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Research article

Drivers of changes in natural resources consumption of Central African countries

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Abstract: Consumption of nine different natural resources has kept an increasing trend in Central African countries from 1970 to 2018. This study therefore, investigates the changes and major determinants that have driven the patterns of resource use in six Central African countries over almost fifty years. We used the logarithmic mean Divisia index (LMDI) method to quantitatively analyze different effects of technology, affluence and population associated with domestic material consumption (DMC) of Cameroon, Chad, Central African Republic, Equatorial Guinea, Democratic Republic of the Congo and Gabon from 1970 to 2018. We further subdivided the affluence effect into energy productivity (GDP/energy) and per capita energy use (energy/cap) and conducted a four-factor LMDI analysis of Cameroon as a case study. The results highlight that decreased affluence during certain periods has slowed down DMC growth in four of six Central African countries except for Cameroon and Equatorial Guinea, while significant technology offset in Equatorial Guinea reduces DMC growth by 28%. Population remains the main positive driving factor of DMC growth, with the highest share in the Democratic Republic of the Congo. The case of Cameroon shows that

technological intensity and energy intensity play different roles in changing DMC. This study confirms that the rising population and economic growth, combined with a gradual improvement in technology in the region are insufficient to reduce natural resource use. A stringent management plan of natural resources for Central African countries should focus on technological improvement while remaining balanced with the future demand for socioeconomic development in the coming decades.

Keywords: domestic material consumption; logarithmic mean Divisia index; energy intensity; technological intensity; Central African countries

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Highlights

- Divergent patterns of resource use in Central African countries
- Resource productivity in Cameroon is the highest of Central African countries
- Population is the main driver of domestic material consumption (DMC)
- Equatorial Guinea presents the highest DMC/capita and highest material intensity
- Decreased affluence is a strong factor deferring the DMC growth

1. Introduction

The United Nations (UN) advocates 17 Sustainable Development Goals (SDGs), an extension of the Millennium Development Goals (MDGs). These SDGs are a blueprint for achieving a better and more sustainable future for all. SDGs address the global challenges we face; poverty, inequality, climate change, environmental degradation, and natural resource degradation and the consequences on the environment during the production and consumption of these resources. The SDGs promote the conservation of natural resources and emphasize economic activities with little or no negative impact on the environment [1]. Particularly, SDG-12 accentuates that current material needs should not lead to the over-extraction of resources or to the degradation of environmental resources [2,3]. Many environmental sustainability assessments have addressed key areas of natural resource conservation under the SDG framework [4,5]. By 2050, 140 billion tons of minerals, ores, fossil fuels, and biomass will be consumed in a year unless the economic growth rate is decoupled from natural resource consumption [6]. Meanwhile, over the last 100 years, the world extraction of construction minerals grew by a factor of 34, ores and minerals by a factor of 27, fossil fuels by a factor of 12 and biomass by a factor of 3.6 [7]. Haberl et al. (2011) compared the metabolic profiles of hunter-gatherers, agrarian, and industrial society and found that industrial society consumes more materials 15–25 t/cap/year compared with just 3-6 t/cap/year for agrarian and 0.5–1 t/cap/year for hunter-gatherers [8].

Index decomposition analysis (IDA) is one popular analytical tool that assesses the effects of a number of determinants. Studies on the decomposition analysis using logarithmic mean Divisia index (LMDI) have been widely carried out [9,10]. The application of LMDI method to decompose resource use growth into its drivers is proven to be effective [11–13]. Quite a number of papers have also analyzed the drivers of greenhouse gas emissions using LMDI decomposition analysis. For example, Yang et al. (2019) analyze the driving forces of China's CO_2 emissions from energy consumption based on the Kaya-LMDI method and conclude that increasing imported electricity has reduced carbon emissions [14]. Wang et al. (2020) employ the LMDI decomposition to analyze the driving force of nitrogen oxides intensity related to the electricity sector in China [15]. Steckel et al. (2019) underline the drivers of carbon emissions and acknowledge that economic development in sub-Saharan Africa continues to increase carbon emissions [16]. Pothen and Schymura (2015) report recent progress on the structural decomposition of global raw material consumption. Studies from the literature have found that affluence is one of the most important drivers to increase resource consumption [17–19]. A study in Austria by Weinzettel and Kovanda (2011) concludes that the critical driver of resource use in Austria is the growth in final demand [20]. Final energy consumption in Iran increased by 67%, and the main driver was economic activities, while energy intensity acted as a deterrent to energy consumption [21]. Meanwhile, in China, the manufacture of non-metallic mineral products increased from 1371 million tons in 1997 to 8173 million tons in 2017, where the factor production structure was the major driving factor [22]. Consequently, factors driving such changes in material use have a significant role in climate mitigation [23]. Reduction in material consumption can be achieved through material efficiency improvement, which can bring multiple benefits and close the emission gap [24,25]. There has been little or no improvement in resource efficiency in African regions, suggesting there is still a long way to go in the continent [26].

The decomposition studies mentioned above are mostly carried out for developed and emerging countries, while in this study we decompose domestic material consumption (DMC) for the first time for six Central African nations. We further divide the technological effect into technological intensity (DMC/energy) and energy intensity (energy/gross domestic product (GDP)) and conduct a four-factor LMDI analysis of Cameroon as a case study. Historical trends and metabolic profiles of natural resource consumption in those countries are discussed in the following analysis.

Decoupling theory devised by the Organization for Economic Cooperation and Development means the relationship between two or more interconnected physical quantities no longer exists [27]. It is the process of breaking the connection between economic activities and resource use. Multiple studies have assessed and evaluated the decoupling of economic growth from resource consumption [28–32]. Logarithmic mean Divisia index (LMDI) is one of the preferred decomposition methods to investigate the decoupling effect because it can handle zero values without the need to explain residual terms [33]. It has also been applied to explore the decoupling of carbon emissions and GDP [34]. Most studies have focused on the drivers of energy-related carbon emissions, with the decomposition of population, energy intensity, and GDP as driving factors [35–41]. Few studies have applied LMDI to the decomposition of non-energy minerals. This study decomposes the driving factors of domestic material consumption in Central African countries to deal with the problem.

With the expansion of economic development in Africa, concerns about the sustainable use of mineral resources are increasing because economic activities entail mineral resources extraction, which may cause environmental problems and exert pressure on sustainability. Central African countries are in the stage of industrialization and will need many mineral resources in the future. If economic development could be decoupled from mineral resources consumption, environmental effects would be greatly reduced [18]. The study by Bekun et al. (2021) shows that renewable energy can improve sub-Saharan Africa's environmental quality in both short and long run [42]. Adedoyin et al. (2021) conclude that rapid economic growth increases carbon emissions in low-income countries but decreases for medium and higher-income countries [43].

Environmental challenges faced by African countries thwart African countries challenges to ensure healthy lives and promote well-being for all at all ages as contained in the Sustainable Development Goals. The effects of natural resource extraction-carbon dioxide emission nexus have been examined in Tunisia and the results showed that natural resource extraction exerts upward pressure on CO_2 emissions from the manufacturing and construction sector as well as from the consumption of gaseous fuels [44]. In 2021, Gyamfi studied the dynamic interaction of natural resources on a consumption-based carbon economy in oil producing sub-Saharan African countries from 1990 to 2018 and the results revealed that natural resources increase consumption-based carbon emission within the range of 0.0159 to 0.2304% [45]. Meanwhile in 2019 Kwakwa and colleagues analyzed the CO_2 emission and energy consumption effect of natural resources extraction in Ghana and the findings revealed that extraction of natural resources increase energy consumption [46]. The major driver of historical CO_2 emission in some African countries has been due to the transition from a biomass to a petroleum fuel economy accompanied by energy intensity of economic output [10]. By the year 2015, the global extraction of metals, minerals, biomass, and fossil fuels reached 89 Gt/year with 75% of global resource extraction used to expand and maintain infrastructure, and machinery [47]. GDP has been seen to grow faster than resource use and a continuation of past resource trends will not lead to a reduction of resource use [48]. Half of extracted materials are used in build ups with recycling contributing just 12% [48].

Against this backdrop, this study explores the driving factors behind domestic material consumption in Central Africa. Population, technology and affluence are the focus of this study because Central African countries are experiencing rapid population and economic growth with high material dependency and significant growth in energy consumption. Slow but steady urban growth has resulted in people's changes in lifestyle, too. The contributions of this study are summarized in two aspects. It enriches the existing research on the drivers of natural resources consumption and provides a new overview to formulate the consumption law of mineral resources in Central Africa. This study fills the gap that previous and much research mainly considered the drivers of energy materials and carbon emissions without the same attention to non-fuel mineral consumption. We aim to (1) identify potential driving forces behind DMC patterns in different Central African countries for over 30 years, (2) decouple the economic development from DMC to understand the influencing factors of DMC patterns and (3) provide suggestions for DMC reduction in Africa.

2. Methods

2.1. Analytical framework and data sources

To analyze trends of material use and material efficiency in Cameroon, Central African Republic, Democratic Republic of the Congo, Chad, Gabon and Equatorial Guinea, we use the accessible international Resource Panel (IRP) database to establish material flow accounts (https://www.resourcepanel.org/global-material-flows-database). The time series covers more than four decades, from 1970 to 2018. The material flow accounts calculated here include crop residues, crops, ferrous ores and non-ferrous combined, grazed biomass and fodder crops, non-metallic minerals with construction dominant, non-metallic minerals with industrial or agricultural dominant, petroleum products, wild catch and harvest and wood. The measure of resource productivity in this study is DMC per unit real gross domestic product (GDP), with GDP specified in U.S. dollars on a constant year (2011). Socioeconomic data were obtained from the Maddison project database, version 2018 [49]. Decomposition analysis can determine the driving forces for changes in natural resource use. Since economic activity has been proven to affect natural resources consumption many times in literature already [13], it must be included in the analysis. The identity function utilized in this paper is standard in analyzing drivers of natural resource use as it takes into consideration population growth and economic activity (GDP).

The total consumption of natural resources can be expressed as the product of three or four factors, e.g., population, GDP, energy, and technology intensity. These are variables that determine the drivers of natural resource use. This is very useful in practice to determine the drivers in terms of more readily available data. Time series data is being utilized for the empirical analysis of this paper, and it span from 1990 to 2018.

2.2. Stationarity tests for time-series data

As our dataset is time-series, we conducted stationarity tests to prevent spurious regressions or invalidation of the t-test. In this study, the maximum likelihood estimation is applied [50]. This technique has been widely used in many studies to investigate interactions among variables [51,52]. Noteworthy is that all variables were log-transformed to eliminate possible heteroscedasticity before the Augmented Dickey–Fuller (ADF) test. An ADF test was utilized to identify whether domestic material consumption (DMC), population and GDP were stationary or not. The ADF results show that all three variables are integrated of order 2, which means that they are co-integrated. A long equilibrium relationship exists between these variables. More methodological details can be found in the work of Zheng et al. (2020) [37]. Similarly, the Zivot–Andrews unit test (Alan et al., 2010) can be compared with the ADF test [53], but this is beyond the scope of this study.

2.3. Three-factor LMDI analysis

The LMDI approach estimates the contribution of each effect to the changes in DMC with a number of favorable properties. This study estimates the effects of population, affluence, and technology in six Central African countries. Equations 1–5 are used to calculate the periodic change of DMC in Cameroon, Chad, Central African Republic, Equatorial Guinea, Democratic Republic of the Congo and Gabon.

$$DMC = P \times \frac{GDP}{P} \times \frac{DMC}{GDP} = P \times A \times T \quad (1)$$

$$\Delta\, DMC = DMC_{t1} - DMC_{t0} = \Delta P \times \Delta A \times \Delta T \quad (2)$$

$$\Delta P = \sum \frac{DMC_{t1} - DMC_{t0}}{lnDMC_{t1} - lnDMC_{t0}} \times \ln \frac{P_{t1}}{P_{t0}} \quad (3)$$

$$\Delta A = \sum \frac{DMC_{t1}\ - DMC_{t0}}{lnDMC_{t1} - DMC_{t0}} \times ln \frac{A_{t1}}{A_{t0}} \quad (4)$$

$$\Delta T = \sum \frac{DMC_{t1}\ - DMC_{t0}}{lnDMC_{t1} - DMC_{t0}} \times ln \frac{T_{t1}}{T_{t0}} \quad (5)$$

where ΔDMC represents the change of DMC over the period between t_0 (the start year) and t_1 (the end year); ΔP, ΔA, and ΔT present the contributions of population (ΔP), affluence (ΔA, per capita real GDP), and technology (ΔT) to DMC change, respectively.

2.4. Four-factor LMDI analysis in light of Kaya identity

Keya identity is used to represent the energy consumption of Cameroon in other to reflect an example of an African country. The Kaya identity was proposed by Japanese scholar Yoichi Kaya at an IPCC seminar to state the four-factor relationship between GHG emissions and the global economy [54]. In light of Kaya identity, here we present a four-factor LMDI analysis of DMC in Cameroon to further investigate the impacts of the energy consumption in society and energy productivity in terms of GDP (Eqs 6–9).

$$DMC=\frac{DMC}{GDP}\times\frac{GDP}{E}\times\frac{E}{P}\times P=T\times EP\times EC\times P \tag{6}$$

$$\Delta\, DMC = DMC_{t1} - DMC_{t0} = \Delta P \times \Delta EC \times \Delta EP \times \Delta T \tag{7}$$

$$\Delta EC = \sum \frac{DMC_{t1} - DMC_{t0}}{lnDMC_{t1} - DMC_{t0}} \times ln\frac{EC_{t1}}{EC_{t0}} \tag{8}$$

$$\Delta EP = \sum \frac{DMC_{t1} - DMC_{t0}}{lnDMC_{t1} - DMC_{t0}} \times ln\frac{EP_{t1}}{EP_{t0}} \tag{9}$$

where E refers to energy consumption of a nation, $\frac{DMC}{GDP}$ refers to technology expressed as T; $\frac{GDP}{E}$ refers to energy productivity per GDP expressed as EP; $\frac{E}{P}$ refers to energy consumption per capita expressed as EC.

This study uses LMDI technique to further decompose changes in DMC [55]. P denotes the population effect, GDP/E measures energy productivity, DMC/GDP measures technological effect, and E/P measures energy consumption per capita. These variables are common items used in most LMDI decomposition analysis related to energy or environmental studies. The LMDI method was preferred because of its additive and multiplicative decomposition forms [33]. Our study employed the additive LMDI method to estimate the absolute changes in DMC. The four-factor decomposition explains a relationship between macroeconomic indicators, including energy productivity, population and per capita energy use and technological improvement, to provide insights into resource policy changes in the long run for Cameroon.

3. Results and discussion

3.1. Evolutionary trend in consumption of natural resources in Central African countries

From 1970 to 2018, Central African countries have consumed a total of 2.5 billion tones of natural resources at a growth rate of 2.2% per year (Figure 1). Wood was the most consumed resource at 598 million metric tons, followed by crops at 515 million metric tons, then crop residues at 407 million metric tons. Of the mineral resources, 315 million metric tons of industrial minerals have been consumed, followed by ferrous ores at 200 million metric tons. Wild catch and harvest have been the least consumed, while only a total of 30 million metric tons of petroleum have been consumed over this period at a growth rate of 2.8% per year (Figure 1). The consumption of construction minerals increased from 9 million metric tons to 23 million metric tons, at a rate of 3.8%/yr, making it the fastest consumption. However, it had lower total consumption of 160 million metric tons. While the consumption of natural resources continues to increase, the trend for industrial minerals decreased in 2005 from 56 million metric tons to 23 million metric tons in 2018. That of petroleum remained relatively low throughout. Central African countries need to improve resource efficiency not only in the agriculture and construction sectors but also in industrial sectors, which will lead to greater environmental benefits.

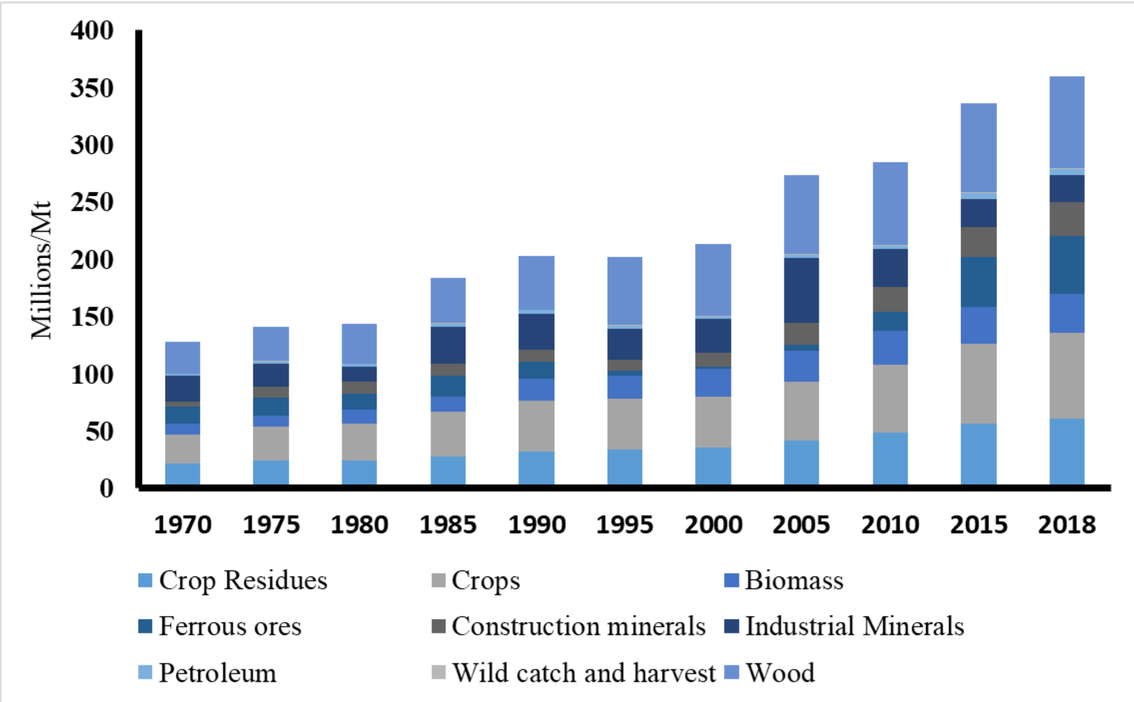

Figure 1. Total natural resources consumed in Central Africa from 1970 to 2018.

3.2. Descriptive statistics

Table 1 reports descriptive statistics in terms of mean, median, standard deviation, Skewness, Kurtosis and Jarque–Bera test for the six countries. Skewness measures the lack of symmetry in data distribution, while kurtosis is the measure of outliers present in the distribution. The Jarque–Bera (goodness-of-fit) test is used to investigate the skewness and kurtosis of our sampling data with respect to a normal distribution. Our results show that skewness for all six countries is approximately symmetrical and kurtosis for all countries indicates no significant outliers. Congo has the highest GDP in terms of mean value compared with other countries. The highest and lowest averages of the population are Congo and Gabon, respectively.

Table 1. Descriptive statistics.

Countries		Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque–Bera	Obs
Cameroon	GDP	10.54162	10.55418	0.192007	−0.527997	2.591829	2.563449	49
	POP	4.129676	4.164684	0.186055	−0.353778	1.881822	3.501911	49
Congo	GDP	10.66235	10.68781	0.108456	−0.145114	2.565009	0.558293	49
	POP	7.640437	7.650327	0.179930	−0.048657	1.752998	3.194156	49
Chad	GDP	9.852579	9.736992	0.297400	0.690970	2.055140	5.721803	49
	POP	3.827622	3.812713	0.165637	0.065597	1.625268	3.893664	49
EQG	GDP	9.534161	9.145274	0.682815	0.328647	1.318803	6.652688	49
	POP	5.613256	5.617000	0.180328	−0.139761	1.932875	2.484480	49
CAR	GDP	9.517137	9.501172	0.064364	0.575218	2.503274	3.205904	49
	POP	3.523146	3.539829	0.150193	−0.149545	1.765247	3.295390	49
Gabon	GDP	9.032955	9.070919	0.105767	−0.538651	1.959872	4.578328	49
	POP	3.013104	3.017451	0.159687	−0.193522	1.905826	2.750167	49

As shown on the Table 1 the mean of GDP is larger than that of population with the highest mean in Congo is largest followed by that of Cameroon, while Gabon is the smallest. The mean of population and GDP is positive in all countries. Furthermore, the standard deviation of variables are bothe very low indicating that the variables are not violatile. The skewness is negative for most variables except for the Chad; both variables and Equatorial Guinea’s population. This implies that the variables are negatively skewed. Meanhile in Chad, skwedness is positive for both variables, and in Equatorial Guinea only population variable is positively skewed. In addition the kurtosis of the variables suggest positive and not excess kurtosis. Consequently, the Jargua–Bera statistics are small which implies that the null hypothesis of the normal distribution of the variables are accepted.

3.3. Domestic material consumption (DMC)

Before addressing the LMDI results, we present historical changes in DMC for six nations by nine different resources. Figure 2 compares the overall annual DMC for Cameroon, the Democratic Republic of the Congo, Chad, Equatorial Guinea, Central African Republic, and Gabon from 1970 to 2018. In total, the Democratic Republic of the Congo has the highest cumulative DMC of 6218 million tonnes (Mt) followed by Cameroon with 2045 million Mt. The DMC of Congo has increased from 88 Mt in 1970 to 190 Mt in 2018, while that of Cameroon has increased from 20 million Mt to about 100 million Mt over the same period. The third highest consumed country is Chad, with a total of 935 million Mt and a compounding growth rate of 3%, followed by the Central African Republic with a total of 486 million Mt and a 3% growth rate. Of these totals, different resources are highly consumed in different countries. Grazed biomass is highly consumed in Chad and the Central African Republic. Wood is the most consumed in Congo at 1.9 gigatonnes (Gt) with a growth rate of 3%, while crops are highly consumed in Cameroon at 643 million Mt with a growth rate of 5%. Construction minerals are mostly consumed in Gabon, and petroleum goods are the most consumed in Equatorial Guinea, with an exceptional growth rate of 19%. Equatorial Guinea shows a rapid growth of DMC, which has increased by a factor of 28 during the past 48 years.

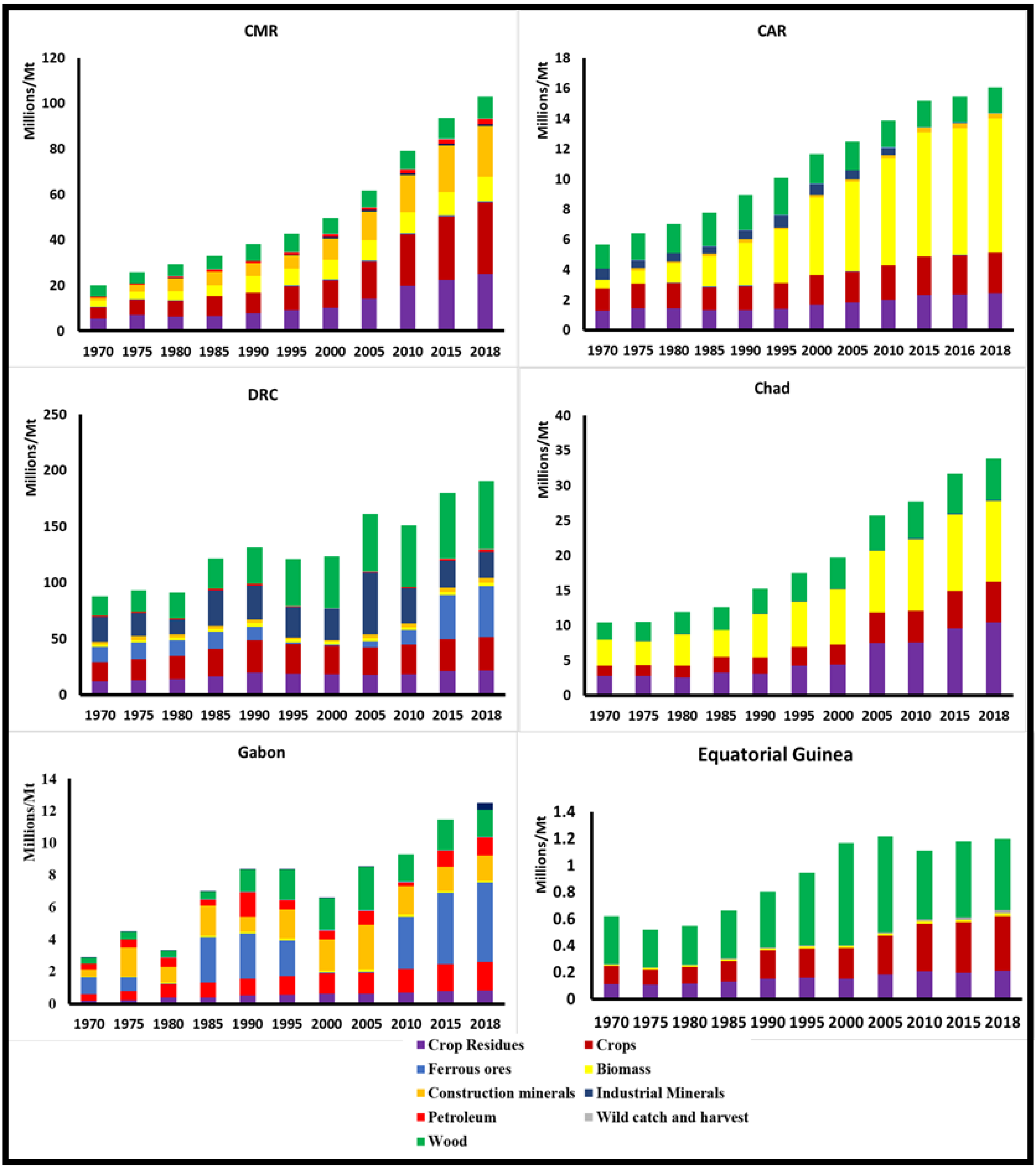

Figure 2. Domestic material consumption of different resources for Central African countries.

3.4. Resource productivity and metabolic profiles

Metabolic profiles (DMC/capita) and resource productivity (GDP/DMC) as intensity indicators were further investigated in those countries. Cameroon with the lowest DMC/cap presents the highest resource productivity (Figure 3). Its DMC/cap remained low at 1 t/cap while resource productivity fluctuated between 0.6 and 1.2 $/kg. As shown in the secondary vertical axis of Figure 3, Equatorial Guinea's DMC/cap increased from 2.5 t/cap in 1970 to 12.4 t/cap in 2018; its resource productivity decreased from 0.3 $/kg to 0.08 $/kg over the same period. Similarly, Gabon's DMC/cap increased from 2.4 to 8 t/cap from 1970 to 2018, while its resource productivity decreased from 0.4 $/kg to 0.1 $/kg over the same time period. Democratic Republic of the Congo with the highest cumulative DMC of 6 Gt in total, is one of the countries with the lowest resource productivity, remaining low at less than 0.1 $/kg.

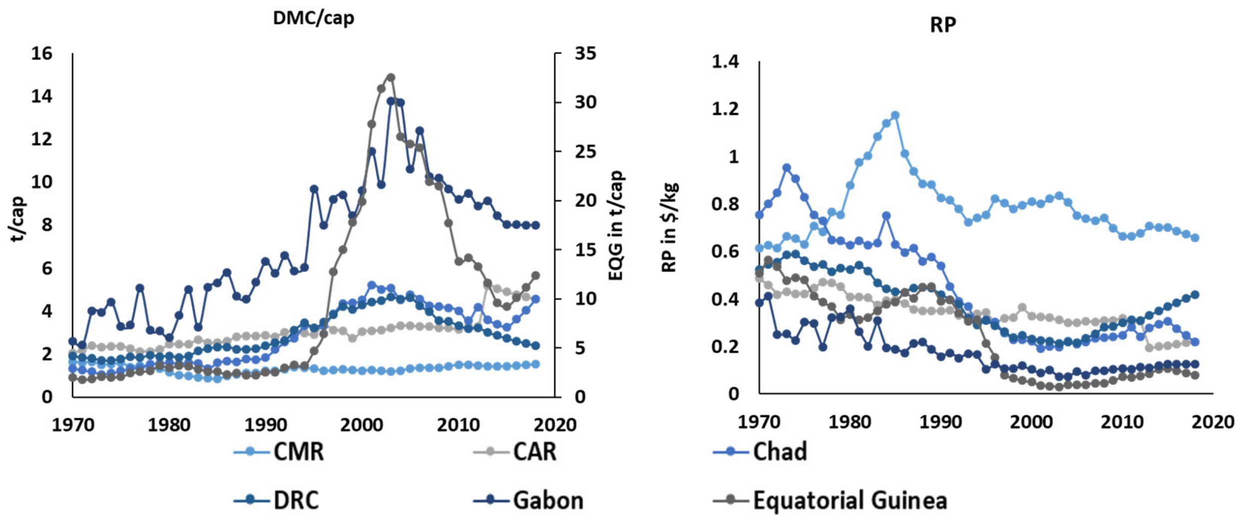

Figure 3. Metabolic profiles and resource productivity in six Central African nations.

Rather than consuming more as would be expected of developing nations, there appear to be no lasting upward trends of DMC/cap for these countries. The low DMC/cap in most time for these nations is in line with its slow economic development and the often-unstable domestic political situations. However, if these countries keep a stable economic growth, the DMC/cap might increase in the future, highlighting the requirements to strengthen resource management. Equatorial Guinea and Gabon present high DMC/cap. Gabon shows strong signs of materialized society as the total consumption of construction and ferrous resources stands at 84 and 82 million Mt, respectively. Meanwhile, the consumption in Equatorial Guinea is dominated by petroleum goods, presenting an insignificant materialization. Regardless, Equatorial Guinea is the only country in Central Africa that has exceeded the value of 10 t/cap, reached 32 t/cap in 2003 and then decreased to 12 t/cap in 2018 (Figure 3). The trend toward higher levels of per capita DMC for Equatorial Guinea results from the region's population becoming affluent over the period. Our following analysis (Section 4) will show that Equatorial Guinea is the only country with the highest affluent contribution compared to the other five countries.

Increasing inefficient use of energy and materials is one among several factors contributing to poor resource productivity observed in some of the Central African countries. Outdated technologies and infrastructure, together with little or no investment and lack of effort, contribute to poor resource productivity in the region. Not underestimating inefficient processes and management further contribute to resource losses. More so, distributional losses from transport and energy carriers such as oil and gas contribute to poor resource productivity as well. The low resource productivity is because of the material-intensive processes of urbanization and an expansion of agricultural and primary activities, which usually leads to lower levels of resource productivity [56]. The level of use of natural resources is largely determined by the economy's structure, not by the national income or economic development [57].

4. Dynamic changes in resource use[1]

4.1. Cameroon

From 1970 to 2018, DMC increased by 82 million Mt, with the population as the major positive driver and the highest positive contribution ratio of 76% in total. Technology and affluence shared the same positive contribution ratio of 12% (Figure 4). There were some specific variations between the different decades. From 1970 to 1980, technology was the main negative driver and offset DMC by 101%, while affluence and population were positive drivers of DMC, each with a contribution ratio of 98% and 112%. From 1980 to 1990, affluence offset DMC while technology and population were the main positive drivers of DMC. The effect of affluence offset was reflected in a DMC decrease of 700000 metric tonnes. From 1990 to 2000, affluence continued to offset DMC while population and technology continued to be positive drivers of DMC. The contribution of technology and population significantly increase DMC by 2.7 million tonnes. The offsetting ratio of affluence was so small at 13% that DMC did not reduce compared to a high contribution ratio of 90% in the previous decade. From 2000 to 2018, affluence, technology and population were positive drivers of DMC (Figure 4). Their positive contribution increased DMC by 18 million metric tonnes from 1990 to 2000 but rather reduced DMC by 5 million metric tonnes from 2010 to 2018. This gross reduction could result from a low positive contribution of technology which was 6%. We, therefore, see an offset in DMC between two periods, one caused by the offset effects of affluence and another caused by the fact that technology was not a stronger positive driver than affluence and population, which left Cameroon with an increase in DMC of 14 million from 1970 to 2018.

[1] Each bar in the graphs represent each period studied. For example, first bar represents 1970–1980, second 1980–1990 and so on and so forth.

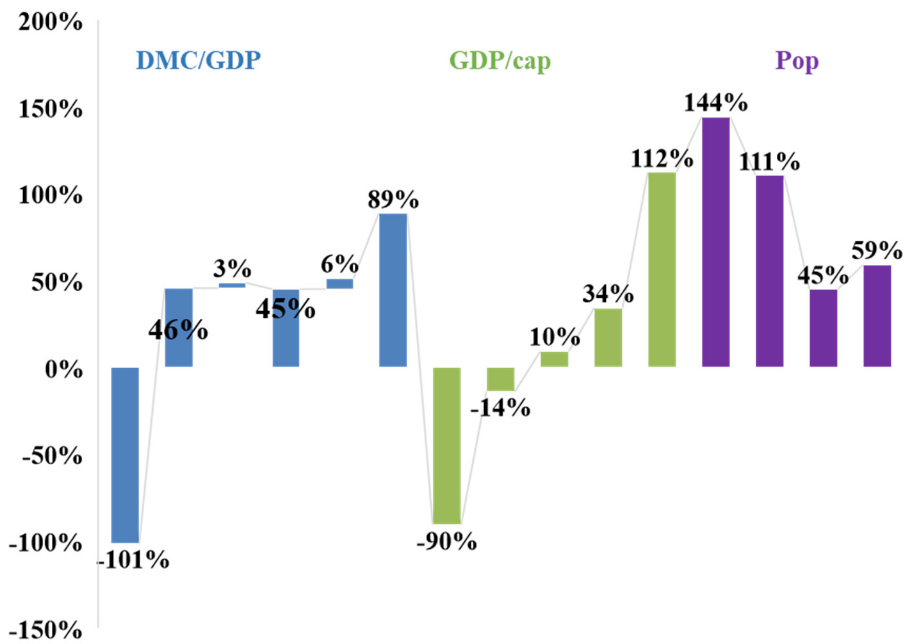

Figure 4. The contribution of DMC changes by different driving forces in Cameroon, 1970–2018.

4.2. Central African Republic (CAR)

There is an objective necessity to note that in this nation, affluence made a downward trend in DMC with a total contribution of 94% despite the fact that its nation's growth in per capita GDP of just 2% from 1970 to 2018. The slow growth in per capita GDP has led to an offset in DMC for all these years. Affluence led to reducing DMC by 400000 metric tonnes from 2000 to 2010 and again by another 1000 metric tonnes from 2010 to 2018 (Figure 5). Population and technology were the main positive drivers of DMC from 1970 to 2018 with contribution ratios of 109% and 87%, respectively. From 1970 to 1980, DMC increase was 10 million metric tonnes, far less than the 82 million tonnes in Cameroon. In Cameroon, technology, affluence and population were positive drivers from 1970 to 2018 with very low contribution ratios, while in CAR, population and technology were the main positive drivers with high contribution ratios. Despite the offsetting effects of affluence, DMC in CAR increased by 840000 metric tonnes from 1970 to 2018. However, this is not a huge increase when compared with Cameroon.

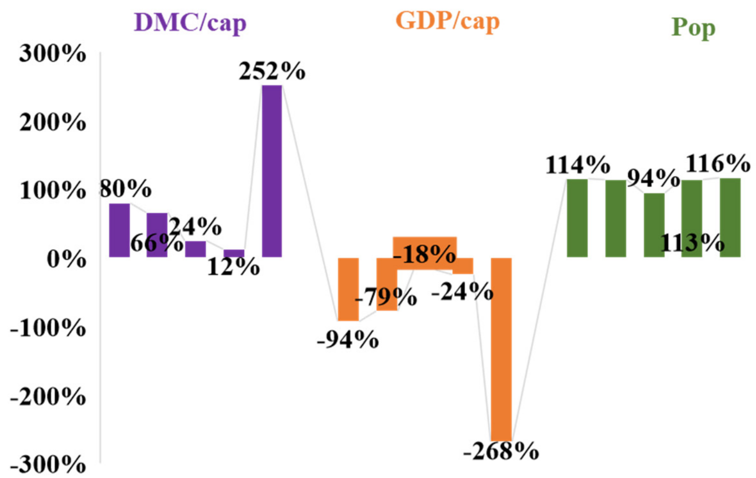

Figure 5. The contribution of DMC changes by different driving forces in CAR, 1970–2018.

4.3. Democratic Republic of the Congo (DRC)

In DRC, population was a strong driver from 1970 to 1980 with a contribution ratio of 803% and then dropped to 86% from 1980 to 1990 (Figure 6). From 1980 to 1990, the negative contribution ratio of affluence was not strong enough to offset DMC. In the next phase, technology and population emerged as strong negative drivers of DMC to the extent that the effects were seen in reducing DMC by 47 million metric tonnes. Technology continued to play the offset role but affluence and population continued to be strong positive drivers of DMC increasing DMC by 34 million metric tonnes and 11 million metric tonnes. While affluence offset DMC by 93% in CAR from 1970 to 2018, it only offset DMC in DRC by 69%. Technology effect offset DMC by 0.6% in DRC. Population presented the highest contribution ratio of 169% from 1970 to 2018 in DRC compared with Cameroon and CAR over the same period and increased DMC by 36 million tonnes.

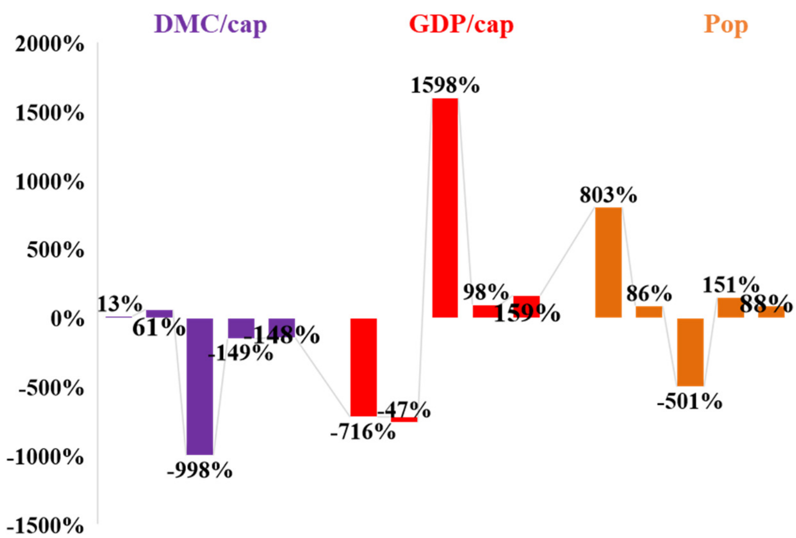

Figure 6. The contribution of DMC changes by different driving forces in DRC, 1970–2018.

4.4. Equatorial Guinea (EQG)

Unlike in CAR, technology was observed to offset resource use in this nation except from 1990–2000. Unlike in Cameroon, CAR and DRC, where population was the main positive driver, affluence was the main positive driver in EQG from 1970 to 2018, with a positive contribution ratio of 75% (Figure 7). The influence of technology offset DMC by 5 million metric tonnes from 2010 to 2018, the same amount of reduction seen in Cameroon during the same period. Unlike DRC, where technology offset DMC from 1970 to 2018 by merely 0.6%, it offset the highest in EQG by 28%. These positive drivers contributed to EQG's increase in resource use by 2 million metric tonnes, 1970–2018.

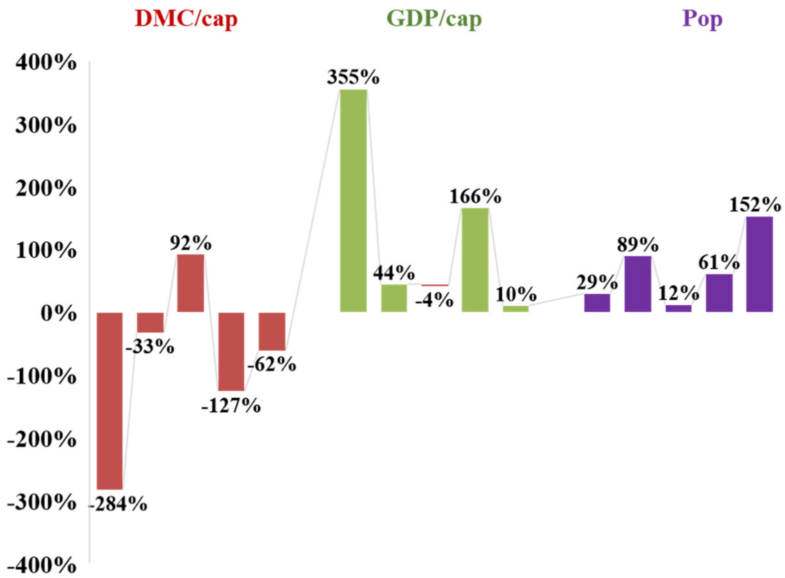

Figure 7. The contribution of DMC changes of different driving forces in EQG 1970–2018 period.

4.5. Chad

Similar to the situation in CAR, affluence offset resource use from 1970 to 2018 by 88% (Figure 8). The only period that affluence did not show an offsetting effect was between 2000 and 2010, when technology became the offsetting variable by 42%. The offsetting effects of affluence were stronger from 2010 to 2018, when DMC diminished by 2 million metric tonnes. Population and technology were positive drivers and increased resource use by 97% and 91%, respectively, from 1970 to 2018. Chad's DMC increased by 21 million tonnes, higher than both CAR and Cameroon.

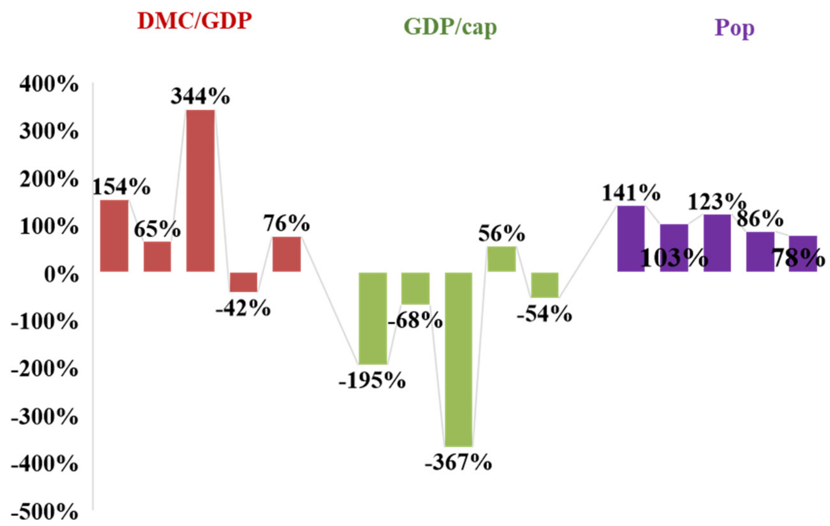

Figure 8. The contribution of DMC changes by different driving forces in Chad, 1970–2018.

4.6. Gabon

From 1970 to 1980, affluence offset resources by 46%, while population and technology were positive drivers of DMC with a contribution ratio of 96% and 50% (Figure 9). The offsetting effects of technology and population from 1990 to 2000 reduced DMC by 6 million metric tonnes. From 1970 to 2018, Gabon's DMC increased by 2 million metric tonnes, the same amount of growth as EQG but caused by different drivers.

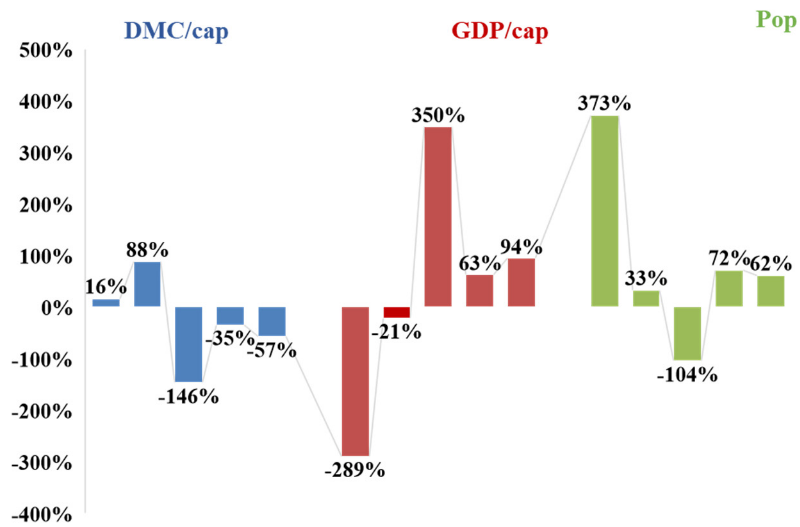

Figure 9. The contribution of DMC changes by different driving forces in Gabon, 1970–2018.

Based on our results, it can be seen that higher consumption of natural resources will threaten environmental sustainability, though it will stimulate economic growth in Central African countries.

Given that considerable quantities of natural resources are consumed in these countries, population can be considered as a substantial driver of the demand for natural resources in these countries (Figure 10), In contrast, some developing countries like China, Peru and South Korea see GDP as a substantial driver of its natural resource demand [58]. Cameroon and DRC had higher resource productivity of 0.8 and 0.4 (Figure 3). Equatorial Guinea and Gabon had the lowest resource productivity of less than 0.1, far lower than the resource productivity reported for South Africa and Chile [58]. While the increase in natural resource use was due to the population effect in Central African countries (Figure 10), it was due to the income effect in the European Union countries, as detailed by Karakaya et al. (2020) [59]. Only Equatorial Guinea's GDP/cap was seen as the main driver of natural resources (Figure 10). Central Africa's consumption of fossil fuels increased from 1.2 million metric tons to 5.3 million from 1970 to 2018, while China increased from 1.2 billion tons to 4.5 billion tons from 1992 to 2017 [60]. In the same light, the consumption of mineral resources increased from 127 million metric tons to 359 million metric tons in Central African countries from 1970 to 2018, which is a far smaller increase compared to the sharp increase in China from 551 million metric tons in 1992 to 4.4billion in 2017 [60]. The economies of Central African countries are developing rapidly with increased dependence on natural resources. Thus an urgent priority for these countries is how to accelerate technological progress to decouple economic growth from natural resource consumption. In the study of Khan et al. (2020) [61], natural resources abundance decrease economic growth in OECD countries, while the abundance of natural resources increases economic growth in Central African countries.

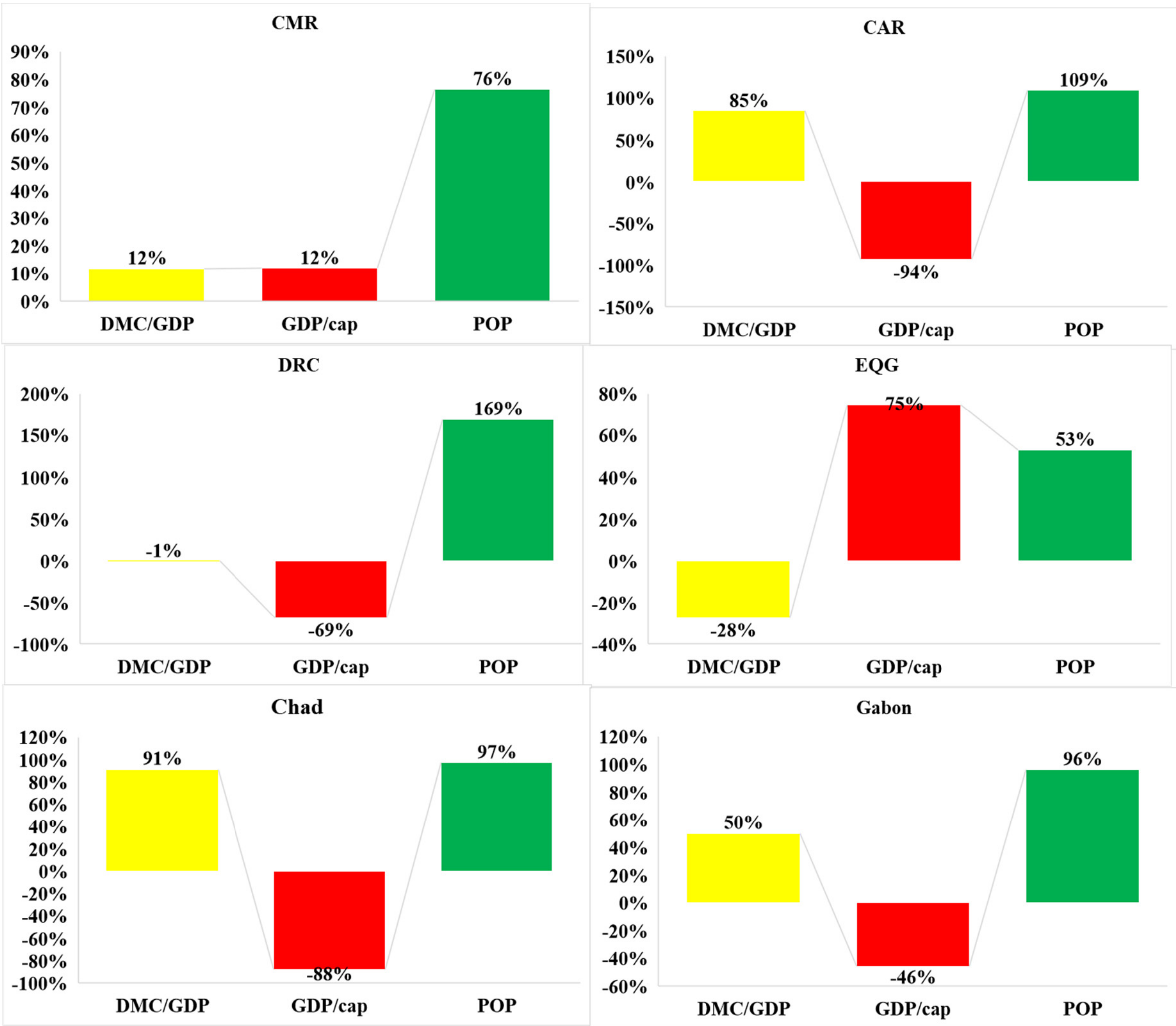

Figure 10. Drivers of DMC from 1970 to 2018 in different Central African countries.

5. The case study of Cameroon

Due to data limitations, we conducted a four-factor LDMI analysis of Cameroon, taking energy into account, from 1990 to 2014. We observed that per capita energy use (energy/cap) was the only effect that offset DMC by 22% (Figure 11). Population continued to be the main positive driver with a contribution ratio of 62% followed by energy productivity (GDP/energy) with 42%, and then general technological improvement (DMC/GDP) with 18% (Figure 11). Looking at specific decades, GDP/energy was the main negative driver from 1990-1995 with a ratio of 168%, while the other effects were positive drivers. From 1995 to 2000, DMC/GDP was the only negative driver contributing a negative share of 46%. The positive effects of the other factors increased DMC by 2 million metric tonnes. From 2000–2010, energy/cap continued to offset DMC but its offsetting effects was not strong enough to diminish DMC. DMC rather remained constant at 5 million tonnes but reduced by 6 million tonnes from 2010–2014. This reduction was caused by offsetting effects of DMC/GDP and also by the low positive contribution ratio of energy/cap. When observing the whole period from 1990–2014, DMC increaseed by 6.8 million by the positive effects of the other three drivers except per capita energy use (energy/cap).

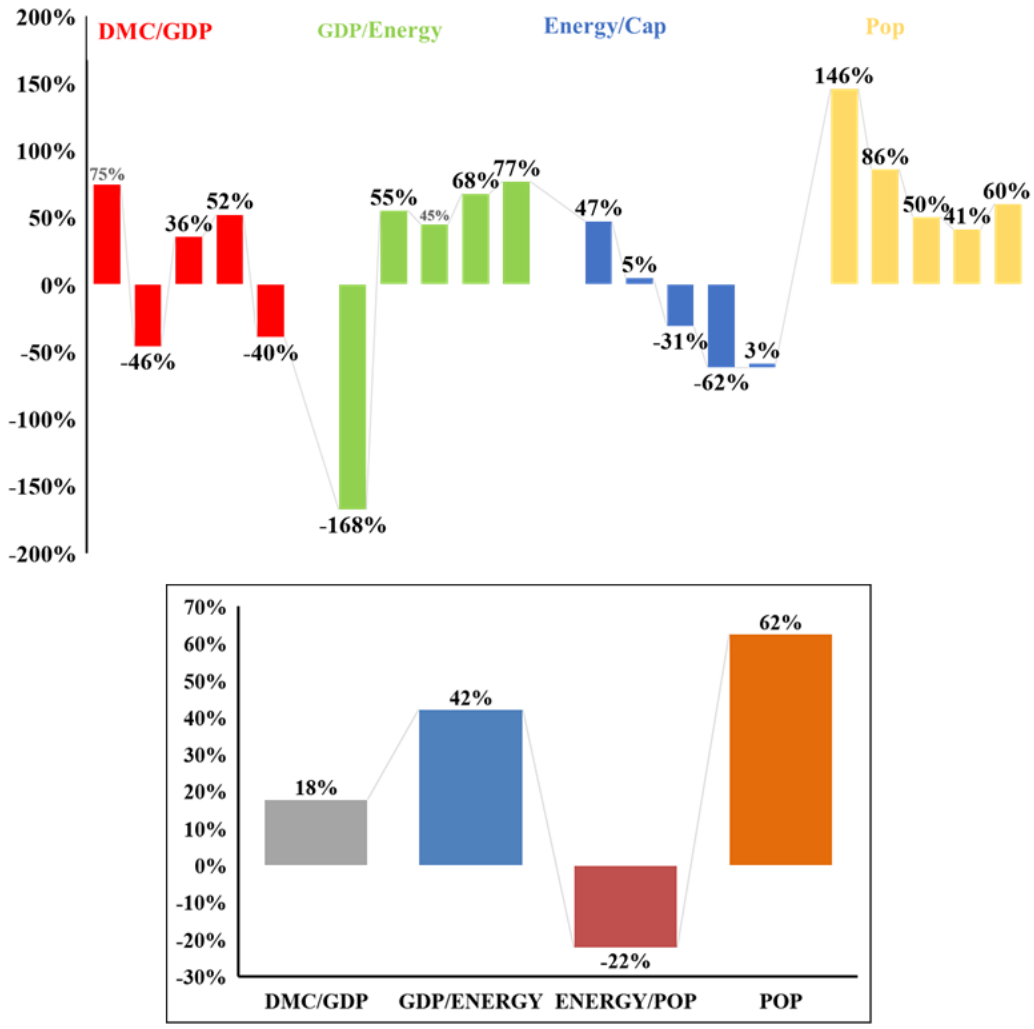

Figure 11. Four-factor decomposition for Cameroon from 1990–2014.

6. Conclusions and policy recommendation

This study presents the first decomposition analysis of domestic material consumption in six Central African countries. The study utilizes the International Resource Panel database for material flows and the Maddison project database for socioeconomic factors. The multiplicative logarithmic mean Divisia index method is used to quantify the effects that drive changes in natural resource consumption over the years.

Our results provide four key insights:

(1) Population is the dominant driver of growing DMC in Cameroon, the Central African Republic and Gabon.

(2) Technology effect offset resource use in four Central African countries (i.e. Cameroon, Democratic Republic of the Congo, Equatorial Guinea and Gabon), while affluence offset in Chad and the Central African Republic. It was particularly noticeable for construction and industrial resources in Cameroon, the Central African Republic and Gabon, showing that infrastructure investments in these countries were a major driver of national DMC growth.

(3) The unusual change in technology and population effects in the Democratic Republic of the Congo and Gabon happened between 1990 and 2000. It reduced DMC by 383% in Gabon and by 641% in the Democratic Republic of the Congo between 1990 and 2000, which might be mainly due to destabilization in those countries.

(4) Countries that have consumed the least resources like Chad and Equatorial Guinea are resource-poor countries. These are import-dependent countries, and the rising difference in DMC indicates a strong dependency ratio.

To achieve decoupling economic growth from natural resources consumption in Central Africa, policy-makers can develop policies based on the following recommendations:

(1) There is a need to implement reduction management of mineral resources in highly consumed countries. Attention should be paid to the construction and petroleum minerals.

(2) There is a call for the formulation of a national decoupling policy. A policy-related reporting and monitoring system of natural resource consumption will reveal whether and when one nation's economic growth can be decoupled from materialization.

(3) Policies should be inclined to improve the utilization of efficiency of natural resources. Technology in the bloc should be improved to reduce the consumption of mineral resources per unit of output and thus improve society's overall resource efficiency and productivity.

Although our study increases the understanding of natural resource consumption in Central Africa, there are still some limitations. The environmental impacts of domestic material consumption are divided into different stages of production, smelting, processing, etc. Due to data limitations, this study failed to clearly separate the consumption stages and categories when analyzing the drivers. For example, the DRC exports a large amount of non-fuel minerals indicating that the environmental burden generated in the extraction phase has a high impact on the country's environment. Future studies should analyze the effect of natural resource extraction on carbon footprint in Central African countries and the geopolitical contexts behind the patterns through the lens of historical resource production and consumption in Central Africa.

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Conflict of interest

The authors declare no conflict of interest.

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