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

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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, unlike gold, 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. However, according to our predictive model, cobalt has the potential to emerge as a contributing factor, similar to gold, if appropriate measures akin to those outlined in section 1502 of the Dodd-Frank Act are not effectively implemented to regulate the utilization of these minerals in the supply chains of corporations.

JEL Codes : F51 , L72 , O13

Keywords : Conflicts , Natural Resources , Energy Transition

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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]. In sum, the literature review shows that conflicts over natural resources can have multiple and complex causes. Conflicts can arise due to unequal access to resources, competition for resource use, environmental degradation, and climate change. 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.

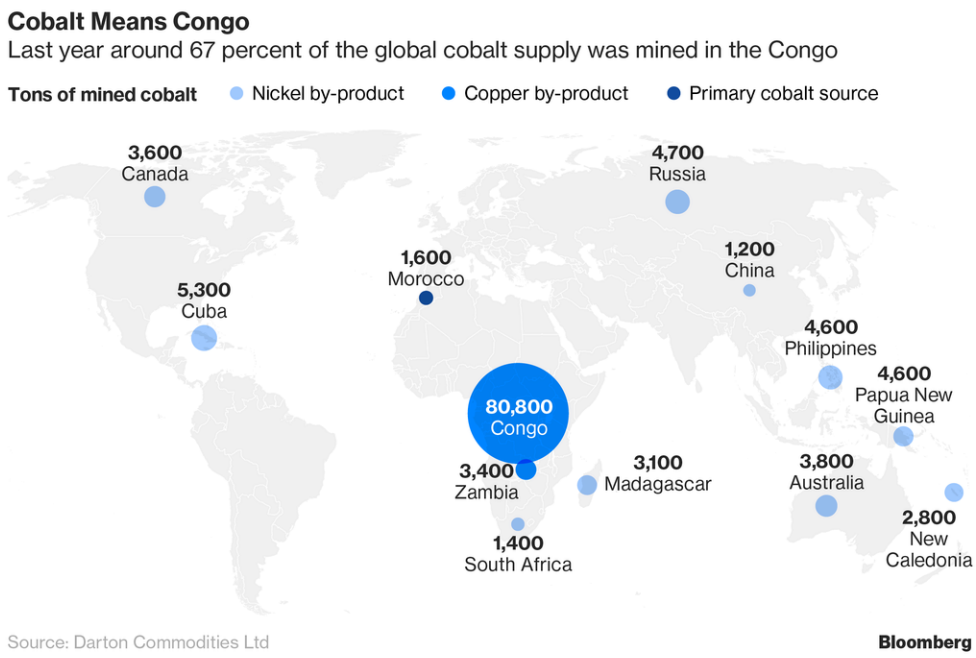
If the democratization of low-carbon technologies for the energy transition appears to lead to a decrease in dependence on fossil fuels, it is in fact creating new ones. In the context of energy transition in which all countries are currently engaged, the demand for certain metals identified as strategic, 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**

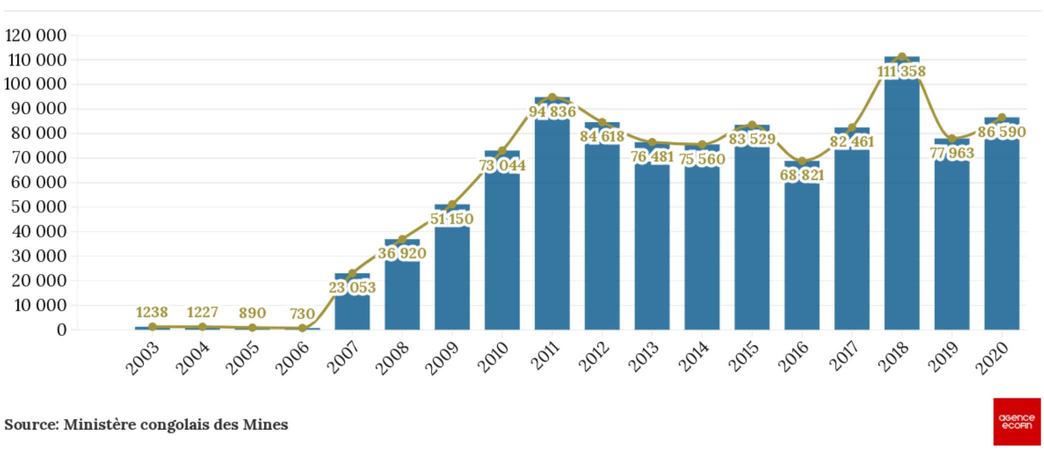
[2] Section 1502 of the Dodd-Frank Wall Street Reform and Consumer Protection Act is also known as the Conflict Minerals provision. It was enacted in 2010 and aimed to address the issue of "conflict minerals" originating from the Democratic Republic of the Congo (DRC) and surrounding countries. Under 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 producers in the world**



Source : Darton commodities Ltd

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



Source : Congolese Minister of Mining

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

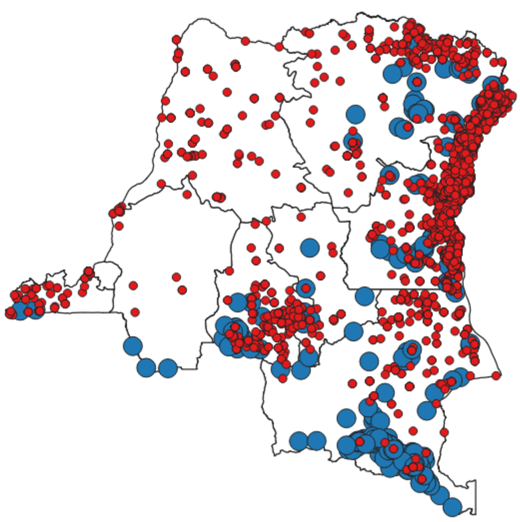
The Democratic Republic of Congo (DRC), also known as Congo-Kinshasa, is a Central African country that shares borders with nine other countries, including Uganda, Rwanda, Burundi, Tanzania, Zambia, Angola, the Republic of Congo, and the Central African Republic. The country is the second-largest country in Africa by area, with a total area of 2,344,858 km², divided into 11 regions and 26 provinces and the fourth-largest population in the African continent, with an estimated population of over 100 million people. 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 3: **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 4: **Distribution of conflicts (red dot) and cobalt mine (blue dot) 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 :

$$\boxed{Conflicts'events_{it} = \beta_1\, Cobalt_{it} + \beta_2\, Precipitation_{it} + \beta_2\, Temperature_{it} + \beta_3\, \triangle X_{it} + \lambda_i + \varphi_t + e_{it}} \tag{1}$$

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 (see table) 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.

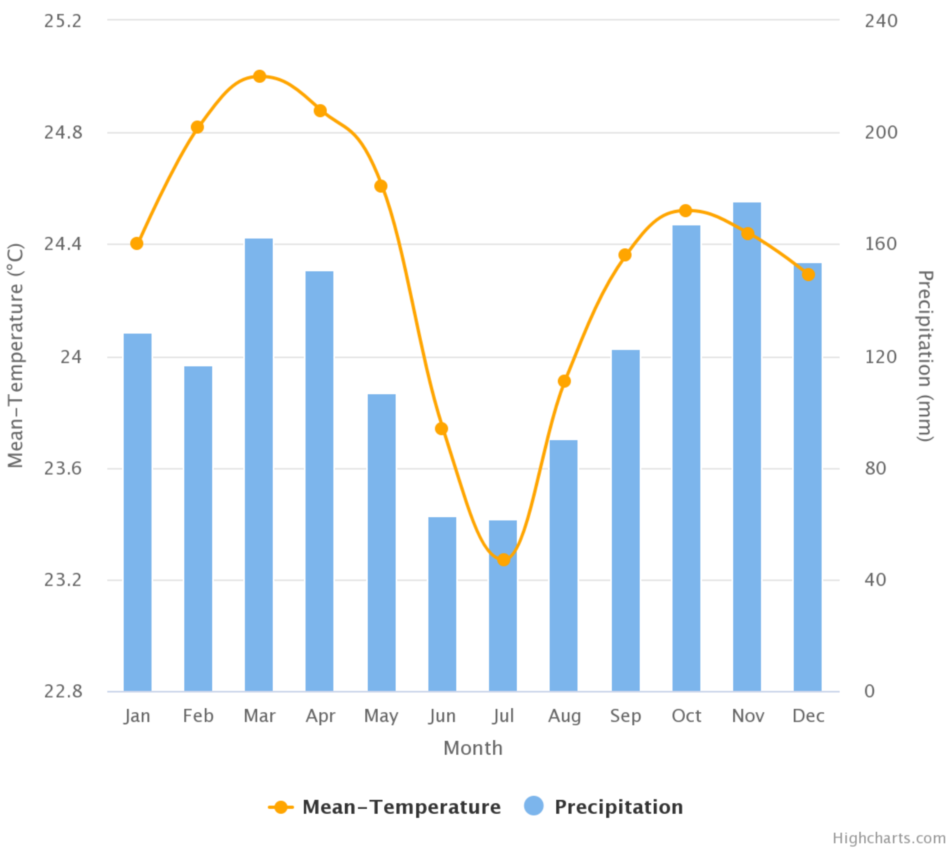
$$\boxed{logit\ Conflicts_{it} = \beta_1\, Cobalt_{it} + \beta_2\, Precipitation_{it} + \beta_2\, Temperature_{it} + \beta_3\, \triangle X_{it} + \lambda_i + \varphi_t + e_{it}} \tag{2}$$

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 a contributing factor, we utilized a combination of multiple datasets. 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 5) 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. Our variable of interest is the annual cobalt production in each region.

Figure 5: **Climatology of Mean-Temperature and Precipitation in DRC from 1991-2020**



Source : World Bank

5 Results

To evaluate the factors influencing conflict in the Democratic Republic of Congo in the preceding years, we utilized both 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 both OLS and PPML estimation technics that climatic factors such as precipitation and the increase of temperature, 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. 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 1 : Panel regression with simple 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 2 : Panel regression with PPML and region fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Conflicts events	Conflicts events	Conflicts events	Conflicts events	Conflicts events	Conflicts events
Cobalt	-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 and copper production per year and per region. 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

Table 2 : Logit regression with conflicts as dummy variable

	(1) Conflicts	(2) Conflicts	(3) Conflicts	(4) Conflicts
Cobalt production	0.0501	0.00940	0.00921	0.0235
	(0.76)	(0.13)	(0.13)	(0.32)
Gold production	1.454***	1.462***	1.466***	1.410***
	(11.57)	(11.49)	(11.13)	(10.70)
Précipitation	-1.795	2.993	3.029	4.046*
	(-1.50)	(1.64)	(1.61)	(1.79)
Forestloss	0.115	0.235*	0.234*	0.222*
	(0.98)	(1.80)	(1.79)	(1.72)
Annual Average Mean Temperature		-1.094***	-1.100***	-1.166***
		(-4.33)	(-4.12)	(-3.86)
$\triangle$ *Temperature*			0.0894	0.134
			(0.12)	(0.17)
$\triangle$ *Precipitation*				-0.000918
				(-0.87)
Constant	11.84	1.942	1.837	-3.835
	(1.41)	(0.19)	(0.18)	(-0.33)
N	220	220	220	220
pseudo R^2	0.023	0.164	0.164	0.167

t statistics in parentheses

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

Table 3 : Panel regression with 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	-0.183	-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)
$\triangle\ Temperature$					25.15	26.00
					(1.53)	(1.59)
$\triangle\ Precipitation$						-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 3 : Panel regression with PPML and region fixed effects for Gold production

	(1)	(2)	(3)	(4)	(5)	(6)
	Nombredeconflits	Nombredeconflits	Nombredeconflits	Nombredeconflits	Nombredeconflits	Nombredeconflits
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)
$\triangle\ Temperature$					0.173	0.319
					(0.20)	(0.37)
$\triangle\ Precipitation$						-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

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

6 Conflict forecast

6.1 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.

Figure 6: **Prediction of the probability of conflicts associated with cobalt production.**

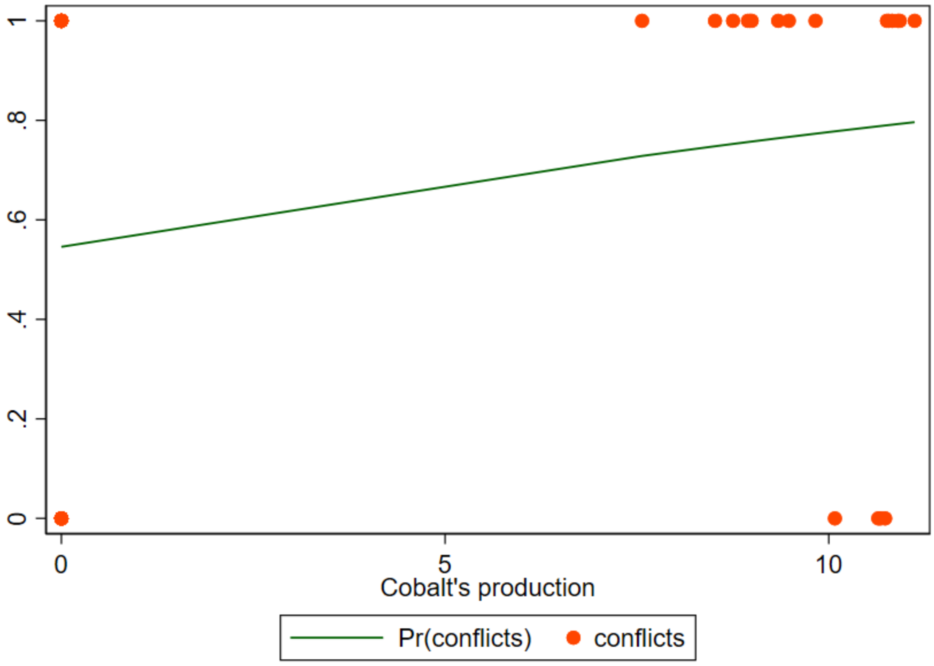
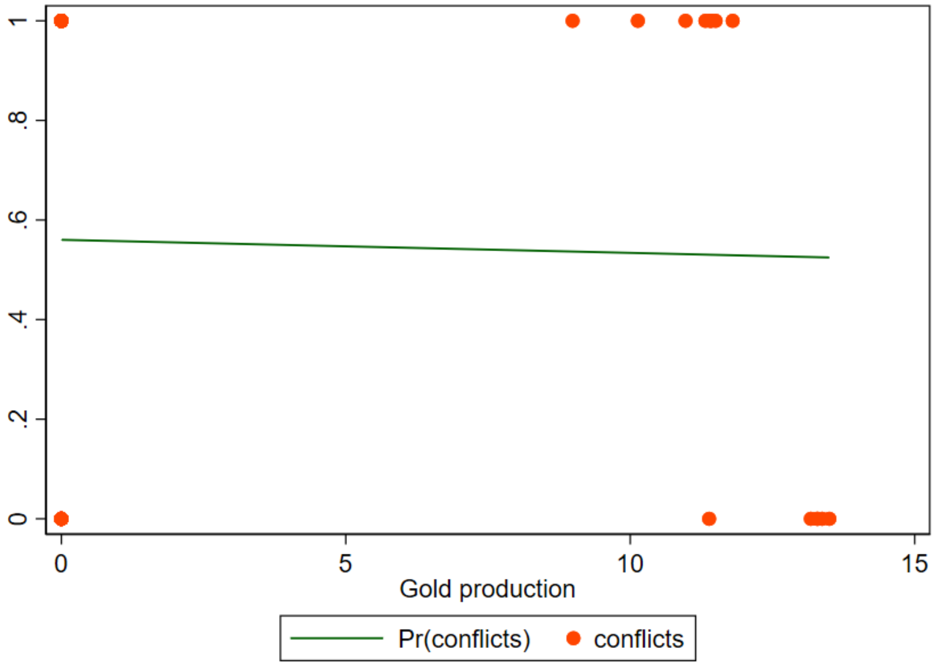


Figure 7: **Prediction of the probability of conflicts associated with gold production.**



Source : Author calculation

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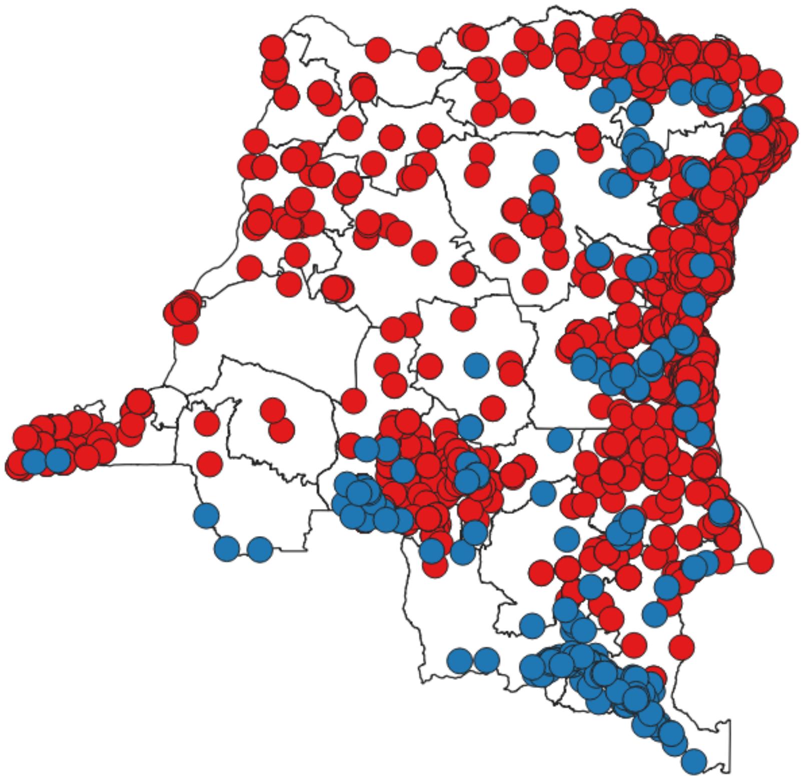
6.2 Appendix

Figure 8: **Distribution of conflicts (red dot) and cobalt mine (blue dot) in the DRC**

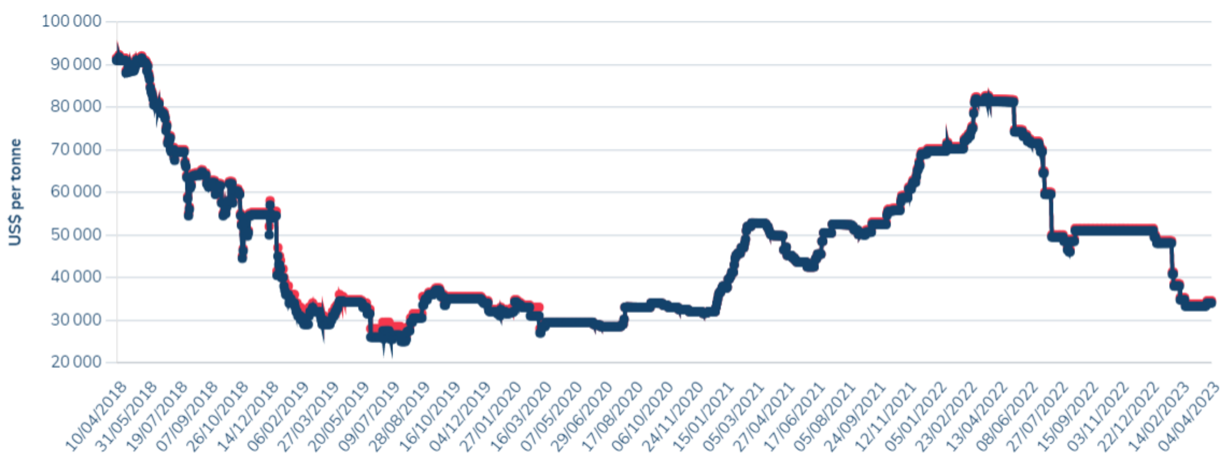


Source : Author calculation

Figure 9: **Evolution of cobalt prices from 2013 to 2018**

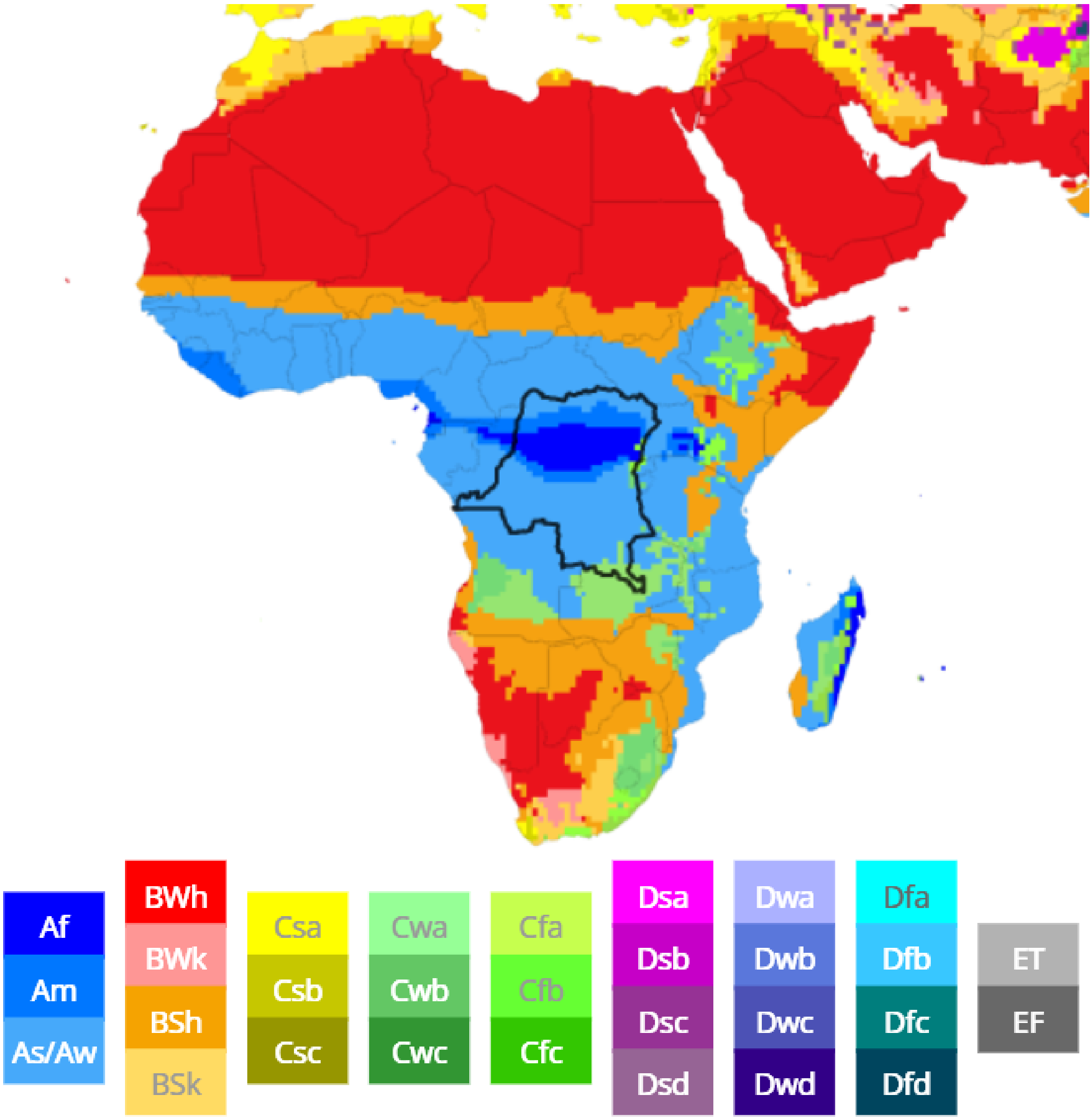
Source : London Metal Exchange

Figure 10: **Evolution of cobalt prices from 2018 to 2023**



Source : London Metal Exchange

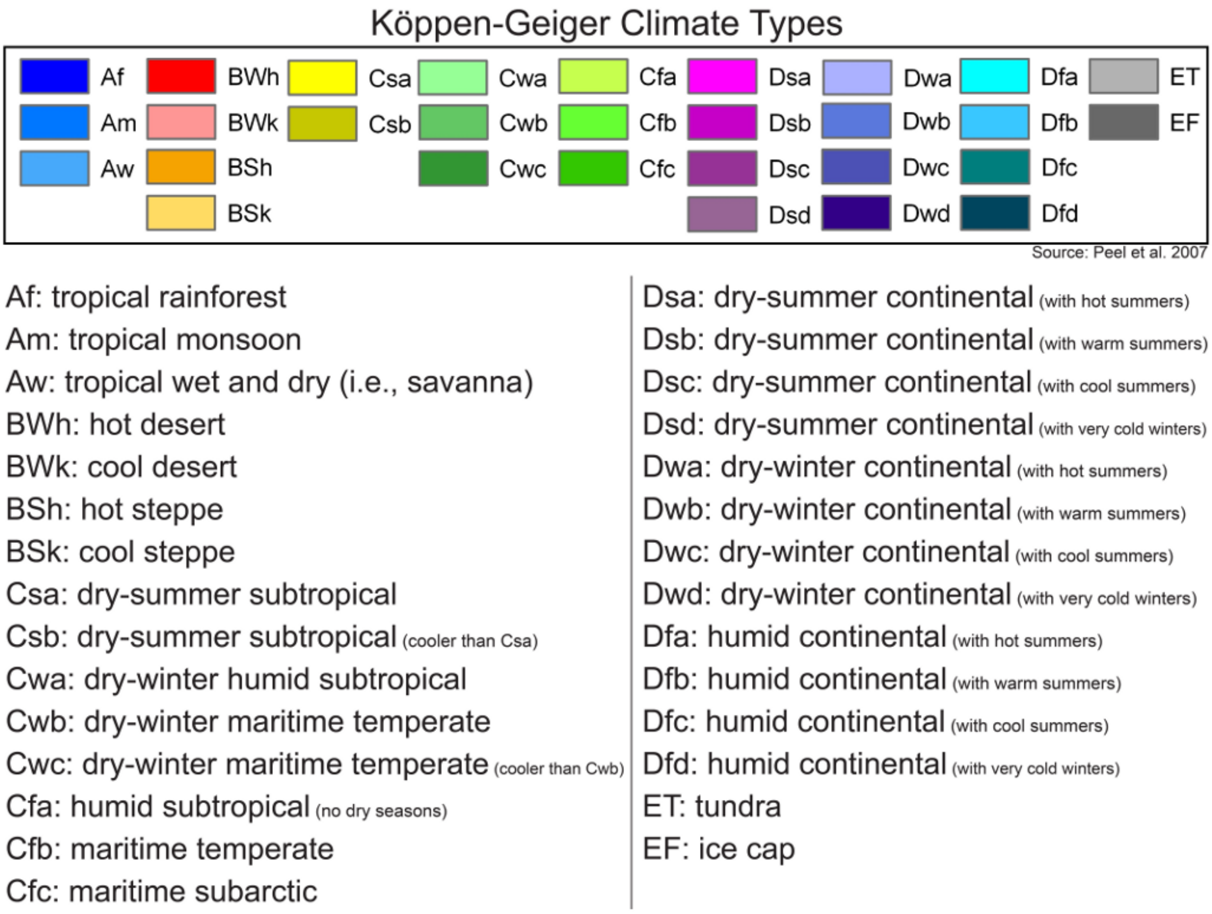
Figure 11: **Koppen-Geiger climate classification in Africa from 1991 to 2020**



Source : World Bank [3]

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

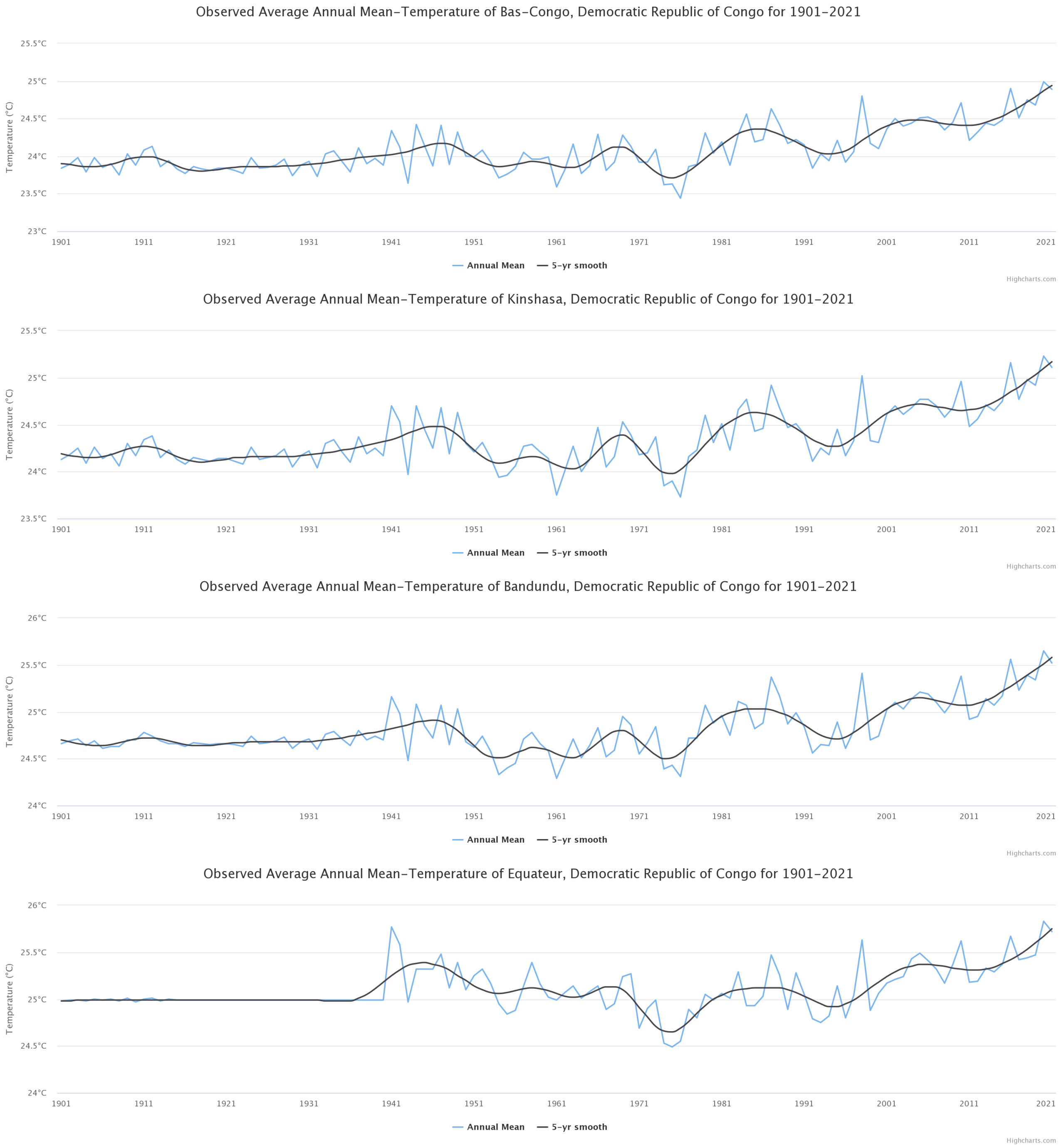
Figure 12: **Koppen-Geiger climate classification in Africa from 1991 to 2020**



Source : World Bank [4]

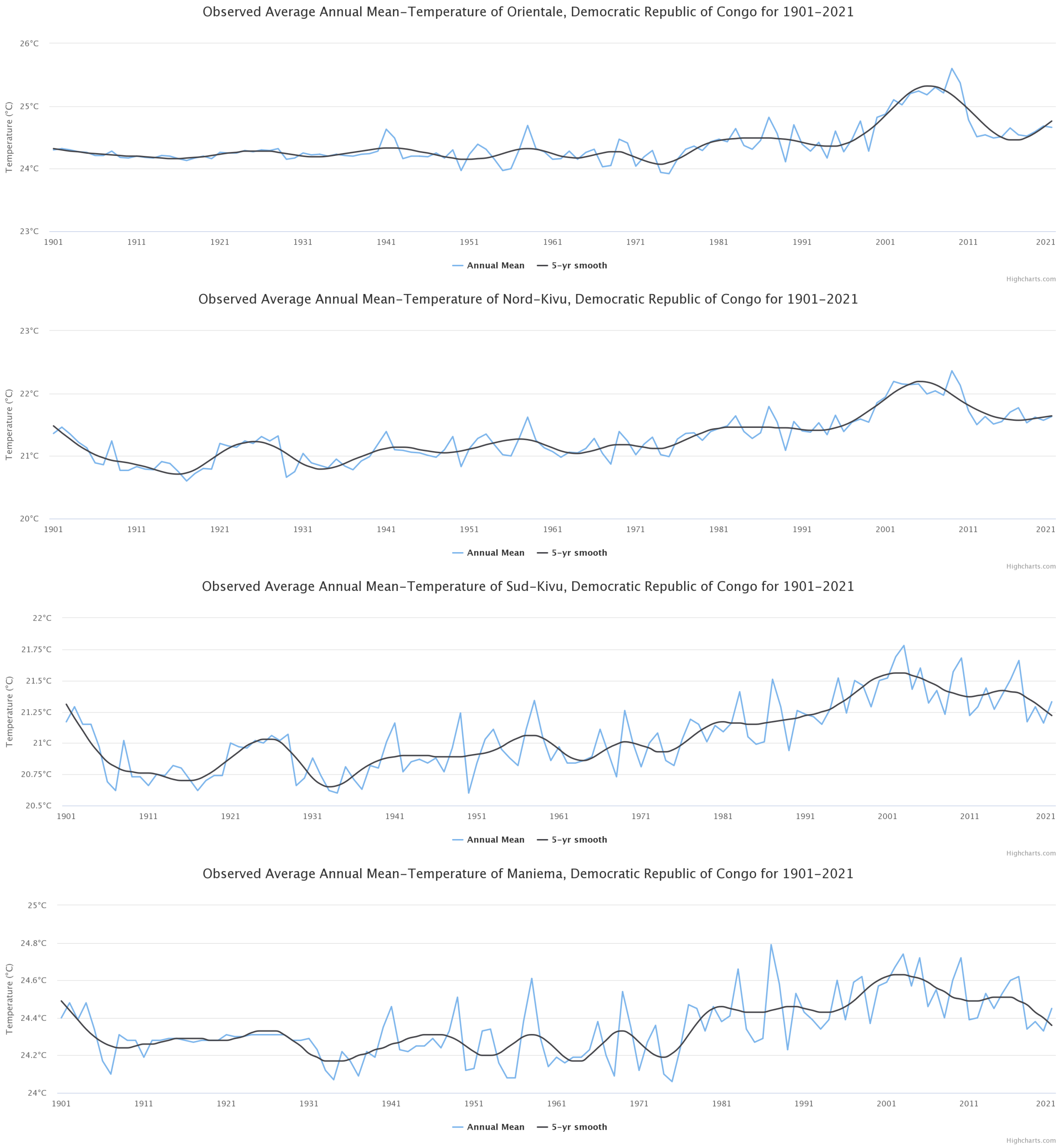
[4] https://open.oregonstate.education/permaculturedesign/chapter/climate-classification-systems/

Figure 13: **Average annual mean temperature in DRC administrative regions**



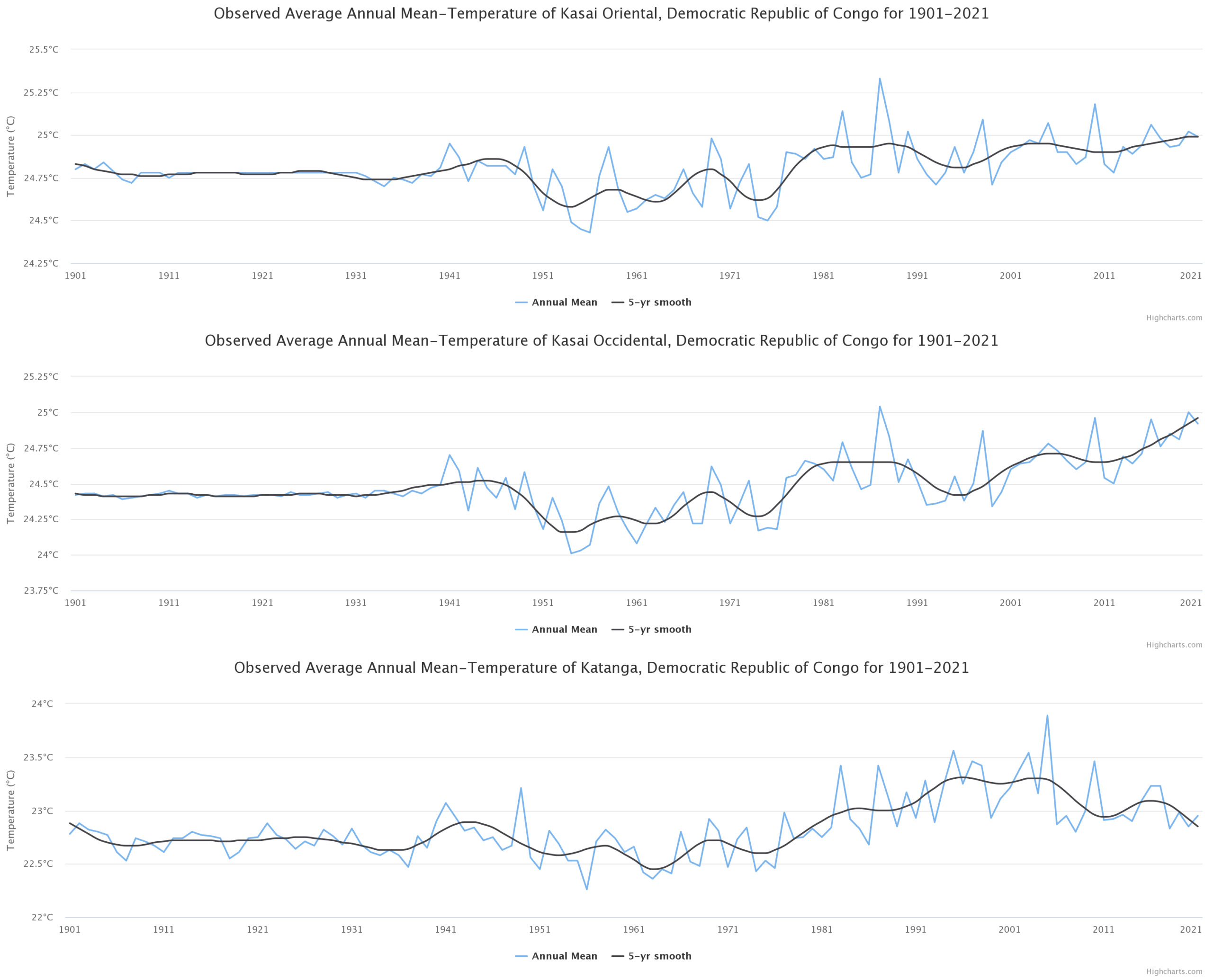
Source : World Bank

Figure 14: **Average annual mean temperature in DRC administrative regions**



Source : World Bank

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



Source : World Bank