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Economic, social and governance adaptation readiness for mitigation of climate change vulnerability: Evidence from 192 countries

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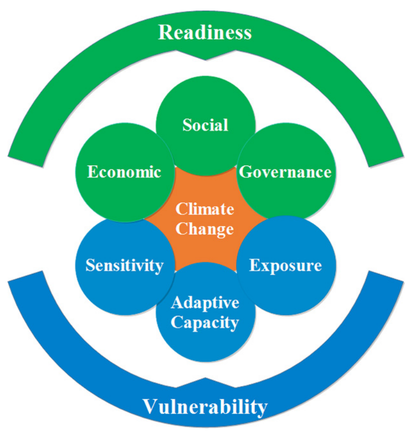
HIGHLIGHTS

- Scandinavian countries have low vulnerability and high climate change readiness.
- African countries have high climate sensitivity and low adaptive capacity.
- Climate change adaptation actions mitigate climate vulnerability.
- Economic, governance and social interventions are critical to climate stress reduction.

GRAPHICAL ABSTRACT



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ABSTRACT

Adaptation strategies have become critical in climate change mitigation and impact reduction, to safeguard population and the ecosystem from irreparable damage. While developed countries have integrated adaptation plans and policies into their developmental agenda, developing countries are facilitating or yet to initiate adaptation policies in their development. This study examines the nexus between climate change vulnerability and adaptation readiness in 192 UN countries using mapping and panel data models. The study reveals Africa as the most vulnerable continent to climate change with high sensitivity, high exposure, and low adaptive capacity. Developed countries, including Norway, Switzerland, Canada, Sweden, United Kingdom, Finland, France, Spain, and Germany, are less vulnerable to climate change due to strong economic, governance and social adaptation readiness. International commitment from developed countries to developing countries is essential to strengthen their resilience, economic readiness and adaptive capacity to climate-related events.

1. Introduction

Changes in climatic conditions have impacted natural and human systems around the globe, due to human interferences with the climatic system within the past decades (IPCC, 2014b). Impacts of the climate-related extreme events (heat waves, floods, droughts, wildfires,

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cyclones, etc.) include ecosystem alterations, disruption of water supply, interruption of food production, damage to settlements and infrastructure and increase in morbidity and mortality, (Field et al., 2014). These hazards occur and have impacts due to lack of social, economic and governance readiness to combat climatic events. However, historical experience proves that societies have adjusted to and have adopted successful adaptation strategies for climate, climate variability and extreme events (IPCC, 2014b). There are several adaptation experiences across the globe embedded in adaptation planning processes. In Africa, governance systems for adaptation are being initiated [disaster risk management (Van Niekerk, 2006), changes in infrastructure and technology, public health measures and ecosystem-based strategies are reducing climate change vulnerability] (Noble et al., 2014). In Asia, climate change adaptation actions incorporated into development planning, early warning systems, integrated water resource management, and integrated coastal zone management are being facilitated (IPCC, 2014b; Noble et al., 2014). In Australia, adaptation planning for sea level rise, drought, and reduced water availability are being implemented (Kiem, 2013). In the Arctic regions, the deployment of adaptive co-management options and infrastructure for communications in some communities are being executed (IPCC, 2014b; Plummer and Baird, 2013). In North, Central and South America, governments are implementing ecosystem-based adaptation (Vignola et al., 2013), adaptation assessment and planning, long-term energy and public infrastructural investments (Easterly and Serven, 2003), integrated water resource management, climate forecasts and resilient crop varieties (Lin, 2011) in the agricultural sector (IPCC, 2014b). In Europe, adaptation planning has been incorporated into environmental protection, coastal management (Pickaver et al., 2004), water resource management, land planning, agricultural risk management (Bielza et al., 2007) and disaster risk management (Fekete et al., 2014), while adaptation policies are being developed (IPCC, 2014b). International cooperation appears to facilitate adaptation readiness to climate change, as evidenced in the sustainable development goals (United Nations, 2015).

Numerous studies have examined the immediate and underlying drivers of climate change (Martin and Saikawa, 2017; Raftery et al., 2017; Sarkodie, 2018), however, studies on vulnerability and adaptation readiness are limited. A recent study by Watson et al. (2013) examined the vulnerability and conservation of species, focusing on biodiversity loss without accounting for other climate-sensitive and vulnerable sectors. Most adaptation assessments have been limited to impacts (Hansen and Stone, 2015), exposure, sensitivity (Miller et al., 2018) and vulnerability, with limited studies examining the effects of adaptation actions (IPCC, 2014b). In contrast, this study for the first time examines the impact of aggregate and disaggregate adaptation readiness on climate change vulnerability using spatial analysis and panel quantile regression model, while accounting for heterogeneity and unconditional distribution across quantiles.

Evidence from the study reveals a decline in climate change vulnerability at a positive economic, governance and social adaptation readiness. While there are global efforts and partnerships to combat climate change and its impact, developed countries appear to have low sensitivity, exposure and high adaptive capacity to climate-related events compared to developing countries.

2. Methods

2.1. Data

Due to the complexity of climate change and its related services, this study employs a wide range of variables and indicators capable of modeling climate change mitigation and adaptation options. Data series for the model estimation is retrieved from ND-GAIN (2018b). Figs. 1 and 2 present the fundamentals and indicators of vulnerability to climate change and the components and indicators of readiness to mitigate climate change. The selection of the 45 indicators used to examine vulnerability to climate change and readiness to mitigate climate change is in accordance with the 17 Sustainable Development Goals by 2030 and the United Nations' indicators of sustainable development: guidelines and methodologies (DiSano, 2002). For easier comparison between countries prior to the economic model estimation, the data series are converted into scores ranging from 0 to 1 following the scaling formula by ND-GAIN (2018b), expressed as:

$$Score = \left\langle Direction - \frac{Raw\ Data - Reference\ Point}{Baseline\ Maximum - Baseline\ Minimum} \right\rangle \quad (1)$$

where *Direction* has two parameters namely; 0 for scoring vulnerability indicators and 1 for scoring readiness indicators. In this case, a vulnerability score of 1 denotes worse state (higher vulnerability to climate change) while a readiness score of 1 denotes a better state (higher readiness to mitigate climate change). As shown in Fig. 1, Climate Vulnerability comprises of 36 indicators from 6 sectors, such as food, water, health, ecosystem services, human habitat and infrastructure. Out of the 36 indicators of vulnerability from the six sectors, 12 indicators each were categorizations under; Exposure, Sensitivity and Adaptive Capacity. On the contrary, readiness to mitigate climate change in Fig. 2 covers 9 indicators under three components, namely economic, governance and social readiness.

The availability of high-quality data series for the model estimation limited the period of the study from 1995 to 2016 conducted in 192 countries under the United Nations. The adoption of a time series data to construct a panel data of 192 countries helps track historical changes and trend of country-specific climate vulnerability and adaptation readiness.

2.2. Study design

This study builds an econometric model based on the linear relationship between vulnerability and readiness expressed with Eq. (2):

$$Vulnerability = f\langle Readiness\rangle \quad (2)$$

The disaggregate effect of readiness on climate change vulnerability is expressed with Eq. (3) as:

$$Vulnerability = f\langle economic, governance, social\rangle \quad (3)$$

Prior to the model estimation, the study first performs a series of unit root tests to examine the stationarity of the panel data set. Both first and second generational unit root tests such as Breitung (Breitung, 1999), Im-Pesaran-Shin (IPS) (Pesaran et al., 2003) and Pesaran's Cross-sectionally Augmented Dickey-Fuller (CADF) (Pesaran, 2007) are employed. The study control for cross-sectional dependence using Pesaran's CADF, an issue which is problematic in panel data settings. At this point, the common factors can have different effects across different cross-sectional units and reduce unobserved common factors required in the model. The first generational unit root tests (Breitung and IPS) follow a simplified first-order autoregressive panel data model expressed as:

$$y_{i,t} = \rho_i y_{i,t-1} + \acute{z}_{i,t}\gamma_i + \epsilon_{i,t} \quad i = 1, \ldots, N; t = 1, \ldots, T \quad (4)$$

where y denotes the observations in the panel, $\epsilon_{i,\ t}$ is mean zero regression error term, $\acute{z}_{i,t}\gamma_i$ denotes the fixed effects (panel-specific means), i represents index panels, and t denotes index time. Thus, the generalized null hypothesis $\rho_i = 1$ versus the alternative hypothesis $\rho_i < 1$. Contrary to the first generation unit root tests based on "deviation from the estimated common factors", Pesaran's CADF (Pesaran, 2007) is based on an augmentation with the cross-sectional means of lagged levels and first-difference of the individual units. The results of the panel unit root tests are presented in Table 1, which confirms the stationary process of the

SECTOR	Food	Water	Health	Ecosystem Services	Human Habitat	Infrastructure
Exposure Component	Projected change of cereal yields	Projected change of annual runoff	Projected change of deaths from climate change induced diseases	Projected change of biome distribution	Projected change of warm period	Projected change of hydropower generation capacity
Exposure Component	Projected population change	Projected change of annual groundwater recharge	Projected change of length of transmission season of vector-borne diseases	Projected change of marine biodiversity	Projected change of flood hazard	Projection of Sea Level Rise impacts
Sensitivity Component	Food import dependency	Fresh water withdrawal rate	Slum population	Dependency on natural capital	Urban concentration	Dependency on imported energy
Sensitivity Component	Rural Population	Water dependency ratio	Dependency on external resource for health services	Ecological footprint	Age dependency ratio	Population living under 5m above sea level
Adaptive Capacity Component	Agriculture capacity (Fertilizer, Irrigation, Pesticide, Tractor use)	Access to reliable drinking water	Medical staffs (physicians, nurses and midwives)	Protected biomes	Quality of trade and transport-related infrastructure	Electricity access
Adaptive Capacity Component	Child malnutrition	Dam capacity	Access to improved sanitation facilities	Engagement in International environmental conventions	Paved roads	Disaster preparedness

Fig. 1. The fundamentals and indicators of vulnerability to climate change. NB: categorized into exposure, sensitivity and adaptive capacity.

data series at first-difference, thus, variables are integrated of order one [$I(1)$].

After satisfying the preconditions of the stationary process at first-difference, the study examines the cointegration of the variables using panel data cointegration tests namely Pedroni (Pedroni, 2004) and Westerlund (Westerlund, 2005). Testing for cointegration of the data series is necessary to ascertain the long-run equilibrium relationship of the $I(1)$ data series under the null hypothesis of no cointegration. The specification of the cointegrating relationship between vulnerability, the disaggregate effect of readiness (economic, governance and social) and readiness are expressed as:

$$vulnerability_{i,t} = \gamma_i + \beta_{1,i}economic_{i,t} + \beta_{2,i}governance_{i,t} + \beta_{3,i}social_{i,t} + \epsilon_{i,t} \quad (5)$$

$$vulnerability_{i,t} = \gamma_i + \beta_{1,i}readiness_{i,t} + \epsilon_{i,t} \quad (6)$$

where γ_i represents the panel specific average (fixed-effects), $\beta_{1,\,i}$, …., $\beta_{3,\,i}$ denotes the panel specific cointegrating parameters, and $\epsilon_{i,\,t}$ is the white noise. Pedroni cointegration produces three statistics, such as modified Phillips-Perron t, Phillips-Perron t, augmented Dickey-Fuller t employ a Bartlett kernel with 4 lags for serial correlation adjustment process. In contrast, Westerlund cointegration produces a variance ratio test statistic with a panel-specific autoregressive parameter. The results from both Pedroni and Westerlund cointegration tests presented in Table 2 reject the null hypothesis of no cointegration at 1% significance level with or without panel-specific time trends. Accordingly, cointegrating relationships between vulnerability, the disaggregate effect of readiness and readiness were confirmed in Table 2.

2.3. Model estimation

The study estimates 15 econometric models with their empirical results presented in Table 3. The specification of Models 1[a]–2[a] follows Pesaran's Pooled Mean-Group (PMG) model useful for large N and T panel data samples expressed as:

$$\Delta y_{i,t} = \varphi \times (y_{i,t-1} + \beta_{i,t}) + \Delta y_{i,t-1}a_1 + \ldots + y_{i,t-p}a_p + \Delta x_{i,t}b_1 + \ldots + \Delta x_{i,t-q}b_q + \varepsilon_{i,t} \quad (7)$$

where y is the dependent variable (vulnerability), x represents the independent variables (economic, governance, social and readiness), φ denotes the error correction speed of adjustment parameter, β represents a $k \times 1$ vector of the parameters, a_1, …, a_p and b_1, …, b_q are the p and q parameters to be estimated, $x_{i,\,t}$ denotes a $1 \times k$ vector of covariates, $i = (1,…,N)$ represents the individual cross-sectional units, $t = (1,…,T_i)$ is the time period, and $\varepsilon_{i,\,t}$ represents the white noise. The PMG model is useful for constraining the long-run effects and beta coefficient equally across all cross-sectional units, however, the short-run coefficient can differ across all cross-sectional units.

The empirical specification of Models 3[b]–4[b] presented in Table 3 follows a pooled ordinary least squares (OLS) regression with Driscoll and Kraay (1998) standard errors. Contrary to the PMG model, Driscoll-Kraay standard errors estimator is a nonparametric technique capable of handling missing values, balanced or unbalanced panel data and

Economic Readiness	Governance Readiness	Social Readiness
Doing business	Political stability and non-violence	Social inequality
	Control of corruption	ICT infrastructure
	Rule of law	Education
	Regulatory quality	Innovation

Fig. 2. Components and indicators of readiness to mitigate climate change and its impacts.

produces robust standard errors when T dimension becomes large (Sarkodie and Strezov, 2019). Importantly, the model has no restrictions on the limiting behavior of the number of cross-sectional units (Driscoll and Kraay, 1998).

Standard panel data regression techniques are limited to mean effects of variables resulting in under- or over- specification and estimation of parameters and relevant coefficients which affect important causal relationships (Sarkodie and Strezov, 2019; Zhu et al., 2016). Contrary to the traditional panel data regression incapable of estimating conditional distribution of climate change indicators in large panel data samples with large cross-sectional units, this study adopts a panel quantile regression technique, which is robust to unobserved country-specific heterogeneity, outliers, and conditional distributions. For brevity, the panel quantile function with unconditional quantile treatment effect and a consistent generalized quantile regression estimator can be expressed as:

$$Q_{vulnerability_{i,t}}(\tau|\alpha_i, x_{i,t}) = \alpha_i + \beta_{1,\tau} economic_{i,t} + \beta_{2,\tau} governance_{i,t} + \beta_{3,\tau} social_{i,t} \quad (8)$$

Table 1
Panel unit root tests.

Variable	Breitung		IPS		Pesaran's CADF	
	Level	1st diff.	Level	1st diff.	Level	1st diff.
Vulnerability	14.897	−27.711*	3.842	−28.069*	−2.365	−3.448*
Economic	8.100	−33.545*	18.937	−24.456*	−1.578	−3.078*
Governance	−0.445	−37.510*	2.019	−26.830*	−2.167	−2.986*
Social	24.623	−21.026*	18.235	−19.668*	−2.311	−2.862*
Readiness	9.353	−34.423*	10.229	−26.715*	−1.967	−3.088*

* $p < 0.01$, the rejection of the null hypothesis at 1% significance level.

where τ denotes τth quantile, α_i represents the non-additive fixed effect, $\beta_{1,\tau}, \ldots, \beta_{3,\tau}$ are the coefficients to be estimated, i indexes cross-sectional units, and t indexes time. τ used in the model estimation ranges from 5th to 95th quantile, corresponding to Models 5^c–15^c presented in Table 3.

2.4. Model validation

To improve the estimation and calculation of the panel quantile regression standard errors, the study applies adaptive Markov Chain Monte Carlo optimization method expounded in Chernozhukov and Hong (2003). The estimated models are validated using marginal effects post-estimation technique with corresponding plots presented in Figs. 3–7. The plots of the marginal effect of estimated models are within the 95% confidence interval, thus, validating the independence of the residuals and the stability of the panel data regression models.

The nexus between vulnerability to climate change and adaptation readiness is corroborated using nonlinear prediction models, such as Lorentzian Peak, Gaussian Peak, and Exponential 3P.

Lorentzian Peak Prediction Model can be expressed as:

$$\frac{a_{i,t} \times {b_{i,t}}^2}{\left((Readiness_{i,t} - c_{i,t})^2 + {b_{i,t}}^2\right)} \quad (9)$$

where a is the peak value, b is the growth rate and c represents the critical point.

Gaussian Peak Prediction Model can be expressed as:

$$a_{i,t} \times \exp\left(-\left(0.5 \times \left(\frac{Readiness_{i,t} - b_{i,t}}{c_{i,t}}\right)^2\right)\right) \quad (10)$$

where a is the peak value, b is the critical point and c represents the growth rate.

Exponential 3P Prediction Model can be expressed as:

$$a_{i,t} \times b_{i,t} \times \exp(c_{i,t} \times Readiness_{i,t}) \quad (11)$$

where a denotes asymptote, b is the scale and c represents the growth rate.

The plot of the nonlinear prediction models is depicted in Fig. 8 with its corresponding parameter estimates presented in Table 4.

2.5. Data availability

Data supporting the findings of this study are publicly available and accessible at ND-GAIN.[1]

3. Results and discussion

To understand the propensity of climate change hazards and impacts on human society, the study presents a choropleth map showing the geographical mean of disaggregate vulnerability indicators of climate change presented in Fig. 9. On a scale of 0–1, the highest mean value (1) in Fig. 9 represents '*worse*' status of a country's disaggregate vulnerability indicator. The intensity of the colors corresponds to the statistical mean differences across geographic regions.

Disaggregate vulnerability indicators include exposure, sensitivity and adaptive capacity to climate change. Exposure measures future climate change stress on human society and its related services. The choropleth map reveals that northern Africa, Europe and some parts of Asia have low exposure to climate change compared to the high

[1] https://gain.nd.edu/our-work/country-index/download-data/.

Table 2
Panel data cointegration tests.

Cointegration	EGS				Readiness			
	No trend		Trend		No trend		Trend	
	Statistic	p-Value	Statistic	p-Value	Statistic	p-Value	Statistic	p-Value
Pedroni								
Modified Phillips-Perron t	6.632	0.000	8.551	0.000	3.538	0.000	4.920	0.000
Phillips-Perron t	−7.006	0.000	−8.164	0.000	−2.906	0.002	−4.340	0.000
Augmented Dickey-Fuller t	−8.191	0.000	−9.641	0.000	−2.735	0.003	−5.910	0.000
Westerlund								
Variance ratio	−2.756	0.003	−2.707	0.003	1.871	0.031	−2.452	0.007

EGS = economic, governance and social.

Table 3
Effects of economic, governance, social and readiness on climate vulnerability. Different model results are presented in each column, with their corresponding standard error in [ ].

	Model 1[a]	Model 2[a]	Model 3[b]	Model 4[b]	Model 5[c]	Model 6[c]	Model 7[c]	Model 8[c]	Model 9[c]	Model 10[c]	Model 11[c]	Model 12[c]	Model 13[c]	Model 14[c]	Model 15[c]
ECT (−1)	−0.153*	−0.180*													
	[0.014]	[0.017]													
Economic		−0.039*		−0.154*	−0.042*	−0.017*	−0.112*	−0.083*	−0.157*	−0.221*	−0.194*	−0.146*	−0.203*	−0.159*	−0.253*
		[0.007]		[0.010]	[0.008]	[0.005]	[0.014]	[0.003]	[0.001]	[0.004]	[0.003]	[0.017]	[0.002]	[0.006]	[0.017]
Governance		0.022*		−0.096*	−0.143*	−0.087*	−0.051*	−0.092*	−0.118*	−0.015*	−0.066*	−0.059*	−0.142*	−0.171*	−0.057*
		[0.005]		[0.010]	[0.008]	[0.009]	[0.004]	[0.004]	[0.002]	[0.003]	[0.009]	[0.020]	[0.002]	[0.006]	[0.010]
Social		−0.132*		−0.226*	−0.075*	−0.109*	−0.122*	−0.199*	−0.191*	−0.209*	−0.237*	−0.180*	−0.179*	−0.179*	−0.367*
		[0.003]		[0.002]	[0.010]	[0.041]	[0.011]	[0.006]	[0.001]	[0.003]	[0.009]	[0.031]	[0.001]	[0.003]	[0.030]
Readiness	−0.087*		−0.464*												
	[0.007]		[0.003]												
_cons			0.634*	0.624*											
			[0.001]	[0.003]											
R^2			0.53	0.57											
MAR					0.146	0.400	0.154	0.042	0.057	0.048	0.230	0.181	0.106	0.207	0.057

MAR = mean acceptance rate. Models 5–15 represents 5^{th} to 95^{th} quantiles used in the model estimation.
* $p < 0.01$, rejection of the null hypothesis at 1% significance level.
[a] Regression with Driscoll-Kraay standard errors.
[b] Regression with Pooled Mean-Group estimator.
[c] Quantile regression for panel data with adaptive MCMC optimization.

exposure levels scattered in Africa and few Asian countries (Fig. 9(a)). The highly exposed countries include Niger, India, Myanmar, Zambia, Angola, North Korea, Sudan, Chad, and Burkina Faso, while countries with low exposure include Mongolia, Czech Republic, Jordan, Libya, Turkmenistan, Uzbekistan, Kazakhstan, Morocco, Algeria, and Tunisia [N = 4224, Mean = 0.44 and Std Dev = 0.08]. The resulting global distribution is largely affected by the projected[2] change in cereal yield (an indicator of hunger), expected[3] change in population, projected change in annual groundwater recharge, expected change in climate change induced diseases and deaths, projected change in vector-borne diseases based on the length of transmission season, predictable change in biome distribution, expected change in marine biodiversity, expected change in hydropower generation capacity (Conway et al., 2015; IPCC, 2014b), projected change in warm, cold periods, impacts of sea level rise and flood hazards. Sensitivity measures the degree to which sectoral dependence by the society is affected by climate change and its impacts. Fig. 9(b) shows that Africa and Asia have a relatively high sensitivity to climate change compared to the low levels in Australia, Europe, North and South America. The highly sensitive countries include Guinea-Bissau, Niger, Chad, Sudan, Mauritania, Uganda, Benin, Uzbekistan, Tajikistan, and Egypt, while countries with low sensitivity include Australia, Canada, Iceland, Russia, Colombia, Norway, Sweden, France, United Kingdom, and Argentina [N = 3762, Mean = 0.40, and Std Dev = 0.10]. The global distribution of the sensitivity component is affected by the dependency on food import, rural population, the rate of freshwater withdrawal, water-dependency ratio (Conway et al., 2015; Owusu and Asumadu, 2016), slum population, dependency on outward resources for health services, natural capital dependency, ecological footprint, urban concentration, age-dependency ratio, dependency on energy imports, and population living five meters above sea level. Adaptive capacity measures a society's ability to mitigate possible damage and willingness to respond to the adverse effect of climate events. Adaptive capacity is relatively low in Africa compared to Asia, but high in Australia, Europe, North and South America, as depicted in Fig. 9(c). Countries with low adaptive capacity include Somalia, Chad, Democratic Republic of Congo, Niger, Eritrea, Papua New Guinea, Afghanistan, Guinea-Bissau, Madagascar, and Liberia, while countries with high adaptive capacity include Italy, Norway, Japan, Finland, United Kingdom, Austria, Netherlands, France, New Zealand, and USA [N = 3960, Mean = 0.51, and Std Dev = 0.17]. The resulting geographical distribution of adaptive capacity is largely influenced by agriculture capacity, child malnutrition, accessibility to reliable drinking water, dam capacity, medical staffs, accessibility to improved sanitation conditions and facilities, protected biomes, international engagement in environmental conventions, quality of trade and transport-related infrastructure and services, paved roads, access to electricity and disaster preparedness (ND-GAIN, 2018a; United Nations, 2015).

[2] "The projected change is calculated based on the percentage change from the baseline projection of the annual average of the actual variable (1980–2009) to the future projections (2040–2069) in line with the Representative Concentration Pathways (RCPs) 4.5 emission scenario" (ND-GAIN, 2018a).
[3] "The expected change is based on the percentage change from the baseline variable in 2010 to the average predicted between 2020 and 2050" (World Bank, 2018).

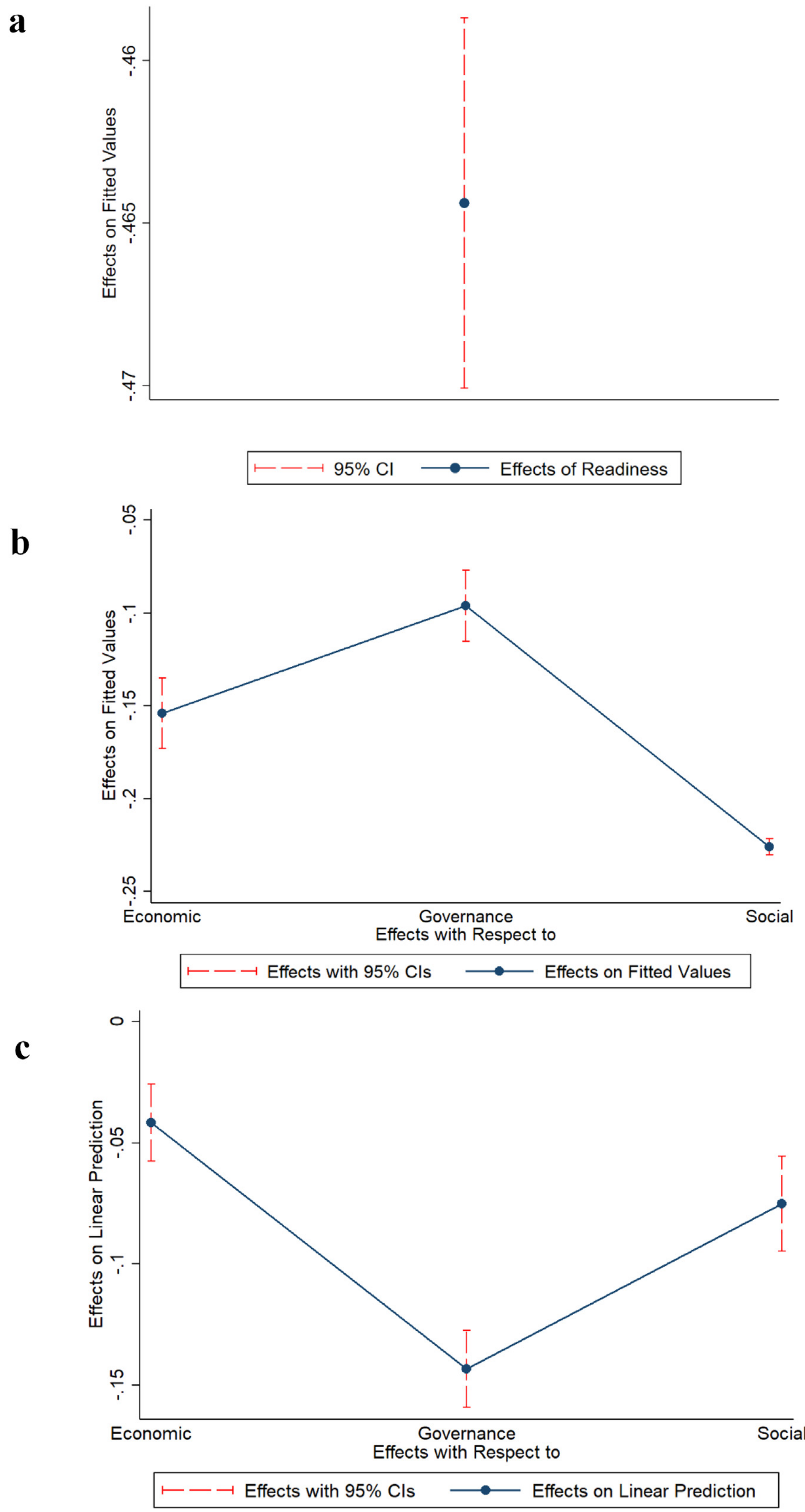

Fig. 3. Diagnostic Test (a) Model 1[a], (b) Model 2[a], and (c) Model 5[c].

Fig. 10 presents a choropleth map showing the geographical mean of disaggregated adaptation readiness of climate change indicators. The indicator comprises economic, governance and social readiness to mitigate climate change. On a scale of 0–1, the lowest mean value (0) in Fig. 10 represents '*better*' status of a country's disaggregate readiness indicator. The intensity of the colors corresponds to the statistical average differences across geographic regions.

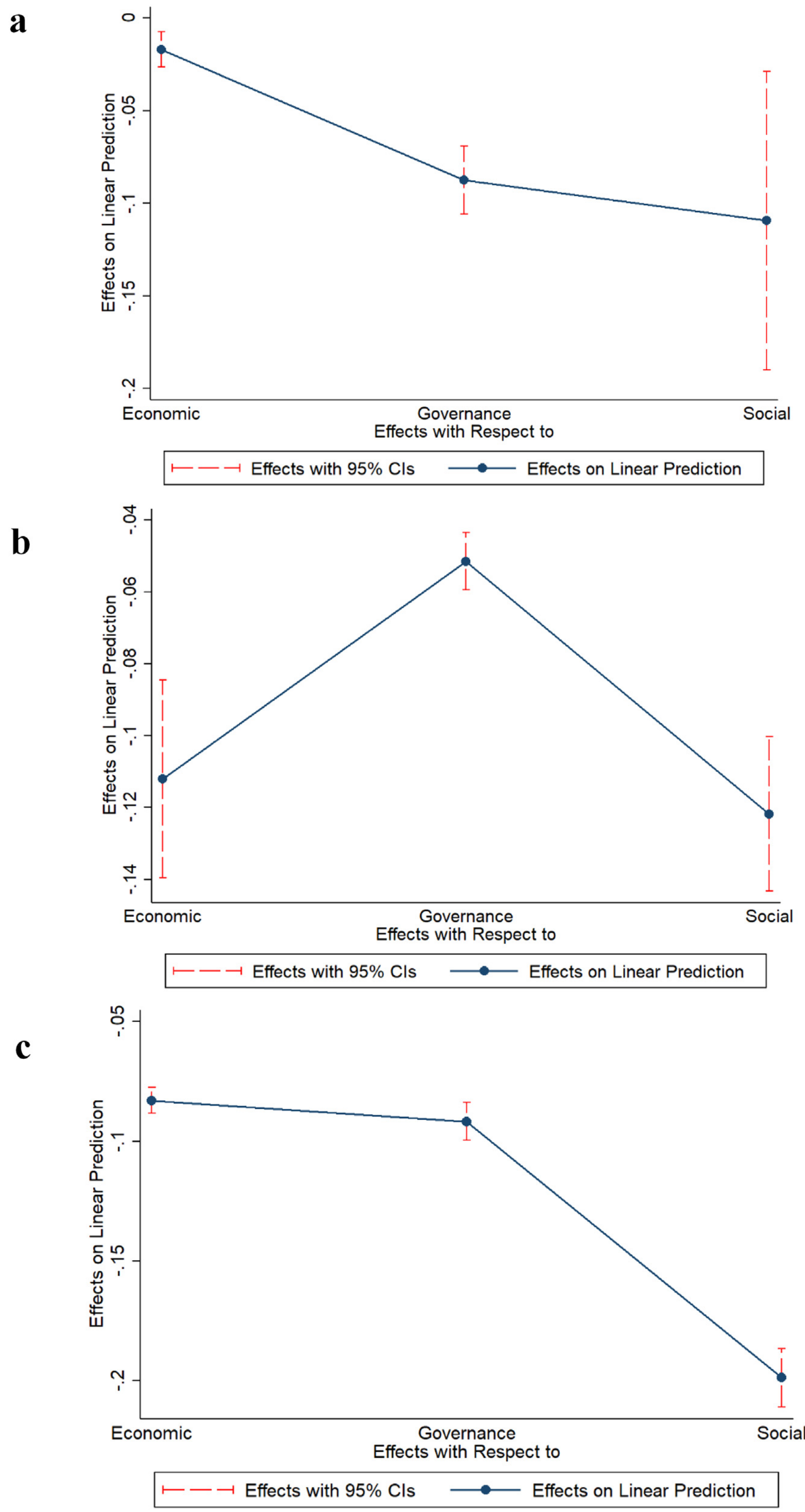

Fig. 4. Diagnostic Test (a) Model 6[c], (b) Model 7[c], and (c) Model 8[c].

Economic readiness measures investment that enables capital mobilization from the private sector. Fig. 10(a) shows that, while Australia, Europe, North, and South America have relatively high economic readiness, Africa and Asia have a low economic readiness to mitigate climate change and its impacts. Countries with high economic readiness include Norway, New Zealand, USA, Iceland, Australia, Finland, United Kingdom, Ireland, Canada, and Estonia, while countries with low economic readiness include Democratic Republic of Congo, Central African Republic,

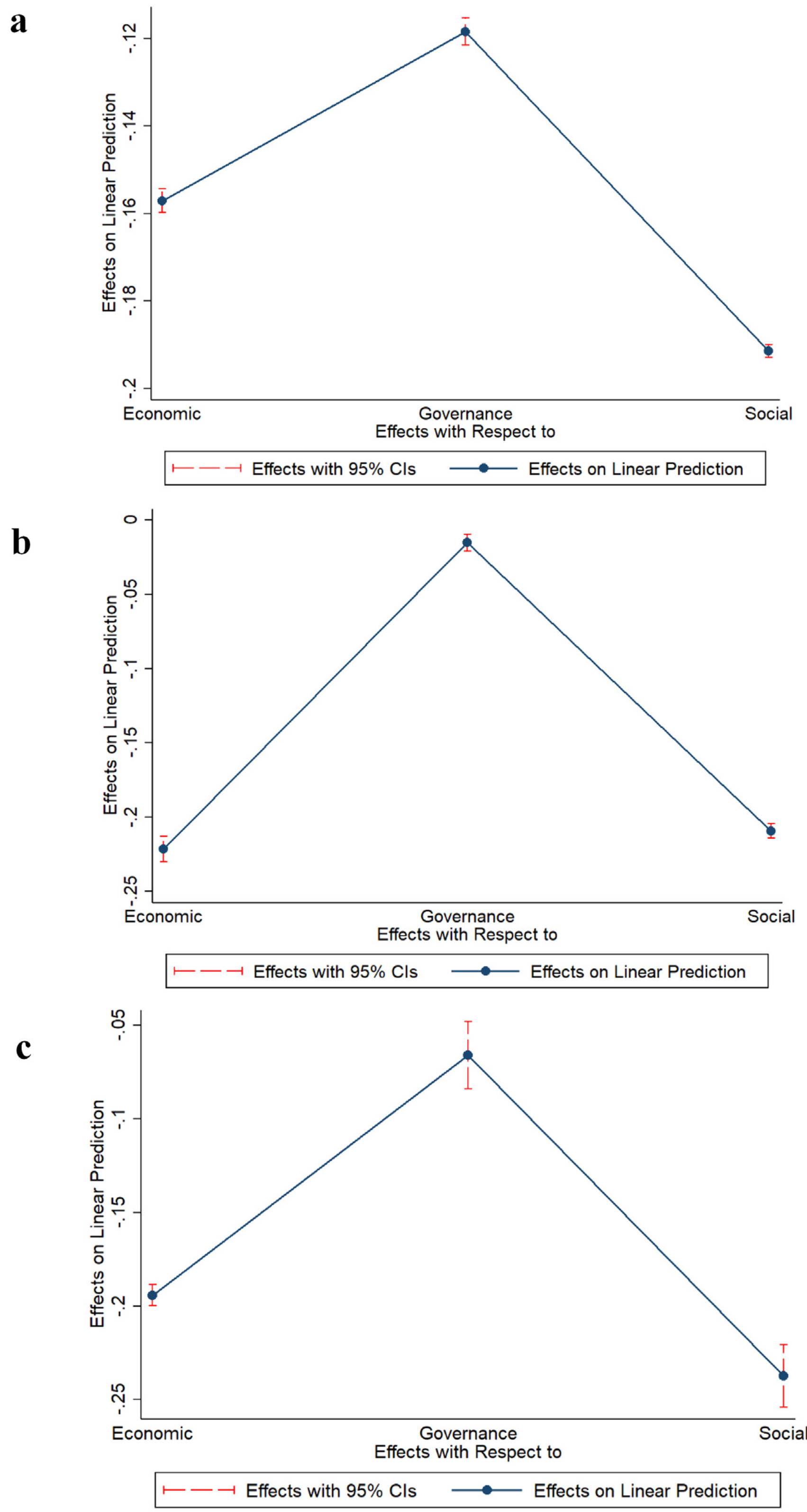

Fig. 5. Diagnostic Test (a) Model 9[c], (b) Model 10[c], and (c) Model 11[c].

Chad, Eritrea, Myanmar, Venezuela, Côte D'Ivoire, Senegal, Benin, and Burkina Faso [N = 3916, Mean = 0.39 and Std Dev = 0.17]. The spatial distribution of economic readiness is affected by the ease of doing business which includes business start-up, acquisition of construction permits, payment of taxes, transboundary trade, access to electricity, property registration, access to credit, investors protection, contract enforcement and resolving insolvency. Governance readiness involves societal stability and institutional quality for investment risks. Governance

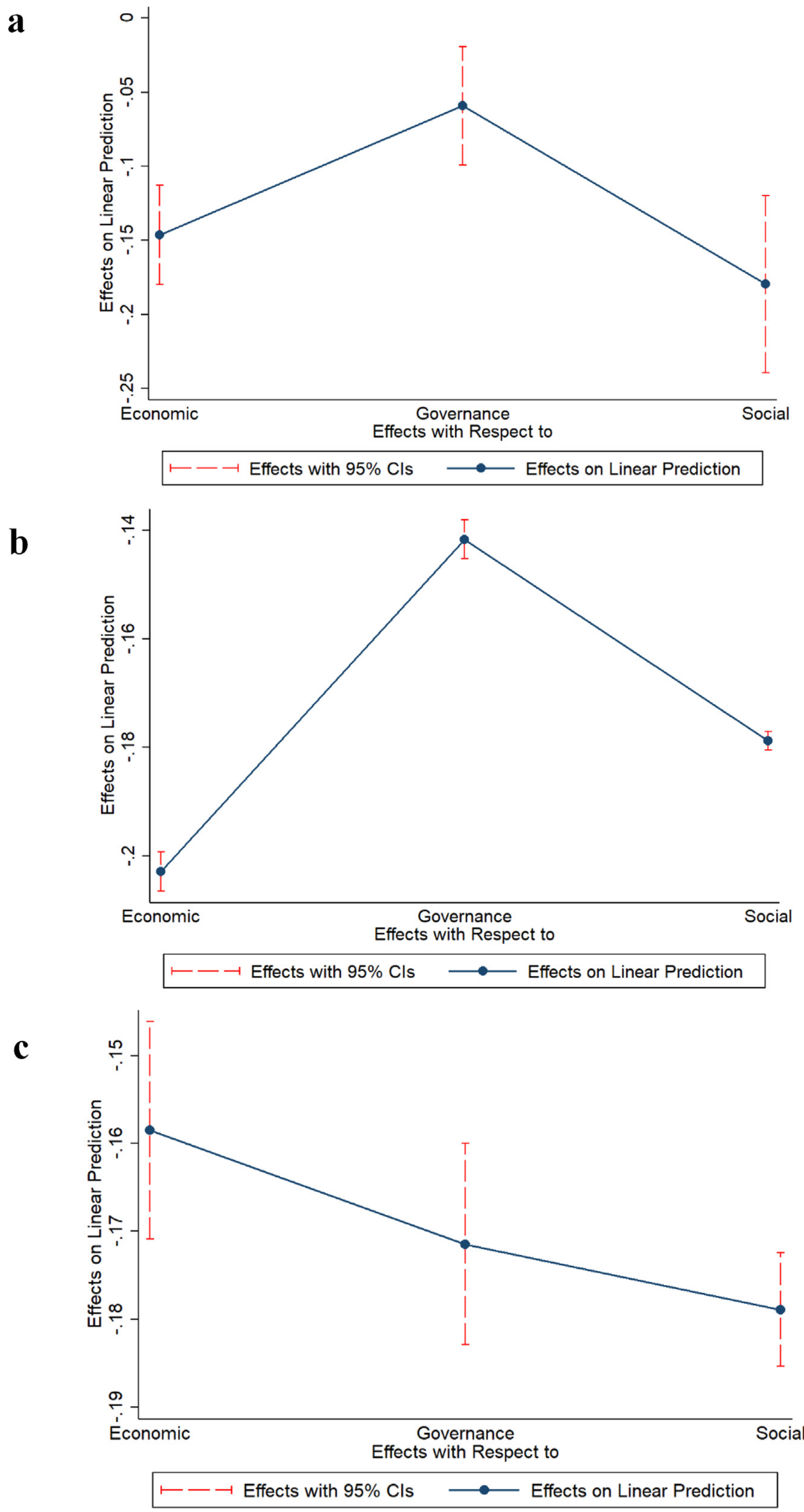

Fig. 6. Diagnostic Test (a) Model 12^{c}, (b) Model 13^{c}, and (c) Model 14^{c}.

readiness appears relatively high in Australia, parts of Europe, North and South America, while a moderate to low governance readiness exists in Africa, Asia and some parts of Europe, as depicted in Fig. 10(b). Top ten countries with high governance readiness include Finland, New Zealand, Denmark, Sweden, Norway, Netherlands, Switzerland, Australia, Canada and Iceland, and countries with low governance

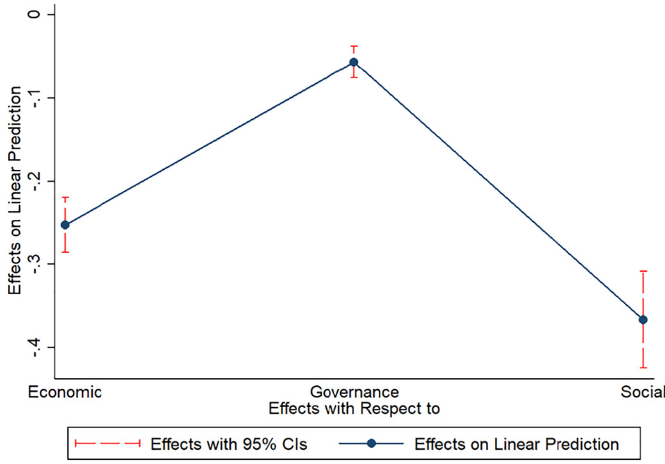

Fig. 7. Diagnostic Test Model 15[c].

Table 4
Parameter estimates of nonlinear prediction model showing the relationship between vulnerability and readiness.

Parameter	Lorentzian Peak	Gaussian Peak	Parameter	Exponential 3P
Peak value	2.191*	23629548*	Asymptote	−1.486*
	[1.876]	[2.1711e+9]		[0.027]
Growth rate	0.718*	−5.418*	Growth rate	−1.652*
	[0.228]	[13.978]		[0.158]
Critical point	−1.033*	−31.919*	Scale	0.57*
	[0.316]	[166.828]		[0.019]
Error measures				
AICc	−10,369.37	−10,355.50		−10,372.70
BIC	−10,344.22	−10,330.35		−10,347.55
SSE	17.212	17.272		17.197
MSE	0.004	0.004		0.004
RMSE	0.066	0.066		0.066
R-square	0.543	0.542		0.544

* $p < 0.05$, the rejection of the null hypothesis at 5% significance level.

readiness include Somalia, Afghanistan, Iraq, Sudan, Myanmar, North Korea, Zimbabwe, Angola, Liberia, and Chad [N = 4136, Mean = 0.50 and Std Dev = 0.18]. The geographical distribution of governance readiness is fairly attributed to political stability, non-violence, level, and control of corruption, regulatory quality (policy formulation and implementation), and the rule of law (law enforcement, policing and property rights). Social readiness encompasses social conditions that promote investment productivity and enable effective and equitable use of investment. Fig. 10(c) reveals a high level of social readiness in Australia, part of Europe, North and South America while low social readiness is evident in Africa, Asia and part of Europe. Countries with relatively high social readiness include South Korea, Finland, Denmark, Norway, Sweden, New Zealand, Austria, Germany, USA, and France. Countries with low social readiness include Eritrea, Zimbabwe, Equatorial Guinea, Lesotho, Papua New Guinea, Myanmar, Botswana, Zambia, Honduras, and Guatemala [N = 4048, Mean = 0.31 and Std Dev = 0.16]. The distribution of social readiness mainly depends on social inequality (income inequality), ICT infrastructure, education, and innovation (science, research, and development expenditure).

Fig. 11 presents a choropleth map showing the geographical mean of vulnerability and adaptation readiness indicators of climate change. Contrary to the disaggregated indicators presented in Figs. 9 and 10, aggregated indicators categorized under vulnerability and adaptation readiness are mapped. On a scale of 0–1, the lowest mean value (0) in

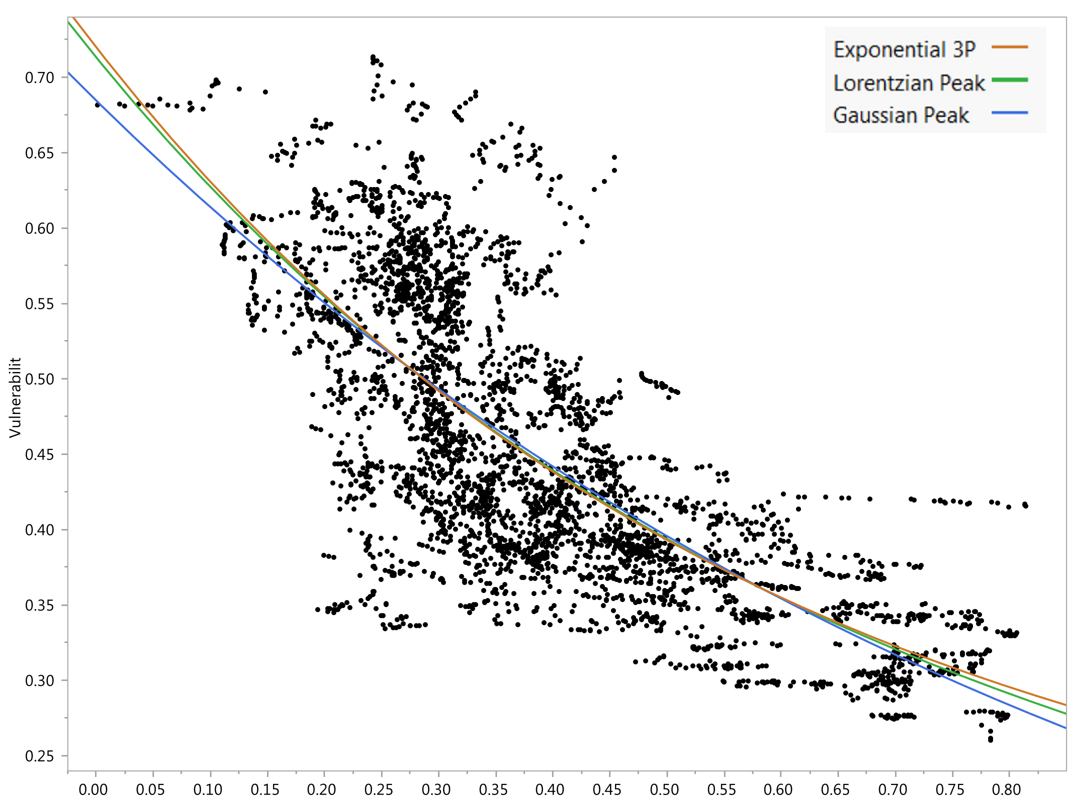

Fig. 8. Nonlinear prediction models showing the nexus between vulnerability and readiness.

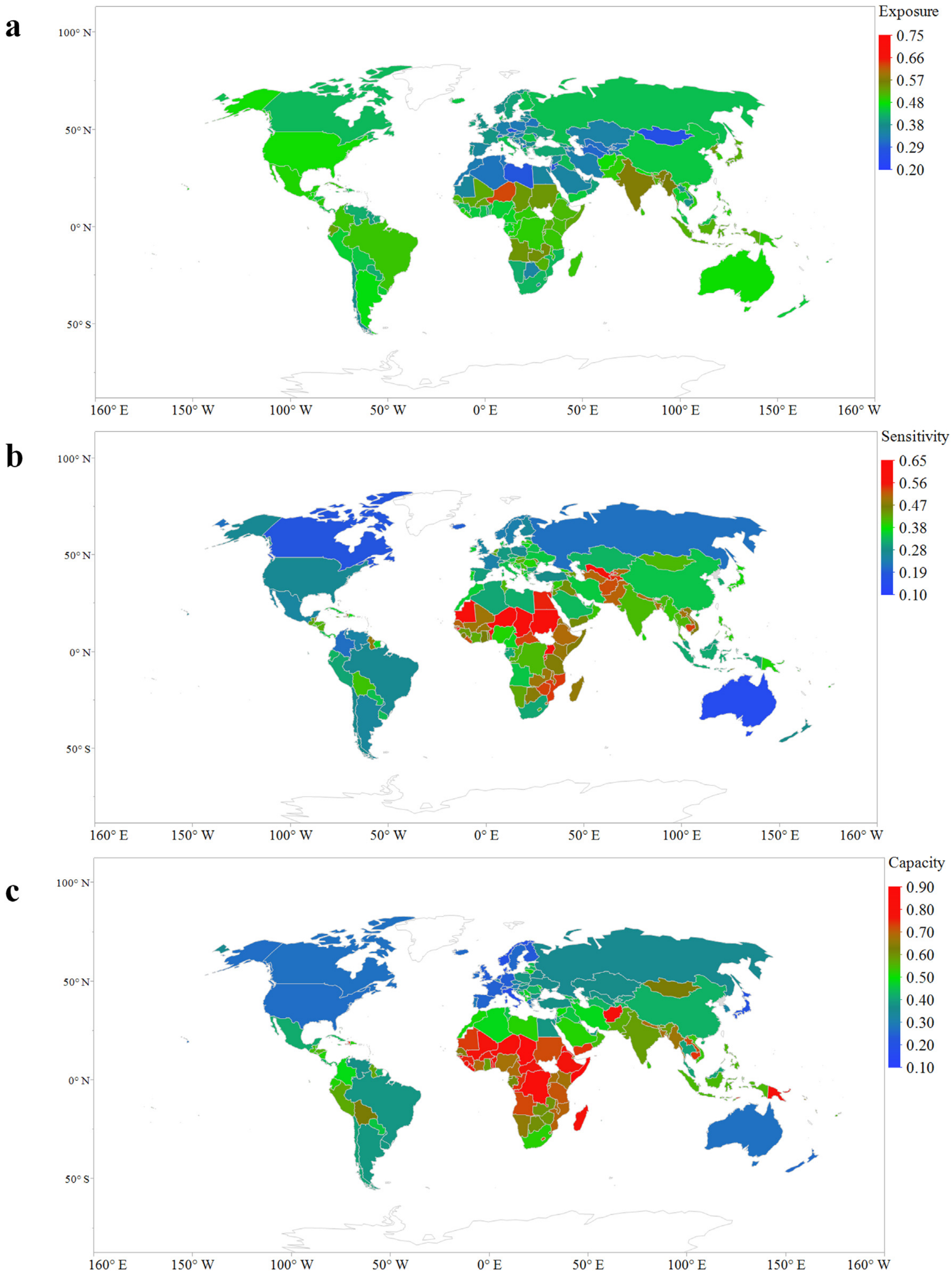

Fig. 9. Choropleth map showing the geographical mean of disaggregate vulnerability indicators of climate change. (a) Exposure [mean range: 0.20–0.75]; (b) sensitivity [mean range: 0.10–0.65]; (c) capacity [mean range: 0.10–0.90].

Fig. 11 represents '*worse*' status of a country's vulnerability while the highest mean value (1) denotes '*better*' status of a country's readiness. The intensity of the colors denotes the statistical mean differences across geographic regions.

Vulnerability measures the propensity of the society negatively affected by climate change and its impacts. While Australia, part of Europe, North, and South America have low vulnerability to climate change, Sub-Saharan Africa is highly vulnerable to climate change hazards, as revealed in Fig. 11(a). Countries with high vulnerability to climate change include Niger, Somalia, Chad, Guinea-Bissau, Liberia, Mali, Sudan, Eritrea, Afghanistan, and Burkina Faso, while countries with very low vulnerability include Norway, Switzerland, Australia,

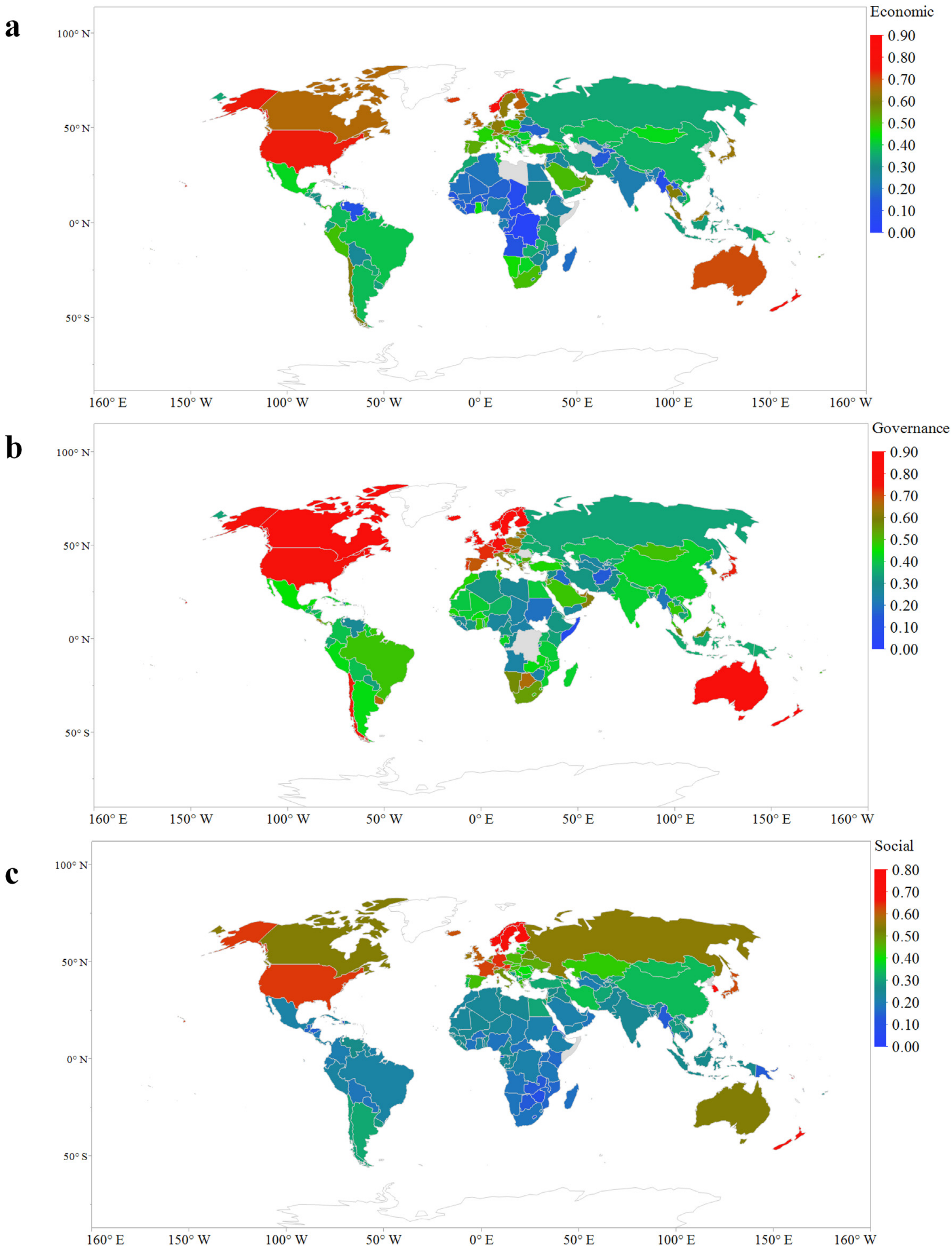

Fig. 10. Choropleth map showing geographical mean of disaggregate adaptation readiness indicators of climate change. (a) Economic [mean range: 0.00–0.90]; (b) governance [mean range: 0.00–0.90]; (c) social [mean range: 0.00–0.80].

Canada, Sweden, United Kingdom, Finland, France, Spain, and Germany [N = 3982, Mean = 0.45 and Std Dev = 0.10]. Readiness involves social and governance willingness to mitigate climate change and the efficient use of investments for adaptation actions. Fig. 11(b) shows that adaptation readiness is relatively high in Australia, Europe, North and South America, contrary to Sub-Saharan Africa. Specifically, countries with high adaptation readiness to mitigate climate change include New Zealand, Norway, Finland, Denmark, Sweden, USA, Iceland, Austria, United Kingdom, and Switzerland, while countries with very low readiness include Somalia, Democratic Republic of Congo, Myanmar, Central African Republic, Eritrea, Chad, Côte D'Ivoire, Afghanistan, Venezuela, and Congo [N = 4202, Mean = 0.40 and Std Dev = 0.15].

The results of the spatial mapping appear to coincide with the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report

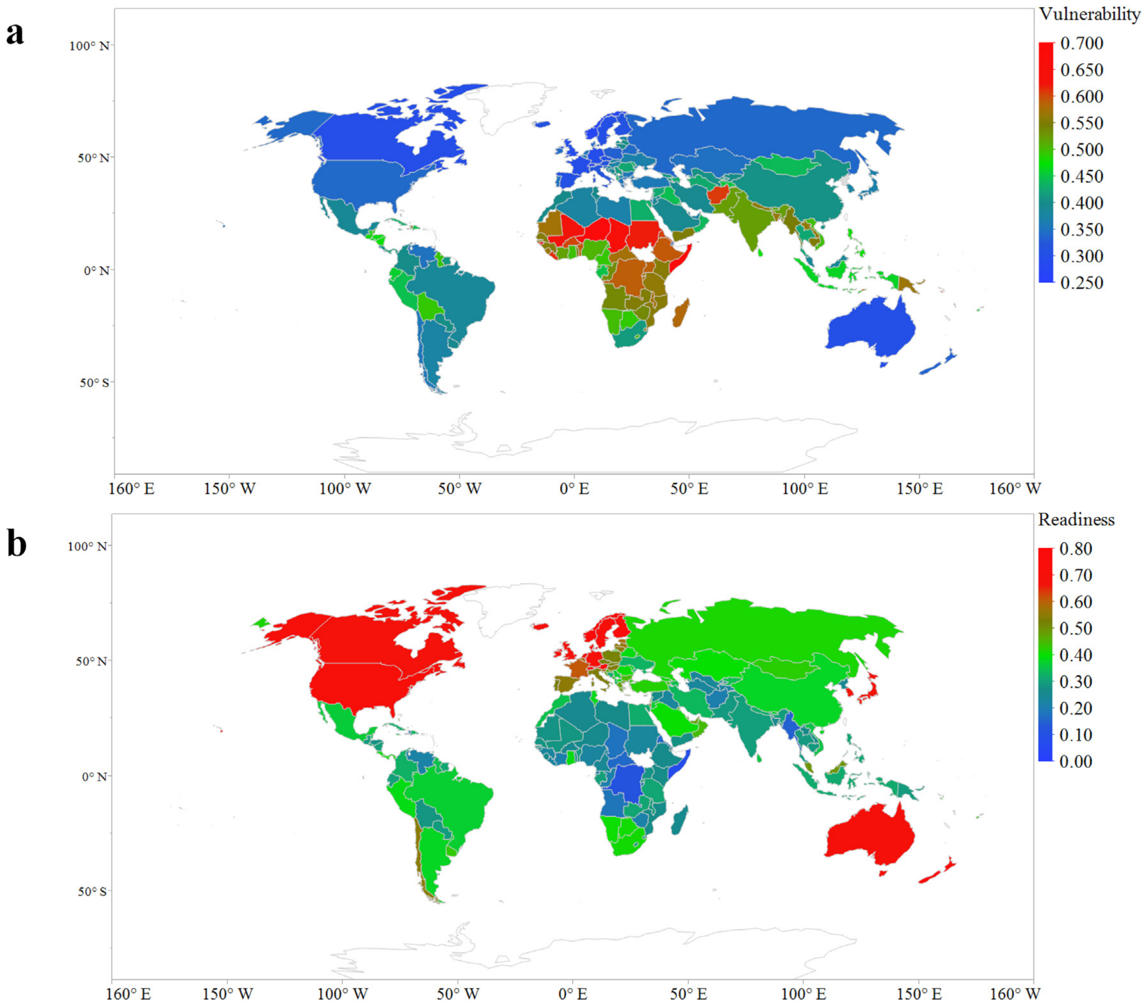

Fig. 11. Choropleth map showing geographical mean of vulnerability and adaptation readiness indicators of climate change. (a) Vulnerability [mean range: 0.25–0.70]; (b) readiness [mean range: 0.00–0.80].

on impacts, adaptation, and vulnerability, which states that Africa is one of the most vulnerable continents to climate variability and climate change. According to the IPCC report, a weak adaptive capacity due to social, economic and governance challenges exacerbates Africa's vulnerability to climate change (IPCC, 2014a).

Fig. 12 illustrates a negative relationship between vulnerability to climate change and adaptation readiness. The baseline results are corroborated by both nonparametric: Spearman's ρ estimation results (Appendix A) and the panel regression results in Table 3. Due to the complexities in examining climate change-related variables, six econometric methods with different parameters were employed to test the validity of the baseline results (Fig. 12). Table 3 reveals that the nexus between vulnerability and readiness yields an error correction of 15% (Model 1[a]) while the relationship between vulnerability, economic, governance, and social readiness yields an error correction of 18% (Model 2[a]). Meaning that the individual effects of adaptation readiness, including economic, governance and social readiness, are more productive in adjusting the previous disequilibrium in climate change vulnerability to near stability in 192 countries. Almost all the 15 models in Table 3 support the role of economic, social and governance adaptation readiness in reducing global climate change vulnerability. Developed countries have low-vulnerability to climate change and its impacts compared to developing and least developed countries, as revealed in the choropleth maps. Hence, socio-economic development and good governance play complementary roles in climate change, provided they incorporate adaptation strategies, such as poverty alleviation [Sustainable Development Goal (SDG) 1], hunger eradication (SDG 2), better nutrition and health (SDG 3), better education (SDG 4), gender equality (SDG 5), clean water and proper sanitation (SDG 6), clean and modern energy (SDG 7), better jobs, enhanced economic growth and reduced income inequality (SDG 8, 10), sustainable cities, communities and industrialization, innovation and better infrastructures (SDG 9, 11), sustainable production and consumption (SDG 12), ecosystem conservation and management (SDG 13–15), and strong and quality institutions coupled with global partnership (SDG 16–17) (United Nations, 2015).

4. Conclusion and policy recommendations

As a contribution to the global targets for combating climate change and its adverse impacts, this study shifts the focus from impact assessment and assessing determinants to the assessment of adaptation actions. The study empirically tests the nexus between climate change vulnerability and adaptation readiness using a panel data of 192 UN countries from 1995 to 2016. Choropleth maps were produced to examine the geographical distribution of climate-related variables. The study employed Pooled Mean Group model estimator, pooled ordinary least squares regression with Driscoll and Kraay standard errors, and panel quantile regression technique with adaptive Markov Chain Monte Carlo optimization method to control for cross-sectional dependence,

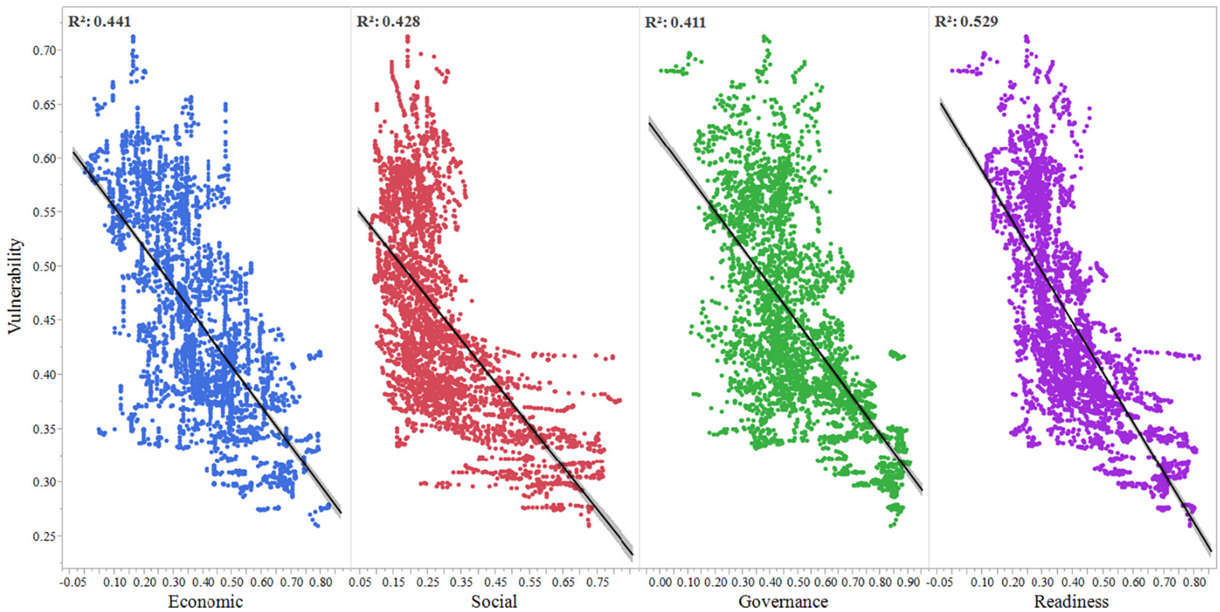

Fig. 12. Vulnerability to climate change versus economic, social, governance, and readiness for climate change mitigation.

heterogeneity, and unconditional distribution across quantiles. The nonlinearity of the model was further tested using nonlinear prediction models, such as Lorentzian Peak, Gaussian Peak, and Exponential 3P. Empirical results from most of the estimating methods, including the Spearman's ρ modeling results, corroborate the contribution of economic, governance and social adaptation readiness in reducing climate change vulnerability.

The study reveals that six sectors, namely food, water, health, ecosystem, human habitat, and infrastructure are vulnerable to climate change. The impact of climate change on food security and food production systems affects cereal yield (maize, rice, and wheat), which contributes to two-thirds of global food consumption (FAO, 2018). This leads to the dependency on food imports if a country's agriculture adaptive capacity is low coupled with a higher food demand due to future changes in population growth. Thus, climate change affects food availability, accessibility, utilization and price stability. The effect of climate change on water resources due to rainfall and temperature variability affects annual runoff, groundwater recharge, freshwater withdrawal rates, and accessibility to reliable drinking water. Climate change is expected to exacerbate health problems and climate-change-induced mortality from water-borne, air-borne, food-borne and vector-borne diseases. Hence, climate-change-induced morbidity and mortality have a high prevalence in developing countries with low-income levels (IPCC, 2014b). Climate change affects terrestrial biome and marine biodiversity due to human pressures and temperature variability. The over-exploitation of available natural resources above its regenerative capacity (biocapacity) at the initial stages of economic development affects the ecological footprint leading to an ecological deficit. The impact of climate change on human habitat has resulted in natural disasters, such as flooding, drought, earthquake, volcanic eruptions, mass movement, and extreme temperatures. Infrastructure capacity in many developing countries has come under threat due to climate change. Hydropower generation capacity has declined in many climate-sensitive regions due to rainfall variability. Sea level rise and storm surge have impacted many settlements and the population living under 5-meter above sea level.

The empirical results reveal that although Africa produces less anthropogenic greenhouse gas emissions, the continent is highly exposed and vulnerable to climate variability and climate-related events due to their dependence on climate-sensitive sectors, such as agriculture and hydropower for energy generation. While economic, governance and social commitment is high and proactive in developed countries like New Zealand, Norway, Finland, Denmark, Sweden, USA, Iceland, Austria, United Kingdom and Switzerland, developing countries, such as Somalia, Democratic Republic of Congo, Myanmar, Central African Republic, Eritrea, Chad, Côte D'Ivoire, Afghanistan, Venezuela and Congo have low adaptive capacity due to limited and sporadic economic, governance and social commitment to climate change adaptation. The policy implications of the study reveal the following requirements for each region:

In Africa — early warning systems and mapping climate change vulnerability; sustainable urban development; agricultural and technological adaptation responses, such as irrigation, climate stress-tolerant crops, and integrated water and land planning.

In Australasia — coastal flood risk management systems, early warning systems, water, and fishing stress reduction.

In Asia — integrated water resource management, early warning systems, urban planning, and sustainable cities, and disaster preparedness.

In North, Central & South America — wetland conservation, integrated water resource management, flood management systems, early heat warning systems, urban planning, and sustainable cities, and the development of drought and temperature resistant crop varieties.

In Europe — wildfire management systems, reduction of air pollution, integrated water resource management, flood management systems, early warning systems, and urban planning and sustainable cities.

This study demonstrates that policymakers need to build the capacity of developing countries and adopt the three-arm of adaptation readiness to mitigate climate change and its impacts.

Declaration

There is no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.11.349.

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