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Too poor to be clean? A quantile ARDL assessment of the environmental Kuznets curve in SADC countries

Andrew Phiri[1] · Simba Mhaka[1] · Lovemore Taonezvi[2]

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Abstract

The purpose of this study is to investigate whether there is a fit of the environmental Kuznets curve for Southern African development community (SADC) countries. To this end, we estimate a quadratic regression between greenhouse gas emissions (CO_2, N_20, CH_4), per capita income and other controls, using the pooled mean group (PMG) and quantile autoregressive distributive lag (QARDL) models applied to annual data spanning from 1990 to 2021. On one hand, the PMG (Pooled mean group) estimators reveal an EKC fit for CO_2 emissions (turning point = \$4675), an inverse EKC for CH4 emissions (turning point = \$6310) and no fit for the N20 emissions. On the other hand, the QARDL estimators further reveal more significant effects existing at the tail end distributions of the curve for all classes of emissions with turning points in the upper (lower) quantiles being higher (lower) than those from the PMG estimators. Further analysis informs us that only Seychelles have crossed the EKC 'turning point' at the upper quantile while the remaining countries are '*too poor to go green.*' Overall, these findings have implications for the debate on climate justice in Africa.

Keywords Environmental Kuznets curve (EKC) · South African development community (SADC) · Pooled mean group (PMG) estimators · Quantile autoregressive distributive lag (QARDL) model

✉ Andrew Phiri
phiricandrew@gmail.com

Simba Mhaka
smhaka78@gmail.com

Lovemore Taonezvi
ascendacademic@gmail.com

1 Department of Economics, Faculty of Business and Economic Studies, Nelson Mandela University, Port Elizabeth 6031, South Africa

2 Department of Entrepreneurship, Faculty of Commerce, BA ISAGO University, Gaborone, Botswana

1 Introduction

The Sustainable Development goals (SDGs) serve as global policy blueprint aimed at improving the quality of life for the earth's inhabitants while simultaneously preserving its environment. Even though these objectives were previously thought to be mutually exclusive (Kelly, 1993), economists and policymakers alike are increasingly recognizing that higher economic activity can be supported by adopting clean energy technologies. The theoretical nucleus of these arguments is embedded in the Environmental Kuznets curve (EKC) popularized by Grossman and Krueger (1991, 1995), which hypothesizes that countries rely on dirty energy sources to pursue economic growth during their early stages of development and yet these economies eventually reach an 'inflexion point' of development, in which higher economic growth can be facilitated through environmentally friendly technologies. Despite its theoretical appeal, the validity of the EKC is not carved in stone, and several authors have concluded that the dynamics of the curve differ across income groups (Abbasi et al., 2023; Bibi & Jamil, 2021; Leal & Marques, 2022; Tachega et al., 2021), inequality levels (Cho, 2021; Ogundipe et al., 2014; Rudzuan, 2019; Wang et al., 2023) and geographical regions (Al-Mulali & Ozturk, 2016; Li et al., 2022; Ntarmah et al., 2021). Moreover, previous studies tend to estimate the shape and 'turning points' of the EKC and yet provide little information as to '*if and when*' the different economies under investigation have crossed their inflexion points.

While African economies are generally recognized as low emitters of green-house gas (GHG) pollutants, Southern African Development Community (SADC) countries, on account of South Africa (as a dominant member state) being one of the highest emitters of GHG globally (Bekun et al., 2019; Magazzino et al., 2021), are the largest regional contributors to climate change in Africa. Over the last two decades, improved growth patterns have been observed in the SADC region and yet such growth has been primarily driven by climate-sensitive sectors such as industry, agriculture, tourism and hospitality, transportation, and real estate. (SADC, 2015). This, in turn, has made the region increasingly prone to the repercussions of global warming as reflected through more frequent occurrences of droughts, floods, cyclones and extreme temperatures, all which put the region at risk of food insecurity, disease and violent conflict (Doku et al., 2021). For these reasons, policymakers in the region have strengthened their efforts to fight global warming and explicitly formulated the 'SADC climate change strategy and action plan' as a policy framework aimed at addressing climate-related risks in the region (SADC, 2015).

An important policy question which our study possess is whether the EKC holds for SADC countries, that is, whether these nations are on a developmental path in which they can grow their economies while reducing GHG emissions or are they '*too poor to go green*'? Despite the voluminous literature conducted for African countries (see Sect. 2 for detailed review of associated literature), there are no studies which have focused exclusively on the SADC regions. Besides, previous research conducted for African countries produce mixed results hence warranting further investigation on the topic. Our study contributes to the literature by providing regional specific evidence for SADC countries using more advanced estimation techniques.

Our study examines the EKC for the SADC region using the pooled mean group (PMG) estimators of Pesaran et al. (1999) and the quantile autoregressive distributive (QARDL) model of Cho et al. (2015) for three measures of GHG emissions, i.e., carbon dioxide (CO_2), nitrous oxide (NO) and methane (CH4). Notably, the PMG estimators have been favored in the literature due to their ability to deal with possible endogeneity and

cross-sectional dependence effects in the regressions as well as for their compatibility with time series of different integration orders (Boukhelkhal, 2022; Demissew & Kotosz, 2020; Rahman et al., 2021; Tenaw & Beyene, 2021; Zoundi, 2017). More recently, the QARDL framework has gained increasing popularity in empirical papers since this model accounts for location asymmetries by capturing the EKC dynamics at different quantile distributions thus revealing possible 'hidden relationships' in the data (Akram et al., 2022; Jahanger et al., 2022; Jin et al., 2022; Sharif et al., 2020; Suki et al., 2020). The QARDL model thus allows us to compute multiple turning points based on different distributions of income, and despite its potential to provide deeper insights into the EKC dynamics, these methods have not been applied to African case studies.

We model linear and nonlinear cointegration effects between environmental degradation and GHG emissions in SADC countries by using the regression coefficients from estimated PMG and QARDL models to determine the shape of the EKC and compute the 'turning points' in the curves. We then analyze the data to determine whether or not the individual SADC economies have crossed these estimated threshold levels of income. From the PMG estimators, we find significant EKC dynamics for CO_2 emissions, inverse EKC for N20 and no relationship for CH4 and for each emission, higher income SADC countries have crossed their threshold levels of income around the mid-1990's while lower income countries are yet to cross these inflexion points. The results from the QARDL estimators imply stronger EKC effects at the tail-end distributions of the relationships and based on the income threshold estimates at the upper quantiles and only Seychelles has crossed the 'turning point' while the incomes of the remaining SADC countries fall below the threshold point.

Altogether, our study reveals that most SADC countries are not on a developmental path toward simultaneously attaining SDGs 1, 3, 11 and 13 of '*ending poverty,*' '*ensuring good health and well-being,*' '*sustainable cities and communities*' and '*combatting climate change,*' respectively, as most of these economies are not technically efficient enough to adopt clean energy sources to support future economic development. Our findings imply that the SDGs cannot be attained without increased climate justice, that is, improving the support which industrialized economies (Annex 1) offer developing economies (Annex II) in mitigating and adapting to climate change. We discuss avenues through which SADC countries can receive increased global support from Annex I countries in promoting more technically efficient production economies capable of sustaining higher growth through green energy sources.

The rest of the study is structured as follows: The following section presents the literature review. The third section outlines the empirical framework and estimation techniques. The fourth section presents the empirical results, while the fifth section concludes the study.

2 Literature review

Theoretically, the traditional EKC can be envisioned as a 'humped-shaped' relationship between GHG emissions and economic activity, describing 'scale effects' (i.e., heavy reliance on 'dirty' energy sources for economic activity) on the ascending portion of the curve and 'technical and substitution effects' (i.e., transition from industrial-based to knowledge-based economy driven by technology and artificial intelligence) on the descending portion of the curve. Empirically, researchers have been interested in fitting the curve to time

series data by estimating a quadratic regression with GHG emissions as the endogenous variable, and economic growth, its squared term and a set of control variables, as exogenous variables. Broadly speaking, researchers have obtained one of the following four outcomes in their empirical analysis (see Sarkodie & Strezov, 2019; Bashir et al., 2021; Koondhar et al., 2021; Pincheira & Zuniga, 2021; Saqib & Benhmad, 2021; Anwar et al., 2022 for bibliometric reviews). Firstly, some studies find evidence of the traditional EKC, that is, an inverse U-shaped relationship between economic activity and GHG emissions. Secondly, other studies find an inverse EKC, in which 'technical effects' are dominant at earlier stages of development (i.e., due to heavy reliance on low-emitting agriculture activities) while 'scale effects' become dominant at higher developmental stages (i.e., due to increasing reliance on high-emitting industry activity). Thirdly, economic activity could have strictly increasing (dominant scale effects) or decreasing effects (dominant technical and substitutions effects) on GHG emissions. Lastly, studies can find an insignificant relationship between the variables.

To keep our review of the empirical literature concise and 'tunnel-focused,' we focus exclusively on panel-based studies examining the EKC for African countries. Following an extensive search on 'Google Scholar' for articles on '*Environmental Kuznets Curve in Africa,*' '*EKC in Africa,*' '*EKC in Sub-Saharan Africa,*' a total number of 32 related articles were filtered out. We summarize the findings from these studies in Table 1 with panel A reporting studies which found evidence in favor of the EKC, panel B reporting studies supporting the inverse EKC and panel C reporting studies which find no evidence of the EKC.

We observe that most studies in the literature confirm the EKC curve for African countries (24 out 32 studies), while few studies either find inverse EKC effects (3 out of 33 studies) or insignificant effects (6 out of 33 studies). We further observe that studies finding an inverse or insignificant EKC effects tend to use smaller samples of less than 40 countries in their analysis (Abid, 2016; Jebli et al., 2015; Lin et al., 2016; Zerbo, 2017; Bah et al., 2020; Demissew & Kotosz, 2020; Ntarmah et al., 2021; Ouédraogo et al., 2022). Moreover, several studies which segregate larger sampled countries into income and resource-intensive groups indicate discrepancies in the results obtained (Alsayed & Malik, 2020; Egbetokun et al., 2018; Hanif, 2018; Tachega et al.,; 2021), implying that the relationship can vary across income and other regional groupings of African countries.

In terms of methodology, most studies have used linear estimation techniques such as POLS and its variants (FE, RE), FMOLS, DLOS, GMM, ARDL/PMG estimators and it is difficult to tell whether the methods applied to different sample sizes contribute to the variety of results obtained. However, we note 2 exceptional studies of Halliru et al. (2020) and Onifade (2022) which use the quantile regressions to investigate location asymmetries in the EKC for ECOWAS and oil-producing countries, respectively, and find significant 'humped-shaped' relationship at different quantiles of distribution. These studies demonstrate that the EKC may be only significant at certain distributional points of the data and therefore, the use of mean-based estimators would be insufficient in revealing these 'hidden' relationships.

More recently, the QARDL methodology has gained increasing popularity as a more flexible variant of the conventional quantile regression model and a number of authors have used the QARDL to investigate the carbon-based EKC at different quantile distributions for individual Asian countries. For instance, Aziz et al. (2020) investigate the EKC for quarterly Pakistan data using the QARDL model and find significant long-run effects at all quantile levels of distributions. Using similar methodology, Jahanger et al. (2022) find that the EKC is only observable at 60–90th quantiles for annual Malaysian data. Furthermore,

Table 1 Summary of previous African-related studies

Author	Country/countries	Period	Variables	estimator	Findings
Panel A: Studies confirming EKC					
Heerink et al. (2001)	52 African countries	1985	CO_2, SO_2, GDP, GDP^2, GINI	POLS	EKC for both CO2 and SO2
Osabuohien et al. (2014)	50 African countries	1995–2010	CO_2, GDP, GDP^2, INST-QUAL, TRADE	DOLS	EKC found
Farhani et al. (2014)	10 MENA countries	1990–2010	CO_2, GDP, GDP^2, EC, TRADE, LAW	FMOLS and DOLS	EKC found
Shahbaz et al. (2016)	19 African countries (5 sadc countries)	1971–2012	CO_2, GDP, GDP^2, EI, GLO	ARDL	EKC for all countries except Sudan and Tanzania where U-shaped relationship is found
Adu and Denkyirah (2017)	7 West African countries	1970–2013	CO_2, GDP, GDP^2, POP, TRADE, ER	FE and RE	EKC (14.59 and 1.64)
Ogundari et al. (2017)	43 African countries	1990–2009	GHG.AGR, GDP, GDP^2, POLITY, TRADE, POP, AGR	FGLS	EKC for GHGH.AGR not for forestation
Sulemana et al. (2017)	48 African countries	1990–2010	CO_2, GDP, GDP^2, POP, FDI, TRADE, DEMO	FE + RE	Humped shaped relationship for Africa ($6295-$7753)
Twerefou et al. (2017)	36 SSA countries	1990–2013	CO_2, GDP, GDP^2, FDI, TRADE, POP	FE, RE, GMM	EKC
Zoundi (2017)	25 African countries	1980–2012	CO_2, GDP, GDP^2, RENEW, EC, POP	DOLS, GMM, DFE, MG, PMG	EKC relationship
Egbetokun et al. (2018)	14 African countries	1996–2015	CO_2, NO_2, GDP, GDP^2, FDI, EDU, POP, AGRIC, INSTIQUAL	GMM	North Africa: EKC for NO2 ($8541), inverse EKC for CH4 ($628) and no relationship for CO2. Southern Africa: EKC for CH4 ($492), no relationship for others
Hanif (2018)	33 SSA countries	1995–2015	CO_2, GDP, GDP^2, EC, RENEW, URB	GMM	EKC for MI, LI and full sample
Adzawla et al. (2019)	Using SSA aggregated data	1970–2012	CO_2, NO_2, CH_4, GDP, GDP^2,	VAR and OLS	EKC for CO2 and NO2

Table 1 (continued)

Author	Country/countries	Period	Variables	estimator	Findings
Alsayed and Malik (2020)	48 African countries	1960–2014	CO_2, GDP, GDP^2	POLS	EKC with higher turning point for HI countries
Avom et al. (2020)	21 SSA countries	1996–2014	CO_2, GDP, GDP^2, ICT, EC, TRADE, FD	POLS	EKC
Halliru et al. (2020)	6 ECOWAS countries	1970–2017	CO_2, GDP, GDP^2, FD, TRADE, HC, BIO	FMOLS, POLS and QR	EKC at all quantiles of distribution
Vural (2020)	8 SSA countries	1980–2014	CO_2, GDP, GDP^2, RENEW, NONREN, TRADE	OLS, DOLS, FMOLS	EKC
Dogan and Kirikkaleli (2021)	SSA aggregated	1972–2014	CO_2, GDP, GDP^2, EC, GPI	ARDL, FMOLS, DOLS	EKC
Kamah et al. (2021)	40 African countries	2001–2018	CO2, GDP, GDP^2, INSTQUAL, FDI, URB, ICT, NR	GMM	EKC
Ouedraogo et al. (2021)	11 oil-producing African countries	1980–2014	CO_2, GDP, GDP^2, OIL, EC	AMG	EKC for LMI and LI (TP = 2415) but not individual countries
Tachega et al. (2021)	54 African countries (high, lower-middle, upper-middle and low)	1990–2015	CO_2, GDP, GDP^2, AGR, RENEW, NONREN	FMOLS and VECM	EKC for all samples excluding high-income countries (TP = $8545 for full sample)
Tenaw and Beyene (2021)	20 SSA countries	1990–2015	CO_2, GDP, GDP^2, EC, FD, URB, FDI	PMG and CCEPMG	EKC for mineral intensive countries
Boukhelkhal (2022)	35 African countries	1980–2016	CO_2, GDP, GDP^2, NONREN, TRADE, FD, AGR, NR	PMG, DCCEMG	EKC
Jian et al. (2022)	16 West African countries	1990—2018	CO_2, GDP, GDP^2, RENEW, URB, IND	AMG and CCEMG	EKC for full sample and LMIC but not for LIC
Onifade (2022)	4 oil-producing countries	1995–2016	CO_2, GDP, GDP^2, NR, EC	DOLS and QR	EKC for lower 4 quantiles
Panel B: Studies confirming inverse EKC					
Ben Jebli et al. (2016)	24 SSA countries	1980–2010	CO_2, GDP, GDP^2, RENEW, TRADE	POLS and FMLOS	U-shaped relationship

Table 1 (continued)

Author	Country/countries	Period	Variables	estimator	Findings
Demissew and Kotosz (2020)	12 EAC	1990–2013	CO_2, GDP, GDP^2, FDI, GLOB, POP, POLITY	PMG	U-shaped long-run relationship (TP = $128.95) and humped-shape short-run relationship (TP = $677.35)
Oeudraogo et al. (2022)	33 Mineral-rich countries (lower-middle, upper-middle and low)	1990–2015	CO_2, GDP, GDP^2, EI, MIN, URB	FMOLS and DOLS	U-shaped relationship for LI and UMI countries and none for LMI countries
Panel C: Studies finding no curve					
Abid (2016)	25 SSA countries	1996–2010	CO_2, GDP, GDP^2,	POLS, RE, FE, GMM	Linear relationship
Lin et al. (2016)	5 African countries (DRC, Egypt, Kenya, Nigeria, South Africa)	1980–2011	CO_2, GDP, GDP^2, EI, URB, POP, ES	FMOLS	Insignificant coefficients
Zerbo (2017)	14 SSA countries	1971–2011	CO_2, GDP, GDP^2,	ARDL	Little evidence of EKC
Bah et al. (2020)	10 African countries	1971–2012	CO_2, SO_2, NO, GDP, GDP^2, EC, URB	DOLS	Linear relationship
Olubusoye and Musa (2021)	43 African countries	1980–2016	CO_2, GDP, EC, URB	ARDL, PMG	Linear relationship
Ntarmah et al. (2021)	39 SSA countries	1990–2018	CO_2, GDP, GDP^2, CREDIT, RENEW, POP, FD	PVAR	Linear relationship

AGR Agricultural output, *GHG.AGR* Greenhouse gas emissions from agricultural activities, *BIO* Biocapacity, *CO2* Carbon emissions, *DEBT* External public debt, *DEMO* Demonstration, *EC* Energy consumption, *EI* Energy Intensity, *ES* Energy structure, *FD* Financial development, *FDI* Foreign direct investment, *GDP* Economic output, *GLO* Globalization, *HC* Human capital, *MIN* Mineral resources endowment, *NO* Nitrous emissions, *NONREN* Non-renewable energy, *NR* Natural resources, *POLITY* Political stability, *POP* Population, *RENEW* Renewable energy, *SO2* Sulfur dioxide emissions, *URB* Urbanization

Akram et al. (2022) applies the QARDL to investigate the EKC in China and find significant effects at all distributions expect the 5th and 10th quantiles, whereas Jin et al. (2022) also investigate the EKC in China using QARDL model and find the curve to be only significant at median to higher quantiles (40–95th).

Our study applies the QARDL to model the EKC for SADC countries and is motivated by three hiatuses identified in the reviewed literature. Firstly, there is much ambiguity on regional effects of the EKC in Africa and while other regional blocs such as the EAC (Demissew and Kotosz) and ECOWAS (Halliru et al., 2020) have received some empirical attention, there are no studies exclusively conducted for SADC countries. Secondly, very few studies have accounted for location asymmetries in African-based studies (Halliru et al., 2020; Onifade, 2022) and notably none of the existing studies have included any individual SADC countries in their analysis. Lastly, none of the previous African studies have used the more advanced QARDL model to investigate short-run and long-run cointegration effects within the EKC at different quantile distributions.

3 Methodology

3.1 Empirical specifications

To conduct our empirical analysis, we specify the following quadratic EKC regression:

$$\mathrm{LnGHG}_{\mathrm{it}} = \beta_0 + \beta_1 \mathrm{LnGDPpc}_{\mathrm{it}} + \beta_2 \mathrm{LnGDPpc}_{\mathrm{it}}^2 + Z_{\mathrm{it}}\beta + \varepsilon_{\mathrm{it}} \tag{1}$$

where β's are the regression coefficients, GHG is the measure of greenhouse gas pollutants, GDP pc is the per capita GDP, Z_{it} is a vector of control variables, τ_t are unobserved country-specific effects, η_i are period-specific effect and $\varepsilon_{\mathrm{it}}$ is a well-behaved disturbance term. Note that we make use of three disaggregated measures of GHG, namely carbon dioxide (CO2), nitrous oxide (N20) and methane (CH4) emissions. Moreover, we follow the previous works of Lin et al. (2016), Sulemana et al. (2017), Twerefou et al. (2017), Hanif (2018), Bah et al. (2020), Bibi and Jamil (2021), Demissew and Kotosz (2020), Kamah et al. (2021), Boukhelkhal (2022), Jian et al. (2022), Oeudraogo et al. (2022), Tenaw and Beyene (2021), Olubusoye and Musa (2021) and (Abdulgadir, 2021a, 2021b, 2023) and select foreign direct investment (FDI), urban population (UP) and agricultural land (AL), all which are expected to exert a positive effect on GHG emissions in African countries. Based on the EKC regression specification, two testable hypotheses are outlined. Firstly, the traditional EKC emerges if $\beta_1 > 0$, $\beta_2 < 0$ (i.e., inverted U-shaped or 'humped' relationship). Secondly, an inverse EKC exists if $\beta_1 < 0$, $\beta_2 > 0$ (i.e., U-shaped relationship). In both cases, the turning point from either positive to negative (for the traditional EKC) or from negative to positive effects (for the inverse EKC) of economic activity on environmental degradation is computed as $\exp\left(-\beta_1/2\beta_2\right)$.

3.2 Pooled mean group (PMG) estimators

To capture the short-run and long-run cointegration effects in the EKC, we make use of the Pool Mean Group (PMG) estimators of Pesaran et al. (1999). Notably, the PMG is a more efficient estimator than other traditional or dynamic estimators since it involves both pooling and averaging and allows short-run coefficients and error correction coefficients to vary

across countries but converge to common long-run trend. In this regard, the PMG estimators provide an added advantage of dealing with possibly heterogeneous dynamics across countries and producing reliable estimates even with relatively small sample sizes. Moreover, the PMG estimators are very flexible in that they are compatible with a mixture of I(0) and I(1) panel time series, hence eliminating the need to pre-test for common integration levels among the data. We re-formulate EKC regression (1) as the following panel autoregressive distributive lag (P-ARDL) specification:

$$\begin{aligned} \text{LnGHG}_{\text{it}} = \sum_{j=1}^{p-1} \lambda_{i,j}\text{LnGHG}_{i,t-j} + \sum\nolimits_{j=0}^{q-1} \delta_{1i,j}\text{LnGDGPpc}_{i,t-j} \\ + \sum\nolimits_{j=0}^{q-1} \delta_{2i,j}\text{LnGDPpc}^2_{i,t-j} + \sum\nolimits_{j=0}^{q-1} \delta_{Xi,j}X_{i,t-j} + \varepsilon_{\text{it}} \end{aligned} \tag{2}$$

where Δ is a first difference operator, $\varepsilon_i = (\varepsilon_{\text{i1}},\ldots,\varepsilon_{\text{iT}})$' is a vector of residual terms, $\lambda_{\text{i,j}}$ and $\delta_{\text{I,j}}$ are vector of regression coefficients. From Eq. (3), the long-run coefficients are computed as $\beta_{0i} = \frac{u}{1-\sum_{j=1}^{p-1}\lambda_{i,j}}$, $\beta_{1\text{i}} = \frac{\sum_{j=0}^{q-1}\delta_{1i,j}}{1-\sum_{j=1}^{p-1}\lambda_{i,j}}$, $\beta_{2\text{i}} = \frac{\sum_{j=0}^{q-1}\delta_{2i,j}}{1-\sum_{j=1}^{p-1}\lambda_{i,j}}$, $\beta_{3\text{i}} = \frac{\sum_{j=0}^{q-1}\delta_{3i,j}}{1-\sum_{j=1}^{p-1}\lambda_{i,j}}$, $\beta_{3\text{i}} = \frac{\sum_{j=0}^{q-1}\delta_{Xi,j}}{1-\sum_{j=1}^{p-1}\lambda_{i,j}}$ and the error correction representation is specified as:

$$\begin{aligned} \Delta\text{LnGHG}_{i,t} = \phi_i\Big(\text{LnGHG}_{i,t-1} - \beta_{0i} - \beta_{1i}\text{LnGDPpc}_{i,t} - \beta_{2i}\text{LnGDPpc}^2_{i,t-j} - \beta_{3i}X_{i,t}\Big) + \sum_{j=1}^{p-1}\lambda^*_{i,j}\Delta\text{LnGHG}_{i,t-j} \\ + \sum_{j=0}^{q-1}\delta^*_{1i,j}\Delta\text{LnGDPpc}_{i,t-j} + \sum_{j=0}^{q-1}\delta^*_{2i,j}\Delta\text{LnGDPpc}^2_{i,t-j} + \sum_{j=0}^{q-1}\delta^*_{Xi,j}\Delta X_{i,t-j} + u_{\text{it}} \end{aligned} \tag{3}$$

where Δ is a first difference operator, $\lambda^*_{i,j} = -\sum_{m=j+1}^{p}\lambda_{i,m}$, $\delta^*_{i,j} = -\sum_{m=j+1}^{q}\delta_{i,m}$, and $\phi_i = -(1-\sum_{j=1}^{p}\lambda_{i,j})$ is the error correction term which measures the speed of adjustment back to steady state equilibrium subsequent to a shock to the system and the parameter is expected to be significantly negative in value.

3.3 Quantile autoregressive distributive (QARDL) model

We also consider the QARDL model of Cho et al. (2015) which is an extension of the conventional ARDL model with the quantile regression process proposed by Koenker and Bassett (1978). By converting Eq. (2) compactly into a quantile format, we obtain our baseline QARDL model specified as:

$$Y_t = \alpha_0(\tau) + \sum_{i=0}^{p}\phi_i(\tau)Y_{t-i} + \sum_{i=0}^{p} * \phi_i(\tau)X_{t-i} + U_t(\tau) \tag{4}$$

where y_{it} is the dependent variable, LnGHG, and X_{it} is the set of covariates{LnGDPpc LnGDPpc2, LnUP, LnAL}. Equation (4) can be re-specified as:

$$Y_t = \alpha_0(\tau) + \sum_{i=0}^{q-1} W\prime_{t-i}\delta_j(\tau) + X\prime_t\gamma(\tau) + \sum_{i=0}^{q}\phi_i(\tau)Y_{t-i} + U_t(\tau) \tag{5}$$

where $(\tau) = \sum_{i=0}^{q-1} W\prime_{t-j}\theta_j(\tau)$, $\text{W}_\text{t} = \Delta X_\text{t}$, and $\delta_j(\tau) = -\sum_{i=0}^{p} * \phi_i(\tau)X_{t-i}$ and the conditional mean function of Y on X is estimated as:

$$\min_{\beta}[\theta \sum |Y_t - X_t\beta| + (1+\theta) \sum |Y_t - X_t\beta|]\{t : \mathrm{FS}_t \geq X_t\beta\}\{t : \mathrm{FS}_t < X_t\beta\} \quad (6)$$

where, $\{Y, t = 1, 2 \ldots, T\}$ is a random sample on the regression process. $Y = \alpha_t + X_t\beta$, with conditional distribution function of $F_{Y/X}(y) = F(Y_t \leq \mathrm{LnGHG}) = F(Y_t - X_t\beta)$ and $\{X_{t,}t = 1, 2 \ldots, T\}$ is the sequences of (row) k-vectors of a known design matrix. The θ^{th} regression quantile, $Q_{Y/X}(\theta), 0 < \theta < 1$ is any solution to minimize problems, β_θ denotes the solution from which the θ^{th} conditional quantile $Q_{Y/X}(\theta) = x\beta_\theta$. Once the estimates from the baseline QARDL regression are obtained, then the long-run estimator is given as:

$$\beta(\tau) = \gamma(\tau)(1 - \sum_{i=0}^{p} *\phi_i(\tau)^{-1} \quad (7)$$

While the short-run and error correction models is estimated as:

$$\Delta Y_t = \alpha_0(\tau) + \zeta_*(\tau)(Y_{t-i} - \beta(\tau)'\mathrm{X}_{t-i}) + \sum_{i=0}^{p-1} \phi_i(\tau)\Delta Y_{t-i} + \sum_{i=0}^{p} * \phi_i(\tau)\Delta X_{t-i} + U_t(\tau) \quad (8)$$

where $(Y_{t-i} - \beta(\tau)'X_{t-i})$ is the quantile error correction term.

4 Data description

The study uses 7 annual time series data collected for 16 SADC countries from the World Bank database over the period 1990–2020. The main dependent variables are the emissions variables, carbon (CO2) emissions, nitrous oxide (N20) emissions and methane (CH4) emissions measured in thousand metric tons of CO_2 equivalent. The main independent variable is US GDP per capita in constant US$, whereas the control variables are foreign direct investment (FDI), urban population (UP) and agricultural land (AL). Note that all variables are transformed into their natural logarithms for empirical purposes denoted using a prefix 'Ln.' Tables 2, 3 and 4 present the summary statistics, correlation matrix and unit root tests of the log-transformed variables, respectively.

From Table 1, some stylized facts are reflected in the descriptive statistics. For instance, the reported averages for the emissions variables reflect the fact that carbon dioxide are the

Table 2 Descriptive statistics

	LnGDPpc	LnCO2	LnN20	LnCH4	LnFDI	LnUP	LnAL
Mean	7.09	7.83	7.78	8.46	18.62	14.47	3.79
Sd	1.16	1.82	2.12	1.87	2.21	1.77	0.56
Max	9.36	13.01	10.20	11.29	23.03	17.52	4.39
Min	5.11	4.25	2.30	4.09	9.21	10.44	1.87
j-b	28.95	103.11	81.51	38.61	101.62	15.98	285.32
p value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Obs	434	434	434	434	434	434	434

Table 3 Correlation matrix

	LnGDPpc	LnCO2	LnN20	LnCH4	LnFDI	LnUP	LnAL
LnGDPpc	1.00						
LnCO2	0.23	1.00					
LnN20	– 0.41	0.68	1.00				
LnCH4	– 0.30	0.78	0.96	1.00			
LnFDI	0.17	0.64	0.57	0.62	1.00		
LnUP	– 0.39	0.75	0.91	0.95	0.59	1.00	
LnAL	– 0.02	0.12	0.08	0.07	– 0.09	0.02	1.00

Table 4 Unit root tests

	int	Int + trend	int	Int + trend	Decision
LnGDPpc	– 0.95 (– 12.09)***	– 0.70 (– 10.25)***	1.85 (– 11.03)***	– 0.75 (– 8.78)***	I(1)
$LnCO_2$	– 1.12 (– 9.95)***	– 1.31 (– 9.14)***	3.02 (– 10.41)***	0.41 (– 9.71)***	I(1)
LnN_20	0.30 (– 10.04)***	– 2.65*** (– 7.70)***	– 0.72 (– 12.80)***	– 1.84** (– 10.99)***	I(1)
$LnCH_4$	0.54 (– 8.66)***	– 0.98 (– 6.85)***	2.09 (– 10.12)***	– 0.27 (– 8.45)***	I(1)
LnFDI	– 8.95*** (– 12.30)***	– 8.54*** (– 9.64)***	– 4.56*** (– 14.59)***	– 3.61*** (– 12.51)***	I(0)
LnUP	5.48 (– 2.39)***	– 0.84 (– 2.64)***	7.50 (– 5.83)***	– 1.03 (– 3.68)***	I(1)
LnAL	(– 1.87)*– (3.71)***	– 0.45 (– 0.94)	– 2.96*** (– 6.99)***	0.76 (– 6.25)***	I(0)

'***', '**', '*' Denote 1%, 5%, 10% critical levels, respectively. First difference statistics reported in ()

largest source of GHG emissions followed by methane and nitrous oxides. Also note that the log transformation of the GDP values indicates that the approximate mean growth rate in the SADC region hovers around 7 percent with very little deviation as shown by the low standard deviation values. Moreover, the Jarque–Bera statistics indicate that all panel series are non-normally distributed and this observation encourages the use of quantile regressions to investigate the environmental degradation–growth relationship at various quantiles of distribution.

From Table 2, the correlation coefficients provide some preliminary evidence on the expected co-movement between economic activity and GHG emissions. We observe positive correlations between GDP and CO_2 while negative correlations are found between GDP and the remaining GHG emissions, i.e., N20 and CH4, and we treat this as preliminary evidence suggesting different shaped EKC relationship existing among different pollutants in the SADC region. The correlations between economic growth and the remaining controls produce positive correlations for FDI (i.e., which is a finding in support of the pollution haven hypothesis) while negative correlations are found for urbanized population and agricultural land.

Lastly, we perform the conventional LLC and IPS panel unit root tests on the time series with an intercept as well as with an intercept and trend. From results reported in Table 3, we fail to reject the unit root null hypothesis at levels for most variables with exception of FDI and agricultural land, which are found to be I(0) stationary variables. The remaining variables are confirmed to be first difference stationary hence confirming their I(1) status. Collectively, our data consist of both I(0) and I(1) series hence rendering the ARDL-type estimators such as the PMG estimators of Pesaran and Shin (1999) or the QARDL estimators of Cho et al. (2015) as a suitable estimation techniques for empirical analysis.

5 Results

5.1 Baseline regression results

We begin our analysis by estimating the EKC regressions using the PMG estimators for the three classes of GHG emissions. The results are reported in Tables 5, with the long-run estimators presented in Panel A, the short-run and error correction term estimates reported in Panel B, while the turning point estimates for the quadratic regressions are reported in Panel C. Note that the optimal lag length for the regressions is selected using the AIC information criterion which mutually shows an optimal lag of 1 for all estimated regressions.

Starting with the quadratic EKC regression reported in Table 4, the long-run coefficients on the LnGDPpc and LnGDPpc^2 variables for CO_2 emissions produce statistically significant estimates of 1.69 and -0.10, respectively, which implies a turning point of 8.45 (i.e., $4675) for the curve. Notably, this finding is consistent with the studies of Zoundi (2017),

Table 5 EKC baseline regressions

	CO_2		N_20		CH_4	
	Estimate	*p* value	Estimate	*p* value	Estimate	*p* value
Panel A: Long-run						
LnGDPpc	1.69	0.00***	−0.07	0.23	−0.35	0.02**
LnGDPpc^2	−0.10	0.00***	0.006	0.12	0.02	0.01**
LnFDI	0.002	0.91	0.006	0.00***	0.03	0.00***
LnUP	1.05	0.00***	−0.07	0.00***	−3.09E−08	0.00***
LnAL	−2.08	0.00***	0.62	0.00***	−0.37	0.00***
Panel B: Short-run						
ΔLnGDPpc	1.99	0.06*	−0.76	0.54	−3.73	0.26
ΔLnGDPpc^2	−0.14	0.03**	0.03	0.65	0.22	0.26
ΔLFDI	0.001	0.81	0.006	0.23	0.003	0.47
ΔLnUPup	−1.99	0.69	1.28	0.25	−7.29E−08	0.98
ΔLnAL	4.15	0.29	−1.65	0.26	−1.92	0.23
ECT(−1)	−0.26	0.00***	−0.52	0.00***	−0.34	0.00***
Panel C:Turning points						
Threshold estimate	8.45 [$4675]		n/a		8.75 [$6310]	

'***', '**', '*' Denote 1%, 5%, 10% critical levels, respectively

Tenaw and Beyene (2021), Boukhelkhal (2022) and Jian et al. (2022) which similarly find a traditional humped-shaped EKC curve for other African samples using similar PMG estimators. Conversely, for N_2O emissions, we obtain long-run estimates of − 0.35 and 0.02 for the LnGDPpc and LnGDPpc^2 variables with an estimated turning point 8.75 ($6310), and the observed U-shaped relationship resembles the inverted EKC relationship obtained in the previous works of Jebli et al. (2015) for 22 African countries, Demissew and Kotosz (2020) for EAC countries and Oeudraogo et al. (2022) for 33 mineral-rich countries for total emissions. Moreover, we observe insignificant estimates on the N20 emissions which is a finding similarly found by Abid (2016), Lin et al. (2016), Zerbo (2017) and Ntarmah et al. (2021) for different African samples albeit for total GHG emissions.

Further note that for all estimated regressions, the control variables produce their expected positive coefficient estimates on the FDI variable which is evidence in support of the haven pollution hypothesis in Africa (Halliru et al., 2020; Gyamfi et al., 2022; Bouzahzah, 2022) while the coefficient estimates on urbanization and agricultural land produce mixed results. The error correction terms in all estimated regressions produce their expected negative and significant estimates, implying that disequilibriums in the system of cointegrated variables are corrected over the steady state such that short-run dynamics eventually converge to the long-run equilibrium.

So far, the analysis has provided insights into the shape of the EKC and yet provides little information on whether the different economies in SADC region have crossed their respective thresholds. We thus further analyze the results by plotting per capita GDP time series for the SADC countries between 1970 and 2020 against their estimated turning points for the different sources of emissions to determine 'if and when' the individual countries crossed their turning points. Figures 1 and 2 present the plots for the CO2 and CH4 emissions using the turning point estimates obtained from the EKC regressions and as can be observed, higher income countries (i.e., Botswana, Mauritius, Namibia, Seychelles and South Africa) have crossed their estimated thresholds in the mid-1990's while lower

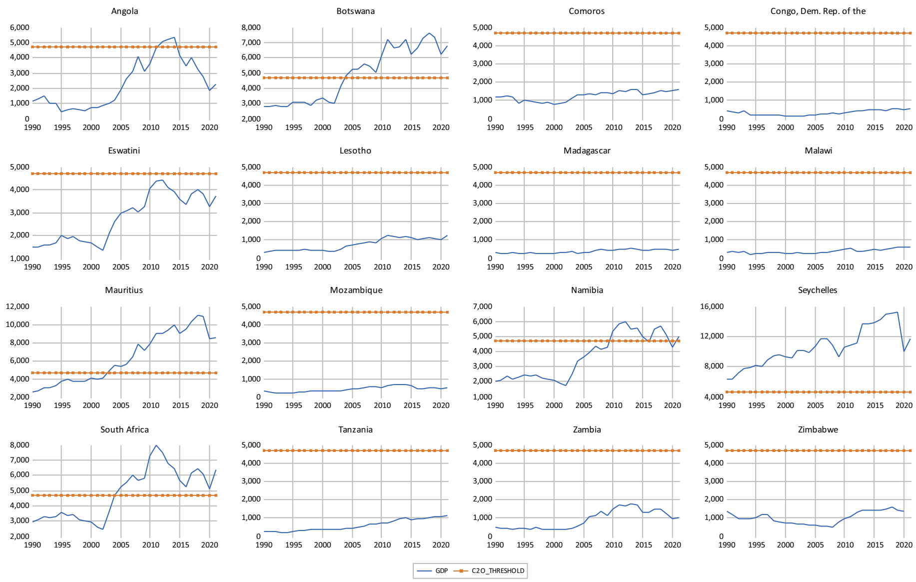

Fig. 1 CO_2 emissions

Fig. 2 CH_4 emissions

income countries (Angola, Comoros, Eswatini, Lesotho, Madagascar, Malawi, Mozambique, Tanzania, Zambia and Zimbabwe). In other words, higher income (lower income) SADC countries have (have not) attained the necessary levels of development to reduce carbon emissions in the region while improved development is conversely accompanied by increasing (decreasing) levels of methane. Therefore, based on the PMG estimators, differences in the fit of the EKC in the SADC region can be attributed to income-differences among the individual countries and similar arguments have been previously put forward (Hanif, 2018; Bibi & Jamil, 2021; Tachega et al., 2021 and Jian et al., 2022) for different African countries.

5.2 Panel QARDL regression results

We now estimate the EKC and its associated turning points at different quantiles of distribution using QARDL estimators. As previous mentioned, these estimators are an extension of panel quantile regression of Koenker and Bassett (1978) within the panel ARDL framework of Pesaran and Shin (1999) and allows one to observe long-run and short-run cointegration effects at various quantiles distributions that differ from the traditional mean-based estimates. We choose quantiles of 0.1, 0.5 and 0.9 to account for 'left tail-end,' 'median,' and right tailed-end' distributions of economic activity and is analogous to extremely low, normal and extremely high-income distributions (Awan et al., 2022). The lag length of the estimated QARDL regressions is set at 1 as determined by the minimization of the AIC.

Tables 6, 7, 8 present the long-run and short-run estimates QARDL along with their turning points for CO_2, N_20 and CH_4 emissions, respectively, and we summarize our findings as follows. Firstly, from Table 6 (Table 8), the EKC for CO_2 (CH_4) emissions retain its long-run humped (U-shaped) relationship as $LnGDP>0$, $LnGDPpc^2<0$ ($LnGDP<0$, $LnGDPpc^2>0$) at 5th and 90th quantiles with turning point estimates of \$5844 and

Table 6 QARDL CO2 emissions

	Quantiles		
	0.1	0.5	0.9
Panel A:Long-run			
Lgdp	0.91 (0.00)***	0.03 (0.89)	1.32 (0.00)***
Lgdp^2	−0.10 (0.00)***	0.02 (012)	−0.07 (0.00)***
Lfdi	0.019 (0.09)*	−0.005 (0.62)	−0.02 (0.23)
Lup	0.35 (0.00)***	0.42 (0.00)***	0.51 (0.00)***
Lal	0.19 (0.00)***	0.08 (0.02)**	−0.05 (0.26)
Panel B:Short-run			
ΔLgdp	0.12 (0.22)	−0.11 (0.24)	−0.06 (0.71)
ΔLgdp^2	−0.004 (0.51)	0.008 (0.21)	0.006 (0.55)
ΔLfdi	0.005 (0.00)***	0.002 (0.31)	0.006 (0.09)*
Δlup	−0.76 (0.00)***	0.48 (0.00)***	2.04 (0.00)***
ΔLal	0.09 (0.00)***	−0.02 (0.84)	−0.14 (0.73)
ECT(−1)	−0.03 (0.00)***	−0.03 (0.00)***	−0.02 (0.00)***
Panel C:Turning points			
Threshold estimate	8.68 [$5844]	N/A	9.42 [$12332]

p values reported in (). '***', '**', '*' denote 1%, 5%, 10% critical levels, respectively

$12,332 ($1525 and $13,359), respectively. Secondly, we find significant EKC effects for N20 at all distributional quantiles and this finding differs from the insignificant estimates previously obtained from the mean-based PMG estimates. For N20 emissions, we estimate turning points of $6974, $4146 and $2143 at 5th, 50th and 90th quantiles, respectively. Thirdly, in all estimated QARDL regressions, evidence of asymmetric relationship between FDI-emissions, UP—emissions and al—emissions across different quantiles while short-run EKC effects are remain scarce even at extreme quantile levels. Lastly, the error correction terms produce their expected negative and significant estimates for the EKC regressions.

Altogether, our findings suggest significant relationships between environment degradation and economic activity at the tail-end quantiles of the cointegration relationships, with the traditional (inverted) EKC found for CO_2 (N_20 and CH_4) emissions. These findings align with those of Halliru et al. (2020) who similarly find significant EKC effects at all quantile distributions for CO_2 emissions using the QARDL model albeit for 6 ECOWAS countries. In further analyzing the GDP per capita time series plots against the thresholds

Table 7 QARDL: N2O

Quantiles	0.1	0.5	0.9
Long-run			
Lgdp	– 0.46 (0.00)***	– 0.30 (0.00)***	– 1.24 (0.00)***
$Lgdp^2$	0.03 (0.00)**	0.018 (0.00)***	0.07 (0.00)***
Lfdi	0.08 (0.00)***	0.04 (0.04)*	– 0.006 (0.43)
Lup	0.39 (0.00)***	0.35 (0.00)***	0.25 (0.00)***
Lal	0.22 (0.00)**	– 0.28 (0.00)***	– 0.32 (0.00)***
Panel B:Short-run			
ΔLgdp	0.32 (0.03)**	0.09 (0.35)	– 0.26 (0.13)
$\Delta Lgdp^2$	– 0.02 (0.05)*	– 0.006 (0.44)	0.03 (0.03)*
ΔLfdi	0.005 (0.04)*	0.002 (0.05)*	0.002 (0.47)
Δlup	– 1.22 (0.00)***	0.03 (0.42)	1.17 (0.00)***
ΔLal	0.49 (0.05)*	0.18 (0.07)*	0.33 (0.00)***
ECT(– 1)	0.001 (0.92)	– 0.007 (0.08)*	– 0.02 (0.04)*
Panel C:Turning points			
Threshold Estimate	7.67 [$2143]	8.33 [$4146]	8.85 [$6974]

p values reported in (). '***', '**', '*' denote 1%, 5%, 10% critical levels, respectively

estimated at different quantiles for the three classes of GHG emissions, reported in Figs. 3 (CO_2), 4 (N2O) and 5 (CH_4), we draw the following conclusions. Income levels in more developed SADC countries such as Botswana, Mauritius, Seychelles and South Africa, cross the lower and median quantile thresholds for all GHG emissions, whereas only Seychelles has incomes levels exceeding the threshold in the upper quantile. Conversely, lower income SADC countries remain below the lower quantile threshold for all classes of emissions. Essentially, the main difference between these findings and those obtained from the PMG estimators is that Seychelles is the only SADC country which has crossed the upper quantile turning point in the estimated EKC relationships.

6 Conclusion

This study investigates the EKC for SADC countries using three measures of emissions (i.e., CO_2, N_2O and CH_4). To this end, we used the PMG and QARDL models applied to annual data sampled between 1990 and 2021, and we further use the estimates to compute

Table 8 QARDL CH_4 emissions

Quantiles	0.1	0.5	0.9
Long-run			
Lgdp	2.28 (0.00)***	−0.49 (0.12)	−0.95 (0.00)***
$Lgdp^2$	−0.18 (0.00)***	−0.009 (0.66)	0.05 (0.02)**
Lfdi	0.47 (0.00)***	0.52 (0.00)***	0.05 (0.11)
Lup	8.53E−08 (0.00)***	6.18E−08 (0.00)***	1.02E−08 (0.00)***
Lal	0.78 (0.00)***	0.63 (0.00)***	0.39 (0.03)*
Panel B:Short-run			
ΔLgdp	0.004 (0.96)	0.04 (0.76)	−0.35 (0.02)**
$\Delta Lgdp^2$	−0.0002 (0.96)	0.002 (0.83)	0.03 (0.00)***
ΔLfdi	0.0001 (0.94)	0.003 (0.06)*	0.009 (0.00)***
Δlup	−6.79E−08 (0.00)***	1.47E−08 (0.00)***	1.95E−07 (0.00)***
ΔLal	8.74E−05 (0.99)***	0.01 (0.66)	0.06 (0.05)*
ECT(−1)	−1.43E−05 (0.99)	−0.01 (0.66)	−0.01 (0.02)**
Panel C:Turning points			
Threshold Estimate	6.333 [$1525]	NA	9.50 [$13359]

p values reported in (). '***', '**', '*' denote 1%, 5%, 10% critical levels, respectively

the turning points of the curve and determine whether SADC countries have crossed these inflexion points. The findings from the PMG estimators reveal an EKC fit for CO2 emissions (turning point = $4675), an inverse EKC for N20 emissions (turning point = $6310) and no fit for the CH4 emissions; and notably, upper-middle income (lower income) countries have (not) crossed their thresholds. Conversely, the findings from the QARDL reveal multiple turning points of between $5844–$12,332 for CO2 (EKC curve), ($1525–$13,359) for N20 (inverse-EKC) and $2143–$4146 for CH4 (inverse-EKC); and notably only Seychelles has crossed the inflexion points at the upper quantiles.

Overall, our findings imply that most SADC countries are 'too poor to go green' and pursuing green policies would be more of 'benevolent gesture' toward mankind as opposed to one which can sustain future economic development in the region. In other words, SADC countries are not 'en route' toward attaining the SDGs of sustainable economic development accompanied by cleaner environment and therefore, increased climate justice is required by the international community toward African countries. We recommend four avenues through which SADC countries can receive increased global support in promoting more technically efficient production economies capable of sustaining higher growth through green energy sources.

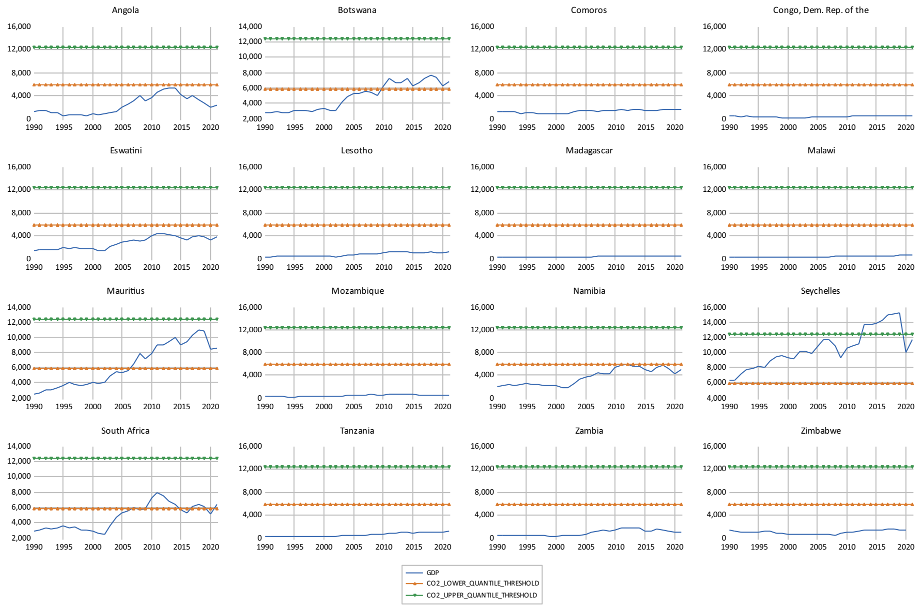

Fig. 3 CO_2 emissions

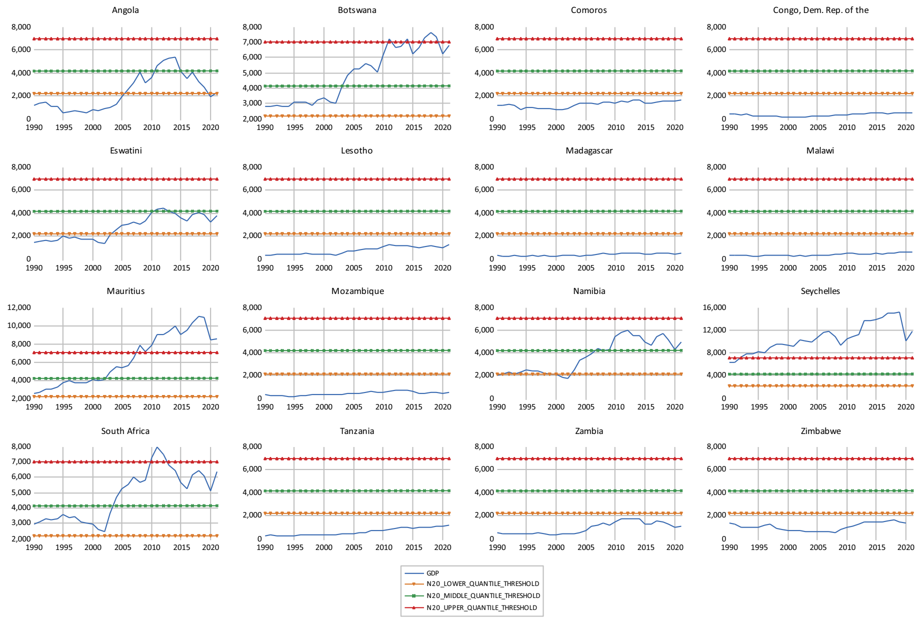

Fig. 4 N_2O emissions

Fig. 5 N_2O emissions

Firstly, we recommend that Annex I countries (i.e., industrialized economies who are most responsible for GHG) increase their issuance of climate financing to African countries who currently receive lower amounts of climate finance compared to other Annex II countries (i.e., developing countries who have contributed less to climate finance but are more affected by it). Secondly, global policymakers may also consider increasing their scope of climate finance donors toward African countries to include other emerging (and high income) economies like China and India who contribute more to global carbon emissions compared to other industrialized economies. Thirdly, SADC countries need to explore markets for green and sustainable investments and increase their participation in Green, Social and Sustainable' (GSS) bonds and Environmental, Social and Governance (ESG) investments. This, in turn, can assist SADC member states secure access to market finance for green investments which can foster the creation sustainable green jobs and income. Lastly, SADC policymakers need to direct their efforts in creating an environmental conducive to attracting green climate investments. This could involve increased public investment in green initiatives, as well as strengthening partnerships with the private sector to promote green growth.

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Data availability Data will be available upon request.

Declarations

Conflict of interest The authors have no competing interest and nothing to declare.

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