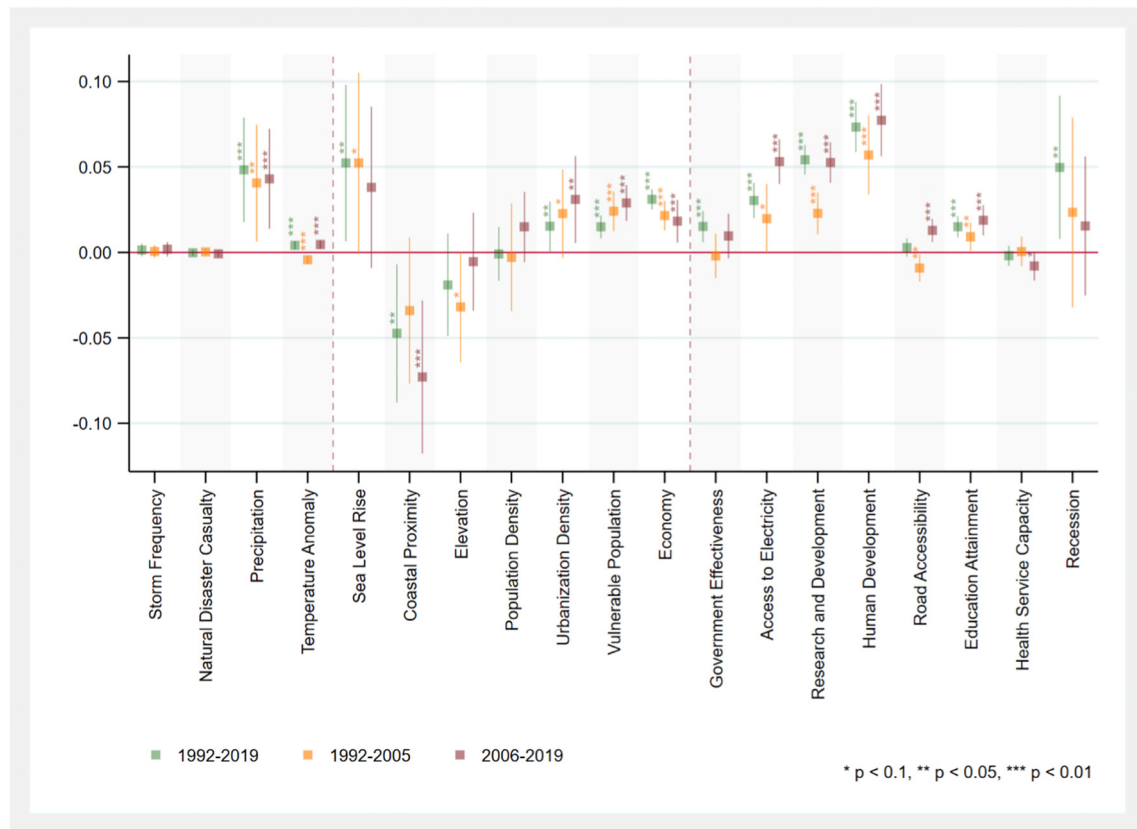


Fig. 1. Coefficient plot representing the regression results.

consistent and pronounced in the most recent period (Column 3). In Table 3, four variables (coastal proximity, elevation, population density, urban density) in sensitivity and five variables (GDPPC, government effect, research and development, education, and hospitals) in adaptive capacity show a contrasting direction between columns 2 and 3.

As a robustness check, we use a quadratic function on those variables, and the results remain broadly the same (Supplementary Table 10). The results signify that the recent technical advancement of renewable energy may exacerbate the phenomenon in which adaptive capacity factors are not considered in renewable energy policy. Since the use of renewables in

Table 3
Renewable energy transition on climate vulnerability.

		(1)		(2)		(3)	
		1992–2019		1992–2005		2006–2019	
Exposure	Storm	0.013**	(0.005)	–0.007	(0.016)	0.012*	(0.007)
	Casualty	0.027***	(0.006)	0.017	(0.013)	0.095	(0.086)
	Precipitation	0.036***	(0.003)	0.027***	(0.008)	0.023***	(0.002)
	Temperature	0.020***	(0.001)	0.005	(0.004)	0.021***	(0.002)
Sensitivity	Sea level rise	0.030***	(0.007)	0.024	(0.019)	0.029***	(0.004)
	Coastal prox.	0.013**	(0.007)	–0.037**	(0.018)	0.021***	(0.004)
	Elevation	0.005	(0.007)	–0.004	(0.016)	0.017***	(0.004)
	Pop density	0.002	(0.007)	–0.027	(0.020)	0.020***	(0.005)
Adaptive capacity	Urban density	0.008***	(0.003)	–0.002	(0.009)	0.022***	(0.002)
	Vulnerable	0.020***	(0.001)	0.018***	(0.003)	0.023***	(0.001)
	GDPPC	–0.012***	(0.003)	0.093***	(0.011)	–0.023***	(0.004)
	Gov effect	–0.029***	(0.002)	0.004	(0.008)	–0.028***	(0.003)
	Elec access	–0.030***	(0.002)	–0.054***	(0.006)	–0.023***	(0.002)
	R&D	0.018***	(0.002)	0.014*	(0.007)	–0.016***	(0.002)
	HDI	–0.023***	(0.002)	–0.019*	(0.010)	–0.024***	(0.003)
	Road	–0.020***	(0.001)	–0.015***	(0.004)	–0.019***	(0.001)
	Education	–0.023***	(0.001)	0.022***	(0.003)	–0.022***	(0.001)
	Hospital	–0.016***	(0.001)	0.005***	(0.002)	–0.019***	(0.001)
	Recess	–0.002	(0.001)	–0.001	(0.004)	–0.003	(0.002)
	Constant	0.533***	(0.012)	0.330***	(0.044)	0.601***	(0.015)
Observation		3388		855		855	
R ²		0.776		0.300		0.550	

Notes: Dependent variables are differences between changes in renewable power generation and climate change vulnerability. The main entries in each column report the coefficients estimated by random effect model. Standard errors in parentheses.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

some countries is significantly less in terms of overall energy use, we conduct another robustness check with the dataset excluding 27 countries in which average renewable power generation is less than one billion kilowatt-hours. The results are broadly the same, with increased R-squared in columns 2 and 3 (Supplementary Table 11).

The basic mismatch between renewable deployment and climate adaptation poses the threat that existing renewable energy policy can aggravate climate inequality. Evidently, a higher level of discrepancy appears at a low level of adaptive capacity in all socioeconomic indicators (i.e., economy, government effectiveness, access to electricity, research and development,

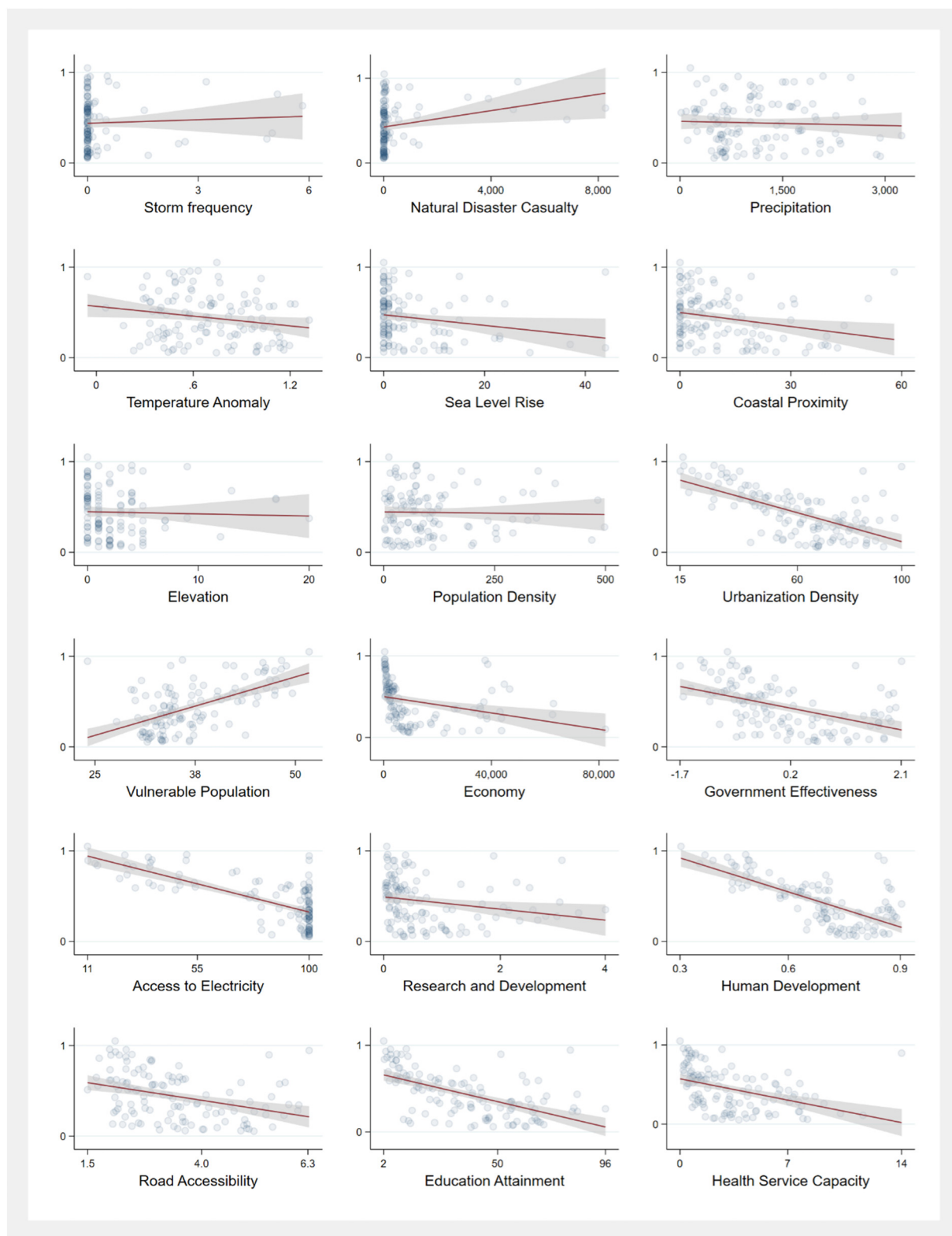


Fig. 2. Correlation plots between climate impact-vulnerability disparity and each indicator.
Notes: Red line is fitting line. Gray area surrounding the fitting line is 95 % coefficient intervals.

human development, road accessibility, education attainment, and health service capacity) representing adaptative capacity (Fig. 2).

Renewable energy has been promoted as a means of coping with climate change globally (Suman, 2021). However, our findings reveal that renewable energy deployment has been promoted less in countries in which the adaptive capacity is relatively low. Instead, an increase in renewable energy deployment is revealed in developed countries that have a higher adaptive capacity.

This phenomenon offsets the positive impact of renewable energy on climate change and may accelerate climate change inequity. Since climate change vulnerability is a collective outcome of climate exposure, sensitivity, and adaptive capacity, socioeconomic factors that influence the ability of a system to deal with climate stimuli are important components to increase climate change resiliency (Füssel and Klein, 2006; Schmidt-Thomé and Greiving, 2013). If this factor is not considered in countries where the adaptive capacity is low, climate inequality may occur, and countries that are vulnerable to climate change may become more vulnerable. To make renewable energy policy effective in reducing the adverse effects of climate change, global societies and countries should reduce climate inequality by considering not only the factors that reduce climate change impact but also the factors to promote adaptive capacity.

5. Conclusion and policy implications

Our study brings empirical evidence and novel insights to broader discussions about climate inequality of the renewable energy transition. To explore the impact of renewable energy deployment on climate change adaptation, we exploit variation in renewables across climate exposure, sensitivity, and adaptive capacity at a global scale using F-AHP and panel data regression.

The study examining the spatial disparity and climate inequality caused by renewable energy policy is novel in four respects. First, we incorporate both climate change impact and vulnerability dimensions into the assessment of renewable energy variation. Second, our research constructs comprehensive and unique indices—the renewables-climate impact index and renewables-climate vulnerability index—to examine the spatiotemporal disparity between the different aspects of renewable energy policy and climate change. Third, we use F-AHP methods to appropriately capture values of relevant indicators representing climate change and to reduce the subjectivity of human judgement. Fourth, we conduct adequate robustness checks with the countries where the use of renewables is significantly less in terms of overall energy use and middle-income countries such as China and India, which have adopted a significant proportion of renewables in the most recent decade.

The empirical results highlight that existing renewable energy implementation fails to adequately address climate change due to spatial inconsistency between policy frameworks and reality. Many countries promote renewables because they help mitigate and adapt to the negative consequences of climate change (Suman, 2021). In reality, however, renewables have been less considered in low-income developing countries that have a low adaptive capacity requiring more renewables. This discrepancy may be further exacerbated by the spatial asymmetry of renewable technology advancement between developed and developing countries. Thus, considering adaptive capacity is essential for improving the efficiency of the renewable energy transition during climate change.

Since renewables may be promoted for varied other reasons—including political factors, energy sovereignty, oil crisis, and broad socio-environmental concerns—driving the uptake of renewables, the spatiotemporal effects may vary in micro-level socio-economic conditions and political contexts. The potential heterogeneous effects on the climate change-renewable nexus may vary in micro-regional level. Thus, we recommend that future studies be conducted at a local level in each climate exposure separately.

CRedit authorship contribution statement

Seung Kyum Kim contributed to conceptualization, methodology, data collection, data analysis, and writing-original draft preparation, validation, manuscript editing, and project administration. Soonae Park contributed to conceptualization, research model development, funding acquisition, and project administration.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary information

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