Caught in the Crossfire : Natural Resources, Energy Transition, and Conflict in the Democratic Republic of Congo

West TOGBETSE*

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Abstract

The global shift towards clean and sustainable energy sources, known as the energy transition, is compelling numerous countries to transition from polluting energy systems to cleaner alternatives, commonly referred to as green energies. In this context, cobalt holds significant importance as a crucial mineral in facilitating this energy transition due to its pivotal role in electric batteries. Considering the Democratic Republic of Congo's reputation for political instability and its position as the largest producer of cobalt, possessing over 50% of the world's reserves, we have conducted an assessment of the potential conflicts that may arise as a result of the rapid increase in cobalt demand. The results show that cobalt does not appear to be a determinant contributing to past conflicts in the Democratic Republic of Congo (DRC). Gold, on the other hand, stands out as one of the coveted metals for rebel groups engaged in rampant exploitation, increases the likelihood of conflicts occurring. However, according to our predictive model, cobalt has the potential to emerge as a contributing factor, similar to gold.

JEL Codes : F51 , L72 , O13

Keywords : Conflicts , Natural Resources , Energy Transition

*Université d'Orléans, CNRS, LEO, FRE 2014, F-45067, Orléans-France. E-mail : koami-west.togbetse@univ-orleans.fr

1 Introduction

Natural resource conflicts have been studied extensively in the literature. These conflicts can occur for a variety of reasons, such as unequal access to resources, competition for resource use, environmental degradation, and climate change. Unequal access to natural resources has been identified as a major cause of conflict. Marginalized groups and poor communities often have limited access to natural resources, which can lead to conflict with other groups over access to these resources Adano et al. [2012]. Resource conflicts can also be exacerbated by competition for the use of these resources. Conflicts can occur between different economic sectors, such as agriculture, fishing, and mining, over the use of land, water, and mineral resources Conca and Dabelko [2002]. Environmental degradation is another source of conflict. Water and air pollution, deforestation, and soil erosion can negatively affect local communities that depend on natural resources for their livelihoods. Conflicts can then arise as communities seek to protect their environment and natural resources Chapin et al. [2005]. Climate change has also been identified as a potential source of conflict. Climate change impacts, such as droughts, floods, and storms, can affect the natural resources and livelihoods of local communities, which can lead to conflicts over access to these resources Nordås and Gleditsch [2015]. Conflicts can arise due to unequal access to resources, competition for resource use, environmental degradation, and climate change. In sum, the literature review shows that conflicts over natural resources can have multiple and complex causes. Effective natural resource management and peaceful conflict resolution are therefore essential to ensure a sustainable future for local communities and to preserve natural ecosystems.

Previous studies have indicated that the revenue generated from natural resources is often detrimental to countries and regions that are involved in their extraction Badeeb et al. [2017] ; Frankel [2010] ; Sala-i Martin and Subramanian [2013] ; Van der Ploeg and Poelhekke [2009]. This is because natural resource rents can lead to a number of negative economic and social outcomes. These include the Dutch Disease, which is when an increase in natural resource rents leads to a decrease in other sectors of the economy; rent-seeking behavior, which is when individuals or groups attempt to gain control. Violent conflicts are serious humanitarian and economic threats in many developing countries. More than three-quarters of countries in sub-Saharan Africa have experienced civil war since 1960 Gleditsch et al. [2002]. Several research Homer-Dixon [1994] ; Hauge and Ellingsen [1998] ; Raleigh and Urdal [2007] have established a positive correlation between resource scarcity and conflict. These studies suggest that deprivation of livelihoods leads individuals to engage in struggles for survival. Adopting a neo-Malthusian perspective, these researchers argue that the growth of populations outpaces the growth of food supplies, leading to competition and, ultimately, conflicts over essential resources.

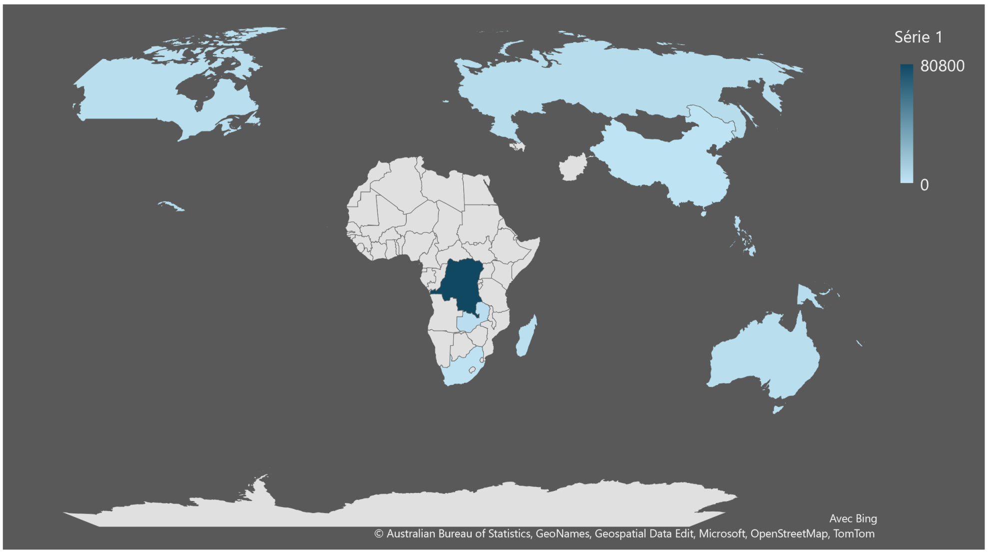
If the democratization of low-carbon technologies for the energy transition appears to lead to a decrease in dependence on fossil fuels, it is in fact creating new ones. In the context of energy transition in which all countries are currently engaged, the demand for certain metals identified as strategic, necessary for this transition, will drastically increase in the coming years. These metals are used in the manufacturing of new technologies called green which have been discovered more intensive in natural resources. These natural resources[1] are found for the most part in developing countries. In this study, we focused on the Democratic Republic of Congo (DRC), the world's largest cobalt producer. In 2020, the cobalt reserves of the Democratic Republic of Congo were estimated at 3.6 billion tons, representing over 50.7% of the world's total reserves of this mineral. Its production in 2022 is 111309 tons against 93 144 tons in 2021. At present, the cobalt market is dominated by two countries : the Democratic Republic of Congo, which produces 68% of the world's cobalt ore, concentrate and intermediate products and Australia. Cobalt has recently gained visibility due to its increasing use in low-carbon technologies,, also known as green technologies (renewable energies and rechargeable batteries). It is present in the magnets of wind turbines, but also and especially in the cathodes of lithium-ion batteries and nickel metal. Criticality is an approach based on the evaluation of risks associated with the production, utilization or end-of-life management of a raw material Graedel and Nuss [2014]. A raw material is considered critical when it is used in multiple industrial sectors, difficult to substitute in the short term, has many industrial applications, has a high economic value and its reserves and production are geographically concentrated. Cobalt has a high level of geological criticality, which must be taken into account depending on the type of batteries used in the transport sector. The primary risk associated with this mineral is geopolitical, due to potential supply issues, as mining production is concentrated in the Democratic Republic of Congo (DRC), a country with a highly unstable political environment.

The findings derived from our analysis indicate that the extraction of cobalt and gold has not been directly implicated in historical conflicts within the Democratic Republic of Congo (DRC). However, the presence of gold mining operations raises the likelihood of conflict, which does not currently hold true for cobalt. Conversely, leveraging novel machine learning techniques, our predictive model demonstrates that considering the significance of cobalt in the economic transition and its growing prominence in recent times, it could potentially serve as a catalyst for future conflicts in the DRC. As a policy recommendation, appropriate measures akin to those outlined in Section 1502 [2] of the Dodd-Frank Act have to be implemented to regulate the utilization of cobalt in the supply chains of corporations. The provision requires companies to disclose their use of certain minerals, specifically tin, tantalum, tungsten, and gold (often referred to as 3TG), if those minerals are necessary to the functionality or production of their products. The concern was that profits from the trade of these minerals were funding armed groups engaged in human rights abuses and fueling conflicts in the region. The aim of the provision is to promote transparency and accountability in supply chains and to discourage the use of conflict minerals. However, Section 1502 has been a subject of debate and criticism. Some argue that it places a burden on companies without effectively addressing the underlying conflict issues, while others contend that it has helped raise awareness and improve responsible sourcing practices.

[1] Aluminum, copper, iron ore, nickel, lithium and steel, as well as some essential rare earth metals such as molybdenum neodymium and indium

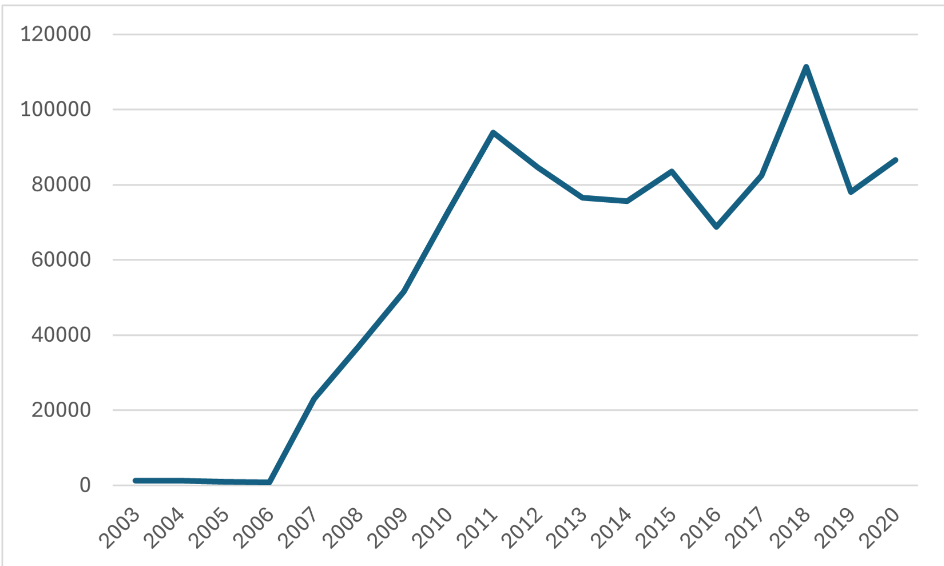
[2] Section 1502 of the Dodd-Frank Wall Street Reform and Consumer Protection Act is also known as the Conflict Minerals provision. It was enacted in 2010 and aimed to address the issue of "conflict minerals" originating from the Democratic Republic of the Congo (DRC) and surrounding countries. Under Section 1502, companies that are subject to the Securities and Exchange Commission's (SEC) reporting requirements are required to conduct a reasonable country of origin inquiry to determine whether the minerals they use originated from the covered countries. If the company determines that the minerals did originate from these countries, they must exercise due diligence on the source and chain of custody of those minerals and file a Conflict Minerals Report with the SEC.

Figure 1: **Map of major cobalt's producers in the world in 2020**



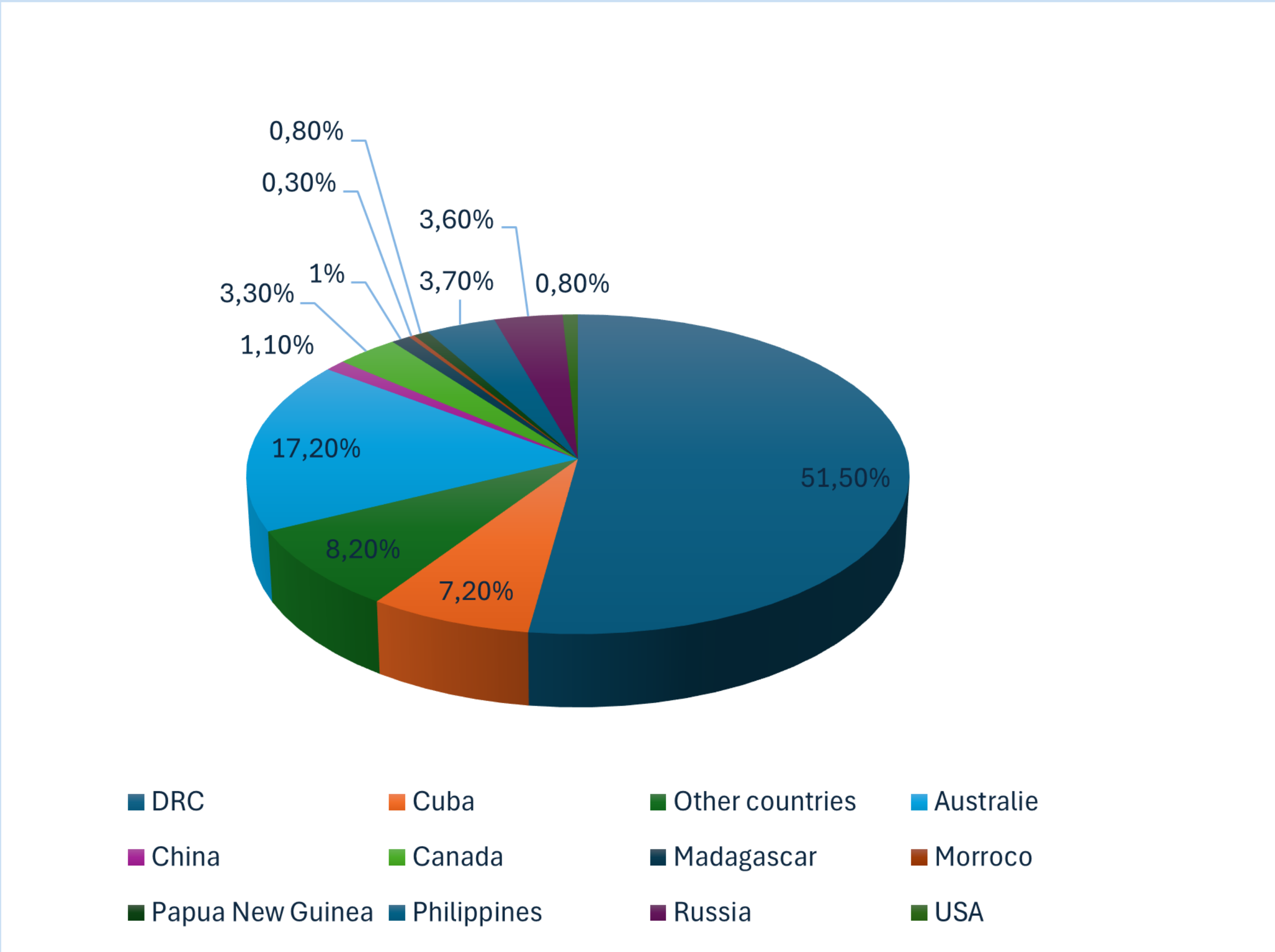
Source : Author calculation with Darton commodities Ltd data

Figure 2: **Annual cobalt production in the DRC**



Source : Author calculation with Congolese Minister of Mining's data

Figure 3: **Distribution of cobalt reserve in 2019**



Source : Author calculation with Energy industry review's data

2 Literature review

Natural resources can play a significant role in promoting economic growth, creating employment opportunities, and generating fiscal revenue. However, many countries that are rich in natural resources or heavily dependent on them are facing low growth rates, high levels of inequality and widespread poverty, poor governance, and an increased likelihood of civil unrest. A substantial body of literature exists to examine the issue of intra-state resource conflicts. This literature can be broadly divided into two categories: studies that focus on the scarcity of resources and its correlation with conflict, and studies that examine the relationship between resource abundance and conflict. Although the examination of resources and intra-state conflict is not a new phenomenon, the main findings from the literature are often conflicting and difficult to compare due to a lack of consistent definitions and measurements for scarcity, abundance, and conflict.

Urdal [2008] examines the relationship between population pressure on renewable natural resources, youth bulges, and differential growth rates between religious groups and the incidence of armed conflict, political violence, and Hindu-Muslim riots in 27 Indian states during the period 1956-2002. The results provide stronger support for the link between resource scarcity and conflict than previous global studies. Additionally, the study suggests that youth bulges have a significant impact on all three forms of violence, and that differential growth rates are positively associated with armed conflict. De Soysa and Neumayer [2007] employed a novel data set on natural resource rents to examine the relationship between resources and conflict. The data distinguishes mineral and energy rents. Results show that neither a dummy variable for major oil exporters nor our resource rents variables predict the onset of civil war using the 1000 battle death threshold defined by Fearon and Laitin (2003) for the period after 1970, for which rent data is available. However, when using a lower threshold of 25 battle deaths, we find that energy wealth, but not mineral wealth, increases the risk of civil war onset. No evidence was found for a non-linear relationship between either type of resources and civil war onset. Our results tentatively support theories based on state capacity models and provide evidence against the looting rebels model of civil war onset.

Tapsoba [2022] present a novel approach for forecasting the timing and location of conflict events based on historical violence data. Our methodology builds upon the work of Tapsoba (2018) and adapts the approach for measuring violence risk over both space and time to conflict prediction. We model violence as a stochastic process with an unknown distribution, and each conflict event on the ground is viewed as a random instance of this process. The underlying distribution is estimated through the use of kernel density estimation methods in a three-dimensional space. We then optimize the smoothing parameters to maximize the probability of future conflict events. Using data from Ivory Coast, we demonstrate the advantages of our approach compared to standard space-time autoregressive models in terms of out-of-sample forecasting performance. Hegre et al. [2019] in their work , presents practical and sustainable solutions for policymakers and researchers to identify and manage potential conflict threats by examining alternative methodologies beyond p-values and instrument plausibility. We contend that the success of conflict prediction is contingent upon the selection of algorithms, which, if chosen carefully, can mitigate the economic and social instability resulting from post-conflict reconstruction. Using a grid-level dataset consisting of 5928 observations from 48 sub-Saharan African countries, and incorporating variables related to conflict, we aimed to predict civil conflict. The objectives of the study were to compare the performance of supervised classification machine learning algorithms against a logistic model, examine the impact of selecting a particular performance metric on policy outcomes, and assess the interpretability of the chosen model. After comparing various class imbalance resampling methods, the synthetic minority over-sampling technique (SMOTE) was utilized to enhance the out-of-sample prediction accuracy of the trained model. The results demonstrate that, depending on the chosen performance metric, different algorithms produce the best model. If recall is the selected metric, gradient tree boosting is the optimal algorithm. On the other hand, if precision or F1 score is the preferred metric, the multilayer perceptron algorithm delivers the best results. Mueller and Rauh [2018] introduces a novel approach to predicting armed conflict through the analysis of newspaper text. Utilizing machine learning techniques, large volumes of newspaper text are transformed into interpretable topics, which are then utilized in panel regression models to predict the onset of conflict. Our methodology incorporates the within-country variation of these topics to predict the timing of conflict, thereby mitigating the tendency to only predict conflict in countries with a history of conflict. The results demonstrate that the within-country variation of topics is an effective predictor of conflict and particularly useful in identifying risks in previously peaceful countries. This approach is advantageous because the topics provide both depth and width, allowing for the capture of changing conflict contexts and the incorporation of stabilizing factors. Topics are composed of dynamic, extensive lists of terms and serve as summaries of the full text, providing a comprehensive view of the conflict landscape.

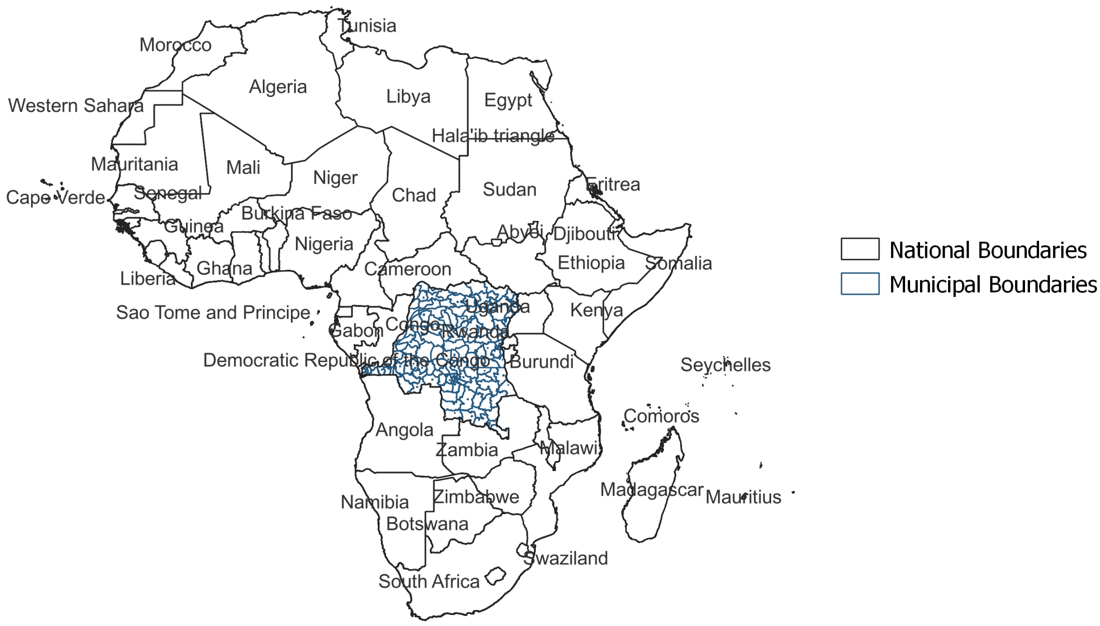
Bazzi et al. [2022] conducted an analysis of the two countries with the most abundant sub-national data available: Colombia and Indonesia. Our study includes a comprehensive examination of two decades of detailed data on various types of violence, along with an analysis of hundreds of annual risk factors. Utilizing a range of machine learning techniques, we aimed to predict violence one year in advance. Our models effectively identified persistent high-violence hotspots. The results indicate that violence is not solely dependent on prior occurrences, as the use of detailed historical data of disaggregated violence proved to be the most effective method. Additionally, socio-economic data can serve as a suitable substitute for these histories. Despite having access to such a wealth of data, our models still struggled to accurately predict new outbreaks or escalations of violence. Even in the best-case scenario with panel data, our results fall short of providing a functional early-warning system. Weidmann and Ward [2010] investigate whether incorporating geographical information can enhance the accuracy of violence predictions. They present a spatially and temporally autoregressive discrete regression model, built upon the framework of Geyer and Thompson, and apply it to geo-located data on conflict events and attributes in Bosnia during the period from March 1992 to October 1995. The results demonstrate the strong spatial and temporal dimensions of violence outbreaks in Bosnia. The authors then evaluate the potential of this model for conflict prediction, using a simulation approach. By comparing the predictive accuracy of the spatial-temporal model to that of a standard regression model that only considers time lags, the results indicate that the inclusion of spatial information significantly improves the forecasts of future conflicts, even in a challenging out-of-sample prediction task.

2.1 The study area

The Democratic Republic of Congo (DRC), also known as Congo-Kinshasa, is a Central African country that shares borders with nine other countries, including Uganda, Rwanda, Burundi, Tanzania, Zambia, Angola, the Republic of Congo, and the Central African Republic. The country is the second-largest country in Africa by area, with a total area of 2,344,858 km², divided into 11 provinces from 1966 to 2015 and 26 provinces since 2015, and the fourth-largest population in the African continent, with an estimated population of over 100 million people. Based on the data available to us, we have kept the administrative division of 1966 - 2015 with the 11 regions. The Congo has a highly diversified relief, with plains, plateaus, and mountains. The highest point in the country is Mount Stanley, located in the Rwenzori Mountains, on the border with Uganda. The Congo River, which flows from north to south through the country, is one of the longest rivers in the world and is an important waterway for transportation of people and goods. The climate of the DRC is mainly tropical, with high temperatures and significant humidity. The country is also rich in natural resources, including minerals such as copper, cobalt, and diamonds. Since its independence in 1960, the DRC has faced numerous challenges, including armed conflicts, economic crises, and disease outbreaks such as HIV/AIDS and Ebola. However, the country has also experienced periods of stability and development, and has a rich cultural and historical heritage.

Figure 4: **Geospatial depiction of the study region within Africa's continental boundaries**

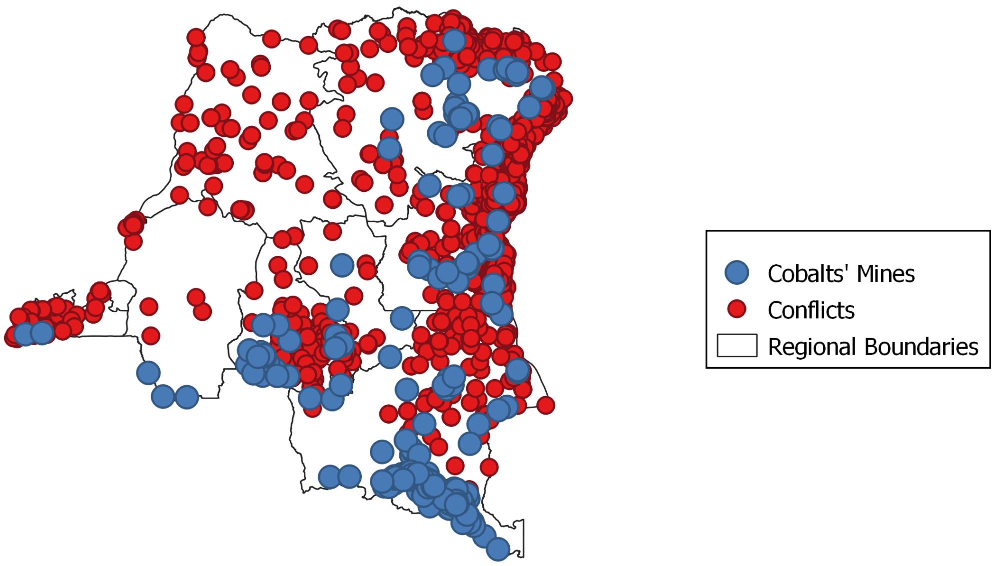
Figure 5: **Geospatial depiction of the study region within Africa's continental boundaries**



3 Stylized fact

Conflict in the Democratic Republic of Congo (DRC) was caused by a combination of factors, including access to natural resources, ethnic and political competition, and regional instability. One of the main factors was access to natural resources, particularly minerals such as coltan, gold and diamonds, which are used in electronics and other high-tech industries around the world. Armed groups used these resources to finance their war, controlling the mines and selling them on international markets. Ethnic and political competition was also an important factor, particularly between the Hutu and Tutsi ethnic groups. Tensions were exacerbated by the 1994 Rwandan genocide, when Hutu extremists killed approximately 800,000 Tutsis and moderate Hutus in Rwanda. Many Hutu refugees fled to Congo, creating a humanitarian crisis that contributed to instability in the region. Finally, regional instability was another important factor. Several neighbouring countries, including Uganda and Rwanda, supported armed groups in the conflict to protect their interests and expand their influence in the region. In sum, the war in the DRC was caused by a complex combination of factors, including access to natural resources, ethnic and political competition and regional instability, all of which contributed to the escalation of the conflict. The Mutanda mine is an open pit copper and cobalt mine owned by Glencore, a major Anglo-Swiss commodity trading, brokering and mining company, located in the province of Katanga, in the southeastern part of the Democratic Republic of the Congo, and is the largest cobalt mine in the world. The importance of cobalt in the energy transition and the resulting surge in demand and prices in global markets could lead to a repeat of historic events.

Figure 6: **Distribution of conflicts and cobalt mine in the DRC**



4 Methodology and Data

4.1 Methodology

This section highlights the empirical strategy adopted to determine the determinants of conflicts in DRC. Previous studies investigating the impact of climate change on conflict have primarily utilized panel data models, as opposed to cross-sectional models, due to their superior advantages Miguel et al. [2004] ; Raleigh and Kniveton [2012] ; Hsiang and Burke [2014] ; Buhaug et al. [2014]; Von Uexkull [2014] ; Burke et al. [2015]. Panel data models are advantageous as they consider both the temporal and individual dimensions, which is not possible in cross-sectional models. Hence, we can formulate the model as follows :

$$\boxed{Conflicts' events_{it} = \beta_1\, Cobalt_{it} + \beta_2\, Precipitation_{it} + \beta_2\, Temperature_{it} + \beta_3 \bigtriangleup X_{it} + \lambda_i + \varphi_t + e_{it}} \quad (1)$$

Where i represents each region according to the administrative division of DRC from 1963 to 2015 and t the time. This gives us a total of 11 regions Table 12 over a period of 31 years (1990 to 2021). Our variables conflicts, cobalt, precipitation, temperature represent respectively for each region over the study period, the number of conflicts that took place, the annual production of cobalt, the annual precipitation , the average mean temperature. Our linear equation was estimated by simple OLS with region fixed effects. It was also estimated by PPML to see the consistency of our results because Silva and Tenreyro [2006] show that PPML outperforms simple OLS and Tobit approaches with heteroskedasticity and many zero observations in the data . We have also estimated our equation, but this time using logistic regression to determine which variables are likely to increase the probability of conflict in the DRC.

$$\boxed{logit\ Conflicts_{it} = \beta_1\, Cobalt_{it} + \beta_2\, Precipitation_{it} + \beta_2\, Temperature_{it} + \beta_3 \bigtriangleup X_{it} + \lambda_i + \varphi_t + e_{it}} \quad (2)$$

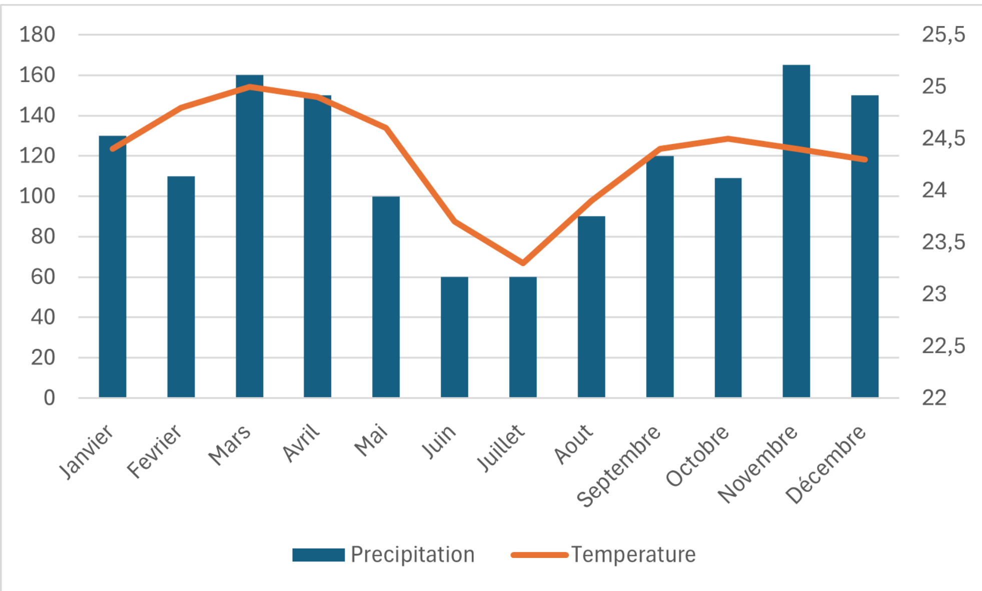
After analyzing the factors driving conflict in the DRC between 1990 and 2021, we have constructed an advanced predictive model to estimate the likelihood of cobalt and gold production-related conflicts in the coming years. This model incorporates fitted value and state-of-the-art machine learning methods to enhance accuracy and precision. In relation to the fitted value approach, we have utilized the residuals obtained from our logistic regression model to forecast the probability of forthcoming conflicts associated with cobalt and gold production. For predictive analysis via machine learning , various machine learning models can be utilized, such as decision trees, neural networks, ensemble methods (like random forest or gradient boosting), support vector machines (SVM), and more. The selection of the model depends on the nature of the data and the prediction objectives. The model is trained on historical data using supervised learning techniques. The model learns to identify relationships between variables and conflicts. The model is evaluated using cross-validation techniques or by dividing the data into training and testing sets. This allows for measuring the accuracy and performance of the model. Once the model is trained and validated, it can be employed to forecast the probability of future conflicts using new input data. The model examines the input variables and provides an estimation of the conflict probability.

4.2 Data

In order to analyze the determinants of conflicts in the Democratic Republic of Congo (DRC) and to investigate whether cobalt mining is or can be a contributing factor, we utilized a combination of multiple datasets. We first used data steming from Dreher et al. [2019] to make a global analysis, restricting information to the democratic republic of congo. This dataset contain for each region, the number of mines, the population, the surface area, and whether there is a port or oil&gas deposits in the region from 1999 to 2013.

The conflict data comprises approximately 5,500 conflicts occurring over a period of 33 years (1989-2021) and was sourced from ACLED. This dataset provides details on conflict locations, actors involved, number of fatalities, the type of violence , starting and ending date. We constructed a panel dataset grouping the conflict data by the 11 regions of the DRC that were part of the administrative division from 1963 to 2015, and associated each region with climate data (Figure 7) such as average temperature and precipitation (provided by the World Bank) and deforestation data (provided by the Forest Global Watch) for each year which represents tree cover loss in hectares at the national level, between 2001 and 2020, classified by percentage of cover. Our variable of interest is the annual cobalt production in each region. Our variable of interest is the annual cobalt production in each region.

Figure 7: **Climatology of Mean-Temperature and Precipitation in DRC from 1991-2020**



Source : World Bank

5 Results

In order to determine the variables that positively influence conflict in the Democratic Republic of Congo, we first ran a logistic regression with the first data set from Dreher et al. [2019] to which we added climatic variables, where our conflict variable takes the value 1 if in this region and during the year in question there was a conflict. The results of the logistic regression show several significant relationships between the variables studied and the probability of conflict in the Democratic Republic of Congo (DRC)

The Mines variable has a positive and significant coefficient in the majority of models, indicating that mining activity is strongly associated with an increase in the probability of conflict. This link can be explained by several factors : competition for resources, where mining intensifies the control struggle for natural resources leading to conflicts between different factions; environmental impact, as mining causes environmental damage affecting local livelihoods such as agriculture, creating social tensions; and the war economy, where mining resources finance armed groups, prolonging and intensifying conflicts.

The coefficients for population density are very high and significant in all models, indicating a strong association between population density and conflict. This can be attributed to increased competition for scarce resources in densely populated areas, such as land, water, and food; exacerbated social and economic tensions in contexts of poverty and underdevelopment; and a broader recruitment base for armed groups in densely populated areas.

The coefficients for Oil & Gas are also positive and significant, indicating that the presence of these resources increases the likelihood of conflict. This phenomenon can be attributed to the covetousness and control of oil and gas resources as major economic assets, and the creation of significant economic rents attracting armed groups seeking to appropriate these revenues.

Coefficients for precipitation are positive and significant, as higher rainfall is associated with increased conflict due to access and logistics challenges, where high rainfall makes access to mining areas more difficult, increasing competition and tensions for resource control, and agricultural impact, where rainfall affects agricultural production, exacerbating social tensions if crops are destroyed or flooding disrupts livelihoods.

The coefficients for the variable “Port dummy” are significant and positive in all models, indicating a strong association between the presence of a port and the probability of conflict. The presence of a port increases the probability of conflict in the region, as ports are strategic transport points for exports and imports, including precious natural resources such as cobalt and oil. Control of these points can be a source of conflict between different armed groups or political factions seeking to monopolize revenues and power.

In summary, our first analysis of the results indicates that conflict in the DRC is strongly influenced by mining activity, population density and the presence of oil and gas resources. Rainfall also plays a role, albeit a secondary one, by increasing logistical challenges and social tensions. Policies aimed at reducing conflict should therefore focus on managing natural resources and reducing demographic tensions, while taking environmental impacts into account.

Table 2 : Logistic regression with Oil-Gas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Conflicts	Conflicts	Conflicts	Conflicts	Conflicts	Conflicts	Conflicts	Conflicts	Conflicts
Mines	0.494***	0.286*	0.292*	0.214	0.687***	0.587**	0.738**	0.905**	0.908**
	(3.19)	(1.74)	(1.75)	(1.28)	(2.87)	(2.17)	(2.25)	(2.55)	(2.55)
Population		2.205***	2.045**	4.001***	5.721***	5.675***	8.224***	9.059***	9.071***
		(3.01)	(2.46)	(3.33)	(3.83)	(3.78)	(4.06)	(4.14)	(4.14)
Area (in km)			0.0709	0.0434	-0.112	-0.0715	-0.352	-0.453	-0.450
			(0.40)	(0.24)	(-0.55)	(-0.34)	(-1.30)	(-1.58)	(-1.56)
Oil & gas				2.205***	4.528***	4.432***	5.843***	6.586***	6.604***
				(2.64)	(3.56)	(3.50)	(3.53)	(3.62)	(3.62)
Precipitation					0.0357***	0.0397***	0.0462***	0.0454***	0.0462***
					(2.77)	(2.81)	(2.75)	(2.71)	(2.63)
Annual average mean temperature						-0.0137	-0.00456	0.0124	0.0118
						(-0.76)	(-0.20)	(0.49)	(0.46)
Forest loss							0.00194	0.000698	0.000642
							(0.19)	(0.07)	(0.06)
△ *Temperature*								-0.0217	-0.0214
								(-1.44)	(-1.41)
△ *Precipitation*									-0.00121
									(-0.15)
Constant	-0.398	-34.31***	-32.69***	-62.79***	-90.52***	-89.70***	-127.3***	-139.5***	-139.6***
	(-1.62)	(-3.04)	(-2.74)	(-3.53)	(-4.02)	(-3.97)	(-4.16)	(-4.22)	(-4.22)
N	135	135	135	135	135	135	117	117	117
pseudo R^2	0.067	0.121	0.122	0.161	0.209	0.212	0.271	0.284	0.284

t statistics in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Table 3 : Logistic regression with Port dummy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Conflicts	Conflicts	Conflicts	Conflicts	Conflicts	Conflicts	Conflicts	Conflicts	Conflicts
Mines	0.494***	0.286	0.292	0.214	0.687***	0.587**	0.738**	0.905**	0.908**
	(2.76)	(1.54)	(1.51)	(1.13)	(2.92)	(2.15)	(1.96)	(2.01)	(2.02)
Population		2.205***	2.045**	4.001***	5.721***	5.675***	8.224***	9.059***	9.071***
		(2.95)	(2.43)	(3.38)	(3.07)	(3.11)	(2.77)	(2.60)	(2.61)
Area (in km)			0.0709	0.0434	-0.112	-0.0715	-0.352	-0.453	-0.450
			(0.40)	(0.24)	(-0.56)	(-0.34)	(-1.20)	(-1.35)	(-1.33)
Port dummy				2.205**	4.528***	4.432***	5.843**	6.586**	6.604**
				(2.54)	(2.94)	(2.90)	(2.45)	(2.33)	(2.34)
Precipitation					0.0357***	0.0397***	0.0462***	0.0454***	0.0462***
					(2.86)	(3.22)	(2.98)	(2.96)	(2.86)
Annual average mean temperature						-0.0137	-0.00456	0.0124	0.0118
						(-0.92)	(-0.22)	(0.46)	(0.43)
Forest loss							0.00194	0.000698	0.000642
							(0.20)	(0.07)	(0.07)
$\triangle$ *Temperature*								-0.0217	-0.0214
								(-1.41)	(-1.38)
$\triangle$ *Precipitation*									-0.00121
									(-0.17)
Constant	-0.398	-34.31***	-32.69***	-62.79***	-90.52***	-89.70***	-127.3***	-139.5***	-139.6***
	(-1.58)	(-2.98)	(-2.70)	(-3.60)	(-3.21)	(-3.25)	(-2.81)	(-2.63)	(-2.64)
N	135	135	135	135	135	135	117	117	117
pseudo R^2	0.067	0.121	0.122	0.161	0.209	0.212	0.271	0.284	0.284

t statistics in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

6 Further analysis

In order to assess the determinants of conflict in the Democratic Republic of Congo in previous years, we used a self-constructed database, this time with a larger time dimension, from 1990 to 2021, but with few variables. We used OLS and PPML regression methods to estimate our model. Silva and Tenreyro [2006] shows that PPML outperfoms simple OLS with Tobit approaches with heteroskedasticity and many zero observations in the data. The findings indicate for our PPML estimation technics that climatic factors such as precipitation and forest loss, rather than cobalt mining, are the primary drivers of conflict in the DRC. Precipitation can impact conflict in a variety of ways, some examples include competition for resources and forced migration. Indeed precipitation can affect the availability of water, which is a critical resource for agricultural and other activities Hendrix and Glaser [2007]. During prolonged drought, conflicts can erupt between communities seeking access to limited water sources.

Regarding extreme rainfall events, such as floods, can destroy homes and infrastructure, as well as crops, forcing local people to migrate to other areas. This forced migration can lead to tensions between local communities and newcomers, all of whom seek access to limited resources. Concerning the impact on the economy , rainfall can impact agriculture and other economic sectors. For example, prolonged drought can reduce agricultural yields, which can lead to higher food prices and increased poverty. This in turn can lead to increased crime and conflict. About the perception of injustice, rainfall can also affect perceptions of injustice. For example, if some communities have access to high quality water sources, while others have to make do with contaminated or limited water sources, this can be perceived as unfair and lead to conflict. It is important to note that rainfall is not the only cause of conflict, but it can contribute to exacerbating tensions and creating conditions for conflict.

Loss of forest cover in the DRC can exacerbate conflict in a number of ways. Deforestation leads to a reduction in available natural resources, intensifying competition between local communities, ethnic groups and companies for access to remaining land and resources. It also causes the displacement of forest-dependent local populations, leading to tensions with established communities and land disputes. Deforestation disrupts the ecological balance, increasing flooding and reducing agricultural yields, exacerbating social and economic tensions. In addition, natural resources are often linked to armed conflict, with armed groups illegally exploiting forests to finance their activities, leading to violent conflicts over control of forest areas. Finally, deforestation affects the livelihoods of local populations, increasing poverty and social tensions. In short, the loss of forest cover in the DRC can exacerbate conflict by fuelling competition for resources, provoking displacement, upsetting the ecological balance, fuelling armed conflict and affecting the livelihoods of local populations.

These results are in perfect agreement with the real situation insofar as cobalt has acquired a great notoriety only very recently and also in Katanga and Kasai Oriental, copper and cobalt mining is largely industrial, while in the two Kivus and in Ituri, the mines are organized on an artisanal basis.

Table 4 : OLS and region fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Conflicts events	Conflicts events	Conflicts events	Conflicts events	Conflicts events	Conflicts events
Cobalt production	-0.276	-0.273	-0.257	-0.0998	0.132	0.176
	(-0.16)	(-0.16)	(-0.09)	(-0.03)	(0.04)	(0.06)
Precipitation		9.392	42.86	44.47	52.09	120.1**
		(1.03)	(1.30)	(1.35)	(1.56)	(2.50)
Forest loss			12.24***	12.34***	10.95**	10.65**
			(2.72)	(2.75)	(2.40)	(2.35)
Annual Average Mean Temperature				-18.85	-32.00**	-32.09**
				(-1.40)	(-2.00)	(-2.02)
$\triangle$ *Temperature*					24.41	25.33
					(1.50)	(1.56)
$\triangle$ *Precipitation*						-0.0444*
						(-1.96)
Constant	16.40***	-52.30	-449.9*	-8.551	270.3	-220.2
	(6.39)	(-0.78)	(-1.88)	(-0.02)	(0.62)	(-0.44)
N	331	331	220	220	220	220
R^2	0.000	0.003	0.048	0.057	0.067	0.085

t statistics in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Table 5 : PPML and region fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Conflicts events	Conflicts events	Conflicts events	Conflicts events	Conflicts events	Conflicts events
Cobalt production	-0.0315	-0.0314	-0.0284	-0.0361	-0.0356	-0.0347
	(-0.90)	(-0.89)	(-0.58)	(-0.70)	(-0.67)	(-0.65)
Precipitation		0.233***	2.672**	2.712**	2.708**	8.254***
		(2.69)	(2.09)	(2.00)	(2.00)	(3.28)
Forest loss			1.019***	1.248***	1.223***	1.257***
			(4.00)	(3.85)	(3.28)	(3.61)
Annual Average Mean Temperature				0.731	0.651	0.770
				(1.14)	(0.92)	(1.12)
$\triangle$ *Temperature*					0.171	0.317
					(0.20)	(0.36)
$\triangle$ *Precipitation*						-0.00350***
						(-2.70)
Constant	3.595***	1.899***	-28.58***	-48.49**	-46.32**	-89.65***
	(24.90)	(2.93)	(-2.73)	(-2.42)	(-2.01)	(-3.56)
N	331	331	220	220	220	220
pseudo R^2	0.453	0.456	0.631	0.638	0.638	0.674

t statistics in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Even if cobalt production in the DRC does not significantly influence past conflict, other minerals might. Coltan, cassiterite and gold have been identified as the coveted minerals Jacquemot* [2009]. According to the author, the militarized fraudulent economy that has taken hold over the past fifteen years in the region is dominated by three minerals : coltan, cassiterite (tin oxide ore), and gold. Cobalt, rubies, semi-precious stones, as well as tropical wood, meat, tea, quinine, and papain are considered ancillary resources. This leads us to establish the link between these minerals of covetousness with the conflicts on our period of study. We thus estimated our model by adding new control variables on gold production per year and per region. Jacquemot* [2009]. The results obtained by OLS and PPML are in line with those obtained previously, i.e. these results suggest that rainfall and loss of forest cover are important factors increasing the conflict in the DRC, while cobalt production and temperature variations show no significant relationship. Stable rainfall also appears to play a role in reducing the conflict. Unfortunately, we have no data to verify the impact of other conflict minerals, such as diamonds, coltan, cassiterite (tin oxide ore), rubies, semi-precious stones, tropical woods, meat, tea, quinine and papain on conflict in the Democratic Republic of Congo.

Table 6 : OLS and region fixed effects for Gold production

	(1)	(2)	(3)	(4)	(5)	(6)
	Conflicts events	Conflicts events	Conflicts events	Conflicts events	Conflicts events	Conflicts events
Gold production	-0.183	-0.169	0.361	0.486	1.562	1.456
	(-0.16)	(-0.15)	(0.08)	(0.10)	(0.32)	(0.30)
Precipitation		9.379	42.85	44.47	52.29	120.2**
		(1.03)	(1.30)	(1.35)	(1.57)	(2.50)
Forest loss			12.27***	12.38***	10.99**	10.69**
			(2.73)	(2.76)	(2.41)	(2.36)
Annual Average Mean Temperature				-18.89	-32.46**	-32.50**
				(-1.41)	(-2.02)	(-2.04)
△ *Temperature*					25.15	26.00
					(1.53)	(1.59)
△ *Precipitation*						-0.0443*
						(-1.95)
Constant	16.34***	-52.27	-450.4*	-7.981	279.4	-211.1
	(6.68)	(-0.78)	(-1.88)	(-0.02)	(0.64)	(-0.42)
N	331	331	220	220	220	220
R^2	0.000	0.003	0.048	0.057	0.068	0.085

t statistics in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Table 7 : PPML and region fixed effects for Gold production

	(1)	(2)	(3)	(4)	(5)	(6)
	Conflicts events	Conflicts events	Conflicts events	Conflicts events	Conflicts events	Conflicts events
Gold production	-0.0445**	-0.0447**	-0.0250	-0.0108	-0.00419	0.000730
	(-2.28)	(-2.29)	(-0.77)	(-0.30)	(-0.09)	(0.01)
Precipitation		0.234***	2.673**	2.715**	2.710**	8.259***
		(2.69)	(2.09)	(2.00)	(2.00)	(3.28)
Forest loss			1.020***	1.247***	1.222***	1.256***
			(4.00)	(3.84)	(3.28)	(3.61)
Annual Average Mean Temperature				0.726	0.646	0.764
				(1.14)	(0.92)	(1.12)
△ *Temperature*					0.173	0.319
					(0.20)	(0.37)
△ *Precipitation*						-0.00350***
						(-2.70)
Constant	3.592***	1.895***	-28.61***	-48.40**	-46.21**	-89.54***
	(24.89)	(2.92)	(-2.74)	(-2.42)	(-2.01)	(-3.56)
N	331	331	220	220	220	220
pseudo R^2	0.454	0.457	0.631	0.638	0.638	0.674

t statistics in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

We have verified the robustness of our results by running a logistic regression on the database we have constructed. This will enable us to determine which variables increase the probability of conflict in the Democratic Republic of

Congo. The results show that gold production is the variable that increases the likelihood of conflict in the DRC's regions. These results are in line with the current situation in the DRC, where it is common knowledge that rebels are currently more involved in artisanal gold mining than in cobalt mining, because cobalt mining is more difficult than gold mining.

Table 8 : Logistic regression

	(1) conflicts	(2) conflicts	(3) conflicts
Cobalt production	0.0501	0.0478	0.0198
	(0.76)	(0.72)	(0.28)
Gold production	1.454***	1.416***	1.279***
	(11.57)	(10.80)	(9.75)
Precipitation	-1.795	-1.889	-3.125**
	(-1.50)	(-1.58)	(-2.12)
Forest loss	0.115	0.127	0.155
	(0.98)	(1.07)	(1.27)
$\triangle\ Temperature$		-0.859	-0.852
		(-1.21)	(-1.20)
$\triangle\ Precipitation$			0.00144
			(1.50)
Constant	11.84	12.39	21.08**
	(1.41)	(1.48)	(2.05)
N	220	220	220
pseudo R^2	0.023	0.028	0.036

t statistics in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

The results of the analyses show several significant relationships between the variables studied and the probability of conflict in the DRC. Cobalt and gold production, taken individually, do not appear to have a significant effect on the probability of conflict. On the other hand, higher levels of rainfall and increased loss of forest cover are strongly associated with increased conflict. This may be explained by the fact that higher rainfall and deforestation exacerbate competition for natural resources and disrupt agricultural activities, thus creating social tensions. Although mean annual temperature does not have a significant direct effect on conflict.

The interaction between cobalt production and rainfall variations suggests that these regions may be more susceptible to tensions. Indeed The risks associated with rainfall and cobalt production in the DRC are significant, particularly as regards arsenic pollution. Rainfall in the DRC exacerbates the dispersion of pollutants, particularly arsenic, from cobalt mining. This pollution affects soil, water and local ecosystems, posing serious risks to human health, such as cancers and neurological disorders, as well as devastating environmental impacts on biodiversity. Contamination of agricultural land also compromises the food security of local communities. Rigorous mine waste management and environmental protection measures are therefore essential to minimize these risks.

Table 9 : PPML and region fixed effects for Gold production

	(1)	(2)	(3)
	Conflicts events	Conflicts events	Conflicts events
Cobalt Production	0.0262	-0.0401	-0.0360
	(0.22)	(-0.79)	(-0.71)
Gold production	-0.0382	0.0217	-0.0218
	(-0.72)	(0.54)	(-0.60)
Precipitation	2.721**	2.676**	2.704**
	(2.00)	(1.97)	(1.99)
Forest loss	1.256***	1.265***	1.253***
	(3.81)	(3.86)	(3.81)
Annual Average Mean Temperature	0.736	0.764	0.746
	(1.15)	(1.19)	(1.13)
Cobalt * Forest loss	-8.62e-08		
	(-0.61)		
Cobalt * $\triangle$ *Precipitation*		0.000795*	
		(1.74)	
Cobalt * $\triangle$ *Temperature*			-0.0304
			(-0.44)
Constant	-48.77**	-49.21**	-48.82**
	(-2.42)	(-2.46)	(-2.40)
N	220	220	220
pseudo R^2	0.638	0.639	0.638

t statistics in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

7 Conflict forecast : Prediction with fitted value of logistic regression

When we perform linear regression on a dataset, we end up with a regression equation which can be used to predict the values of a response variable, given the values for the explanatory variables. We can then measure the difference between the predicted values and the actual values to come up with the residuals for each prediction. This helps us get an idea of how well our regression model is able to predict the response values. The results of a logistic regression model and the results of a prediction with fitted values are two distinct but related elements. When fitting a logistic regression model, you obtain results that provide information about the relationship between the independent variables and the binary dependent variable. These results typically include regression coefficients, standard errors, p-values, and confidence intervals. They allow for the interpretation of the relative impact of each independent variable on the probability of the binary event. Fitted values represent predictions of the dependent variable based on the independent variables from the fitted logistic regression model. Fitted values correspond to the predicted values of the binary dependent variable based on observed values of the independent variables. Fitted values are usually expressed as probabilities (e.g., the probability of success in the case of a logistic regression model). The difference between the two lies in their nature. The results of a logistic regression model provide information about the relationships between variables and the effects of coefficients, while fitted values are specific predictions based on these relationships and coefficients. Fitted values can be used to estimate the probability of the binary event for new observations, while the results of the logistic regression model provide an overall interpretation of the effects of the independent variables on the dependent variable. In summary, the results of a logistic regression model are estimations of the effects of independent variables, while fitted values are specific predictions of the dependent variable based on these estimations.

8 Analysis with Split data

The results indicate a significant shift in the relationship between cobalt production and conflict events in the Democratic Republic of Congo (DRC) before and after 2006. Prior to 2006, increased cobalt production was associated with a reduction in conflict events, suggesting a stabilizing effect. This effect can be linked to the relatively lesser importance of cobalt during that period, making it a less coveted resource. However, as cobalt production expanded substantially in the following years, this relationship changed, showing a weak positive association with conflict. The increase in cobalt's importance and market demand likely made it a more coveted resource, contributing to increased conflict events. This shift underscores the evolving dynamics in the mining sector and highlights the need for adaptive and responsive policies to manage resource production and mitigate conflict effectively.

Table 10 : PPML and region fixed effects for Gold production

	Conflicts events Before 2006	Conflicts events After 2006
Cobalt production	-0.167***	0.0477*
	(-3.89)	(1.66)
Constant	2.447***	4.274***
	(15.49)	(28.66)
N	176	144
pseudo R^2	0.340	0.605

t statistics in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Table 11 : PPML and region fixed effects for Gold production

	Conflicts events Year < or = 2006	Conflicts events Year > 2006
Cobalt production	-0.158***	0.0477*
	(-4.11)	(1.66)
Constant	2.465***	4.274***
	(16.53)	(28.66)
N	187	144
pseudo R^2	0.356	0.605

t statistics in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Figure 8: **Prediction of the probability of conflicts associated with cobalt production.**

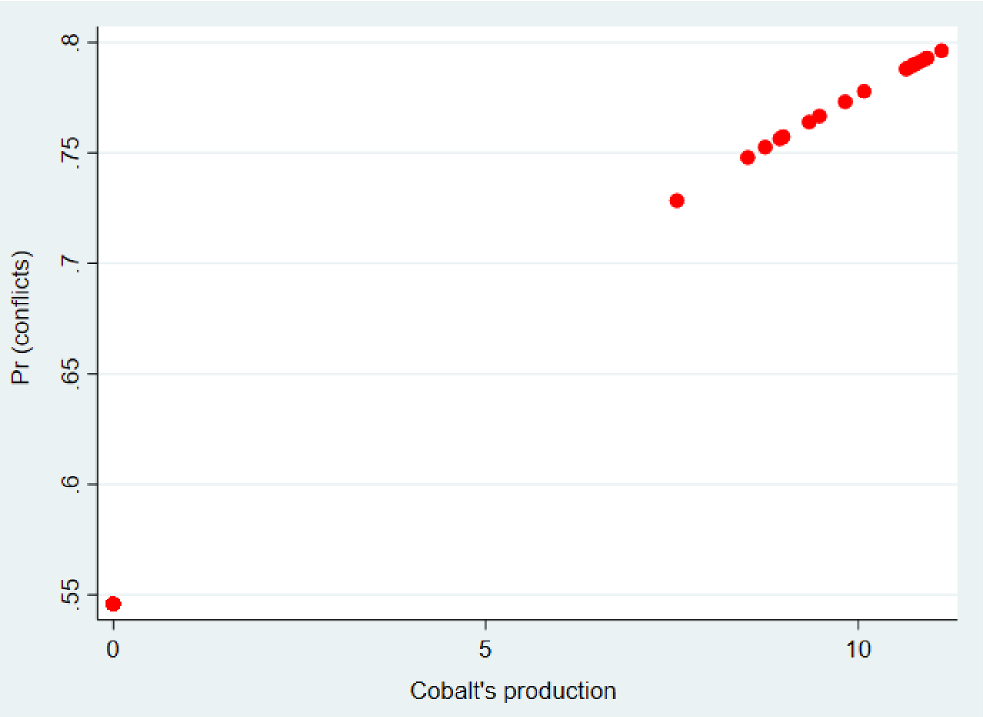
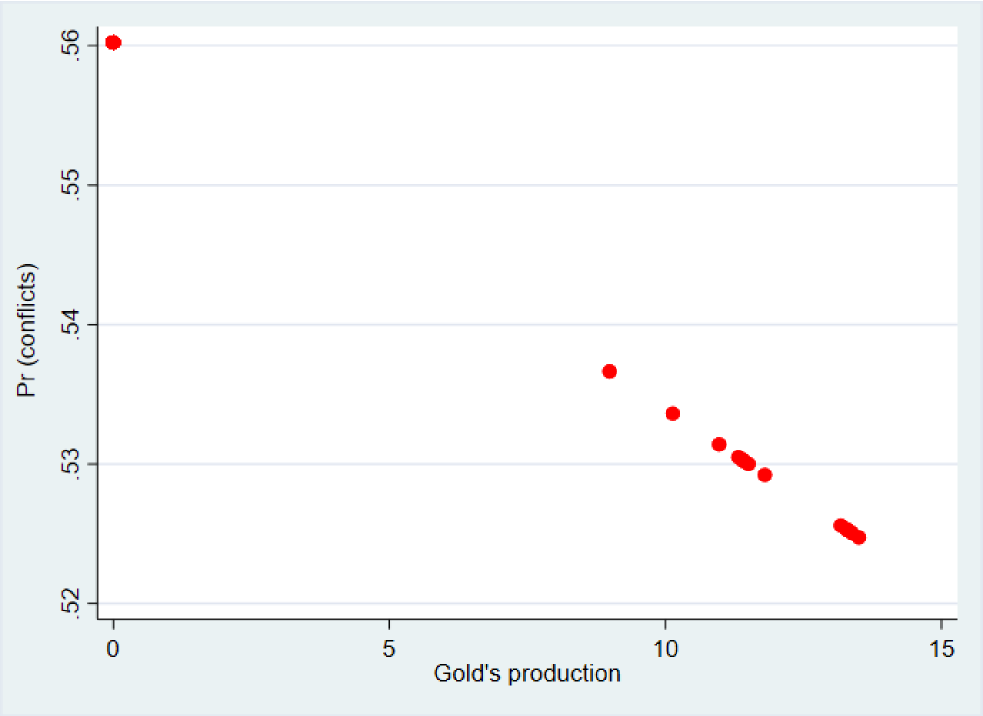


Figure 9: **Prediction of the probability of conflicts associated with gold production.**



Source : Author calculation

9 Conclusion and policy implication

The results of this study highlight the multiple factors contributing to conflict in the DRC, in particular the impact of natural resources and environmental conditions. Mining activities, particularly cobalt and gold extraction, are strongly associated with an increased likelihood of conflict. This is due to increased competition for resources, negative environmental impacts, and the financing of armed groups by mining revenues. In addition, population density and the presence of oil and gas resources are also significant factors, intensifying social and economic tensions. Rainfall, with its effect on access and logistics in mining areas, as well as its impact on agricultural production, exacerbates local tensions and increases the risk of conflict. Deforestation also plays a crucial role, upsetting the ecological balance, displacing populations and affecting livelihoods, thereby amplifying social tensions. Pollution from cobalt mining, particularly arsenic contamination, poses serious risks to human health and the environment, jeopardizing food security and local biodiversity. Ports, as strategic transportation points for natural resources, are potential hotbeds of conflict, due to covetousness and control of the revenues generated. The Democratic Republic of Congo (DRC) stands as a microcosm of the intricate interplay between socio-economic factors and environmental dynamics in shaping conflict patterns. Our comprehensive analysis, drawing upon a synthesis of existing literature and empirical findings, sheds light on the multifaceted nature of conflict in the region and offers insights into potential pathways for conflict mitigation and resolution. In exploring the determinants of conflict in the DRC, our examination begins with an overview of the historical context and geopolitical landscape. The DRC's tumultuous past, characterized by colonization, resource exploitation, and internal strife, has laid the groundwork for persistent conflict dynamics. Through a nuanced examination of various empirical studies, we delineate the intricate web of factors contributing to conflict, spanning from economic variables such as mining activity and natural resource abundance to climatic influences such as precipitation and forest loss.

Our analysis underscores the pivotal role of mining activity in exacerbating conflict dynamics in the DRC. The presence of valuable mineral resources, notably cobalt, gold, and coltan, has fueled competition and power struggles, leading to armed conflicts and socio-economic disruptions. The extraction and trade of these minerals, often conducted through illicit channels, have perpetuated cycles of violence and instability, further exacerbating grievances among local communities and armed factions. Furthermore, our investigation highlights the significant impact of environmental factors, particularly precipitation patterns and deforestation, on conflict dynamics in the DRC. Climatic variability, including fluctuations in rainfall and temperature, can exert profound effects on agricultural productivity, water availability, and ecosystem stability, thereby amplifying resource scarcity and inter-community tensions. Deforestation, driven by industrial exploitation and agricultural expansion, not only diminishes vital ecological services but also exacerbates land disputes and displacement, contributing to socio-economic inequalities and conflict vulnerabilities. In synthesizing our findings, it becomes evident that conflict in the DRC is a multifaceted phenomenon shaped by a confluence of socio-economic, environmental, and political factors. Addressing the root causes of conflict necessitates a holistic approach that integrates sustainable development strategies, natural resource management initiatives, and conflict resolution mechanisms. Policy interventions aimed at promoting peace and stability in the region must prioritize equitable resource distribution, community empowerment, and environmental conservation efforts. Moreover, as part of international efforts to promote ethical sourcing and prevent the financing of armed conflicts through the exploitation of mineral resources, measures akin to those outlined in the Dodd-Frank Act should be extended to include cobalt. The Dodd-Frank Wall Street Reform and Consumer Protection Act, enacted in 2010, includes a provision known as Section 1502, which requires companies to disclose their use of conflict minerals (tin, tantalum, tungsten, and gold) sourced from the DRC and neighboring countries. The aim is to cut off funding to armed groups engaged in violent conflict and human rights abuses in these regions. By implementing stringent regulations and due diligence mechanisms across global supply chains, stakeholders can help ensure that cobalt extraction and trade in the DRC adhere to ethical standards and do not perpetuate conflict dynamics. This includes promoting transparency, accountability, and responsible sourcing practices among multinational corporations, while empowering local communities to benefit equitably from their natural resources.

In conclusion, the quest for peace and prosperity in the Democratic Republic of Congo demands concerted efforts to address the underlying drivers of conflict, from economic exploitation and environmental degradation to social inequalities and governance challenges. Through a comprehensive and interdisciplinary approach, grounded in rigorous research and informed by local realities, we can strive towards a future where the people of the DRC can thrive in peace and security.

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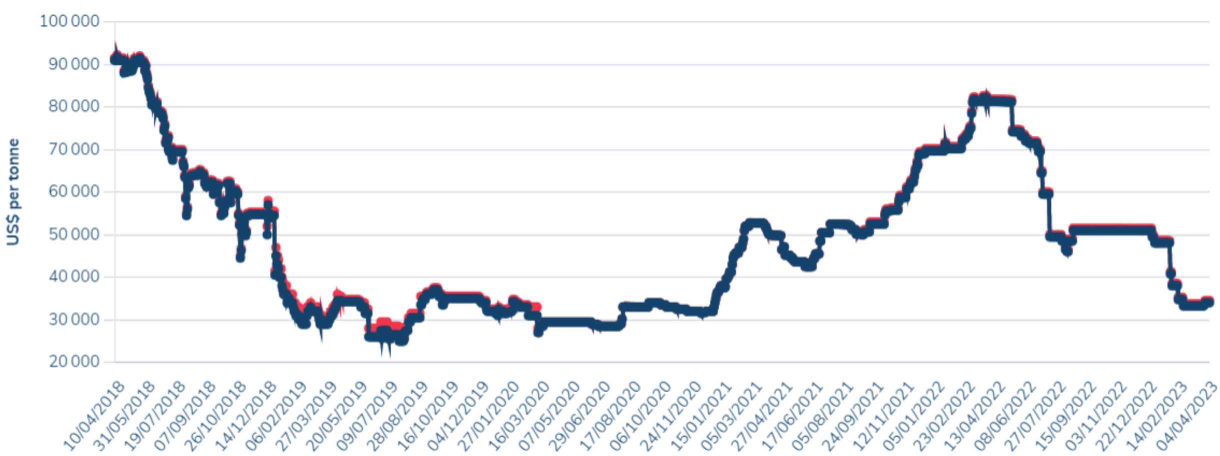
10 Appendix

10.1 Figures

Figure 10: **Evolution of cobalt prices from 2013 to 2018**

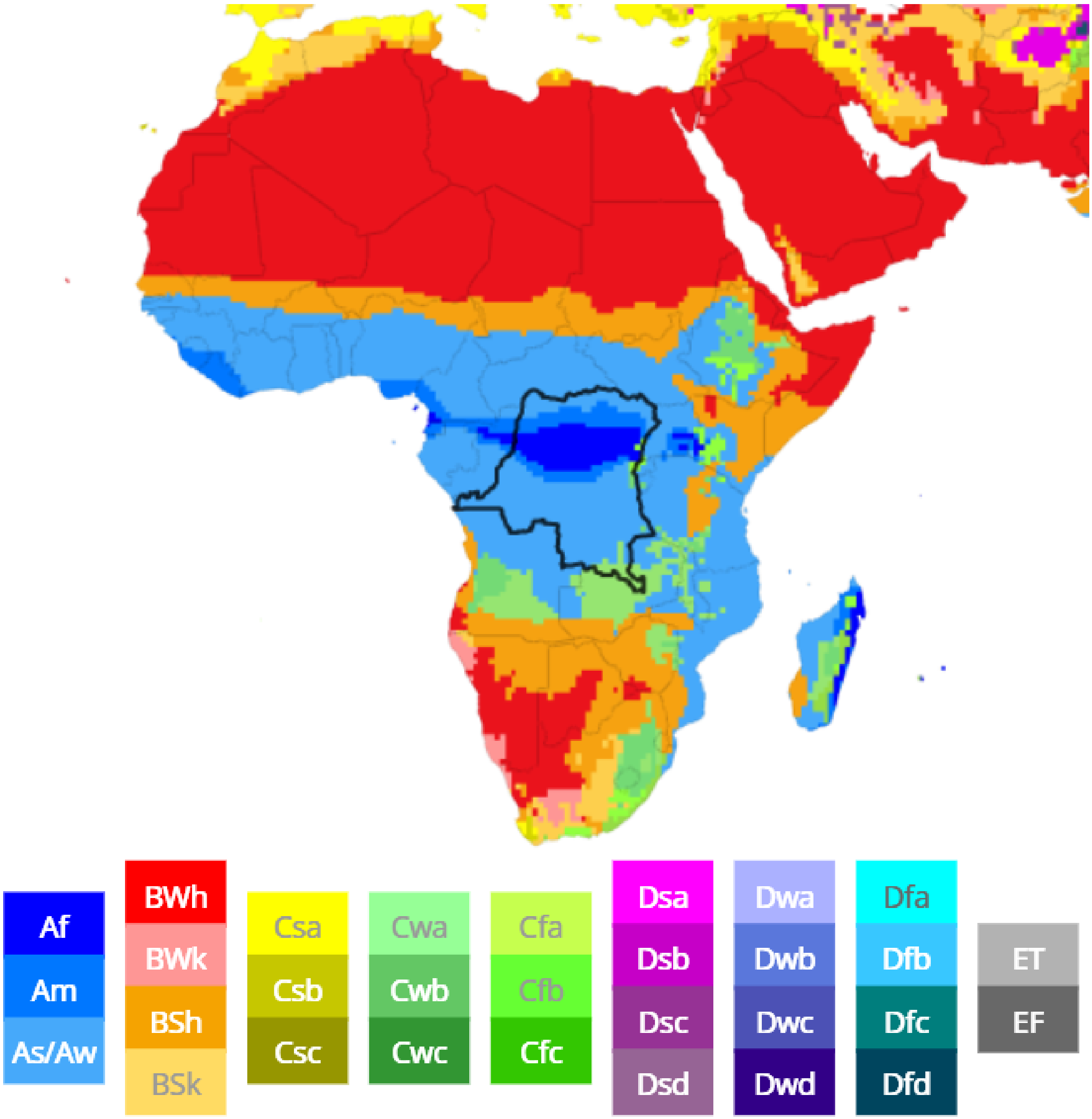
Source : London Metal Exchange

Figure 11: **Evolution of cobalt prices from 2018 to 2023**



Source : London Metal Exchange

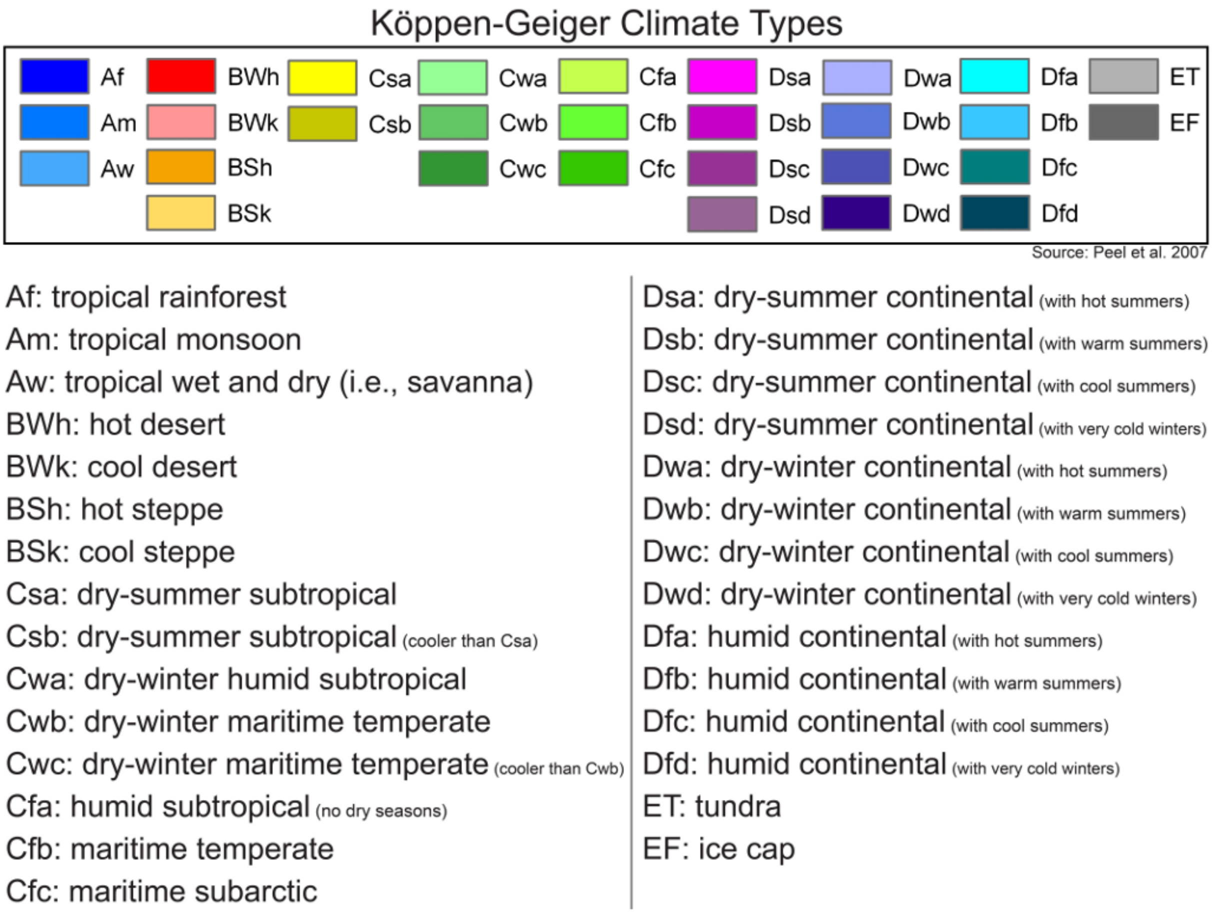
Figure 12: **Koppen-Geiger climate classification in Africa from 1991 to 2020**



Source : World Bank [3]

[3]https://open.oregonstate.education/permaculturedesign/chapter/climate-classification-systems/

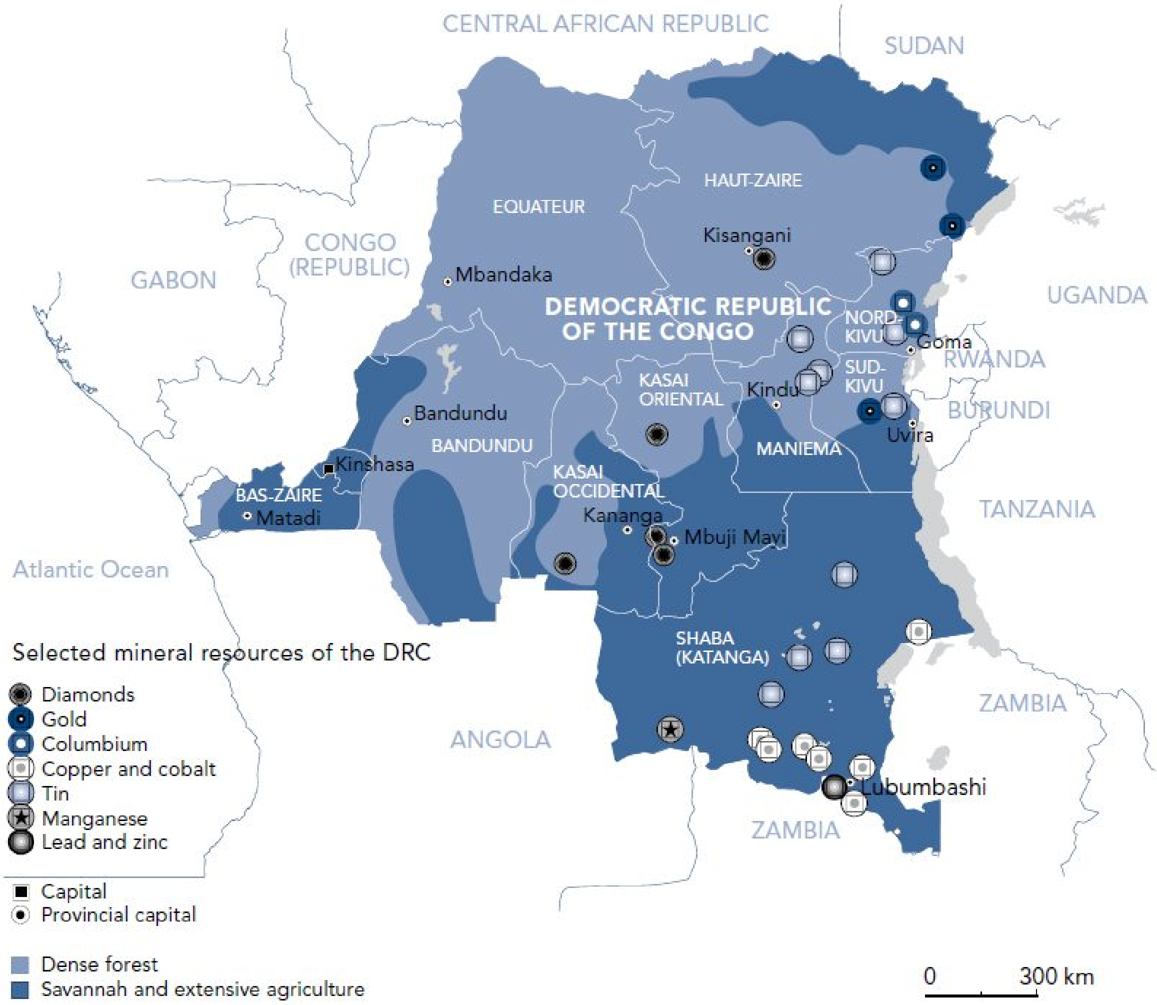
Figure 13: **Koppen-Geiger climate classification in Africa from 1991 to 2020**



Source : World Bank [4]

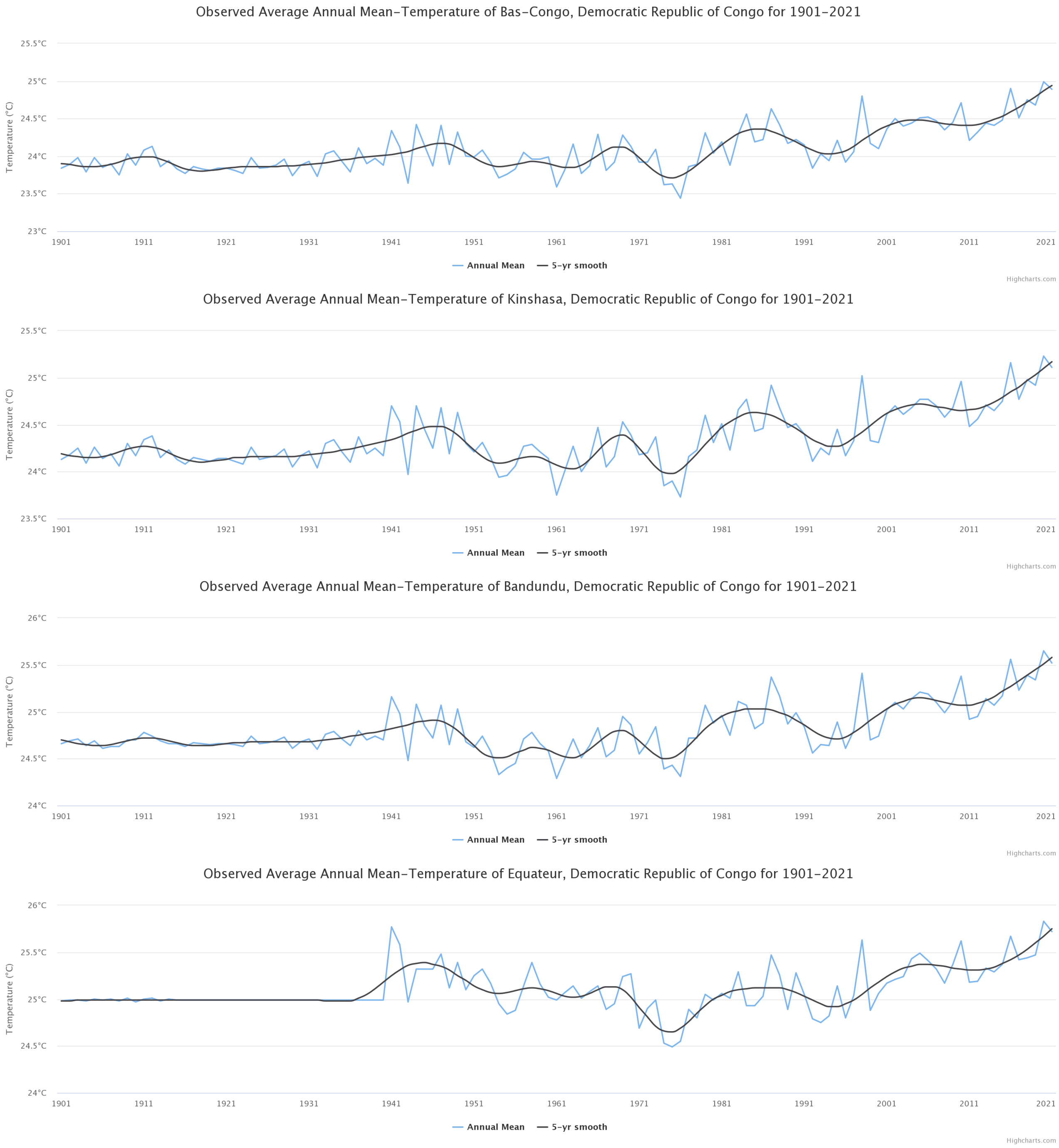
[4]https://open.oregonstate.education/permaculturedesign/chapter/climate-classification-systems/

Figure 14: **Koppen-Geiger climate classification in Africa from 1991 to 2020**



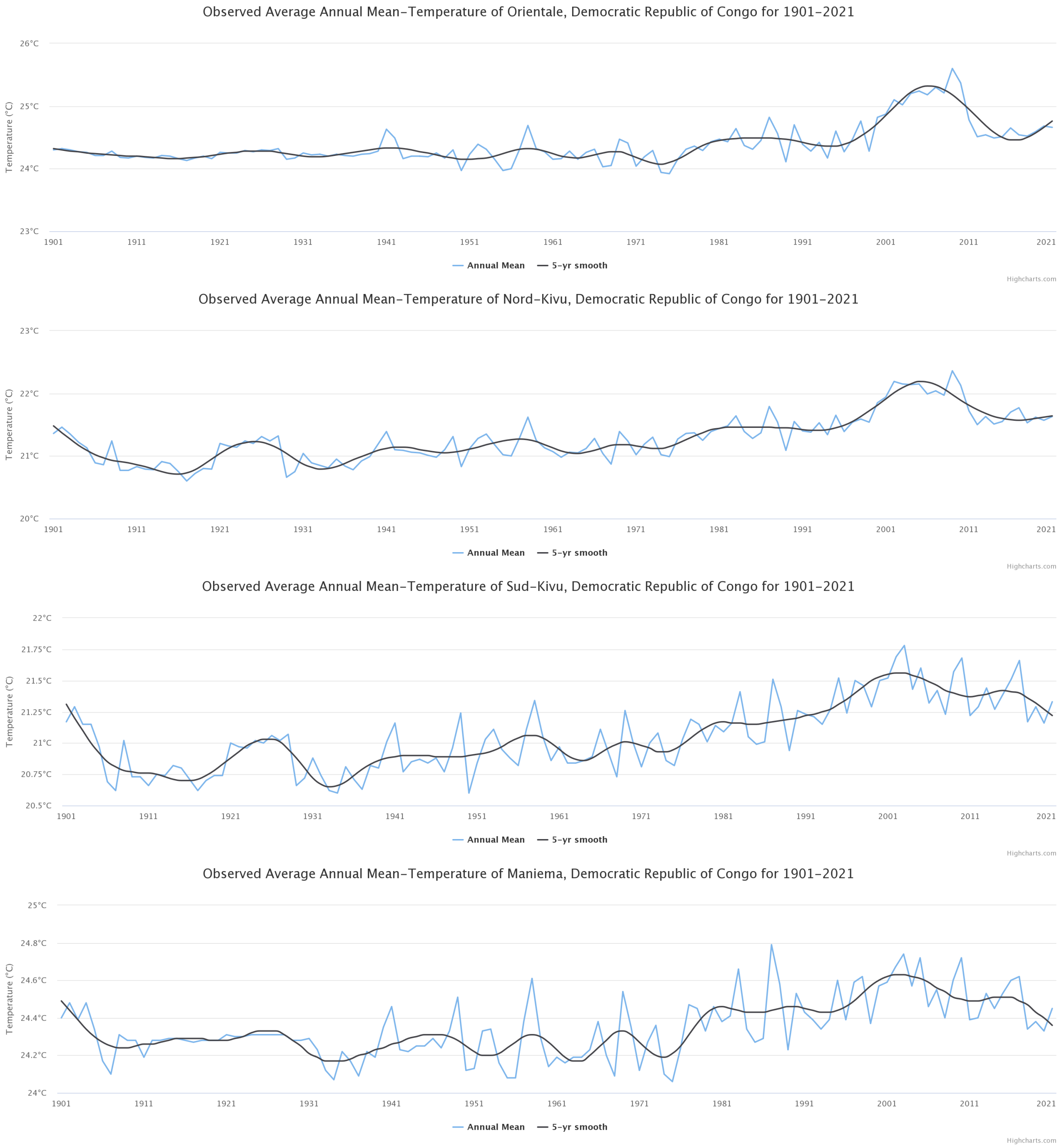
Source : World Bank

Figure 15: **Average annual mean temperature in DRC administrative regions**



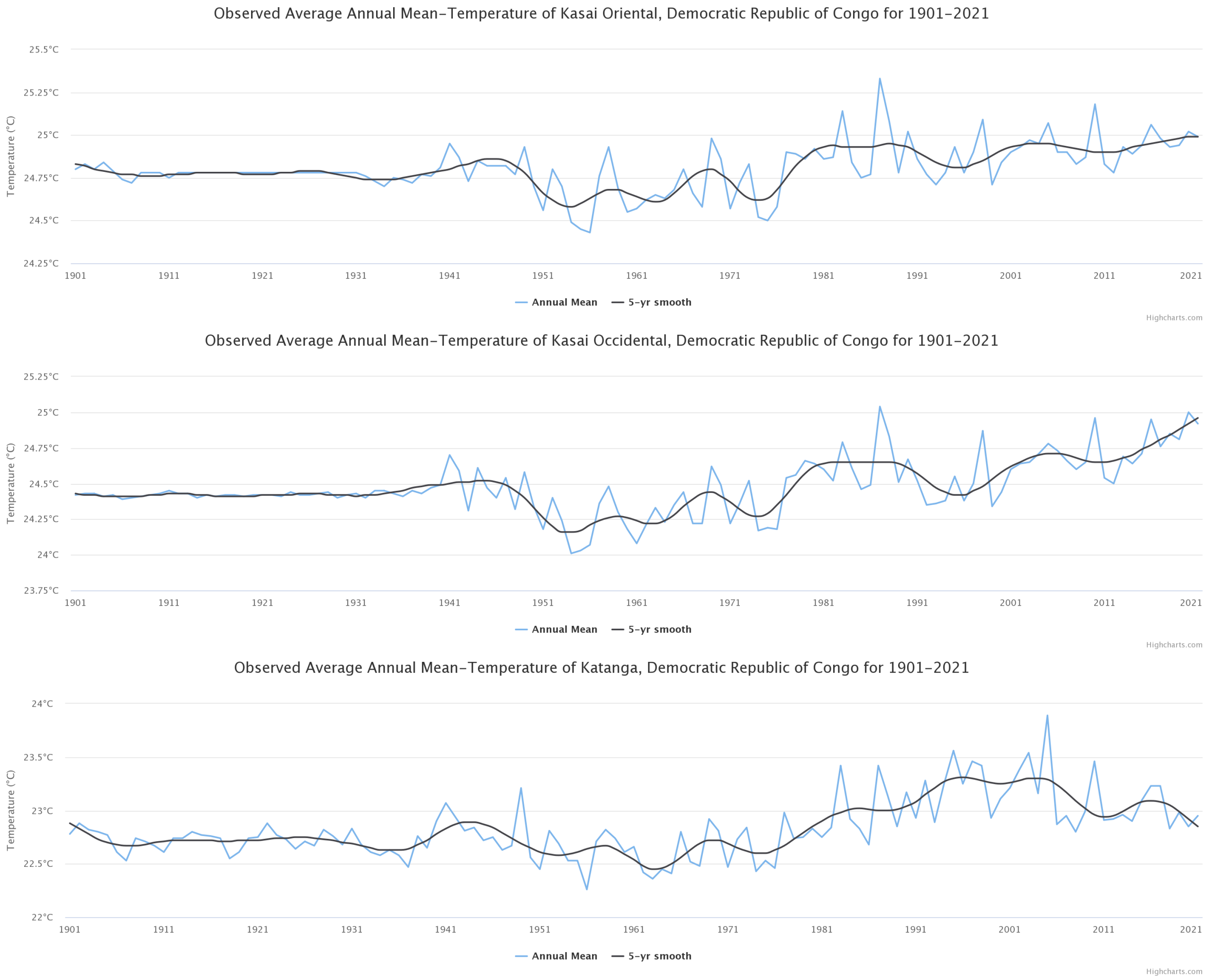
Source : World Bank

Figure 16: **Average annual mean temperature in DRC administrative regions**



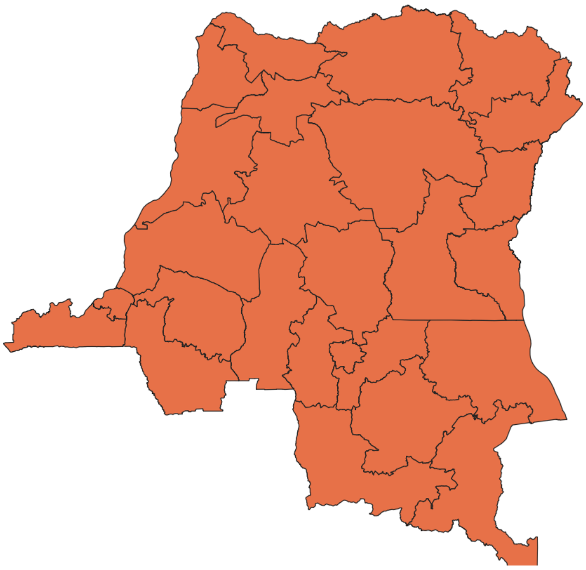
Source : World Bank

Figure 17: **Average annual mean temperature in DRC administrative regions**



Source : World Bank

Figure 18: **Geospatial depiction of the Democratic Republic of Congo regional boundaries.**



Source : Author calculation

10.2 Tables

Provinces
Bas-Uélé
Haut-Uélé
Ituri
Tshopo
Bas-Congo (Kongo-Central)
Kwango
Kwilu
Mai-Ndombe
Kinshasa
Kasaï
Kasaï-Central
Kasaï-Oriental
Lomami
Sankuru
Haut-Lomami
Lualaba
Haut-Katanga
Nord-Kivu
Sud-Kivu
Maniema
Tanganyika
Mongala
Nord-Ubangi
Sud-Ubangi
Équateur
Tshuapa

Table 1: List of provinces in the Democratic Republic of Congo since 2015

Provinces	**Code ISO**
Bandundu	CD-BN
Bas-Congo	CD-BC
Équateur	CD-EQ
Kasaï-Occidental	CD-KW
Kasaï-Oriental	CD-KE
Katanga	CD-KA
Kinshasa	CD-KN
Maniema	CD-MA
Nord-Kivu	CD-NK
Orientale	CD-OR
Sud-Kivu	CD-SK

Table 2: List of former provinces of the Democratic Republic of Congo from 1966 to 2015, used for the study

Table 3: Descriptive statistics of our database combined with Axel Dreher's database

Variable	**N**	**Mean**	**Sd**	**Min**	**Max**
Conflicts events	135	41.56168	0	0	424
Conflicts	135	0.5481481	0.4995299	0	1
Mines	135	12.33333	28.08436	0	91
Population	135	5639678	1659014	3122871	8950579
Area (in km)	135	260384.2	170600.1	11051.63	505005.9
Port dummy	135	0.1111111	0.3154401	0	1
Oil & Gas	135	0.1111111	0.3154401	0	1
Forest loss	117	642950.1	574186.5	5194	2695198
N	135				

Table 4: Descriptive statistics of the self-constructed database

Variable	**N**	**Mean**	**Sd**	**Min**	**Max**
Conflicts events	331	16.24773	48.53901	0	459
Conflicts	331	0.5589124	0.4972689	0	1
Précipitation	331	1925.571	7857.757	960.99	144411.2
Annual Average Mean Temperature	331	24.07205	1.374943	21.15	25.83
Cobalt production	331	1684.251	8509.776	0	67448
Gold production	331	11350.59	76715.55	0	730000
Forest Loss	220	559276.8	568905.3	5194	2695198
$\triangle Temperature$	331	-0.0038066	0.2197326	-1.02	0.73
$\triangle Precipitation$	331	422.5465	7852.901	-901.9	142829.5
Region id	331	6.126888	3.184561	1	11
N	331				

	Conflicts events	Conflicts	Précipitation	AAMT	Cobalt production	Gold production	Forest loss
Conflicts events	1.0000						
Conflicts	0.2978*	1.0000					
Precipitation	0.0351	0.0453	1.0000				
Annual Average Mean Temperature	-0.3101*	-0.3103*	-0.0957	1.0000			
Cobalt production	-0.0302	0.0651	-0.0176	-0.1464*	1.0000		
Gold production	-0.0464	-0.1201*	-0.0092	0.0756	-0.0291	1.0000	
Forest loss	0.0472	0.0587	0.3436*	0.3336*	0.0526	-0.0280	1.0000

Table 5: Correlation matrix of our database combined with Axel Dreher's database

	Conflicts events	Conflicts	Mines	Population	Area (in km)	Port dummy	Forest loss	Oil&gas
Conflicts events	1.0000							
Conflicts	0.3276	1.0000						
Mines	0.0027	0.1632	1.0000					
Population	0.4271	0.4607	0.2839	1.0000				
Area (in km)	0.1220	0.2911	0.4733	0.5843	1.0000			
Port dummy	-0.0991	-0.0907	-0.1432	-0.5384	-0.4283	1.0000		
Forest loss	-0.1200	-0.0056	-0.0000	0.0403	0.5402	-0.2481	1.0000	
Oil&gas	-0.0991	-0.0907	-0.1432	-0.5384	-0.4283	1.0000	-0.2481	1.0000

Table 6: Correlation matrix of the self-constructed database