The impact of conservation of nature and wildlife on conflict

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Abstract

The protection of nature and wildlife is crucial today. More and more studies, however, speak of violent incidents involving protected areas. To investigate the relationship between protected areas and low-intensity conflict, this article addresses the factors that increase the likelihood of low-intensity conflict when protected areas are established. Widely accepted explanations of rebellion focus on the grievance argument. As with the establishment of a protected area local communities are deprived of land and resources, this article argues that social unrest is likely to increase when protected areas are established. However, building on Ostrom's "Governing the Commons" theory, intercommunal conflicts as well as social unrest are likely to decrease when a protected area is created. The literature on protected areas and its impact on conflict is vast, but primarily conducted qualitatively. By doing a quantitative study, this article attempts to fill an important gap in the literature. The results of this analysis cautiously suggest that current protected areas in Africa still provoke discontent, as low-intensity conflict increases when the amount of protected areas increases. Future studies are needed to further study the mechanisms that make conflict involving protected areas more or less likely.

Keywords: conservation, protected area, conflict, grievances, governing the commons

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Every second, approximately a chunk of forest equivalent to the size of a soccer field is lost in order to fulfill the demands of the growing population (Derouin, 2019; Gamborg et al., 2012). Albeit the conservation of nature and wildlife is indispensable in present times, current research reports emerging conflicts related to conservation. Thus, the aim of this thesis is to examine how conservation of nature and wildlife lead to conflict.

Firstly, the protection of nature and wildlife is crucial today because forests are home to 80% of terrestrial biodiversity, three-quarters of the Earth's freshwater comes from forested watersheds, and people partly rely on trees for firewood, timber, and charcoal (Derouin, 2019). Gibbs et al. (2018) further stress that the destruction of forests leads to an increase in CO2 emissions, which further accelerates climate change and causes direct economic losses. Moreover, it entails risks for wildlife, endangers human health, and contributes to the emergence of conflict (European Commission, n.d; Salehyan, 2014; Mach et al., 2019).

The current COVID-19 pandemic further emphasizes the urgency to conserve nature and wildlife. According to Lovejoy, a leading US scientist who coined the term 'biological diversity, the pandemic most probably finds its origin in "the persistent and excessive intrusion in nature and the vast illegal wildlife trade" (Weston, 2020). This pandemic also has serious consequences for nature and wildlife as there has been an increase in land-grabbing, deforestation, illegal mining, and wildlife poaching in many rural areas (Troeng et al., 2020).

Therefore, it is important to research how nature and wildlife can best be protected, such as through the establishment of conservation areas, which remain the "fundamental building blocks of virtually all national and international conservation strategies" (Dudley, 2008, p.2). They reduce deforestation (Andam et al., 2008), protect wild plants and animals (Millennium Ecosystem Assessment, 2005), and can further signify a nations culture and identity (Carruthers, 1995; Runte, 1979). This study refers to the International Union for

Conservation of Nature's (IUCN) definition of a "protected area" (PA), which is "a clearly defined geographical space, recognized, dedicated and managed, through legal or other effective means, to achieve the long term conservation of nature with associated ecosystem services and cultural values" (Dudley, 2008, p. 8).

However, the literature shows that dilemmas and conflicts might arise from the establishment of a PA. More recently, scholars and journalists have increasingly reported the problem of militarily trained rangers in protected areas. Their research shows the impact on conflict and rising human rights violations against local communities (Lunstrum, 2014; Verweijen & Marijnen, 2016; Duffy et al., 2019; Schlindwein, 2020). Hence, this thesis seeks to answer the research question: To what extent does the establishment of PAs lead to low-intensity conflict?

The research relies on two theories to answer the question. Based on Ostrom's (1990) theory of "Governing the Commons," this paper hypothesizes that the establishment of PAs can mitigate low-intensity conflict. Nevertheless, scholars foresee that conflicts will arise from the establishment of PAs. These conflicts can be traced back to deprivations that people experience when a PA is established. Based on Gurr's (1970) "grievance-theory," the second hypothesis predicts that low-intensity conflict increases due to the formation of a PA. In order to ascertain which of these two hypotheses will prevail, an ordinary least square (OLS) regression and a multiple regression is conducted, using "PAs in one year" and "the total number of PAs" as the independent variables and the "number of low-intensity conflicts" as the dependent variable.

The results of the OLS regression analyses provide support for the second hypothesis, suggesting that low-intensity conflict increases when more PAs are established in Africa. However, the results of the multiple regression analyses indicate no significant relationship between PAs and low-intensity conflict. Thus, further research is needed to address the various questions that arises from this analysis.

Literature Review

The importance of PAs is widely acknowledged. However, the need to establish them is based on the myth that nature should be separated from people as nature would be harmed whenever people would try to live among it (Lewis, 1996). This section entails a short historical overview, which is provided to further the understanding of conflicts that emerge from the establishment of PAs.

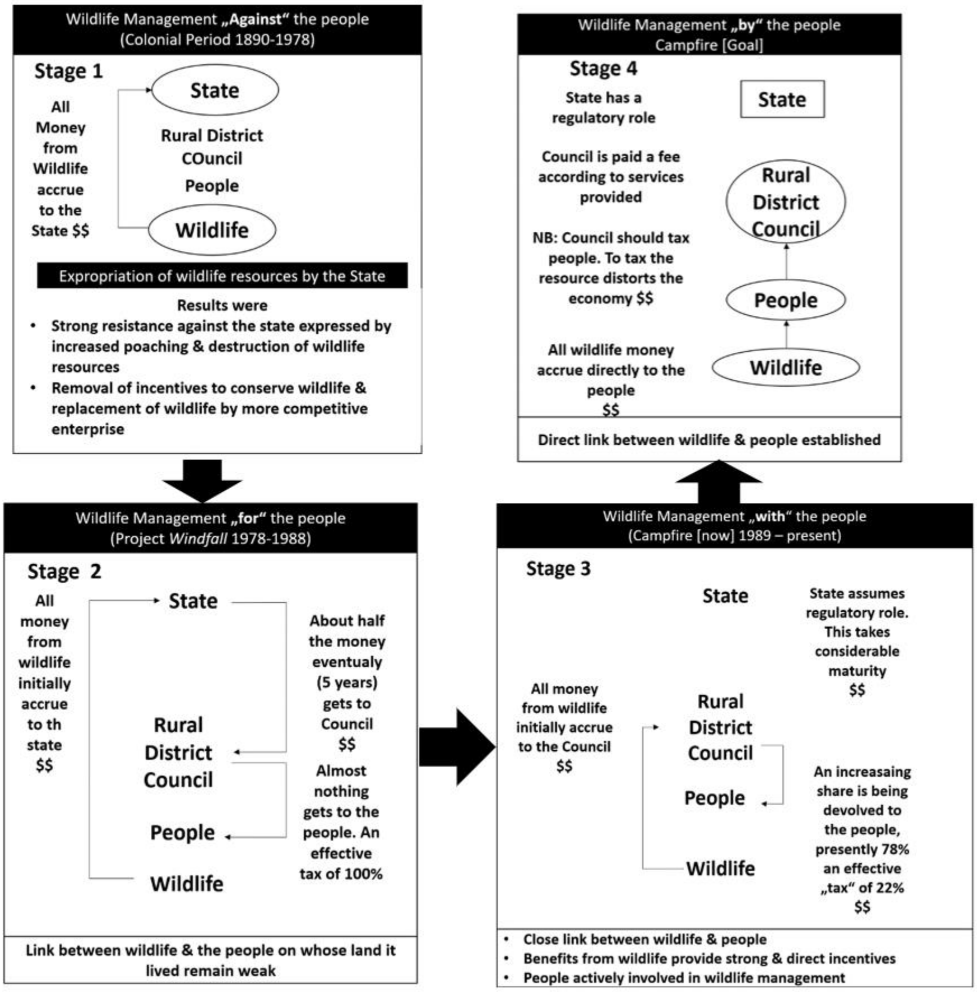
The idea of conservation stems from, inter alia, philosopher George Catlin’s notion of preserving landscapes, wildlife, and Native Americans (Nash, 1973). In the early 19th century, Americans generally shared this perception and saw Native Americans as an integral part of the wilderness. However, after the American Civil War in 1865, this idea was largely ignored due to the rise of movements that idealized uninhabited wilderness and emphasized its preservation.

In addition, at the Yosemite, the Yellowstone, and the Glacier National Parks, policies were instated in 1891 to preserve nature for the enjoyment of scenic beauty (Nash, 1973). However, this led to the expulsion of Native Americans from their ancestral lands (Spence, 1999). Similarly, in Africa, the traditional values of African people and European ideas related to the ownership of nature and wildlife clashed. For instance, with the colonialization of Tanzania and South Africa by the Germans, Dutch, and British in the 19th and 20th century, wildlife became an exclusive commodity for the enjoyment of the ruling White group (Carruthers, 1995). The colonizers created parks from which local African communities, among others the Maasai, were excluded, thereby alienating them from their natural systems.

As the history of biodiversity conservation is characterized by socially exclusive strategies, local communities continue to hold negative perceptions toward PAs. Subsequently, the establishment of PAs led and continues to lead to various conflicts between the communities and the PAs (Mola-Yudego & Gritten, 2010; Anthony, 2007). Nowadays, scholars also discuss the importance of community-based natural resource management (CBNRM) to prevent these kind of conflicts (DeGeorges & Reilly, 2009; Lewis, 1996). CBNRM became particularly popular in the mid-to-late 1970s and was founded by the United States Agency for International Development (USAID). Figure one shows the stages from wildlife management against the people towards devolution and CBNRM (for the original version see Appendix Figure 6) (DeGeorges & Reilly, 2009).

Figure 1

Community-Based Wildlife Management



Nevertheless, current PAs still fail to sustain wildlife populations and to "involve those who bear [the] most costs of their establishment" (Roe et al., 2000, p. 4). Therefore, it is important to further investigate the factors that influence the emergence of conflict between the local communities and the PA managers (DeGeorges & Reilly, 2009).

Thus far, the literature on the conservation of nature and wildlife has examined conflicts pertaining to PAs from different perspectives. Part of the literature has predominantly investigated the coexistence of wildlife and humans. Due to population growth and deforestation for agricultural purposes, farmers increasingly live in close proximity to wildlife (McLennan & Hill, 2012). This often results in human-wildlife conflict because wildlife can cause serious damage to human livelihoods or lives, by for example destroying the crops on which the people rely on (Woodroffe et al., 2005).

Other scholars, including those referenced in this study, focus on the conflicts that emerges from "human interactions between those seeking to conserve species and those with other goals" (Redpath et al., 2013, p. 100). It mostly occurs "when two or more parties with strongly held opinions clash over conservation objectives and when one party is perceived to assert its interests at the expense of another" (Redpath et al., 2013, p. 100).

For example, Mukherjee (2009) demonstrates this problem in her analysis of the Kanha National Park of Madhya Pradesh in India. Her research illustrates how the goal of preserving nature and wildlife in its most primal form through the complete removal of human residents from the park led to latent conflicts such as the illegal grazing of cattle. However, since her analysis cannot explain the origins of other types of conflicts in relation to PAs, one cannot draw inferences about other cases, and it remains unclear whether the establishment of PAs necessarily results in low-intensity conflict.

In their work, Soliku & Schraml (2018) pay attention to this knowledge gap by assessing the similarities and differences that characterize disparate protected conflict areas in developing and developed states. They find that conflicts concerning PAs in developing states are mainly driven by their impacts on the livelihoods of local communities (Soliku & Schraml, 2018). This further confirms the findings outlined above. They also indicate that PA conflicts are determined by geographical location, and specific socio-economic and cultural contexts. Moreover, Soliku and Schraml (2018) emphasize that it is vital to improve “our understanding of PA conflicts including why, when and where they occur to contribute to their management and minimize their potential damage” (p. 137). However, since they rely on qualitative studies in their assessment, they cannot examine other variables that might simultaneously influence the emergence of conflict.

Another part of the literature focus on the conflict that emerges from environmental crime, including the overexploitation of nature and wildlife and illegal wildlife trade. The peak of elephant poaching in Africa in 2011 (CITES, 2016) lead conservationists and scholars to suggest strategies on how to tackle this issue more effectively. Some proposed solutions that include forceful or armed forms of conservation (Asiyambi, 2016; Barbora, 2017; Massé & Lunstrum, 2016; Verweijen & Marijnen, 2018) and the development and application of military-style approaches (Annecke & Masubele, 2016; Büscher, 2018; Duffy et al., 2015).

However, Duffy et al. (2019) criticize this approach and outline the problematic consequences that result from the “militarization of conservation.” Upon, evaluating such in-depth studies, it can be concluded that the militarization of conservation contributes to inequality, which enables possible human rights violations and can lead to a cycle of violence (Duffy et al. 2019). Nonetheless, Duffy et al. (2019) do not offer any solutions or alternative strategies concerning how to effectively protect nature and wildlife. Moreover, it is not clear if this issue is generally valid or only present in specific national parks. However, as Duffy et al. (2019) state, it is important to further investigate the question of whether militarized conservation ultimately contributes to rising levels of violence between the rangers of a PA and local communities.

It is evident that the literature on PA conflicts mainly examines single cases or small studies to illustrate the different kinds of conflicts that can occur. Although this furthers one's understanding of conflict processes in specific contexts, it makes it more difficult to evaluate and control for other variables that influence the emergence of conflict. Therefore, it is important to further aggregate the mechanisms between PAs and conflict. Although scholars agree on the need to take an inclusive and integrative approach in order to avoid conflict between local communities and the PAs, no single study exists that measures whether an increase in PA conflicts can be determined. By means of a large-N quantitative study, this paper attempts to fill this important gap in the literature as it examines whether low-intensity conflict necessarily increases when a PA is created.

Theoretical Framework

Although the history of PAs has been overshadowed by the enforcement of Western values and ideals of uninhabited nature on others, PAs play an important role in the conservation of the world's biodiversity. Furthermore, they provide opportunities to generate economic resources, strengthen food security, and improve human health (Hag, 2016). This analysis predicts that protected areas thereby also have the opportunity to mitigate conflict, which is further elaborated in the next section.

Based on rational choice theory, each person is assumed to try to maximize his or her own interests. "The tragedy of the commons" assumes that humans are thereby tempted to exploit common-pool resources (Hardin, 1968). Hardin (1968) argues that assigning ownership of the resource system to the state or enforcing privatization of natural resources is necessary to solve the challenges posed by the "tragedy of the commons." One issue with Hardin's theory regarding the "tragedy of the commons" is that it assumes that people are entrapped in this dilemma with no chance of overcoming it themselves (Ostrom, 1990).

Ostrom (1990) further addresses the question of "how to enhance the capabilities of those involved to change the constraining rules of the game" (p. 7). She argues that solutions for the "tragedy of the commons" are more effectively achieved through voluntary organization rather than through coercion. Subsequently, institutions that include the local community or allocate ownership of the resource system to a defined group of "commoners" are capable of solving the tragedy of the commons. Over the last decade, many governments and state conservation organizations have revised their conservation policies in favor of environmental justice (Adams & Jeanrenaud 2008; Kothari, 2008) and CBNRM (Agrawal, 2003; Kreuter et al., 2010).

However, de Georges and Reilly (2009) argue that CBNRM is only successful when full devolution of ownership of land and natural resources from the government to local communities takes place. This is in line with Ostrom's (1990) perception that the success of CBNRM depends on the participation of the local communities themselves. Thus, the focus in the outlined theories remains on the protection of nature and the need to solve intercommunal conflicts.

Other scholars point out that various other conflicts can emerge from unsustainable resource extraction (Böhmelt et al., 2014). A large body of research further argues that the extraction of resources can also fuel riots and protests (Frederiksen, 2019; Himley, 2010) and violence against civilians through "competition for territorial control, promoting looting and rent-seeking" (Kishi, n.d.), or financing conflict (Kahl, 2006; Ross, 2004).

However, PAs provide institutions with the opportunity to protect and manage the resources at hand (Millennium Ecosystem Assessment, 2005). Figure 2 illustrates that PAs can additionally offer an inclusive and distributive institution (Roy, 2018) that provide access to the resources on which the local communities rely on. Since Roy (2018) claims that especially transformative strategies can help in managing post resource-related conflicts, I hypothesize that:

H_1: *The establishment of PAs mitigates inter-communal conflict as well as riots and protests.*

Figure 2

Illustration of Hypothesis 1

Although the international realm increasingly acknowledges the importance of inclusive management strategies, multiple case studies provide evidence that PA conflicts still occur. Understanding and explaining these conflicts can help to "to keep conflicts channeled within a set of agreed norms that foster peaceful discussion of differences" (National Research Council, 2000, p. 2) in order to sustain wildlife, nature and people's livelihoods.

Moore and Jaggers (1990) additionally emphasize the relevance of synthesizing socio-psychological and political conflicts in addition to structural determinist approaches in order to explain intrastate conflict. Taken together, the models complement each other and explain through different levels of analysis why rebellion, revolution, and social movements occur.

Gurr's (1970) work best explains the socio-psychological processes that can lead to rebellion. He argues that the translation of individual deprivation into relative deprivation can enable an individual to "articulate his or her frustrations in rebellious action" (Moore & Jaggers, 1990, p. 23). Relative deprivation means that there is tension between one's actual situation and what they feel they should be able to achieve. This frustration is the "primary source of human capacity for violence" (Gurr, 1970, p. 36). He adds that based on the rational choice model, people only act out their frustrations if "they believe that they stand a chance of relieving some of their discontent through violence" (Gurr, 1970, p. 210).

In addition, Stewart (2008) is also a strong proponent of the "grievance" argument (Keen, 2012). She emphasizes that grievances can result from perceived "horizontal inequalities," meaning inequalities in economic, social or political dimensions or the cultural status between culturally defined groups (Stewart, 2008). Stewart et al.'s (2008) research additionally suggests that horizontal inequalities have a mediate effect on the conflict-inducing potential of natural resources which can translate into both separatist struggles and local-level conflict. Empirical evidence supports this notion as countries with severe social and economic horizontal inequalities have a higher probability of experiencing a possibly longer conflict with greater intensity (Ostby, 2008; Ross, 2004).

As mentioned before, PAs can generate economic benefits by, for example allowing tourism within PAs. However, Vodouhe et al. (2010) indicate that in the past few centuries a negligible amount of the earned revenue from PAs was invested in local level development (see also DeGeorges & Reilly, 2009; Mukherjee, 2009). Most benefits of PAs appear to be provided for the country at large and not for the local communities who live in close proximity to the PAs (Lewis, 1996), which might further increase the grievances within the state.

By contrast, Collier and Hoeffler (2004) present an economic model that portrays rebellion as an industry, whereby profit is generated from looting. Their theory, which is called "greed theory", assumes that people join rebellions because of private incentives, and economic profit (greed), not grievances. Hoeffler (2011) states that there is more empirical evidence for the "greed-thesis" rather than for the "grievance-thesis" because income, democracy and natural resources are strongly interlinked. Furthermore, Hoeffler (2011) indicates that poor economic opportunities, low income, and a history of violent conflict makes civil war more likely to take place.

Other scholars argue that resource extraction from mining firms can further grievances due to land expropriation, insufficient job opportunities and social disruptions (Frederiksen, 2019; Himley, 2010; Ross, 2004). In this context, it is not the mining firms, but the PAs that are "driving off the people who have long inhabited the area or depriving them of any benefits from the appropriation of their traditional lands" (Klare, 2001, p. 208). In Africa alone, 14 to 39.5 million people are estimated to have been internally displaced due to the creation of parks and PAs between 1970 and 2000 (Geisler & Sousa, 2000).

Another mechanism that explains why the establishment of PAs can lead to more grievances can be the increased militarization of PAs. Due to poaching, the population of forest elephants has dropped by approximately 62 percent, rhino-poaching incidents have multiplied 20-fold within six years and bears and Asian big cats are threatened by extinction (INTERPOL-UN Environment, 2016). In response to this, the rangers in PAs are trained from the country's military to protect wildlife resources and forests from the poachers. Unfortunately, the strategy of militarized conservation can mirror and recreate past injustices (Duffy et al., 2019). For example, these current tactics of PAs include rangers, who are invading and raiding homes in the hopes of uncovering evidence of wildlife crimes (Büscher, 2018). This is further leading to the creation of informant networks, which creates cultures of mistrust within communities. These strategies increase the likelihood that different groups will feel that they have been treated unfairly and consequently further their grievances.

Thus, the grievance theory provides a strong theoretical foundation for the argument that PAs can increase conflict. However, as indicated in the beginning of the theoretical framework, grievances only explain the socio-psychological approach on an individual level and do not sufficiently address the dynamics of the conflict process itself (Moore and Jaggers, 1990).

As Moore and Jaggers (1990) state, it is additionally important to examine, which structural factors lead to the emergence of revolutionary situations. Relying on Skocpol's (1979) "States and Social Revolutions" work, they indicate that social movements can only be successful if a state's capacity is weakened (Moore & Jaggers, 1990). Ross (2004) also argues that weak rule of law influences the capacity of a state to attract investment in its manufacturing sector, causing these states to face a heightened risk of civil war (Ross, 2004). Another study by Öberg and Melander (2010) shows that high bureaucratic quality is strongly associated with civil peace in autocratic regimes as the quality of government institutions can influence information structures. "By contributing to well-informed decision making on [the] part of the authorities," the probability of civil war can be reduced (Öberg & Melander, 2010, p. 21).

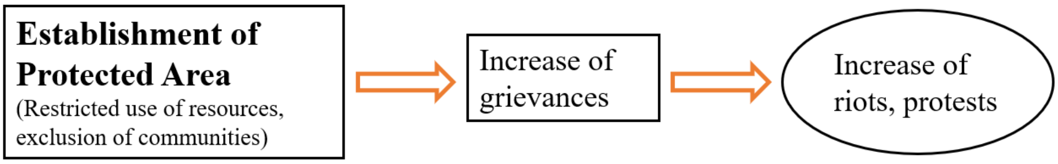
A great deal of the examined literature focuses largely on large-scale or violent conflicts, including civil wars. Armed conflicts involve more opportunity costs for the participants because they require funding, high levels of organization and are riskier (Hendrix & Salehyan, 2012). Moreover, when a system of domination is absolute, individuals are aware that they cannot change the existing socio-political structure (Scott, 1990). Instead they rely on alternative means, such as through non-compliance and passive means, to resist the system (Scott, 1990). For example, Mukherjee (2009) finds in her case study that "relatively powerless groups unite in their hopelessness to protest against a system or institution that has its own agendas in conservation" (Mukherjee, 2009, p. 52).

When a PA imposes restrictions on the use of forests and wildlife resources or forces the reallocation of local communities, low-intensity conflicts in the form of social unrest and protests are consequently more likely to occur (Sandell, 2006; Vodouhe et al., 2010). Based on this theoretical framework, I have formulated a second hypothesis which is further illustrated in Figure 3:

H_2: *The establishment of a PA increases social unrest in the form of demonstrations, riots, and extra-governmental violence.*

Figure 3

Illustration of Hypothesis 2



Research Design

To evaluate the hypotheses, this research applies event data on violent low-intensity conflict in Africa between 1996 and 2018. The study focuses on Africa, because most PA conflicts have historically taken place there (Soliku & Schraml, 2018). In addition, Africa is rich in resources, which many scholars predict will have a negative effect on conflict (Mildner et al., 2011). Therefore, the mitigating effect that PAs might have on resource-related conflicts is claimed to be strongest in Africa.

For over a century, PAs were managed by centralized bureaucracies, which excluded local communities from the management of PAs (Kothari, 2008). However, this has changed as an increasing number of countries have started to recognize the participation of local communities and indigenous and community conserved areas (ICCA) from the 1990's (Kothari, 2008). Thus, the time span of 1996 to 2018 is most representative for the purpose of examining conflict involving PAs as it covers the beginning of the implementation of more integrative management strategies (Kothari, 2008).

To measure the dependent variable of both hypotheses one and two, the Social Conflict Analysis Database (SCAD) (Salehyan et al., 2012) is used. Since there is no theory that predicts that PAs will affect conflict beyond the country's borders where the PA is located, this analysis focuses on intra-state conflict. SCAD provides the required data because it includes information on demonstrations, riots, and inter-communal conflicts taking place within a country (Salehyan et al., 2016). Furthermore, SCAD includes all African countries with a population of over one million inhabitants.

To identify the actors who are most likely to participate in riots and demonstrations, this study refers to the domain categories from the Social Conflict Analysis Database – Organizational Properties (SCAD-OP) (Salehyan et al., 2019). The database further categorizes the actors that are involved in the conflict from 1 to 18, so that researchers can track the activities of a group over time. “Generic citizens” (15), and ‘Criminals’ (11) are most related to people who want to express their grievances as a result of the establishment of the PAs. “Generic citizens” are “participants in general rallies, political movements, non-specific social movement campaigns, and other activities” (Salehyan et al., 2019, p. 3). Individuals that are not able to organize themselves in big social movements or rebellions to question the state engage in different forms of conflict, including “pilfering, slander, arson, [and] sabotage” (Scott, 1985, p. 29). “Criminals” are most strongly related to this group of people, as they are defined as “individuals and groups who are part of criminal enterprises or whose behavior explicitly suggests criminal intent” (Salehyan et al., 2019, p. 2). They use violence, but do not mean to reform the government or overthrow the state or state-specific institutions (Salehyan et al., 2019; Scott, 1985).

SCAD further classifies the types of conflict events from one to ten. The first hypothesis assumes that PAs mitigate demonstrations, riots, and inter-communal conflict. Thus, the focus is on organized and spontaneous demonstrations, organized and spontaneous riots and extra-governmental violence. While in an organized demonstration or riot a clear leader or dominant organization can be identified, this characteristic is missing in spontaneous demonstrations or riots. The main difference between demonstrations and riots is that demonstrations are largely peaceful, whereas riots include “violent actions toward members of a distinct “other” group or government authority” (Salehyan & Hendrix, 2016, p.4). Extra-governmental violence is defined as a distinct violent event where neither the perpetrators nor the victims are associated with governmental actors (Salehyan & Hendrix, 2016). Based on the previously elaborated theoretical framework, hypothesis two will focus on the same event types, but predicts an increase in these conflicts. Table 1 portrays the frequency of the different conflict events, showing that more spontaneous conflict events and extra-governmental violence take place in Africa.

Table 1

Frequency of conflict events

Type of conflict events	**Frequency**
Organized demonstration	54
Spontaneous demonstration	440
Organized violent riot	14
Spontaneous violent riot	523
Extra-government violence	692

To measure the dependent variable (Conflict Counts) for the first and second hypothesis, the number of conflict events occurring in Africa will be counted for each year. When counting the events, special attention is given to the different issues related to an event. Soliku and Schraml (2018) argue that PA conflicts in developing countries are mostly driven by their impact on livelihoods, which refers to access to land, food, usage of PA resources to perform religious and cultural rites and obtaining the permission to allow livestock to graze in a park. Thus, conflict events with issues related to economy or jobs; food, water or subsistence; ethnic discrimination or ethnic issues; economic resources or assets and others or those that are not specified are considered. An overview of the selection of the conflict events and actors involved can be found in the appendix in Table 4.

To determine if there is an increase or decrease in low-intensity conflict after the PA was founded, the number of PAs established in one year will be considered as the first independent variable (PAs). Moreover, in a second analysis, the study examines the effect of the total number of PAs on low-intensity conflict, constituting the second independent variable (Total PAs). In doing so, this study can also assess to what extent the quantity of protected areas influences low-intensity conflict. The World Database on Protected Areas (WDPA) is "the most comprehensive global database of marine and terrestrial PAs" (IUCN & UNEP-WCMC, 2017). It contains all required information for the analysis and is therefore determined to be the most useful database.

In addition, a range of different control variables which are typical for the literature on social conflict will also be used. The outlined theories explain that good governance indicators and the capacity of the state impact the probability of low-intensity conflict arising (Ross, 2004; Öberg & Melander, 2010). The Polity2 variable is determined as best fitting this criterion because it includes different governance types ranging from autocracies (-10) to democracies (+10) (Marshall et al., 2017). The inclusion of this variable should not be seen "as an acceptance of the counter-proposal that autocracy and democracies are alternatives or opposites" (Marshall et al., 2017, p. 17). In fact, a higher democratic score implies the presence of institutions through which citizens can express their preferences but also their grievances. Moreover, it includes the existence of institutionalized constraints on the executive power and guarantees civil liberties to all citizens. Lastly, the rule of law, systems of checks and balances and freedom of press are included in this conceptualization of democracy as well (Marshall et al., 2017).

Furthermore, Hendrix and Salehyan (2012) argue that the level of development and economic growth are important control variables. They state that "the negative relationship between economic development and civil conflict is the most robust finding to emerge from the conflict literature" (Hendrix & Salehyan, 2012, p. 7). Thus, GDP growth per year (GDP) is added as a control variable.

By providing a better quality of life and increasing the probability of attaining access to public goods, human welfare can decrease the possibility of violence emerging (Rezaeedaryakenari et al., 2017). Since the infant mortality rate, measured by the number of deaths of children under one per 1000 live births is said to be a good indicator for measuring human welfare (Rezaeedaryakenari et al., 2017), it is included as a control variable (infant mortality) in the analysis. Lastly, this study controls for population size (population) because a higher population size is a consistently strong predictor of social unrest and violence (Hendrix & Salehyan, 2012; Rezaeedaryakenari et al. 2017; Weinberg & Bakker, 2014). Raleigh and Hegre (2009) even find that the frequency of conflict events in Africa tends to be proportional to the population size of the area in question.

Moreover, all development-related variables are from the World Bank, as it presents the most current and accurate global development data available while further including national, regional and global estimates (World Bank, 2020). Below, table one shows the summary statistics of variables used in the analysis.

Table 2

Summary statistics of variables used in the analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	N	Mean	Std. deviation	Variance	Min	Max
Conflict Count	1219	1.40	4.180	17.471	0	65
Conflict Count (lagged)	1166	1.462	4.263	18.173	0	65
PAs (in one year)	1173	1.51	7.908	62.533	0	185
Total PAs	1173	19.39	52.685	2775.758	0	482
GDP	1140	3.118	3.165	1.002	-9.783	9.785
Infant Mortality	1219	62.199	28.323	802.193	10.200	156.400
Population	1212	18,127,324.74	26,627,73.54	7.090	76,417	195,874,740
Population (lag)	1212	15.766	1.585	2.511	11.24	19.09
Polity2	1151	1.41	5.244	27.497	-9	10
Valid N (listwise)	1030					

In order to prevent autocorrelation that might arise from model misspecifications, the study includes a lagged variable of the counted conflict events (Conflict Counts (lagged)). In addition, the histogram of population (see Assumptions in the appendix) displays that its data is right-skewed and as such might influence the regression analysis by one or few cases. In order to reduce the skew, the population variable is logged. As this study aims to generalize the findings outside of the sample, it examines whether the underlying conditions for linearity, independent errors, homoscedasticity and normally distributed errors are met. Lastly, in order to avoid multicollinearity, this study checks whether perfect linear relationships exist between two or more of the predictor variables. Fortunately, there are no issues with the types of variables identified as there are no constraints on the variability of the outcome.

Results & Analysis

Estimation of the models

As already stated in the research design, this study will conduct an analysis with data from 1996 to 2018, including 53 countries from Africa. Since the dependent variable is estimated by count data (regarding the number of conflict events which occur in one year), the analysis includes an OLS regression model (see Model 1 and Model 3 in Table 3). The OLS regression analysis can help to identify whether the independent variables can explain the emergence of low-intensity conflict in the country where the PA is located in. Moreover, the analysis contains a multiple regression analysis to study the joint effect of the independent variable and the control variables on low-intensity conflict (see Model 2 and Model 4 in Table 3).

Assumptions

In addition, the analysis checks for the underlying assumptions of the regression models. The first analysis shows that most assumptions are met and the results are presented under "Assumptions" in the appendix. However, the scatterplot of the values of the residuals against the values of the outcome predicted by the model (see Assumptions in the appendix) shows that the assumption of homoscedasticity has been violated. This is not surprising, because there is a large gap between the largest and smallest observed value for both the independent and dependent variable. Hence, in order to account for the impact of heteroscedasticity, this analysis runs an OLS regression analysis and multiple regression analysis using robust standard errors and clustered standard errors for comparison reasons (see Robust Standard Errors and Clustered Standard Errors in the appendix) (Astivia & Zumbo, 2019).

Furthermore, the scatterplot of the values of residuals against the values of the outcome predicted by the model shows that the data is extremely skewed and not normally distributed.

As the dependent variable consists of count data and the assumption of linearity is violated, the Poisson and negative binomial (NB) regression analyses are estimated. The descriptive statistics in table one show that the variance of both the dependent variable and its predictor variables are much higher than the mean. Thus, the NB regression is evaluated to present the best fit for the model (Model 5 and 6). For comparison reasons, the Poisson model is executed as well (see Poisson in the appendix). The results from Model 1 to 6 of the analysis are presented below in Table 3.

Table 3

Estimation Results

	OLS (1) PA	**ML (2) PA**	**OLS (3) ToPA**	**ML (4) ToPA**	**NB (5) PA**	**NB (6) ToPA**
(Constant)	1.383***	-10.296***	1.111***	-9.968***	-11.531***	-11.281***
	(0.138)	(1.491)	(1.143)	(1.502)	(0.7803)	(0.7936)
PAs (in one year)	0.050**	0.020			0.009	
	(0.016)	(0.014)			(0.0055)	
Total PAs			0.016***	0.005*		0.001
			(0. 002)	(0.002)		(0.0008)
GDP		-8.716*		-8.074*	-7.328***	-7.075***
		(0.000)		(0.000)	(1.5963)	(1.5999)
Infant Mortality		-0.004		-0.002	-0.006***	-0.006**
		(0.004)		(0.005)	(0.0018)	(0.0019)
Population (log)		0.730***		0.697***	0.723***	0.703***
		(0.094)		(0.697)	(0.0481)	(0.0497)
Polity2		0.035		0.028	0.019	0.015
		(0.023)		(0.023)	(0.0106)	(0.0110)
Conflict Count (lagged)		0.351***		0.345***	0.105***	0.107***
		(0.094)		(0.030)	(0.0150)	(0.0151)
R^2	0.009	0.243	0.043	0,245		
Adj. R^2	0.008	0.239	0.042	0,241		
F	9.588**	54.836***	46.489***	55.329***		
N	1030	1030	1030	1030	1030	1030
-2LL					-1295.729	-1295.316
AIC					2605.458	2604.631

Note: OLS and negative binomial regression coefficients with standard errors in brackets.
***p<0.001, **p<0.01, *p<0.05

Model 1 and Model 2

Model 1 shows that 0.9% of the variance in the number of conflict events can be explained using the number of established national parks in one year. As the second model adds more variables, the value of R^2 automatically increases. Thus, the value of the adjusted R^2 is observed as it corrects for the number of explanatory variables in the model. In the second model, 23.9% of the variance in the number of conflict events can be explained using the number of established PAs in one year. This shows an increased fit of the model as more variance in the dependent variable can be explained. The adjusted value of 0.239 is very close to the observed value of R^2 (0.243), which indicates that the cross-validity of this model is very good (Field, 2013).

The increase in the adjusted R^2 yields an F-ratio of 54.836, which is significant ($p<0.001$). The p-values are significant at the 0.1 level (Model 1) and at the 0.001 level (Model 2). Thus, the ability to predict the outcome variable compared to not fitting the model significantly improves.

For the independent variable, the value of the t-test equals 3.097 and the corresponding p-value is 0.002. Therefore, the probability under the null hypothesis of obtaining a t-value of 3.097 or more extreme is 0.002 (0.2%). Thus, the null hypothesis can be rejected at any conventional level of statistical significance. The B-value of 0.050 for the independent variable shows that as the number of PAs established in one year increases by one unit, the conflict counts increase by 0.050 units. Although the establishment of PAs has a rather low influence on increased units of conflict counts, the null hypothesis can be rejected at any conventional level of statistical significance. Thus, this result is in alignment with the second hypothesis, which foresees an increase in low-intensity conflict when a PA is established.

It is interesting to observe that the independent variable loses its significance in the second model when the control variables are added. Whereas GDP growth, Population size and lagged Conflict Count hold significant values, Infant Mortality and Polity2 are not significant. The value of -8.716 for GDP indicates a negative relationship between GDP and low-intensity conflict. As GDP growth per year increases by one unit, conflict counts will decrease by 8.716 units. This interpretation is true only if the other variables in this model are held constant. Moreover, the value of the mortality rate of infants indicates a negative relationship as well. Thus, as the infant mortality rate increases by one unit, conflict counts will decrease by 0.004 units. However, as indicated earlier, this interpretation is true only if the other variables in this model are also held constant. This also applies to all following interpretations of the results. Moreover, Infant Mortality is not significant and thus the result should be viewed with caution.

The population size is positively associated with conflict. When the population increases by one unit, conflict counts will increase by 0.730 units. In addition, an increase of the Polity2 variable by one unit would increase the conflict count by 0.064 units. However, its p-value is not significant ($p>0.5$). When comparing the two OLS regression models to the OLS regression models using robust standard errors and clustered standard errors it is evident that the results of the analyses are very similar. The only difference is that the p-value for the independent variable using robust standard errors in the first model is significant at the 0.5 level and in the model using clustered standard errors the p-value is not significant.

Model 3 and Model 4

A comparison between the relationship of the number of newly established PAs in one year and low-intensity conflict and the relationship between the overall amount of PAs in a country and low-intensity conflict show that a difference in the significance values can be observed. The results of Model 3 and Model 4 indicate that the value of the total number of PAs stays significant in the fourth Model while the variable of PAs loses its significance in the second model. The control variables show the same significant results as in Model 1 and Model 2.

In addition, Model 3 shows that 4.2% of the variance in the number of conflict events can be explained by the overall amount of PAs in a country. Adding controls to the third model increases the variance that can be explained by 19.9%, which shows an increased fit of the model. Similarly, the adjusted R^2 (0.241) is very close to the observed value of R^2 (0.245), which indicates that the cross-validity of this model is very good (Field, 2013). The increase of the adjusted R^2 yields an F-ratio of 55.329, which is significant ($p<0.001$). Thus, the ability to predict the outcome variable significantly improves over an intercept-only model. Moreover, the overall fit of Model 4 is better than in Model 2 as greater variance in the outcome variable can be explained (0.241 > 0.239).

For the independent variable in Model 3 (total number of PAs), the probability under the null hypothesis of obtaining a t-value of 6.818 or more extreme is 0.000 (0%). Therefore, the null hypothesis can be rejected at any conventional level of statistical significance ($p<0,001$). As the total amount of PAs increases by one unit, conflict counts will increase by 0.016 units. In the fourth Model the null hypothesis for the independent variable can be rejected at any conventional level of statistical significance as well (Beta = 0.005, $p<0.5$).

The direction of relationships between the control variables and the dependent variable in the fourth model does not differ from the second model. The same holds for the p-values of Population size ($p<0.001$), Conflict Count (lagged) ($p<0,001$) and GDP ($p<0.5$), for which the null hypothesis can be rejected at any conventional level of statistical significance (also in the analysis using robust standard errors and clustered standard errors). However, the comparison with the regression models, using robust standard errors and clustered standard errors, shows that the analysis fails to reject the null hypothesis for the total number of protected areas.

Model 5 and Model 6

As the assumption of linearity is violated in this analysis and the observed variance is much higher than the mean, the interpreted results are compared to a NB regression analysis.

For the first independent variable (newly established PAs in one year) in Model 5, no substantial changes from Model 2 are recorded. However, the sixth model shows that the null hypothesis for the second independent variable (total amount of protected areas) cannot be rejected at any conventional level of statistical significance.

Another difference that is observed is that Model 5 and Model 6 display lower B-values. As units in the included variables increase, the increase of units in conflict counts is therefore lower than in the first two models. The only exception is infant mortality, for which the B-values increase in the NB regression analysis (B= -0.006). Although the displayed value has a rather low effect on conflict counts, the null hypothesis for Infant Mortality can be rejected at the 0.01 level in the negative binomial regression in Model 5 and Model 6. The other control variables do not differ from Model 2 and Model 4 because this analysis again solely shows significant results for Population ($p<0.001$), GDP ($p<0.001$) and Conflict Count (lagged) ($p<0.001$).

When comparing the NB regression models to the Poisson regression models the result of the Polity2 variable is specifically notable. While in all other model specifications the study fails to reject the null hypothesis for Polity2, the null hypothesis for Polity2 can be rejected in the Poisson regression analysis ($p<0.5$). Also, the results of the Poisson regression model show no significant values for the infant mortality rate at any statistical level of significance ($p>0.5$).

The overall fit of the model can additionally be examined by looking at the Akaike's Information Criterion (AIC). As in the first four models, the overall fit of the model is higher when the total amount of PAs in one country is examined (2604.631<2605.458). The AIC shows additionally a higher model fit for the NB regression than for the Poisson regression analysis (2604.631<3937.058).

Most of the results of the control variables are largely consistent with the findings in the literature as across all model specifications GDP and population show significant results.

However, according to the results of the NB regression analysis, an increasing mortality rate results in decreasing levels of violence. Although the B-coefficient for infant mortality displays a rather minimal value (B= -0.006), this result challenges any expectations of this analysis. However, when the B-coefficients from the NB regression are compared with the B-coefficients of all other model specifications (see Table 3 and the appendix), the significance value of the mortality rate becomes insignificant. Therefore, the result of the infant mortality rate should not be viewed without caution. Further research might benefit from using other control variables for the measurement of human development, such as the Human Development Index (Jahan, n.d.) or the Night Light Development Index (Elvidge et al., 2012).

Furthermore, the theoretical section of this thesis indicates that weak state capacity, weak rule of law and low bureaucratic qualities are more likely to trigger conflict and social movements. However, this analysis fails to reject the null hypothesis for Polity 2 at any conventional level of statistical significance except for the Poisson regression analysis. One possible explanation for this result might be a mismeasurement of the weak state capacity. Future studies might want to include the variable of “bureaucratic quality “and “tax capacity”, which Hendrix (2010) suggests being good indicators for measuring the capacity of the state.

Discussion

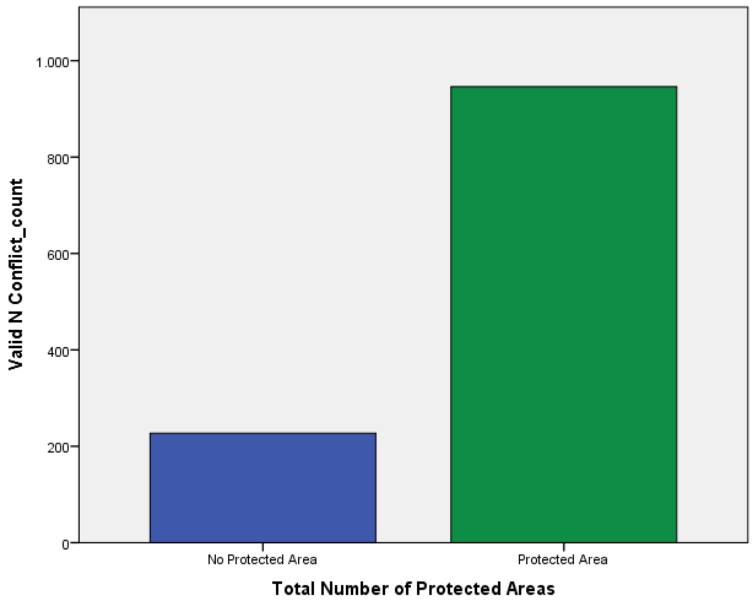
Initially this analysis argued that the establishment of a PA would result in increasing levels of low-intensity conflict. Although the OLS regression models for both independent variables show significant results, this study fails to reject the null hypothesis regarding PAs and total number of PAs in the multiple regression analyses using robust standard errors and clustered standard errors as well as in the NB and Poisson regression analyses. The establishment of PAs might be positively correlated with low-intensity conflict, but their B-coefficients show only a marginal, positive effect. Thus, caution is advised in making inferences regarding the relationship from PAs and low-intensity conflict.

Conclusion & Implications

This study aimed to answer following research question: To what extent does the establishment of PAs lead to low-intensity conflict? The results of the Large-N quantitative research for the two independent variables are only partly statistically significant. In the OLS regression analysis there is predominantly support for the second hypothesis. Especially when looking at the total amount of PAs that exist in a country each year and its relation to low-intensity conflict, the analysis rejects the null hypothesis. Also, it is evident that across all model specifications, the findings indicate a consistently positive association between both the establishment of PAs and the total amount of PAs with low-intensity conflict. Figure 4 supports this assumption, illustrating that there is more conflict when a PA is established compared to when a PA is not established.

Figure 4

PAs and Conflict



Although this study suggests that the presence of more PAs increases low-intensity conflict, this result should be viewed with caution.

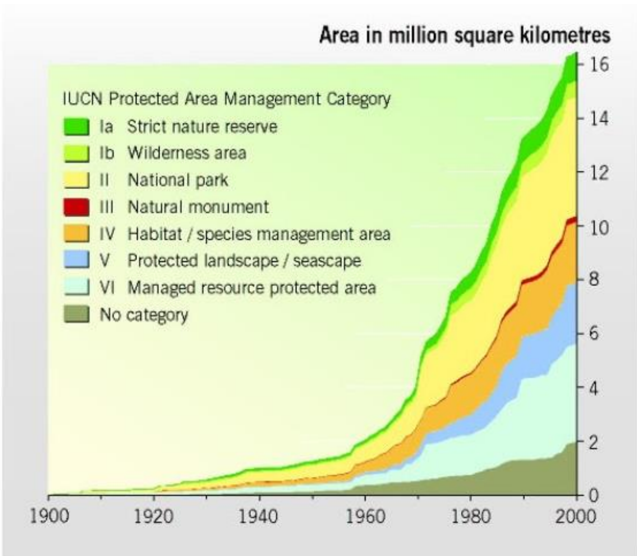
Firstly, this study focuses solely on low-intensity conflict, which includes riots, demonstrations and extra-governmental violence. As Mukherjee (2009) finds in her study, some groups might not have the possibility or the resources to engage in open forms of conflict such as protests and demonstrations. As such, further research could examine latent types of conflict, such as illegal grazing and illegal hunting with regard to the establishment of PAs.

Secondly, this study tested whether grievances about the establishment of new PAs would occur at the state-level. Although the study shows significant results, the values that explain the change in the dependent variable are rather low. Raleigh and Urdal (2007) point out that violent political conflicts do not necessarily affect all parts of a country equally. Further research, therefore, could benefit from analyzing the relationship at a sub-national level to examine whether conflict specifically increases in the districts in which a PA is located.

Thirdly, this analysis overgeneralized the term of PAs despite their varying degrees of management in order to include as many PAs as possible. Many PAs would have been excluded if this study would have only focused on PAs that are included in the categorization of the IUCN, displayed in Figure 5.

Figure 5

Trends in terrestrial surface under protected areas



Source: UNEP World Conservation Monitoring Centre, World Database on Protected Areas[7]

In addition, this study based its expectations on the assumption that most PAs that were established from the 1990s onward would include more integrative management strategies. In order to explain whether different management strategies can explain low-intensity conflict, future research could benefit from differentiating between the different management strategies of PAs.

The empirical findings give raise to one scientific implication. Albeit the coefficients of the independent variables display a rather marginal effect on low-intensity conflict, this study can constitute the foundation for future quantitative studies, dealing with the relationship between PAs and conflict. As the introduction and literature review in this thesis have already stated, quantitative studies are necessary to further examine the mechanisms that make conflict involving PAs more or less likely. This study did the first step and future quantitative studies might learn from its limitations.

This thesis does not want to imply that countries should stop establishing protected areas in order to prevent low-intensity conflict. It rather wants to address that low-intensity conflict can emerge when protected areas are established and that future studies are needed to find solutions to prevent or decrease the chances of low-intensity conflict. In addition, policy makers and PA managers cannot draw strong inferences from this analysis. However, they should internalize that their way of managing the PA might influence the way of how the PA is perceived by others and thereby influencing the possibility to increase the levels of low-intensity conflict.

This thesis contributes to the discussion of how nature and wildlife can best be protected by shedding light on the fact that although inclusive management strategies are widely accepted, low-intensity conflict still increases when PAs are established. This means that the perfect solution regarding PA management does not exist yet and further research is needed.

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Appendix

List of Abbreviations

AIC	Akaike's Information Criterion
CBNRM	community-based natural resource management
IUCN	The international union for Conservation of Nature
NB	Negative binomial
OLS	Ordinary least squares
PA	Protected Area
SCAD	Social conflict analysis database
SCAD-OP	Social Conflict Analysis Database – Organizational Properties
WDPA	World Database on Protected Areas

Figure 6

Original Version of Community-Based Wildlife Management

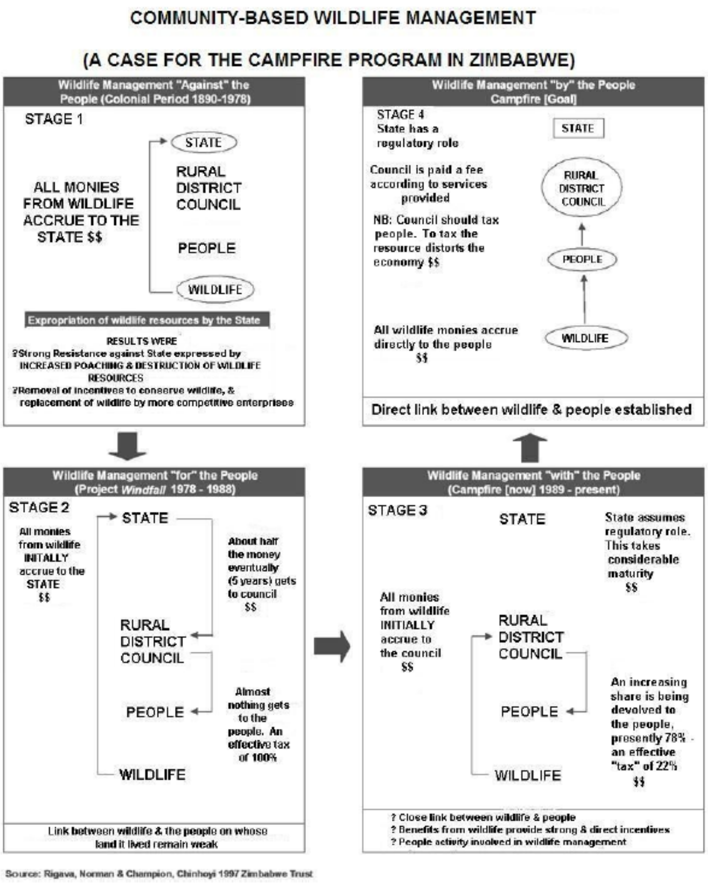


Table 4

The count of conflict events in SCAD

	Conflict events	Actors	Issues
H1 + H2	Organized and spontaneous demonstrations Organized and spontaneous riots Extra-governmental violence	‘Generic Citizen’ ‘Criminal’ In the dataset actors such as: citizens, civilians, communities, hunters, poachers, internally displaced persons, criminals, indigenous people, herders were selected	economy, jobs food, water, subsistence ethnic discrimination, ethnic issues economic, resources/assets other not specified

Output

The dataset, output and syntax of the analysis can be accessed through this link:

https://drive.google.com/drive/folders/1FSMgD1EGyTtZjgNMRIm4sbRB5brLDBwb?usp=sharing

THESIS DATA.sav contains the dataset that I created and worked with.

Syntax BAP.sps and Output BAP.spv contain the results of my first analyses.

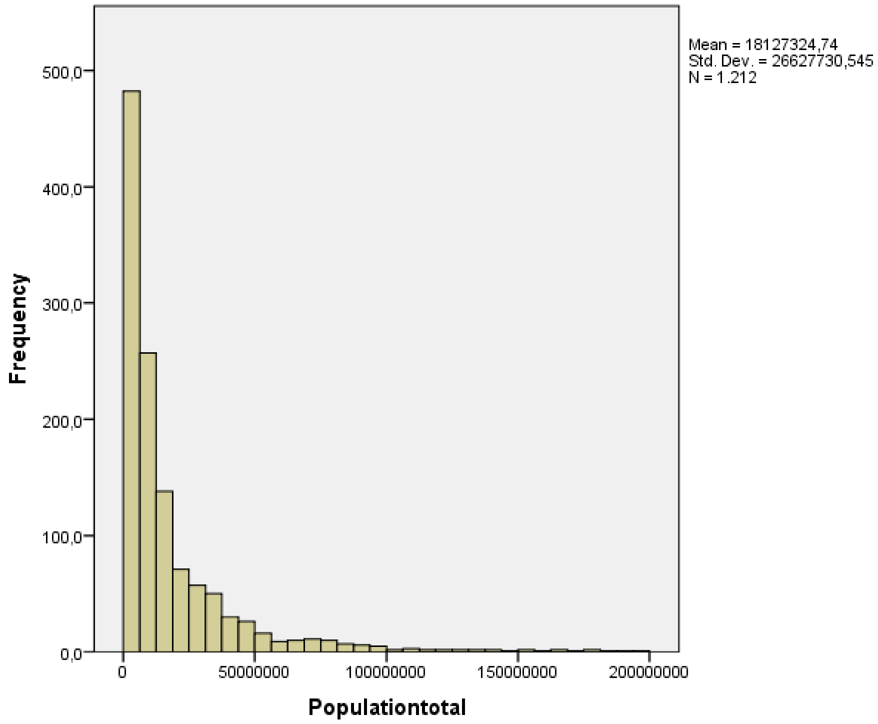
Syntax1.sps and Output1.spv contain the latest results of my analysis which I also included below.

Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Polity2	1151	-9	10	1,41	5,244	27,497
numbeProtectedWithOutIUCN	1173	0	185	1,51	7,908	62,533
GDP growth per year	1140	-9,783E+14	9,785E+14	3,11777E+14	3,16481E+14	1,002E+29
InfantMortality	1219	10,200	156,400	62,19902	28,323004	802,193
Conflict_count	1219	0	65	1,40	4,180	17,471
Conflict Count (lagged)	1166	,00	65,00	1,4623	4,26301	18,173
total number of protectec areas without IUCN category	1173	0	482	19,39	52,685	2775,758
log_population	1212	11,24	19,09	15,7655	1,58454	2,511
Valid N (listwise)	1030					

Assumptions



Correlations

		Conflict_count	numbeProtectedWithOutIUCN	total number of protectec areas without IUCN category	Polity2	GDP growth per year	InfantMortality	Conflict Count (lagged)	log_population
Pearson Correlation	Conflict_count	1,000	,096	,208	,058	-,014	-,055	,440	,348
	numbeProtectedWithOutIUCN	,096	1,000	,370	,035	-,045	-,111	,078	,099
	total number of protectec areas without IUCN category	,208	,370	1,000	,171	-,061	-,284	,230	,244
	Polity2	,058	,035	,171	1,000	,041	-,089	,075	-,047
	GDP growth per year	-,014	-,045	-,061	,041	1,000	-,013	,014	,185
	InfantMortality	-,055	-,111	-,284	-,089	-,013	1,000	-,070	,005
	Conflict Count (lagged)	,440	,078	,230	,075	,014	-,070	1,000	,357
	log_population	,348	,099	,244	-,047	,185	,005	,357	1,000
Sig. (1-tailed)	Conflict_count	.	,001	,000	,032	,326	,040	,000	,000
	numbeProtectedWithOutIUCN	,001	.	,000	,131	,074	,000	,006	,001
	total number of protectec areas without IUCN category	,000	,000	.	,000	,024	,000	,000	,000
	Polity2	,032	,131	,000	.	,096	,002	,008	,067
	GDP growth per year	,326	,074	,024	,096	.	,337	,325	,000
	InfantMortality	,040	,000	,000	,002	,337	.	,013	,434
	Conflict Count (lagged)	,000	,006	,000	,008	,325	,013	.	,000
	log_population	,000	,001	,000	,067	,000	,434	,000	.
N	Conflict_count	1030	1030	1030	1030	1030	1030	1030	1030
	numbeProtectedWithOutIUCN	1030	1030	1030	1030	1030	1030	1030	1030
	total number of protectec areas without IUCN category	1030	1030	1030	1030	1030	1030	1030	1030
	Polity2	1030	1030	1030	1030	1030	1030	1030	1030
	GDP growth per year	1030	1030	1030	1030	1030	1030	1030	1030
	InfantMortality	1030	1030	1030	1030	1030	1030	1030	1030
	Conflict Count (lagged)	1030	1030	1030	1030	1030	1030	1030	1030
	log_population	1030	1030	1030	1030	1030	1030	1030	1030

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	numbeProtectedWithOutIUCN[b]	.	Enter
2	total number of protectec areas without IUCN category[b]	.	Enter
3	GDP growth per year, Polity2, Conflict Count (lagged), InfantMortality, log_population[b]	.	Enter

a. Dependent Variable: Conflict_count

b. All requested variables entered.

Model Summary[d]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,096[a]	,009	,008	4,355	,009	9,588	1	1028	,002	
2	,209[b]	,044	,042	4,281	,034	37,002	1	1027	,000	
3	,495[c]	,245	,240	3,812	,202	54,649	5	1022	,000	2,085

a. Predictors: (Constant), numbeProtectedWithOutIUCN

b. Predictors: (Constant), numbeProtectedWithOutIUCN, total number of protectec areas without IUCN category

c. Predictors: (Constant), numbeProtectedWithOutIUCN, total number of protectec areas without IUCN category, GDP growth per year, Polity2, Conflict Count (lagged), InfantMortality, log_population

d. Dependent Variable: Conflict_count

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	181,885	1	181,885	9,588	,002[b]
	Residual	19500,425	1028	18,969		
	Total	19682,311	1029			
2	Regression	860,037	2	430,019	23,463	,000[c]
	Residual	18822,274	1027	18,327		
	Total	19682,311	1029			
3	Regression	4830,784	7	690,112	47,490	,000[d]
	Residual	14851,527	1022	14,532		
	Total	19682,311	1029			

a. Dependent Variable: Conflict_count

b. Predictors: (Constant), numbeProtectedWithOutIUCN

c. Predictors: (Constant), numbeProtectedWithOutIUCN, total number of protectec areas without IUCN category

d. Predictors: (Constant), numbeProtectedWithOutIUCN, total number of protectec areas without IUCN category, GDP growth per year, Polity2, Conflict Count (lagged), InfantMortality, log_population

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	1,383	,138		10,000	,000	1,112	1,655		
	numbeProtectedWithOutIUCN	,050	,016	,096	3,097	,002	,018	,082	1,000	1,000
2	(Constant)	1,105	,143		7,708	,000	,824	1,387		
	numbeProtectedWithOutIUCN	,012	,017	,022	,679	,497	-,022	,046	,863	1,158
	total number of protectec areas without IUCN category	,016	,003	,200	6,083	,000	,011	,021	,863	1,158
3	(Constant)	-9,961	1,503		-6,630	,000	-12,909	-7,013		
	numbeProtectedWithOutIUCN	,012	,015	,022	,767	,443	-,018	,042	,862	1,160
	total number of protectec areas without IUCN category	,004	,003	,054	1,681	,093	-,001	,009	,717	1,395
	Polity2	,028	,023	,033	1,198	,231	-,018	,074	,951	1,052
	GDP growth per year	-7,997E-16	,000	-,057	-2,041	,041	,000	,000	,944	1,059
	InfantMortality	-,002	,005	-,012	-,411	,681	-,011	,007	,909	1,100
	Conflict Count (lagged)	,345	,030	,344	11,639	,000	,287	,403	,844	1,185
	log_population	,696	,096	,222	7,251	,000	,508	,884	,789	1,267

a. Dependent Variable: Conflict_count

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	total number of protectec areas without IUCN category	,200[b]	6,083	,000	,186	,863	1,158	,863
	Polity2	,054[b]	1,750	,080	,055	,999	1,001	,999
	GDP growth per year	-,010[b]	-,314	,753	-,010	,998	1,002	,998
	InfantMortality	-,044[b]	-1,423	,155	-,044	,988	1,012	,988
	Conflict Count (lagged)	,435[b]	15,526	,000	,436	,994	1,006	,994
	log_population	,342[b]	11,651	,000	,342	,990	1,010	,990
2	Polity2	,023[c]	,756	,450	,024	,970	1,031	,839
	GDP growth per year	-,001[c]	-,026	,979	-,001	,996	1,004	,861
	InfantMortality	,005[c]	,158	,875	,005	,919	1,088	,804
	Conflict Count (lagged)	,414[c]	14,501	,000	,412	,947	1,056	,823
	log_population	,316[c]	10,564	,000	,313	,941	1,063	,820

a. Dependent Variable: Conflict_count

b. Predictors in the Model: (Constant), numbeProtectedWithOutIUCN

c. Predictors in the Model: (Constant), numbeProtectedWithOutIUCN, total number of protectec areas without IUCN category

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions							
				(Constant)	numbeProtectedWithOutIUCN	total number of protectec areas without IUCN category	Polity2	GDP growth per year	InfantMortality	Conflict Count (lagged)	log_population
1	1	1,193	1,000	,40	,40						
	2	,807	1,216	,60	,60						
2	1	1,652	1,000	,14	,16	,19					
	2	,808	1,429	,61	,44	,00					
	3	,540	1,749	,24	,41	,81					
3	1	3,966	1,000	,00	,00	,01	,01	,02	,01	,01	,00
	2	1,294	1,751	,00	,24	,17	,02	,02	,01	,05	,00
	3	,880	2,123	,00	,22	,00	,63	,00	,00	,07	,00
	4	,822	2,196	,00	,08	,00	,23	,00	,00	,64	,00
	5	,526	2,747	,00	,45	,67	,08	,00	,00	,12	,00
	6	,419	3,077	,00	,00	,01	,00	,87	,04	,00	,00
	7	,091	6,612	,01	,00	,11	,00	,05	,94	,00	,01
	8	,003	35,836	,99	,00	,03	,02	,03	,00	,10	,99

a. Dependent Variable: Conflict_count

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-1,49	25,16	1,47	2,167	1030
Std. Predicted Value	-1,364	10,934	,000	1,000	1030
Standard Error of Predicted Value	,146	2,691	,297	,157	1030
Adjusted Predicted Value	-1,51	29,68	1,47	2,240	1030
Residual	-15,755	57,276	,000	3,799	1030
Std. Residual	-4,133	15,025	,000	,997	1030
Stud. Residual	-4,530	15,117	-,001	1,009	1030
Deleted Residual	-19,676	57,977	-,007	3,900	1030
Stud. Deleted Residual	-4,574	17,147	,003	1,058	1030
Mahal. Distance	,518	511,852	6,993	20,527	1030
Cook's Distance	,000	,765	,004	,034	1030
Centered Leverage Value	,001	,497	,007	,020	1030

a. Dependent Variable: Conflict_count

Statistics

Coo_1_Large

N	Valid	1030
	Missing	189

Coo_1_Large

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	,00	1030	84,5	100,0	100,0
Missing	System	189	15,5		
Total		1219	100,0		

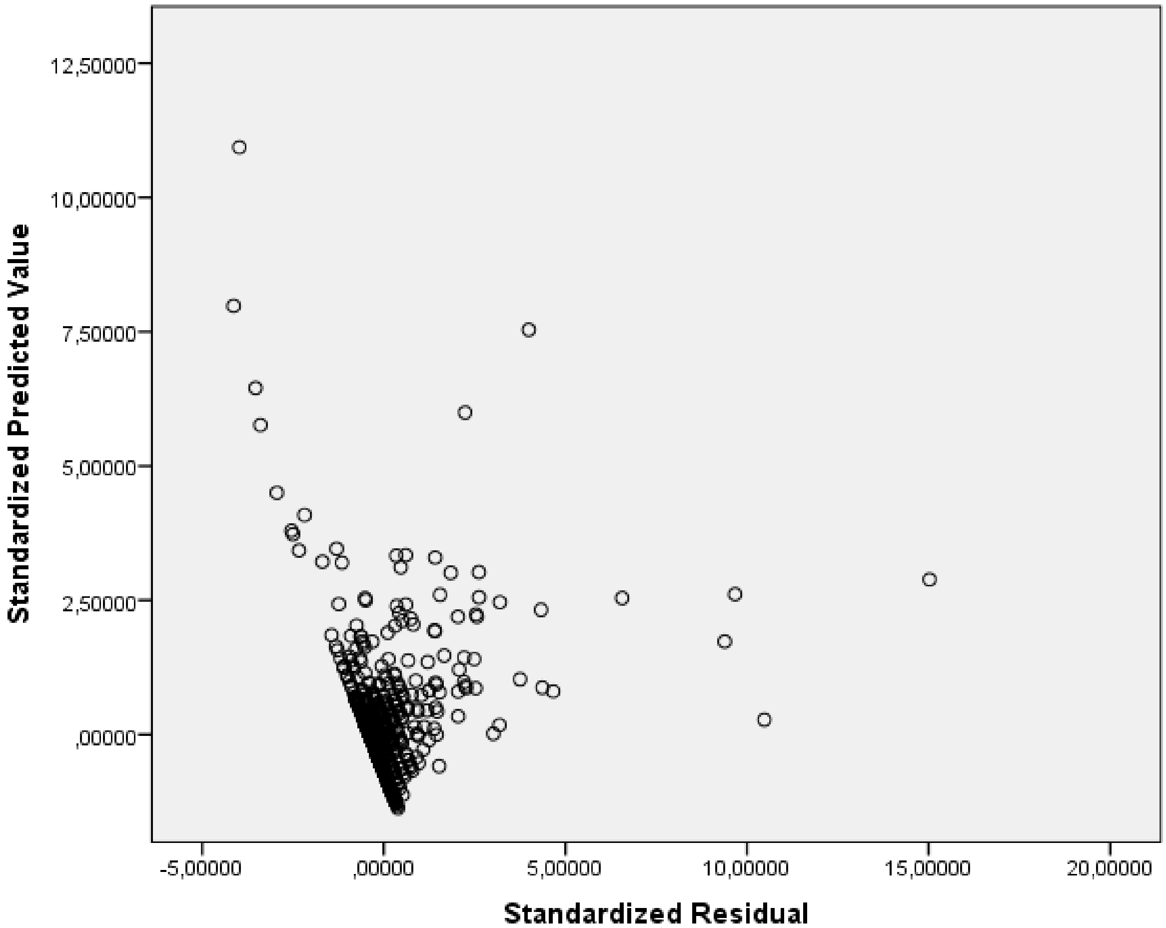
Statistics

ZRE_1_95_new

N	Valid	1030
	Missing	189

ZRE_1_95_new

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	,00	993	81,5	96,4	96,4
	1,00	37	3,0	3,6	100,0
	Total	1030	84,5	100,0	
Missing	System	189	15,5		
Total		1219	100,0		



Assumptions Model 1 and Model 2

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-1,72	25,61	1,47	2,157	1030
Std. Predicted Value	-1,478	11,189	,000	1,000	1030
Standard Error of Predicted Value	,145	2,645	,283	,138	1030
Adjusted Predicted Value	-1,74	30,13	1,47	2,229	1030
Residual	-15,607	57,113	,000	3,804	1030
Std. Residual	-4,090	14,969	,000	,997	1030
Stud. Residual	-4,646	15,055	-,001	1,007	1030
Deleted Residual	-20,131	57,774	-,008	3,884	1030
Stud. Deleted Residual	-4,693	17,055	,003	1,055	1030
Mahal. Distance	,488	493,601	5,994	18,992	1030
Cook's Distance	,000	,894	,003	,034	1030
Centered Leverage Value	,000	,480	,006	,018	1030

a. Dependent Variable: Conflict_count

Assumptions Model 3 and Model 4

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-1,48	25,15	1,47	2,165	1030
Std. Predicted Value	-1,361	10,942	,000	1,000	1030
Standard Error of Predicted Value	,136	1,826	,289	,124	1030
Adjusted Predicted Value	-1,50	29,67	1,47	2,233	1030
Residual	-15,692	57,265	,000	3,800	1030
Std. Residual	-4,117	15,025	,000	,997	1030
Stud. Residual	-4,530	15,117	-,001	1,009	1030
Deleted Residual	-19,671	57,965	-,004	3,897	1030
Stud. Deleted Residual	-4,574	17,145	,003	1,057	1030
Mahal. Distance	,318	235,311	5,994	11,296	1030
Cook's Distance	,000	,874	,004	,039	1030
Centered Leverage Value	,000	,229	,006	,011	1030

a. Dependent Variable: Conflict_count

Explanation of Assumptions. The frequency table of the variable ZRE_2_95 shows if there is any concern for outliers. According to Field (2013) the percentage of cases that have a residual that is greater than two standard deviations should not be higher than five percent. As the percentage in this study is only 3.6 percent there is no cause of concern.

Also, there is no cause of concern for influential cases as there are no cases which have a Cook's distance that is higher than 1. To check for the assumption of independent errors, the Durbin-Watson test is used. Durbin and Watson (1951) state that values below two indicate a positive correlation and values below one or above three are definitely a cause of concern. The value in Model 1 and Model 2 is 2.091 and the value in Model 3 and Model 4 is 2.086. This indicates that the residual terms are uncorrelated and positively correlated and there is no cause of concern. Another underlying assumption for the OLS regression is that there should be no perfect multicollinearity. Bowerman and O'Connell (1990) state that no VIF-value should be greater than 10 and the average VIF-value should not be substantially greater than 1. Menard (1995) further specifies that the tolerance value should not be below 0.2. These conditions are met in all Models and therefore this study safely concludes that there is no collinearity within the data.

Linear Regression Model 1 and Model 2

Descriptive Statistics

	Mean	Std. Deviation	N
Conflict_count	1,47	4,374	1030
numbeProtectedWithOutlUCN	1,64	8,332	1030
Polity2	1,72	5,218	1030
GDP growth per year	3,13524E+14	3,12153E+14	1030
InfantMortality	61,60427	26,794483	1030
Conflict Count (lagged)	1,4777	4,36113	1030
log_population	15,9854	1,39351	1030

Correlations

		Conflict_count	numbeProtectedWithOutlUCN	Polity2	GDP growth per year	InfantMortality	Conflict Count (lagged)	log_population
Pearson Correlation	Conflict_count	1,000	,096	,058	-,014	-,055	,440	,348
	numbeProtectedWithOutlUCN	,096	1,000	,035	-,045	-,111	,078	,099
	Polity2	,058	,035	1,000	,041	-,089	,075	-,047
	GDP growth per year	-,014	-,045	,041	1,000	-,013	,014	,185
	InfantMortality	-,055	-,111	-,089	-,013	1,000	-,070	,005
	Conflict Count (lagged)	,440	,078	,075	,014	-,070	1,000	,357
	log_population	,348	,099	-,047	,185	,005	,357	1,000
Sig. (1-tailed)	Conflict_count	.	,001	,032	,326	,040	,000	,000
	numbeProtectedWithOutlUCN	,001	.	,131	,074	,000	,006	,001
	Polity2	,032	,131	.	,096	,002	,008	,067
	GDP growth per year	,326	,074	,096	.	,337	,325	,000
	InfantMortality	,040	,000	,002	,337	.	,013	,434
	Conflict Count (lagged)	,000	,006	,008	,325	,013	.	,000
	log_population	,000	,001	,067	,000	,434	,000	.
N	Conflict_count	1030	1030	1030	1030	1030	1030	1030
	numbeProtectedWithOutlUCN	1030	1030	1030	1030	1030	1030	1030
	Polity2	1030	1030	1030	1030	1030	1030	1030
	GDP growth per year	1030	1030	1030	1030	1030	1030	1030
	InfantMortality	1030	1030	1030	1030	1030	1030	1030
	Conflict Count (lagged)	1030	1030	1030	1030	1030	1030	1030
	log_population	1030	1030	1030	1030	1030	1030	1030

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	numbeProtectedWithOutIUCN[b]	.	Enter
2	Polity2, GDP growth per year, Conflict Count (lagged), InfantMortality, log_population[b]	.	Enter

a. Dependent Variable: Conflict_count

b. All requested variables entered.

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,096[a]	,009	,008	4,355	,009	9,588	1	1028	,002	
2	,493[b]	,243	,239	3,815	,234	63,304	5	1023	,000	2,091

a. Predictors: (Constant), numbeProtectedWithOutIUCN

b. Predictors: (Constant), numbeProtectedWithOutIUCN, Polity2, GDP growth per year, Conflict Count (lagged), InfantMortality, log_population

c. Dependent Variable: Conflict_count

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	181,885	1	181,885	9,588	,002[b]
	Residual	19500,425	1028	18,969		
	Total	19682,311	1029			
2	Regression	4789,717	6	798,286	54,836	,000[c]
	Residual	14892,594	1023	14,558		
	Total	19682,311	1029			

a. Dependent Variable: Conflict_count

b. Predictors: (Constant), numbeProtectedWithOutIUCN

c. Predictors: (Constant), numbeProtectedWithOutIUCN, Polity2, GDP growth per year, Conflict Count (lagged), InfantMortality, log_population

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1,383	,138		10,000	,000	1,112	1,655		
	numbeProtectedWithOutIUCN	,050	,016	,096	3,097	,002	,018	,082	1,000	1,000
2	(Constant)	-10,296	1,491		-6,908	,000	-13,221	-7,371		
	numbeProtectedWithOutIUCN	,020	,014	,039	1,413	,158	-,008	,049	,971	1,029
	Polity2	,035	,023	,041	1,497	,135	-,011	,080	,978	1,023
	GDP growth per year	-8,716E-16	,000	-,062	-2,236	,026	,000	,000	,955	1,047
	InfantMortality	-,004	,004	-,024	-,879	,380	-,013	,005	,976	1,025
	Conflict Count (lagged)	,351	,029	,350	11,911	,000	,293	,409	,856	1,169
	log_population	,730	,094	,233	7,770	,000	,546	,914	,826	1,211

a. Dependent Variable: Conflict_count

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance	Collinearity Statistics VIF	Collinearity Statistics Minimum Tolerance
1	Polity2	,054[b]	1,750	,080	,055	,999	1,001	,999
	GDP growth per year	-,010[b]	-,314	,753	-,010	,998	1,002	,998
	InfantMortality	-,044[b]	-1,423	,155	-,044	,988	1,012	,988
	Conflict Count (lagged)	,435[b]	15,526	,000	,436	,994	1,006	,994
	log_population	,342[b]	11,651	,000	,342	,990	1,010	,990

a. Dependent Variable: Conflict_count

b. Predictors in the Model: (Constant), numbeProtectedWithOutIUCN

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	numbeProtectedWithOutIUCN	Polity2	GDP growth per year	InfantMortality	Conflict Count (lagged)	log_population
1	1	1,193	1,000	,40	,40					
	2	,807	1,216	,60	,60					
2	1	3,774	1,000	,00	,00	,01	,02	,01	,01	,00
	2	1,000	1,942	,00	,63	,05	,01	,00	,14	,00
	3	,880	2,071	,00	,23	,66	,00	,00	,08	,00
	4	,822	2,142	,00	,10	,25	,00	,00	,63	,00
	5	,420	2,997	,00	,01	,00	,89	,04	,00	,00
	6	,101	6,118	,01	,02	,01	,05	,93	,02	,01
	7	,003	34,427	,99	,01	,01	,03	,00	,12	,99

a. Dependent Variable: Conflict_count

Linear Regression Model 3 and Model 4

Descriptive Statistics

	Mean	Std. Deviation	N
Conflict_count	1,47	4,374	1030
total number of protectec areas without IUCN category	21,80	55,785	1030
Polity2	1,72	5,218	1030
GDP growth per year	3,13524E+14	3,12153E+14	1030
InfantMortality	61,60427	26,794483	1030
Conflict Count (lagged)	1,4777	4,36113	1030
log_population	15,9854	1,39351	1030

Correlations

		Conflict_count	total number of protectec areas without IUCN category	Polity2	GDP growth per year	InfantMortality	Conflict Count (lagged)	log_population
Pearson Correlation	Conflict_count	1,000	,208	,058	-,014	-,055	,440	,348
	total number of protectec areas without IUCN category	,208	1,000	,171	-,061	-,284	,230	,244
	Polity2	,058	,171	1,000	,041	-,089	,075	-,047
	GDP growth per year	-,014	-,061	,041	1,000	-,013	,014	,185
	InfantMortality	-,055	-,284	-,089	-,013	1,000	-,070	,005
	Conflict Count (lagged)	,440	,230	,075	,014	-,070	1,000	,357
	log_population	,348	,244	-,047	,185	,005	,357	1,000
Sig. (1-tailed)	Conflict_count	.	,000	,032	,326	,040	,000	,000
	total number of protectec areas without IUCN category	,000	.	,000	,024	,000	,000	,000
	Polity2	,032	,000	.	,096	,002	,008	,067
	GDP growth per year	,326	,024	,096	.	,337	,325	,000
	InfantMortality	,040	,000	,002	,337	.	,013	,434
	Conflict Count (lagged)	,000	,000	,008	,325	,013	.	,000
	log_population	,000	,000	,067	,000	,434	,000	.
N	Conflict_count	1030	1030	1030	1030	1030	1030	1030
	total number of protectec areas without IUCN category	1030	1030	1030	1030	1030	1030	1030
	Polity2	1030	1030	1030	1030	1030	1030	1030
	GDP growth per year	1030	1030	1030	1030	1030	1030	1030
	InfantMortality	1030	1030	1030	1030	1030	1030	1030
	Conflict Count (lagged)	1030	1030	1030	1030	1030	1030	1030
	log_population	1030	1030	1030	1030	1030	1030	1030

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	total number of protectec areas without IUCN category[b]	.	Enter
2	GDP growth per year, Polity2, Conflict Count (lagged), InfantMortality, log_population[b]	.	Enter

a. Dependent Variable: Conflict_count

b. All requested variables entered.

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,208[a]	,043	,042	4,280	,043	46,489	1	1028	,000	
2	,495[b]	,245	,241	3,811	,202	54,670	5	1023	,000	2,086

a. Predictors: (Constant), total number of protectec areas without IUCN category

b. Predictors: (Constant), total number of protectec areas without IUCN category, GDP growth per year, Polity2, Conflict Count (lagged), InfantMortality, log_population

c. Dependent Variable: Conflict_count

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	851,577	1	851,577	46,489	,000[b]
	Residual	18830,734	1028	18,318		
	Total	19682,311	1029			
2	Regression	4822,226	6	803,704	55,329	,000[c]
	Residual	14860,085	1023	14,526		
	Total	19682,311	1029			

a. Dependent Variable: Conflict_count

b. Predictors: (Constant), total number of protectec areas without IUCN category

c. Predictors: (Constant), total number of protectec areas without IUCN category, GDP growth per year, Polity2, Conflict Count (lagged), InfantMortality, log_population

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1,111	,143		7,756	,000	,830	1,392		
	total number of protectec areas without IUCN category	,016	,002	,208	6,818	,000	,012	,021	1,000	1,000
2	(Constant)	-9,968	1,502		-6,636	,000	-12,916	-7,021		
	total number of protectec areas without IUCN category	,005	,002	,062	2,059	,040	,000	,010	,808	1,238
	Polity2	,028	,023	,033	1,178	,239	-,018	,073	,951	1,051
	GDP growth per year	-8,074E-16	,000	-,058	-2,062	,039	,000	,000	,945	1,059
	InfantMortality	-,002	,005	-,012	-,419	,676	-,011	,007	,910	1,099
	Conflict Count (lagged)	,345	,030	,344	11,633	,000	,287	,403	,844	1,185
	log_population	,697	,096	,222	7,265	,000	,509	,885	,790	1,267

a. Dependent Variable: Conflict_count

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance	Collinearity Statistics VIF	Collinearity Statistics Minimum Tolerance
1	Polity2	,023[b]	,735	,462	,023	,971	1,030	,971
	GDP growth per year	-,001[b]	-,042	,966	-,001	,996	1,004	,996
	InfantMortality	,005[b]	,153	,878	,005	,920	1,088	,920
	Conflict Count (lagged)	,414[b]	14,496	,000	,412	,947	1,056	,947
	log_population	,316[b]	10,574	,000	,313	,941	1,063	,941

a. Dependent Variable: Conflict_count

b. Predictors in the Model: (Constant), total number of protectec areas without IUCN category

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	total number of protectec areas without IUCN category	Polity2	GDP growth per year	InfantMortality	Conflict Count (lagged)	log_population
1	1	1,364	1,000	,32	,32					
	2	,636	1,465	,68	,68					
2	1	3,899	1,000	,00	,01	,01	,02	,01	,01	,00
	2	1,091	1,890	,00	,25	,14	,02	,01	,19	,00
	3	,837	2,159	,00	,01	,68	,00	,00	,30	,00
	4	,661	2,429	,00	,55	,15	,00	,00	,40	,00
	5	,419	3,051	,00	,01	,00	,87	,05	,00	,00
	6	,091	6,556	,01	,13	,00	,05	,94	,00	,01
	7	,003	35,530	,99	,04	,02	,03	,00	,10	,99

a. Dependent Variable: Conflict_count

Robust Standard Errors Model 1

Model Information

Dependent Variable	Conflict_count
Probability Distribution	Normal
Link Function	Identity

Case Processing Summary

	N	Percent
Included	1173	96,2%
Excluded	46	3,8%
Total	1219	100,0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Conflict_count	1173	0	65	1,37	4,206
Covariate	numbeProtectedWithOutlUCN	1173	0	185	1,51	7,908

Goodness of Fit[a]

	Value	df	Value/df
Deviance	20520,041	1171	17,524
Scaled Deviance	1173,000	1171	
Pearson Chi-Square	20520,041	1171	17,524
Scaled Pearson Chi-Square	1173,000	1171	
Log Likelihood[b]	-3342,883		
Akaike's Information Criterion (AIC)	6691,765		
Finite Sample Corrected AIC (AICC)	6691,786		
Bayesian Information Criterion (BIC)	6706,967		
Consistent AIC (CAIC)	6709,967		

Dependent Variable: Conflict_count
Model: (Intercept), numbeProtectedWithOutlUCN

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
11,853	1	,001

Dependent Variable: Conflict_count
Model: (Intercept), numbeProtectedWithOutlUCN

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	111,805	1	,000
numbeProtectedWithOutlUCN	4,476	1	,034

Dependent Variable: Conflict_count
Model: (Intercept), numbeProtectedWithOutlUCN

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square	Hypothesis Test df	Hypothesis Test Sig.	Exp(B)	95% Wald Confidence Interval for Exp(B) Lower	95% Wald Confidence Interval for Exp(B) Upper
(Intercept)	1,293	,1223	1,053	1,532	111,805	1	,000	3,643	2,866	4,629
numbeProtectedWithOutlUCN	,053	,0252	,004	,103	4,476	1	,034	1,055	1,004	1,108
(Scale)	17,494[a]	,7223	16,134	18,968						

Dependent Variable: Conflict_count
Model: (Intercept), numbeProtectedWithOutlUCN

a. Maximum likelihood estimate.

Robust Standard Errors Model 2

Model Information

Dependent Variable	Conflict_count
Probability Distribution	Normal
Link Function	Identity

Case Processing Summary

	N	Percent
Included	1030	84,5%
Excluded	189	15,5%
Total	1219	100,0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Conflict_count	1030	0	65	1,47	4,374
Covariate	Polity2	1030	-9	10	1,72	5,218
	numbeProtectedWithOutlUCN	1030	0	185	1,64	8,332
	GDP growth per year	1030	-9,110E+14	9,785E+14	3,13524E+14	3,12153E+14
	InfantMortality	1030	10,200	149,200	61,60427	26,794483
	Conflict Count (lagged)	1030	,00	65,00	1,4777	4,36113
	log_population	1030	12,91	19,09	15,9854	1,39351

Goodness of Fit[a]

	Value	df	Value/df
Deviance	14892,594	1023	14,558
Scaled Deviance	1030,000	1023	
Pearson Chi-Square	14892,594	1023	14,558
Scaled Pearson Chi-Square	1030,000	1023	
Log Likelihood[b]	-2837,229		
Akaike's Information Criterion (AIC)	5690,458		
Finite Sample Corrected AIC (AICC)	5690,599		
Bayesian Information Criterion (BIC)	5729,956		
Consistent AIC (CAIC)	5737,956		

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, numbeProtectedWithOutlUCN, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
287,222	6	,000

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, numbeProtectedWithOutIUCN, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	32,053	1	,000
Polity2	2,661	1	,103
numbeProtectedWithOutIUCN	1,657	1	,198
GDP growth per year	6,117	1	,013
InfantMortality	,565	1	,452
Conflict Count (lagged)	13,061	1	,000
log_population	38,895	1	,000

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, numbeProtectedWithOutIUCN, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-10,296	1,8186	-13,860	-6,732	32,053	1	,000	3,377E-5	9,560E-7	,001
Polity2	,035	,0212	-,007	,076	2,661	1	,103	1,035	,993	1,079
numbeProtectedWithOutIUCN	,020	,0159	-,011	,052	1,657	1	,198	1,021	,989	1,053
GDP growth per year	-8,716E-16	3,5241E-16	-1,562E-15	-1,809E-16	6,117	1	,013	1,000	1,000	1,000
InfantMortality	-,004	,0053	-,014	,006	,565	1	,452	,996	,986	1,006
Conflict Count (lagged)	,351	,0972	,161	,542	13,061	1	,000	1,421	1,174	1,719
log_population	,730	,1170	,500	,959	38,895	1	,000	2,075	1,650	2,610
(Scale)	14,459[a]	,6371	13,262	15,763						

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, numbeProtectedWithOutIUCN, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population

a. Maximum likelihood estimate.

Robust Standard Errors Model 3

Model Information

Dependent Variable	Conflict_count
Probability Distribution	Normal
Link Function	Identity

Case Processing Summary

	N	Percent
Included	1173	96,2%
Excluded	46	3,8%
Total	1219	100,0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Conflict_count	1173	0	65	1,37	4,206
Covariate	total number of protectec areas without IUCN category	1173	0	482	19,39	52,685

Goodness of Fit[a]

	Value	df	Value/df
Deviance	19819,377	1171	16,925
Scaled Deviance	1173,000	1171	
Pearson Chi-Square	19819,377	1171	16,925
Scaled Pearson Chi-Square	1173,000	1171	
Log Likelihood[b]	-3322,506		
Akaike's Information Criterion (AIC)	6651,013		
Finite Sample Corrected AIC (AICC)	6651,033		
Bayesian Information Criterion (BIC)	6666,215		
Consistent AIC (CAIC)	6669,215		

Dependent Variable: Conflict_count
Model: (Intercept), total number of protectec areas without IUCN category

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
52,606	1	,000

Dependent Variable: Conflict_count
Model: (Intercept), total number of protectec areas without IUCN category

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	68,842	1	,000
total number of protectec areas without IUCN category	13,706	1	,000

Dependent Variable: Conflict_count
Model: (Intercept), total number of protectec areas without IUCN category

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	1,049	,1265	,801	1,297	68,842	1	,000	2,855	2,229	3,659
total number of protectec areas without IUCN category	,017	,0045	,008	,026	13,706	1	,000	1,017	1,008	1,026
(Scale)	16,896[a]	,6977	15,583	18,321						

Dependent Variable: Conflict_count
Model: (Intercept), total number of protectec areas without IUCN category

a. Maximum likelihood estimate.

Robust Standard Errors Model 4

Model Information

Dependent Variable	Conflict_count
Probability Distribution	Normal
Link Function	Identity

Case Processing Summary

	N	Percent
Included	1030	84,5%
Excluded	189	15,5%
Total	1219	100,0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Conflict_count	1030	0	65	1,47	4,374
Covariate	total number of protectec areas without IUCN category	1030	0	482	21,80	55,785
	Polity2	1030	-9	10	1,72	5,218
	GDP growth per year	1030	-9,110E+14	9,785E+14	3,13524E+14	3,12153E+14
	InfantMortality	1030	10,200	149,200	61,60427	26,794483
	Conflict Count (lagged)	1030	,00	65,00	1,4777	4,36113
	log_population	1030	12,91	19,09	15,9854	1,39351

Goodness of Fit[a]

	Value	df	Value/df
Deviance	14860,085	1023	14,526
Scaled Deviance	1030,000	1023	
Pearson Chi-Square	14860,085	1023	14,526
Scaled Pearson Chi-Square	1030,000	1023	
Log Likelihood[b]	-2836,103		
Akaike's Information Criterion (AIC)	5688,207		
Finite Sample Corrected AIC (AICC)	5688,348		
Bayesian Information Criterion (BIC)	5727,705		
Consistent AIC (CAIC)	5735,705		

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, total number of protectec areas without IUCN category, Polity2

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
289,473	6	,000

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, total number of protectec areas without IUCN category, Polity2

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	30,591	1	,000
log_population	35,566	1	,000
Conflict Count (lagged)	12,243	1	,000
InfantMortality	,128	1	,720
GDP growth per year	5,135	1	,023
total number of protectec areas without IUCN category	,732	1	,392
Polity2	2,115	1	,146

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, total number of protectec areas without IUCN category, Polity2

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-9,968	1,8023	-13,501	-6,436	30,591	1	,000	4,686E-5	1,370E-6	,002
log_population	,697	,1169	,468	,926	35,566	1	,000	2,008	1,597	2,525
Conflict Count (lagged)	,345	,0986	,152	,538	12,243	1	,000	1,412	1,164	1,713
InfantMortality	-,002	,0054	-,013	,009	,128	1	,720	,998	,987	1,009
GDP growth per year	-8,074E-16	3,5630E-16	-1,506E-15	-1,091E-16	5,135	1	,023	1,000	1,000	1,000
total number of protectec areas without IUCN category	,005	,0057	-,006	,016	,732	1	,392	1,005	,994	1,016
Polity2	,028	,0189	-,010	,065	2,115	1	,146	1,028	,990	1,067
(Scale)	14,427[a]	,6357	13,234	15,729						

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, total number of protectec areas without IUCN category, Polity2

a. Maximum likelihood estimate.

Clustered Standard Errors Model 1

Sample Design Information

		N
Unweighted Cases	Valid	1173
	Invalid	46
	Total	1219
Population Size		2354211,000
Stage 1	Strata	1
	Units	51
Sampling Design Degrees of Freedom		50

Variable Information

		Mean
Dependent Variable	Conflict_count	1,38
Covariates	numbeProtectedWithOutlUCN	1,51

Model Summary[a]

R Square	,010

a. Model: Conflict_count = (Intercept) + numbeProtectedWithOutlUCN

Tests of Model Effects[a]

Source	df1	df2	Wald F	Sig.
(Corrected Model)	1,000	50,000	2,279	,137
(Intercept)	1,000	50,000	15,605	,000
numbeProtectedWithOutlUCN	1,000	50,000	2,279	,137

a. Model: Conflict_count = (Intercept) + numbeProtectedWithOutlUCN

Parameter Estimates[a]

			95% Confidence Interval		Hypothesis Test		
Parameter	Estimate	Std. Error	Lower	Upper	t	df	Sig.
(Intercept)	1,294	,328	,636	1,953	3,950	50,000	,000
numbeProtectedWithOutlUCN	,053	,035	-,018	,124	1,509	50,000	,137

a. Model: Conflict_count = (Intercept) + numbeProtectedWithOutlUCN

Covariances of Parameter Estimates[a]

	(Intercept)	numbeProtectedWithOutlUCN
(Intercept)	,107	-,001
numbeProtectedWithOutlUCN	-,001	,001

a. Model: Conflict_count = (Intercept) + numbeProtectedWithOutlUCN

Correlations of Parameter Estimates[a]

	(Intercept)	numbeProtectedWithOutlUCN
(Intercept)	1,000	-,077
numbeProtectedWithOutlUCN	-,077	1,000

a. Model: Conflict_count = (Intercept) + numbeProtectedWithOutlUCN

Clustered Standard Errors Model 2

Sample Design Information

		N
Unweighted Cases	Valid	1030
	Invalid	189
	Total	1219
Population Size		2067807,000
Stage 1	Strata	1
	Units	49
Sampling Design Degrees of Freedom		48

Variable Information

		Mean
Dependent Variable	Conflict_count	1,47
Covariates	Polity2	1,73
	InfantMortality	61,56503
	GDP growth per year	3,13571E+14
	numbeProtectedWithOutlUCN	1,64
	Conflict Count (lagged)	1,4796
	log_population	15,9857

Model Summary[a]

R Square	,243

a. Model: Conflict_count = (Intercept) + Polity2 + InfantMortality + GDP + numbeProtectedWithOutlUCN + lag_Confl_c + log_population

Tests of Model Effects[a]

Source	df1	df2	Wald F	Sig.
(Corrected Model)	5,000	44,000	21,128	,000
(Intercept)	1,000	48,000	7,107	,010
Polity2	1,000	48,000	1,396	,243
InfantMortality	1,000	48,000	,315	,577
GDP	1,000	48,000	5,999	,018
numbeProtectedWithOutlUCN	1,000	48,000	1,598	,212
lag_Confl_c	1,000	48,000	30,308	,000
log_population	1,000	48,000	9,433	,004

a. Model: Conflict_count = (Intercept) + Polity2 + InfantMortality + GDP + numbeProtectedWithOutlUCN + lag_Confl_c + log_population

Parameter Estimates[a]

			95% Confidence Interval		Hypothesis Test		
Parameter	Estimate	Std. Error	Lower	Upper	t	df	Sig.
(Intercept)	-10,308	3,867	-18,083	-2,533	-2,666	48,000	,010
Polity2	,035	,029	-,024	,093	1,182	48,000	,243
InfantMortality	-,004	,007	-,018	,010	-,561	48,000	,577
GDP	-8,736E-16	3,567E-16	-1,591E-15	-1,564E-16	-2,449	48,000	,018
numbeProtectedWithOutlUCN	,020	,016	-,012	,053	1,264	48,000	,212
lag_Confl_c	,351	,064	,223	,479	5,505	48,000	,000
log_population	,731	,238	,252	1,209	3,071	48,000	,004

a. Model: Conflict_count = (Intercept) + Polity2 + InfantMortality + GDP + numbeProtectedWithOutlUCN + lag_Confl_c + log_population

Clustered Standard Errors Model 3

Sample Design Information

		N
Unweighted Cases	Valid	1173
	Invalid	46
	Total	1219
Population Size		2354211,000
Stage 1	Strata	1
	Units	51
Sampling Design Degrees of Freedom		50

Variable Information

		Mean
Dependent Variable	Conflict_count	1,38
Covariates	total number of protectec areas without IUCN category	19,43

Model Summary[a]

R Square	,044

a. Model: Conflict_count = (Intercept) + ToPA_NoC

Tests of Model Effects[a]

Source	df1	df2	Wald F	Sig.
(Corrected Model)	1,000	50,000	58,694	,000
(Intercept)	1,000	50,000	10,355	,002
ToPA_NoC	1,000	50,000	58,694	,000

a. Model: Conflict_count = (Intercept) + ToPA_NoC

Parameter Estimates[a]

Parameter	Estimate	Std. Error	95% Confidence Interval Lower	95% Confidence Interval Upper	Hypothesis Test t	Hypothesis Test df	Hypothesis Test Sig.
(Intercept)	1,050	,326	,395	1,706	3,218	50,000	,002
ToPA_NoC	,017	,002	,012	,021	7,661	50,000	,000

a. Model: Conflict_count = (Intercept) + ToPA_NoC

Covariances of Parameter Estimates[a]

	(Intercept)	ToPA_NoC
(Intercept)	,107	,000
ToPA_NoC	,000	,000

a. Model: Conflict_count = (Intercept) + ToPA_NoC

Correlations of Parameter Estimates[a]

	(Intercept)	ToPA_NoC
(Intercept)	1,000	-,340
ToPA_NoC	-,340	1,000

a. Model: Conflict_count = (Intercept) + ToPA_NoC

Clustered Standard Errors Model 4

Sample Design Information

		N
Unweighted Cases	Valid	1030
	Invalid	189
	Total	1219
Population Size		2067807,000
Stage 1	Strata	1
	Units	49
Sampling Design Degrees of Freedom		48

Variable Information

		Mean
Dependent Variable	Conflict_count	1,47
Covariates	Polity2	1,73
	InfantMortality	61,56503
	GDP growth per year	3,13571E+14
	Conflict Count (lagged)	1,4796
	log_population	15,9857
	total number of protectec areas without IUCN category	21,83

Model Summary[a]

R Square	,245

a. Model: Conflict_count = (Intercept) + Polity2 + InfantMortality + GDP + lag_Confl_c + log_population + ToPA_NoC

Tests of Model Effects[a]

Source	df1	df2	Wald F	Sig.
(Corrected Model)	5,000	44,000	50,631	,000
(Intercept)	1,000	48,000	6,371	,015
Polity2	1,000	48,000	,878	,353
InfantMortality	1,000	48,000	,085	,772
GDP	1,000	48,000	4,786	,034
lag_Confl_c	1,000	48,000	25,489	,000
log_population	1,000	48,000	8,057	,007
ToPA_NoC	1,000	48,000	3,458	,069

a. Model: Conflict_count = (Intercept) + Polity2 + InfantMortality + GDP + lag_Confl_c + log_population + ToPA_NoC

Parameter Estimates[a]

			95% Confidence Interval		Hypothesis Test		
Parameter	Estimate	Std. Error	Lower	Upper	t	df	Sig.
(Intercept)	-9,980	3,954	-17,929	-2,030	-2,524	48,000	,015
Polity2	,027	,029	-,031	,086	,937	48,000	,353
InfantMortality	-,002	,007	-,015	,011	-,291	48,000	,772
GDP	-8,092E-16	3,699E-16	-1,553E-15	-6,546E-17	-2,188	48,000	,034
lag_Confl_c	,345	,068	,207	,482	5,049	48,000	,000
log_population	,698	,246	,204	1,192	2,838	48,000	,007
ToPA_NoC	,005	,003	,000	,010	1,859	48,000	,069

a. Model: Conflict_count = (Intercept) + Polity2 + InfantMortality + GDP + lag_Confl_c + log_population + ToPA_NoC

Negative Binomial Regression Model 5

Model Information

Dependent Variable	Conflict_count
Probability Distribution	Negative binomial (1)
Link Function	Log

Case Processing Summary

	N	Percent
Included	1030	84,5%
Excluded	189	15,5%
Total	1219	100,0%

Case Processing Summary

	N	Percent
Included	1030	84,5%
Excluded	189	15,5%
Total	1219	100,0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Conflict_count	1030	0	65	1,47	4,374
Covariate	Polity2	1030	-9	10	1,72	5,218
	numbeProtectedWithOutl UCN	1030	0	185	1,64	8,332
	GDP growth per year	1030	-9,110E+14	9,785E+14	3,13524E+14	3,12153E+14
	InfantMortality	1030	10,200	149,200	61,60427	26,794483
	Conflict Count (lagged)	1030	,00	65,00	1,4777	4,36113
	log_population	1030	12,91	19,09	15,9854	1,39351

Goodness of Fit[a]

	Value	df	Value/df
Deviance	1066,021	1023	1,042
Scaled Deviance	1066,021	1023	
Pearson Chi-Square	2250,160	1023	2,200
Scaled Pearson Chi-Square	2250,160	1023	
Log Likelihood[b]	-1295,729		
Akaike's Information Criterion (AIC)	2605,458		
Finite Sample Corrected AIC (AICC)	2605,567		
Bayesian Information Criterion (BIC)	2640,019		
Consistent AIC (CAIC)	2647,019		

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, numbeProtectedWithOutIUCN, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
838,474	6	,000

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, numbeProtectedWithOutIUCN, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	218,381	1	,000
Polity2	3,334	1	,068
numbeProtectedWithOutIUCN	2,657	1	,103
GDP growth per year	21,073	1	,000
InfantMortality	12,529	1	,000
Conflict Count (lagged)	48,992	1	,000
log_population	226,278	1	,000

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, numbeProtectedWithOutIUCN, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	Upper	Hypothesis Test Wald Chi-Square	df	Sig.	Exp(B)	95% Wald Confidence Interval for Exp(B) Lower	Upper
(Intercept)	-11,531	,7803	-13,061	-10,002	218,381	1	,000	9,816E-6	2,127E-6	4,531E-5
Polity2	,019	,0106	-,001	,040	3,334	1	,068	1,019	,999	1,041
numbeProtectedWithOutIUCN	,009	,0055	-,002	,020	2,657	1	,103	1,009	,998	1,020
GDP growth per year	-7,328E-16	1,5963E-16	-1,046E-15	-4,199E-16	21,073	1	,000	1,000	1,000	1,000
InfantMortality	-,006	,0018	-,010	-,003	12,529	1	,000	,994	,990	,997
Conflict Count (lagged)	,105	,0150	,076	,135	48,992	1	,000	1,111	1,079	1,144
log_population	,723	,0481	,629	,817	226,278	1	,000	2,060	1,875	2,264
(Scale)	1[a]									
(Negative binomial)	1[a]									

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, numbeProtectedWithOutIUCN, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population

a. Fixed at the displayed value.

Negative binomial Regression Model 6

Model Information

Dependent Variable	Conflict_count
Probability Distribution	Negative binomial (1)
Link Function	Log

Case Processing Summary

	N	Percent
Included	1030	84,5%
Excluded	189	15,5%
Total	1219	100,0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Conflict_count	1030	0	65	1,47	4,374
Covariate	Polity2	1030	-9	10	1,72	5,218
	GDP growth per year	1030	-9,110E+14	9,785E+14	3,13524E+14	3,12153E+14
	InfantMortality	1030	10,200	149,200	61,60427	26,794483
	Conflict Count (lagged)	1030	,00	65,00	1,4777	4,36113
	log_population	1030	12,91	19,09	15,9854	1,39351
	total number of protectec areas without IUCN category	1030	0	482	21,80	55,785

Goodness of Fit[a]

	Value	df	Value/df
Deviance	1065,194	1023	1,041
Scaled Deviance	1065,194	1023	
Pearson Chi-Square	2270,325	1023	2,219
Scaled Pearson Chi-Square	2270,325	1023	
Log Likelihood[b]	-1295,316		
Akaike's Information Criterion (AIC)	2604,631		
Finite Sample Corrected AIC (AICC)	2604,741		
Bayesian Information Criterion (BIC)	2639,192		
Consistent AIC (CAIC)	2646,192		

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population, total number of protectec areas without IUCN category[a]

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
839,300	6	,000

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population, total number of protectec areas without IUCN category[a]

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	202,085	1	,000
Polity2	1,757	1	,185
GDP growth per year	19,556	1	,000
InfantMortality	8,530	1	,003
Conflict Count (lagged)	50,319	1	,000
log_population	200,530	1	,000
total number of protectec areas without IUCN category	3,857	1	,050

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population, total number of protectec areas without IUCN category

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square	Hypothesis Test df	Hypothesis Test Sig.	Exp(B)	95% Wald Confidence Interval for Exp(B) Lower	95% Wald Confidence Interval for Exp(B) Upper
(Intercept)	-11,281	,7936	-12,836	-9,726	202,085	1	,000	1,261E-5	2,662E-6	5,974E-5
Polity2	,015	,0110	-,007	,036	1,757	1	,185	1,015	,993	1,037
GDP growth per year	-7,075E-16	1,5999E-16	-1,021E-15	-3,939E-16	19,556	1	,000	1,000	1,000	1,000
InfantMortality	-,006	,0019	-,009	-,002	8,530	1	,003	,995	,991	,998
Conflict Count (lagged)	,107	,0151	,077	,137	50,319	1	,000	1,113	1,081	1,146
log_population	,703	,0497	,606	,800	200,530	1	,000	2,020	1,833	2,227
total number of protectec areas without IUCN category	,001	,0008	3,033E-6	,003	3,857	1	,050	1,001	1,000	1,003
(Scale)	1[a]									
(Negative binomial)	1[a]									

Dependent Variable: Conflict_count
Model: (Intercept), Polity2, GDP growth per year, InfantMortality, Conflict Count (lagged), log_population, total number of protectec areas without IUCN category

a. Fixed at the displayed value.

Poisson Model 5

Model Information

Dependent Variable	Conflict_count
Probability Distribution	Poisson
Link Function	Log

Case Processing Summary

	N	Percent
Included	1030	84,5%
Excluded	189	15,5%
Total	1219	100,0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Conflict_count	1030	0	65	1,47	4,374
Covariate	Polity2	1030	-9	10	1,72	5,218
	GDP growth per year	1030	-9,110E+14	9,785E+14	3,13524E+14	3,12153E+14
	InfantMortality	1030	10,200	149,200	61,60427	26,794483
	Conflict Count (lagged)	1030	,00	65,00	1,4777	4,36113
	log_population	1030	12,91	19,09	15,9854	1,39351
	numbeProtectedWithOutIUCN	1030	0	185	1,64	8,332

Goodness of Fit[a]

	Value	df	Value/df
Deviance	2901,368	1023	2,836
Scaled Deviance	2901,368	1023	
Pearson Chi-Square	5818,321	1023	5,688
Scaled Pearson Chi-Square	5818,321	1023	
Log Likelihood[b]	-1958,523		
Akaike's Information Criterion (AIC)	3931,046		
Finite Sample Corrected AIC (AICC)	3931,156		
Bayesian Information Criterion (BIC)	3965,607		
Consistent AIC (CAIC)	3972,607		

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, Polity2, numbeProtectedWithOutIUCN

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
2196,440	6	,000

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, Polity2, numbeProtectedWithOutIUCN

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	77,004	1	,000
log_population	99,175	1	,000
Conflict Count (lagged)	9,831	1	,002
InfantMortality	3,405	1	,065
GDP growth per year	10,737	1	,001
Polity2	5,938	1	,015
numbeProtectedWithOutIUCN	3,393	1	,065

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, Polity2, numbeProtectedWithOutIUCN

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-13,939	1,5884	-17,052	-10,825	77,004	1	,000	8,841E-7	3,931E-8	1,989E-5
log_population	,880	,0884	,707	1,053	99,175	1	,000	2,411	2,028	2,867
Conflict Count (lagged)	,026	,0083	,010	,042	9,831	1	,002	1,026	1,010	1,043
InfantMortality	-,006	,0035	-,013	,000	3,405	1	,065	,994	,987	1,000
GDP growth per year	-7,561E-16	2,3075E-16	-1,208E-15	-3,038E-16	10,737	1	,001	1,000	1,000	1,000
Polity2	,036	,0149	,007	,066	5,938	1	,015	1,037	1,007	1,068
numbeProtectedWithOutIUCN	,005	,0029	,000	,011	3,393	1	,065	1,005	1,000	1,011
(Scale)	1[a]									

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, Polity2, numbeProtectedWithOutIUCN

a. Fixed at the displayed value.

Poisson Model 6

Model Information

Dependent Variable	Conflict_count
Probability Distribution	Poisson
Link Function	Log

Case Processing Summary

	N	Percent
Included	1030	84,5%
Excluded	189	15,5%
Total	1219	100,0%

Continuous Variable Information

		N	Minimum	Maximum	Mean	Std. Deviation
Dependent Variable	Conflict_count	1030	0	65	1,47	4,374
Covariate	Polity2	1030	-9	10	1,72	5,218
	GDP growth per year	1030	-9,110E+14	9,785E+14	3,13524E+14	3,12153E+14
	InfantMortality	1030	10,200	149,200	61,60427	26,794483
	Conflict Count (lagged)	1030	,00	65,00	1,4777	4,36113
	log_population	1030	12,91	19,09	15,9854	1,39351
	total number of protectec areas without IUCN category	1030	0	482	21,80	55,785

Goodness of Fit[a]

	Value	df	Value/df
Deviance	2907,379	1023	2,842
Scaled Deviance	2907,379	1023	
Pearson Chi-Square	5829,241	1023	5,698
Scaled Pearson Chi-Square	5829,241	1023	
Log Likelihood[b]	-1961,529		
Akaike's Information Criterion (AIC)	3937,058		
Finite Sample Corrected AIC (AICC)	3937,167		
Bayesian Information Criterion (BIC)	3971,619		
Consistent AIC (CAIC)	3978,619		

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, Polity2, total number of protectec areas without IUCN category

a. Information criteria are in smaller-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
2190,429	6	,000

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, Polity2, total number of protectec areas without IUCN category

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	77,928	1	,000
log_population	101,149	1	,000
Conflict Count (lagged)	9,808	1	,002
InfantMortality	2,546	1	,111
GDP growth per year	9,253	1	,002
Polity2	5,492	1	,019
total number of protectec areas without IUCN category	,163	1	,687

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, Polity2, total number of protectec areas without IUCN category

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-13,889	1,5734	-16,973	-10,805	77,928	1	,000	9,290E-7	4,254E-8	2,029E-5
log_population	,876	,0872	,706	1,047	101,149	1	,000	2,402	2,025	2,850
Conflict Count (lagged)	,026	,0083	,010	,042	9,808	1	,002	1,026	1,010	1,043
InfantMortality	-,006	,0039	-,014	,001	2,546	1	,111	,994	,986	1,001
GDP growth per year	-7,506E-16	2,4675E-16	-1,234E-15	-2,670E-16	9,253	1	,002	1,000	1,000	1,000
Polity2	,035	,0147	,006	,063	5,492	1	,019	1,035	1,006	1,065
total number of protectec areas without IUCN category	,000	,0010	-,002	,002	,163	1	,687	1,000	,998	1,002
(Scale)	1[a]									

Dependent Variable: Conflict_count
Model: (Intercept), log_population, Conflict Count (lagged), InfantMortality, GDP growth per year, Polity2, total number of protectec areas without IUCN category

a. Fixed at the displayed value.

HCREG, Hayes

Hayes and Cai (2007) discuss heteroskedasticity-consistent standard error estimators in their article and recommend the use of one of these estimators routinely when conducting hypothesis tests using the OLS regression model. Therefore, their software is applied to account for the observed heteroscedasticity. Unfortunately, an error code is displayed when more than four variables are entered in the model

```
Run MATRIX procedure:

HC Method
 3

Criterion Variable
 Conflict

Model Fit:
       R-sq          F        df1        df2          p
      ,0458     4,7918     3,0000  1101,0000      ,0025

Heteroscedasticity-Consistent Regression Results
              Coeff     SE(HC)          t      P>|t|
Constant     1,0369      ,1326     7,8201      ,0000
Polity2       ,0193      ,0195      ,9935      ,3207
numbePro      ,0144      ,0241      ,5968      ,5508
ToPA_NoC      ,0155      ,0050     3,0664      ,0022

------ END MATRIX -----
```

```
Run MATRIX procedure:
Error encountered in source line #  1412

Error # 12417
Source operand is singular for INV.
Execution of this command stops.
Error encountered in source line #  1413

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'B' is undefined
Error encountered in source line #  1413

Error # 12345
Undefined operand for NROW or NCOL.
Error encountered in source line #  1414

Error # 12417
Source operand is singular for INV.
Execution of this command stops.
```

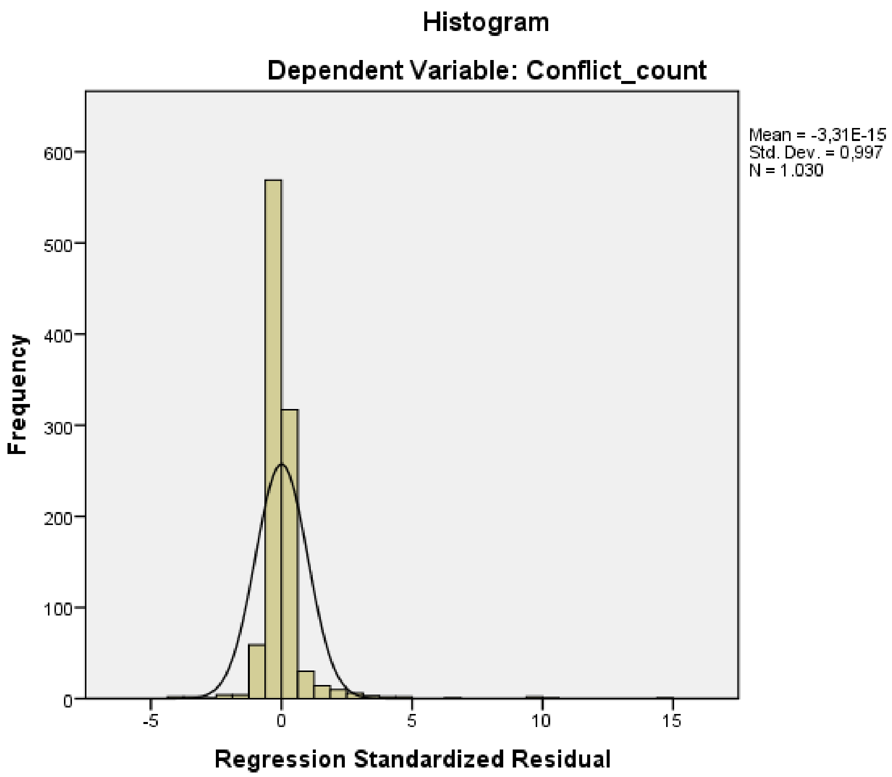
```
Error encountered in source line #  1417

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'INVXTX' is undefined
Error encountered in source line #  1417

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Matrix - 'INVXTX' is undefined
Error encountered in source line #  1417

Error # 12343
Undefined operand in matrix multiply.
Error encountered in source line #  1419

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'B' is undefined
Error encountered in source line #  1419

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Matrix - 'B' is undefined
Error encountered in source line #  1419

Error # 12343
Undefined operand in matrix multiply.
Error encountered in source line #  1420

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'RESID' is undefined
Error encountered in source line #  1420

Error # 12347
Undefined operand for binary operator.
Error encountered in source line #  1421

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'B' is undefined
Error encountered in source line #  1421

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Matrix - 'B' is undefined
Error encountered in source line #  1421

Error # 12343
Undefined operand in matrix multiply.
Error encountered in source line #  1422

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'RESID' is undefined
```

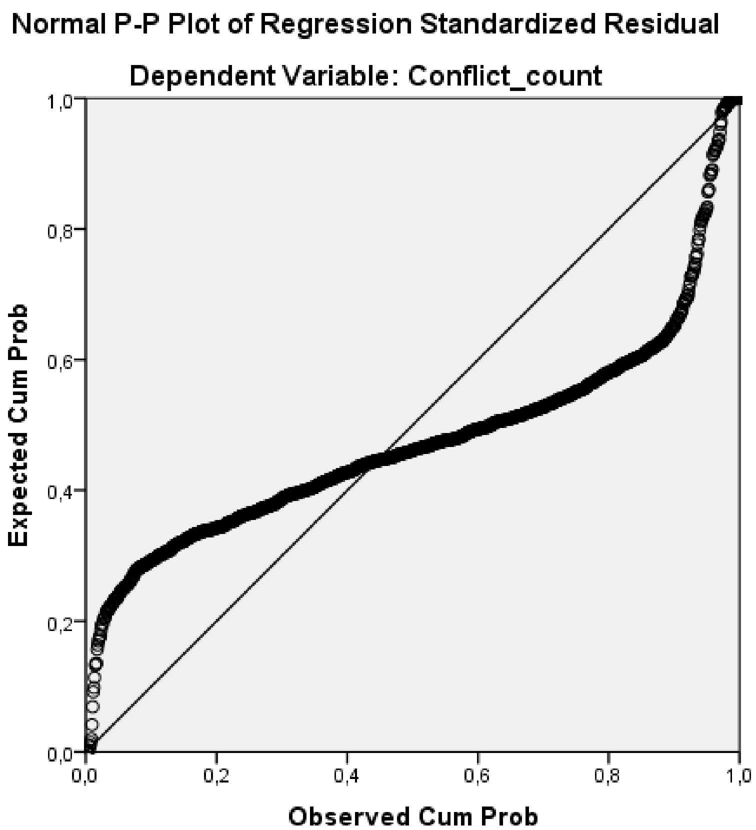
```
Error encountered in source line #  1422

Error # 12396
Undefined source operand in one of the CMAX, CMIN, CSSQ, CSUM.
Error encountered in source line #  1424

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'K' is undefined
Error encountered in source line #  1424

Error # 12339
Loop "TO" value undefined or non-scalar.
Error encountered in source line #  1447

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'INVXTX' is undefined
Error encountered in source line #  1447

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Matrix - 'INVXTX' is undefined
Error encountered in source line #  1447

Error # 12343
Undefined operand in matrix multiply.
Error encountered in source line #  1448

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'K' is undefined
Error encountered in source line #  1448

Error # 12347
Undefined operand for binary operator.
Error encountered in source line #  1468

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'B' is undefined
Error encountered in source line #  1468

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Matrix - 'B' is undefined
Error encountered in source line #  1468

Error # 12343
Undefined operand in matrix multiply.
Error encountered in source line #  1469

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'F' is undefined
Error encountered in source line #  1469
```

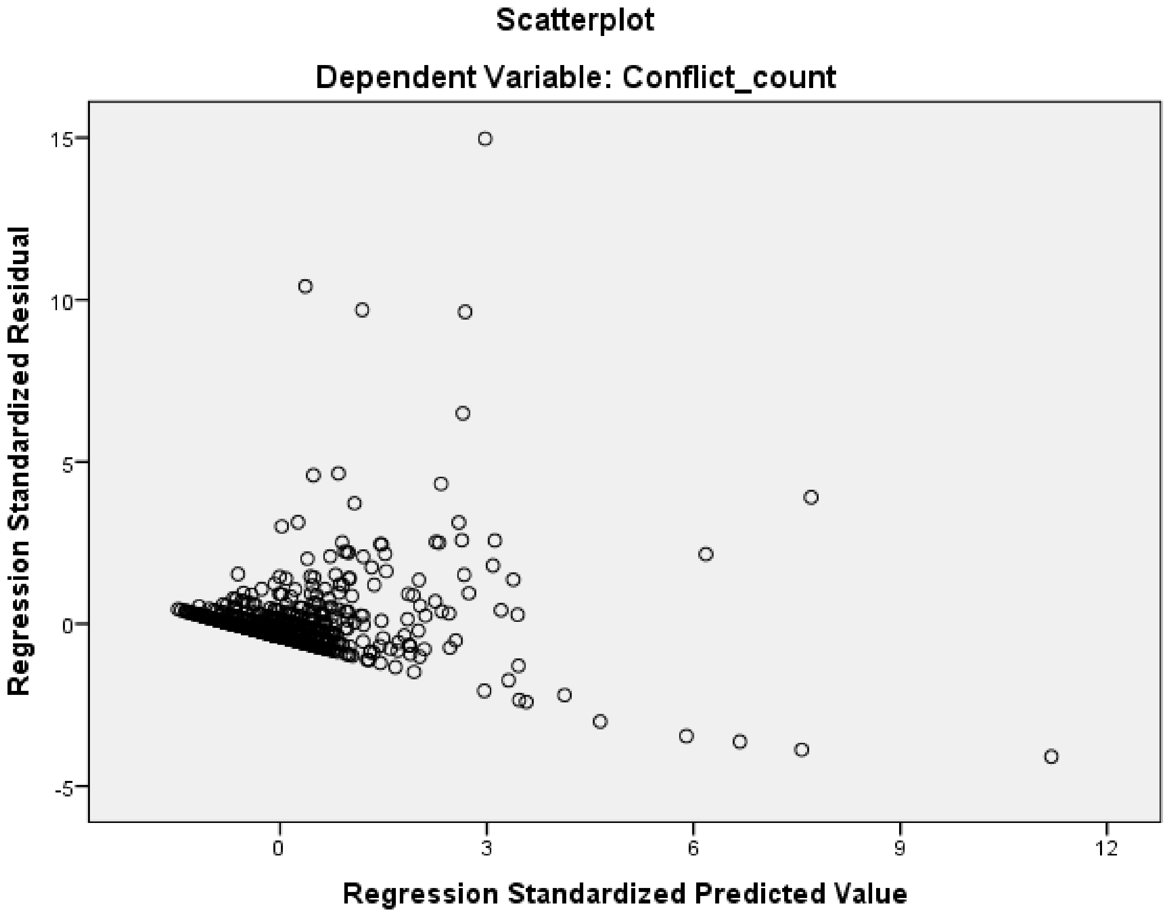
```
Error # 12428
First argument is undefined for MOD, or CHICDF, or TCDF, or FCDF.
Error encountered in source line #  1470

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'ESS' is undefined
Error encountered in source line #  1470

Error # 12347
Undefined operand for binary operator.
Error encountered in source line #  1471

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'R2' is undefined
Error encountered in source line #  1471

Error # 12363
Undefined operand in the expression inside brackets.

HC Method
 3

Criterion Variable
 Conflict
Error encountered in source line #  1476

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'PF' is undefined
Error encountered in source line #  1476

Error # 12332
Undefined variable in PRINT.
Error encountered in source line #  1477

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'HC' is undefined
Error encountered in source line #  1477

Error # 12366
Undefined operand in DIAG.
Error encountered in source line #  1478

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'B' is undefined
Error encountered in source line #  1478

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Matrix - 'SEBHC' is undefined
Error encountered in source line #  1478
```

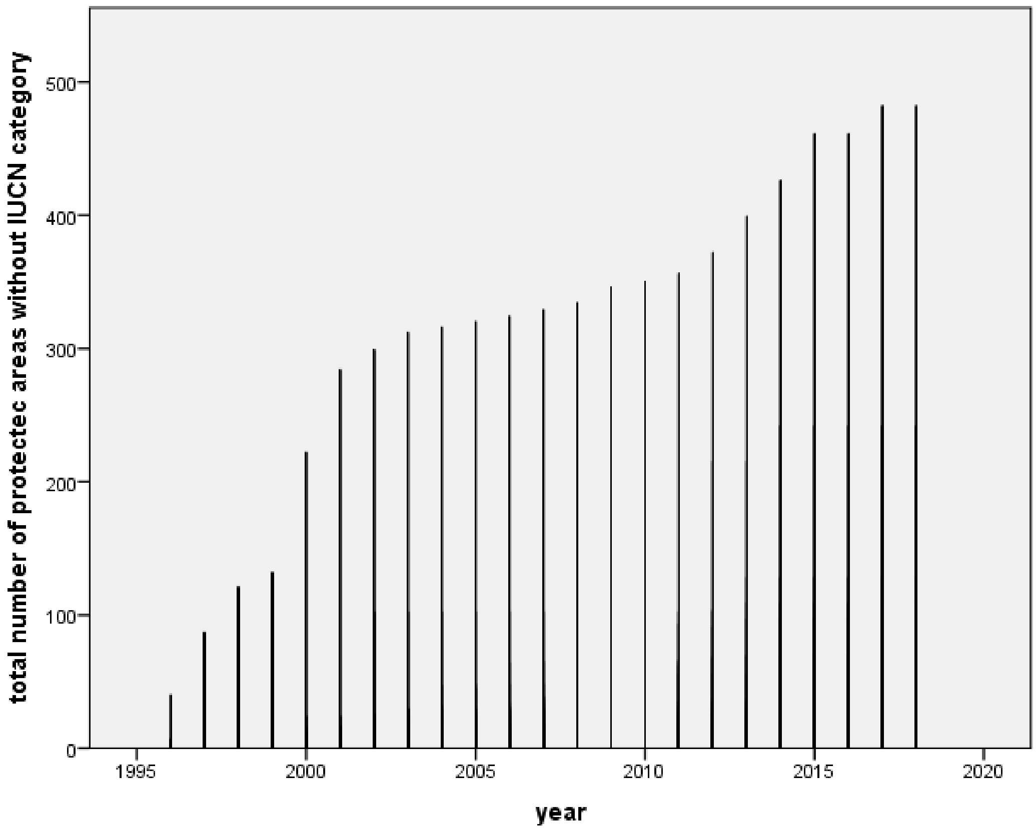
```
Error # 12347
Undefined operand for binary operator.
Error encountered in source line #  1479

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'TE' is undefined
Error encountered in source line #  1479

Error # 12346
Undefined operand for unary operator.
Error encountered in source line #  1480

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'B' is undefined
Error encountered in source line #  1480

Error # 12363
Undefined operand in the expression inside brackets.
Error encountered in source line #  1482

Error # 12492
An attempt has been made to use previously undefined matrix (or scalar).
Execution of this command stops.
Matrix - 'OPUT' is undefined
Error encountered in source line #  1482

Error # 12332
Undefined variable in PRINT.

------ END MATRIX -----
```

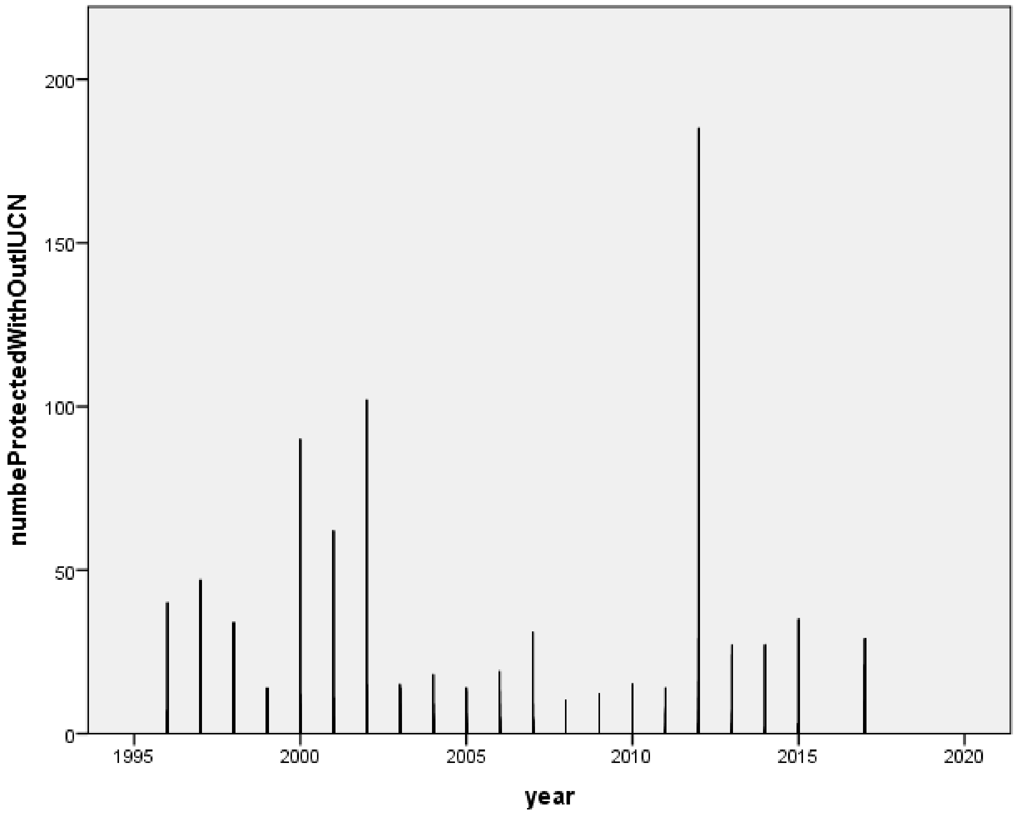
Graphs

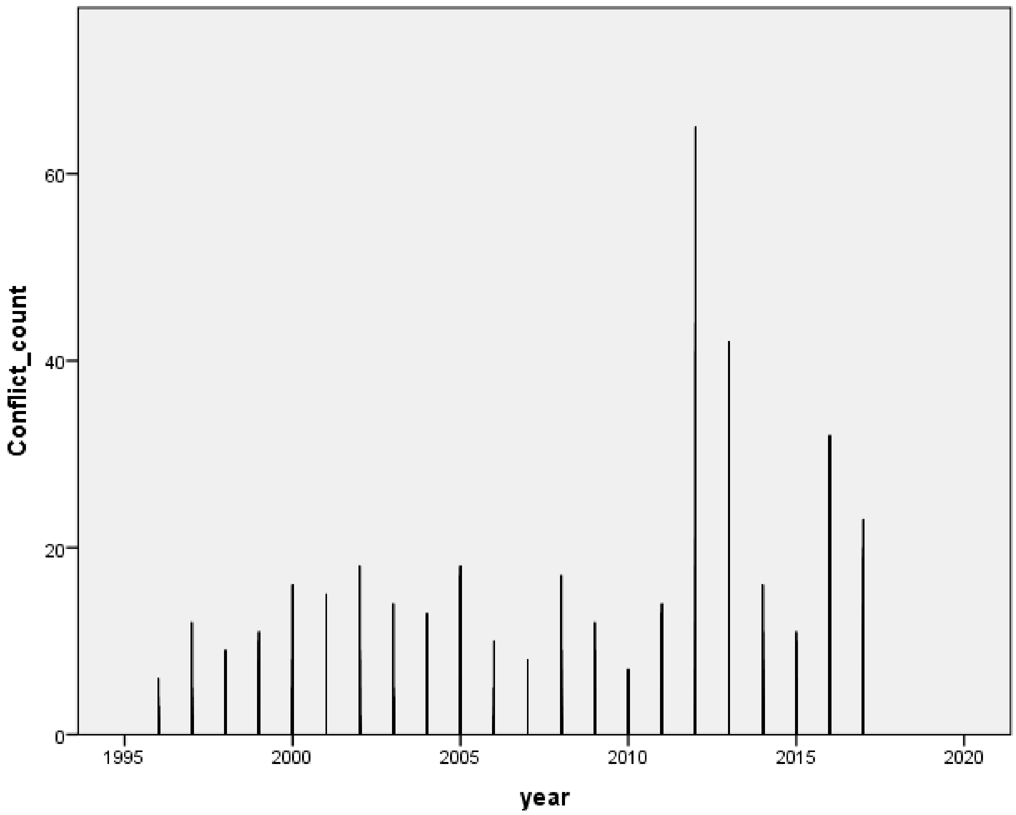

Histogram
Dependent Variable: Conflict_count
Mean = -3,31E-15
Std. Dev. = 0,997
N = 1.030
Frequency
600
500
400
300
200
100
0
-5
0
5
10
15
Regression Standardized Residual

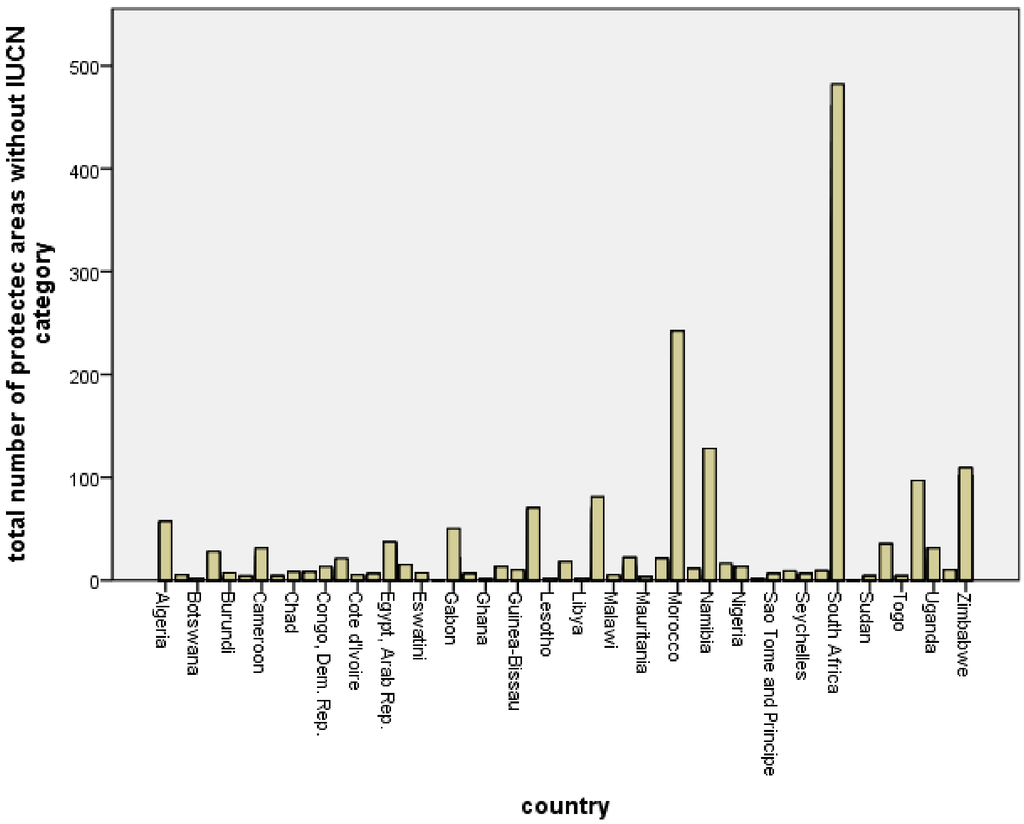

Normal P-P Plot of Regression Standardized Residual
Dependent Variable: Conflict_count
Expected Cum Prob
1,0
0,8
0,6
0,4
0,2
0,0
0,0
0,2
0,4
0,6
0,8
1,0
Observed Cum Prob

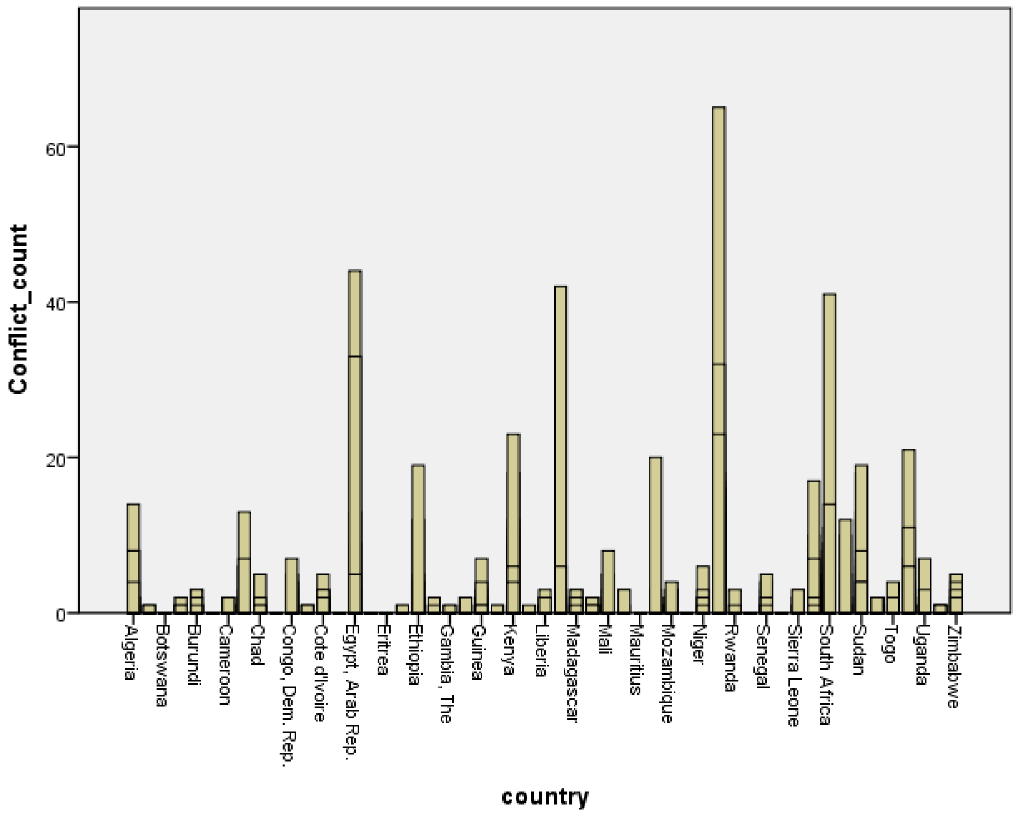

Scatterplot
Dependent Variable: Conflict_count
Regression Standardized Residual
15
10
5
0
-5
0
3
6
9
12
Regression Standardized Predicted Value

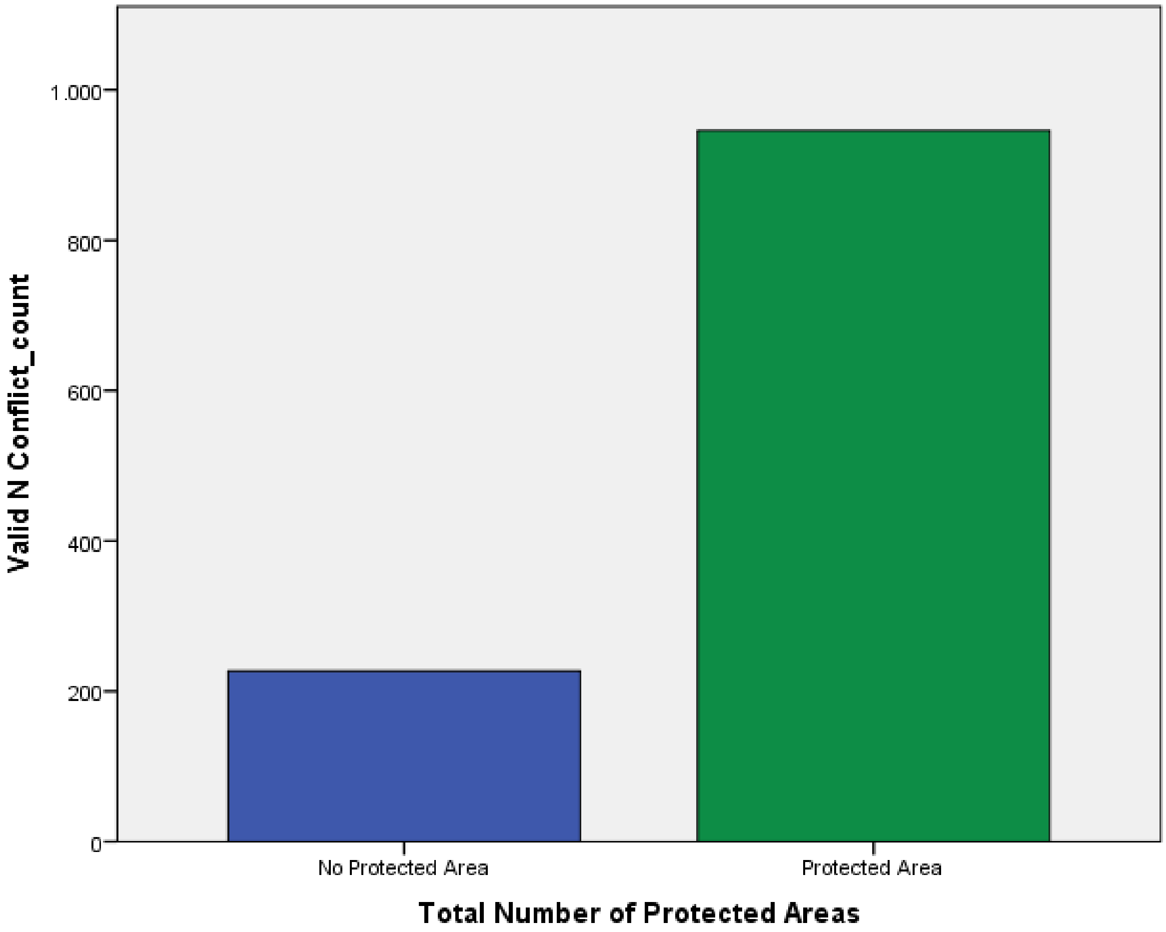

total number of protectec areas without IUCN category
500
400
300
200
100
0
1995
2000
2005
2010
2015
2020
year


numbeProtectedWithOutIUCN
200
150
100
50
0
1995
2000
2005
2010
2015
2020
year


Conflict_count
60
40
20
0
1995
2000
2005
2010
2015
2020
year


total number of protectec areas without IUCN category
0
100
200
300
400
500
Algeria
Botswana
Burundi
Cameroon
Chad
Congo, Dem. Rep.
Cote d'Ivoire
Egypt, Arab Rep.
Eswatini
Gabon
Ghana
Guinea-Bissau
Lesotho
Libya
Malawi
Mauritania
Morocco
Namibia
Nigeria
Sao Tome and Principe
Seychelles
South Africa
Sudan
Togo
Uganda
Zimbabwe
country


Conflict_count
0
20
40
60
Algeria
Botswana
Burundi
Cameroon
Chad
Congo, Dem. Rep.
Cote d'Ivoire
Egypt, Arab Rep.
Eritrea
Ethiopia
Gambia, The
Guinea
Kenya
Liberia
Madagascar
Mali
Mauritius
Mozambique
Niger
Rwanda
Senegal
Sierra Leone
South Africa
Sudan
Togo
Uganda
Zimbabwe
country



Valid N Conflict_count
1.000
800
600
400
200
0
No Protected Area
Protected Area
Total Number of Protected Areas

Syntax of SPSS

lag dependent variable

```
DO IF(year=1996)
RECODE lag_Confl_c(ELSE=999)
END IF
EXECUTE.

RECODE lag_confl_c (999=SYSMIS)
EXECUTE.

MEANS lag_confl_c BY year
EXECUTE.

* Encoding: UTF-8.
```

Log population

```
DATASET ACTIVATE DataSet1.
COMPUTE log_population=LN(Populationtotal).
EXECUTE.
```

Descriptive Statistics

```
DESCRIPTIVES VARIABLES=Polity2 numbeProtectedWithOutIUCN GDP
            InfantMortality Conflict_count
   lag_Confl_c ToPA_NoC log_population
  /STATISTICS=MEAN STDDEV VARIANCE MIN MAX.
```

Regression Model 1 to Model 4

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Conflict_count
  /METHOD=ENTER numbeProtectedWithOutIUCN
  /METHOD=ENTER Polity2 GDP InfantMortality lag_Confl_c log_population
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /RESIDUALS DURBIN HISTOGRAM(ZRESID) NORMPROB(ZRESID)
  /CASEWISE PLOT(ZRESID) OUTLIERS(2)
  /SAVE PRED ZPRED ADJPRED MAHAL COOK LEVER ZRESID DRESID SDRESID
            SDBETA SDFIT COVRATIO.

REGRESSION
```

```
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Conflict_count
  /METHOD=ENTER ToPA_NoC
  /METHOD=ENTER Polity2 GDP InfantMortality lag_Confl_c log_population
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /RESIDUALS DURBIN HISTOGRAM(ZRESID) NORMPROB(ZRESID)
  /CASEWISE PLOT(ZRESID) OUTLIERS(2)
  /SAVE PRED ZPRED ADJPRED MAHAL COOK LEVER ZRESID DRESID SDRESID
        SDBETA SDFIT COVRATIO.
```

Regression checking for assumptions

```
REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) R ANOVA COLLIN TOL CHANGE
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Conflict_count
  /METHOD=ENTER numbeProtectedWithOutIUCN
  /METHOD=ENTER ToPA_NoC
  /METHOD=ENTER Polity2 GDP InfantMortality lag_Confl_c log_population
  /SCATTERPLOT=(*ZRESID ,*ZPRED)
  /RESIDUALS DURBIN HISTOGRAM(ZRESID) NORMPROB(ZRESID)
  /CASEWISE PLOT(ZRESID) OUTLIERS(2)
  /SAVE PRED ZPRED ADJPRED MAHAL COOK LEVER ZRESID DRESID SDRESID
        SDBETA SDFIT COVRATIO.

COMPUTE Coo_1_Large=COO_1 > 1 = 1.
EXECUTE.

COMPUTE Lev_1_Large=LEV_1 > 0.014 = 1.
EXECUTE.

COMPUTE ZRE_1_95_new=ZRE_1 > 1.95 | ZRE_1 <  - 1.96 = 1.
EXECUTE.

FREQUENCIES VARIABLES=Coo_1_Large
  /ORDER=ANALYSIS.
```

```
FREQUENCIES VARIABLES=Lev_1_Large
  /ORDER=ANALYSIS.

FREQUENCIES VARIABLES=ZRE_1_95_new
  /ORDER=ANALYSIS.
```

Robust Standard Errors Model 1 to Model 4

```
* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 GDP InfantMortality lag_Confl_c log_population
        ToPA_NoC
    Polity_ToPa_centered numbeProtectedWithOutIUCN
  /MODEL Polity2 GDP InfantMortality lag_Confl_c log_population
        numbeProtectedWithOutIUCN
    INTERCEPT=YES

* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 numbeProtectedWithOutIUCN GDP InfantMortality
        lag_Confl_c
    log_population
  /MODEL Polity2 numbeProtectedWithOutIUCN GDP InfantMortality lag_Confl_c
        log_population
    INTERCEPT=YES
 DISTRIBUTION=NORMAL LINK=IDENTITY
  /CRITERIA SCALE=MLE COVB=ROBUST PCONVERGE=1E-006(ABSOLUTE)
        SINGULAR=1E-012 ANALYSISTYPE=3(WALD)
    CILEVEL=95 CITYPE=WALD LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
        (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 numbeProtectedWithOutIUCN GDP InfantMortality
        lag_Confl_c
    log_population ToPA_NoC
  /MODEL Polity2 GDP InfantMortality lag_Confl_c log_population ToPA_NoC
        INTERCEPT=YES
 DISTRIBUTION=NORMAL LINK=IDENTITY
  /CRITERIA SCALE=MLE COVB=ROBUST PCONVERGE=1E-006(ABSOLUTE)
        SINGULAR=1E-012 ANALYSISTYPE=3(WALD)
    CILEVEL=95 CITYPE=WALD LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
        (EXPONENTIATED).
```

```
* Generalized Linear Models.
GENLIN GDPperCapitaGrowthannual WITH Polity2 numbeProtectedWithOutIUCN GDP
        InfantMortality
  lag_Confl_c log_population ToPA_NoC
 /MODEL Polity2 GDP InfantMortality lag_Confl_c log_population ToPA_NoC
        INTERCEPT=YES
 DISTRIBUTION=NORMAL LINK=IDENTITY
 /CRITERIA SCALE=MLE COVB=ROBUST PCONVERGE=1E-006(ABSOLUTE)
        SINGULAR=1E-012 ANALYSISTYPE=3(WALD)
  CILEVEL=95 CITYPE=WALD LIKELIHOOD=FULL
 /MISSING CLASSMISSING=EXCLUDE
 /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
        (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH numbeProtectedWithOutIUCN
 /MODEL numbeProtectedWithOutIUCN INTERCEPT=YES
 DISTRIBUTION=NORMAL LINK=IDENTITY
 /CRITERIA SCALE=MLE COVB=ROBUST PCONVERGE=1E-006(ABSOLUTE)
        SINGULAR=1E-012 ANALYSISTYPE=3(WALD)
  CILEVEL=95 CITYPE=WALD LIKELIHOOD=FULL
 /MISSING CLASSMISSING=EXCLUDE
 /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
        (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH ToPA_NoC
 /MODEL ToPA_NoC INTERCEPT=YES
 DISTRIBUTION=NORMAL LINK=IDENTITY
 /CRITERIA SCALE=MLE COVB=ROBUST PCONVERGE=1E-006(ABSOLUTE)
        SINGULAR=1E-012 ANALYSISTYPE=3(WALD)
  CILEVEL=95 CITYPE=WALD LIKELIHOOD=FULL
 /MISSING CLASSMISSING=EXCLUDE
 /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
        (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH ToPA_NoC Polity2 GDP InfantMortality lag_Confl_c
        log_population
 /MODEL log_population lag_Confl_c InfantMortality GDP ToPA_NoC Polity2
        INTERCEPT=YES
 DISTRIBUTION=NORMAL LINK=IDENTITY
```

```
  /CRITERIA SCALE=MLE COVB=ROBUST PCONVERGE=1E-006(ABSOLUTE)
        SINGULAR=1E-012 ANALYSISTYPE=3(WALD)
    CILEVEL=95 CITYPE=WALD LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
        (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH ToPA_NoC Polity2 numbeProtectedWithOutIUCN GDP
        InfantMortality
    lag_Confl_c log_population
  /MODEL log_population lag_Confl_c InfantMortality GDP ToPA_NoC Polity2
        INTERCEPT=YES
 DISTRIBUTION=NORMAL LINK=IDENTITY
  /CRITERIA SCALE=MLE COVB=ROBUST PCONVERGE=1E-006(ABSOLUTE)
        SINGULAR=1E-012 ANALYSISTYPE=3(WALD)
    CILEVEL=95 CITYPE=WALD LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
        (EXPONENTIATED).
```

Clustered Standard Errors Model 1 to Model 4

```
* Complex Samples General Linear Model.
CSGLM  Conflict_count WITH Polity2 InfantMortality GDP numbeProtectedWithOutIUCN
        lag_Confl_c
    log_population
  /PLAN FILE='C:\Users\Testlauf\Documents\Leiden University\3rd Year\bachelor '+
    'project\THESIS\SPSS\new_file.csaplan'
  /MODEL Polity2 InfantMortality GDP numbeProtectedWithOutIUCN lag_Confl_c
        log_population
  /INTERCEPT INCLUDE=YES SHOW=YES
  /STATISTICS PARAMETER SE CINTERVAL TTEST
  /PRINT SUMMARY VARIABLEINFO SAMPLEINFO
  /TEST TYPE=F PADJUST=LSD
  /MISSING CLASSMISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Complex Samples General Linear Model.
CSGLM  Conflict_count WITH Polity2 InfantMortality GDP lag_Confl_c log_population
        ToPA_NoC
  /PLAN FILE='C:\Users\Testlauf\Documents\Leiden University\3rd Year\bachelor '+
    'project\THESIS\SPSS\new_file.csaplan'
  /MODEL Polity2 InfantMortality GDP lag_Confl_c log_population
  /INTERCEPT INCLUDE=YES SHOW=YES
```

```
  /STATISTICS PARAMETER SE CINTERVAL TTEST
  /PRINT SUMMARY VARIABLEINFO SAMPLEINFO
  /TEST TYPE=F PADJUST=LSD
  /MISSING CLASSMISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Complex Samples General Linear Model.
CSGLM  Conflict_count WITH Polity2 InfantMortality GDP lag_Confl_c log_population
        ToPA_NoC
  /PLAN FILE='C:\Users\Testlauf\Documents\Leiden University\3rd Year\bachelor '+
    'project\THESIS\SPSS\new_file.csaplan'
  /MODEL Polity2 InfantMortality GDP lag_Confl_c log_population ToPA_NoC
  /INTERCEPT INCLUDE=YES SHOW=YES
  /STATISTICS PARAMETER SE CINTERVAL TTEST
  /PRINT SUMMARY VARIABLEINFO SAMPLEINFO
  /TEST TYPE=F PADJUST=LSD
  /MISSING CLASSMISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Complex Samples General Linear Model.
CSGLM  Conflict_count WITH Polity2 InfantMortality GDP lag_Confl_c log_population
        ToPA_NoC
    Polity_ToPa_centered
  /PLAN FILE='C:\Users\Testlauf\Documents\Leiden University\3rd Year\bachelor '+
    'project\THESIS\SPSS\new_file.csaplan'
  /MODEL Polity2 InfantMortality GDP lag_Confl_c log_population ToPA_NoC
        Polity_ToPa_centered
  /INTERCEPT INCLUDE=YES SHOW=YES
  /STATISTICS PARAMETER SE CINTERVAL TTEST
  /PRINT SUMMARY VARIABLEINFO SAMPLEINFO
  /TEST TYPE=F PADJUST=LSD
  /MISSING CLASSMISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Complex Samples General Linear Model.
CSGLM  Conflict_count WITH Polity2 InfantMortality GDP lag_Confl_c log_population
        ToPA_NoC
    Polity_ToPa_centered numbeProtectedWithOutIUCN polity2_protectedarea_centered
  /PLAN FILE='C:\Users\Testlauf\Documents\Leiden University\3rd Year\bachelor '+
    'project\THESIS\SPSS\new_file.csaplan'
  /MODEL Polity2 InfantMortality GDP lag_Confl_c log_population
        numbeProtectedWithOutIUCN
    polity2_protectedarea_centered
  /INTERCEPT INCLUDE=YES SHOW=YES
```

```
  /STATISTICS PARAMETER SE CINTERVAL TTEST
  /PRINT SUMMARY VARIABLEINFO SAMPLEINFO
  /TEST TYPE=F PADJUST=LSD
  /MISSING CLASSMISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Complex Samples General Linear Model.
CSGLM  Conflict_count WITH numbeProtectedWithOutIUCN
  /PLAN FILE='C:\Users\Testlauf\Documents\Leiden University\3rd Year\bachelor '+
    'project\THESIS\SPSS\new_file.csaplan'
  /MODEL numbeProtectedWithOutIUCN
  /INTERCEPT INCLUDE=YES SHOW=YES
  /STATISTICS PARAMETER SE CINTERVAL TTEST
  /PRINT COVB CORB SUMMARY VARIABLEINFO SAMPLEINFO
  /TEST TYPE=F PADJUST=LSD
  /MISSING CLASSMISSING=EXCLUDE
  /CRITERIA CILEVEL=95.

* Complex Samples General Linear Model.
CSGLM  Conflict_count WITH ToPA_NoC
  /PLAN FILE='C:\Users\Testlauf\Documents\Leiden University\3rd Year\bachelor '+
    'project\THESIS\SPSS\new_file.csaplan'
  /MODEL ToPA_NoC
  /INTERCEPT INCLUDE=YES SHOW=YES
  /STATISTICS PARAMETER SE CINTERVAL TTEST
  /PRINT COVB CORB SUMMARY VARIABLEINFO SAMPLEINFO
  /TEST TYPE=F PADJUST=LSD
  /MISSING CLASSMISSING=EXCLUDE
  /CRITERIA CILEVEL=95.
```

Negative Binomial Regression

```
* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 numbeProtectedWithOutIUCN GDP InfantMortality
        lag_Confl_c
    log_population
  /MODEL Polity2 numbeProtectedWithOutIUCN GDP InfantMortality lag_Confl_c
        log_population
    INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
        MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
        ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
```

```
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
          (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 GDP InfantMortality lag_Confl_c log_population
          ToPA_NoC
  /MODEL Polity2 GDP InfantMortality lag_Confl_c log_population ToPA_NoC
          INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
          MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
          ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
          (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 GDP InfantMortality lag_Confl_c log_population
          ToPA_NoC
    Polity_ToPa_centered
  /MODEL Polity2 GDP InfantMortality lag_Confl_c log_population ToPA_NoC
          Polity_ToPa_centered
    INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
          MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
          ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
          (EXPONENTIATED).
```

Poisson

```
DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
          MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
          ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
```

```
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
            (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 GDP InfantMortality lag_Confl_c log_population
            ToPA_NoC
    Polity_ToPa_centered numbeProtectedWithOutIUCN
  /MODEL Polity2 GDP InfantMortality lag_Confl_c log_population ToPA_NoC
            INTERCEPT=YES
 DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
            MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
            ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
            (EXPONENTIATED).

* Generalized Linear Models.
GENLIN lag_Confl_c WITH Polity2 GDP InfantMortality log_population ToPA_NoC
            Polity_ToPa_centered
    numbeProtectedWithOutIUCN Populationtotal
  /MODEL Polity2 GDP InfantMortality ToPA_NoC Polity_ToPa_centered Populationtotal
            INTERCEPT=YES
 DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
            MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
            ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
            (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 GDP InfantMortality log_population ToPA_NoC
            Polity_ToPa_centered
    numbeProtectedWithOutIUCN Populationtotal
  /MODEL Polity2 GDP InfantMortality ToPA_NoC Polity_ToPa_centered Populationtotal
            INTERCEPT=YES
 DISTRIBUTION=POISSON LINK=LOG
```

```
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
        MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
        ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
        (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 GDP InfantMortality log_population ToPA_NoC
        Polity_ToPa_centered
    numbeProtectedWithOutIUCN Populationtotal
  /MODEL Polity2 GDP InfantMortality ToPA_NoC Populationtotal INTERCEPT=YES
 DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
        MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
        ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
        (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 GDP InfantMortality log_population ToPA_NoC
        Polity_ToPa_centered
    numbeProtectedWithOutIUCN Populationtotal
  /MODEL Polity2 GDP InfantMortality ToPA_NoC log_population INTERCEPT=YES
 DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
        MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
        ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
        (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 GDP InfantMortality log_population ToPA_NoC
        Polity_ToPa_centered
    numbeProtectedWithOutIUCN Populationtotal Populationgrowthannual lag_Confl_c
```

```
  /MODEL Polity2 GDP InfantMortality ToPA_NoC Populationgrowthannual lag_Confl_c
            INTERCEPT=YES
 DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
            MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
            ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
            (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 GDP InfantMortality log_population ToPA_NoC
            Polity_ToPa_centered
    numbeProtectedWithOutIUCN Populationtotal Populationgrowthannual lag_Confl_c
  /MODEL Polity2 GDP InfantMortality ToPA_NoC Populationgrowthannual lag_Confl_c
            log_population
    INTERCEPT=YES
 DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100
            MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
            ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
            (EXPONENTIATED).

* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 GDP InfantMortality lag_Confl_c log_population
    numbeProtectedWithOutIUCN
  /MODEL log_population lag_Confl_c InfantMortality GDP Polity2
            numbeProtectedWithOutIUCN
    INTERCEPT=YES
 DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=ROBUST
            MAXITERATIONS=100 MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
            ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
            (EXPONENTIATED).
```

```
* Generalized Linear Models.
GENLIN Conflict_count WITH Polity2 GDP InfantMortality lag_Confl_c log_population
      ToPA_NoC
  /MODEL log_population lag_Confl_c InfantMortality GDP Polity2 ToPA_NoC
      INTERCEPT=YES
 DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=ROBUST
      MAXITERATIONS=100 MAXSTEPHALVING=5
    PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012
      ANALYSISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD
    LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT CPS DESCRIPTIVES MODELINFO FIT SUMMARY SOLUTION
      (EXPONENTIATED).
```

Hayes checking and accounting for heteroskedasticity

```
* Encoding: UTF-8.
* Written by Andrew F. Hayes and Li Cai
* www.afhayes.com
* Version 2.0
* Copyright 2019
* See Hayes and Cai (2007, Behavior Research Methods, vol 39, p. 709-722).

preserve.
set printback=off.
DEFINE hcreg (dv =!charend ('/')/iv =!charend ('/')
      /test = !charend('/') !default (0)/lag=!charend('/') !default(0)
      /const = !charend('/') !default(1)
      /method = !charend ('/') !default (3)
      /covmat = !charend('/') !default(0)).
PRESERVE.
set length = none.
SET MXLOOP = 100000000.
MATRIX.
GET x/file = */variables = !dv !iv/names = dv/missing = omit.
compute newey=0.
compute y=x(:,1).
compute x=x(:,2:ncol(x)).
compute iv5 = x.
compute pr = ncol(x).
compute n = nrow(x).
compute L = ident(pr).
```

```
compute lag=abs(trunc(!lag)).
compute method=trunc(!method).
do if (method=6).
  compute method=1.
  compute newey=1.
end if.
do if (lag > (n-1)).
  compute lag=0.
end if.
compute tss=cssq(y)-(((csum(y)&**2)/n)*(!const <> 0)).
do if (!const = 0).
  compute iv = t(dv(1,2:ncol(dv))).
  compute df2 = n-pr.
else.
  compute iv = t({"Constant", dv(1,2:ncol(dv))}).
  compute con = make(n,1,1).
  compute x={con,x}.
  compute df2 = n-pr-1.
  compute L1 = make(1,pr,0).
  compute L = {L1;L}.
end if.
compute x2=x.
compute dv=dv(1,1).
compute b = inv(t(x)*x)*t(x)*y.
compute k = nrow(b).
compute invXtX = inv(t(x)*x).
compute h = x(:,1).
loop i=1 to n.
  compute h(i,1)= x(i,:)*invXtX*t(x(i,:)).
end loop.
compute resid = (y-(x*b)).
compute mse = csum(resid&**2)/(n-ncol(x)).
compute pred = x*b.
compute ess= cssq(resid).
 do if (method = 2 or method = 3).
  loop i=1 to k.
    compute x(:,i) = (resid&/(1-h)&**(1/(4-method)))&*x(:,i).
  end loop.
 end if.
 do if (method = 0 or method = 1).
  loop i=1 to k.
    compute x(:,i) = resid&*x(:,i).
  end loop.
 end if.
```

```
 do if (method = 5).
   loop i=1 to k.
    compute x(:,i) = sqrt(mse)&*x(:,i).
  end loop.
 end if.
do if (method = 4).
 compute mn = make(n,2,4).
 compute pr3 = n-df2.
 compute mn(:,2) = (n*h)/pr3.
 compute ex=rmin(mn).
  loop i=1 to k.
    compute x(:,i) = (resid&/(1-h)&**(ex/2))&*x(:,i).
  end loop.
 end if.
compute hc = invXtX*t(x)*x*invXtX.
compute hcn=(n/(n-k))*t(x)*x.
do if (method = 1).
  compute hc = (n/(n-k))&*hc.
  do if (newey=1).
  compute hc=hcn.
  compute matsum2=make(k,k,0).
    loop Lp = 1 to lag.
      compute sum=(1-(Lp/(lag+1))).
      compute matsum=make(k,k,0).
      loop ts=(Lp+1) to n.
        compute mat=(resid(ts,1)*resid((ts-Lp),1))*(t(x2(ts,:))*x2((ts-Lp),:)+t(x2((ts-Lp),:))*
    x2(ts,:)).
        compute matsum=matsum+mat.
      end loop.
      compute matsum2=matsum2+(sum*matsum).
    end loop.
    compute nwy=(n/(n-k))*matsum2.
    compute nwy=hc+nwy.
    compute hc=invxtx*nwy*invxtx.
  end if.
end if.
compute F = (t(t(L)*b)*inv(t(L)*hc*L)*((t(L)*b)))/pr.
compute pf = 1-fcdf(f,pr,df2).
compute r2 = (tss-ess)/tss.
compute pf = {r2,f,pr,df2,pf}.
do if (method < 5 and newey = 0).
print method/title = "HC Method"/format F1.0.
end if.
print dv/title = "Criterion Variable"/format A8.
```

```
print pf/title = "Model Fit:"/clabels = "R-sq" "F" "df1" "df2" "p"/format F10.4.
compute sebhc = sqrt(diag(hc)).
compute te = b&/sebhc.
compute p = 2*(1-tcdf(abs(te), n-nrow(b))).
compute oput = {b,sebhc, te, p}.
do if (method < 5 and newey=0).
  print oput/title = 'Heteroscedasticity-Consistent Regression Results'/clabels
        = "Coeff" "SE(HC)" "t" "P>|t|"/rnames = iv/format f10.4.
end if.
do if (method = 1 and newey=1).
  print oput/title = 'Regression Results with Newey-West Standard Errors'/clabels
        = "Coeff" "N-W SE" "t" "P>|t|"/rnames = iv/format f10.4.
  print lag/title="Lag specified:"/format=F3.0.
  print/title="Note: The Newey-West option assumes the data are sorted as a time series ".
  print/title="      with the earliest time at the top and latest time at the bottom."/space=0.
  do if (lag=0).
    print/title="      With lag=0, Newey-West standard errors are equivalent to HC1."/space=0.
  end if.
end if.
do if (method = 5).
print oput/title = 'OLS Regression Results Assuming Homoscedasticity'/clabels
       = "Coeff" "SE" "t" "P>|t|"/rnames = iv/format f10.4.
end if.
compute iv2 = t(iv).
do if (!covmat = 1).
print hc/title = 'Covariance Matrix of Parameter Estimates'/cnames =
      iv/rnames = iv2/format f10.4.
end if.
do if (!test > 0 and !test < pr).
 compute L2 = make(pr-!test+!const,!test,0).
 compute L = {L2;L((pr+1-!test+!const):(pr+!const),(pr-!test+1):(pr))}.
 compute F = (t(t(L)*b)*inv(t(L)*hc*L)*((t(L)*b)))/!test.
 compute pf = 1-fcdf(f,!test,df2).
 compute pf = {f,!test,df2,pf}.
 print pf/title = "Setwise Hypothesis Test"
    /clabels = "F" "df1" "df2" "p"/format F10.4.
 compute iv = t(iv((pr+1-!test+!const):(pr+!const),1)).
 print iv/title = "Variables in Set:"/format A8.
end if.
END MATRIX.
RESTORE.
!ENDDEFINE.
```

Heteroskedasticity test Hayes

```
HCREG dv=Conflict_count/iv=lag_Confl_c Polity2 numbeProtectedWithOutIUCN GDP
        InfantMortality
   ToPA_NoC log_population/method=3
  /covmat=1/const=1/lag=1.

restore.

* Encoding: UTF-8.
* Written by Andrew F. Hayes and Li Cai
* www.afhayes.com
* Version 2.0
* Copyright 2019
* See Hayes and Cai (2007, Behavior Research Methods, vol 39, p. 709-722).

preserve.
set printback=off.
DEFINE hcreg (dv =!charend ('/')/iv =!charend ('/')
        /test = !charend('/') !default (0)/lag=!charend('/') !default(0)
        /const = !charend('/') !default(1)
        /method = !charend ('/') !default (3)
        /covmat = !charend('/') !default(0)).
PRESERVE.
set length = none.
SET MXLOOP = 100000000.
MATRIX.
GET x/file = */variables = !dv !iv/names = dv/missing = omit.
compute newey=0.
compute y=x(:,1).
compute x=x(:,2:ncol(x)).
compute iv5 = x.
compute pr = ncol(x).
compute n = nrow(x).
compute L = ident(pr).
compute lag=abs(trunc(!lag)).
compute method=trunc(!method).
do if (method=6).
  compute method=1.
  compute newey=1.
end if.
do if (lag > (n-1)).
  compute lag=0.
end if.
compute tss=cssq(y)-(((csum(y)&**2)/n)*(!const <> 0)).
```

```
do if (!const = 0).
  compute iv = t(dv(1,2:ncol(dv))).
  compute df2 = n-pr.
else.
  compute iv = t({"Constant", dv(1,2:ncol(dv))}).
  compute con = make(n,1,1).
  compute x={con,x}.
  compute df2 = n-pr-1.
  compute L1 = make(1,pr,0).
  compute L = {L1;L}.
end if.
compute x2=x.
compute dv=dv(1,1).
compute b = inv(t(x)*x)*t(x)*y.
compute k = nrow(b).
compute invXtX = inv(t(x)*x).
compute h = x(:,1).
loop i=1 to n.
  compute h(i,1)= x(i,:)*invXtX*t(x(i,:)).
end loop.
compute resid = (y-(x*b)).
compute mse = csum(resid&**2)/(n-ncol(x)).
compute pred = x*b.
compute ess= cssq(resid).
 do if (method = 2 or method = 3).
  loop i=1 to k.
    compute x(:,i) = (resid&/(1-h)&**(1/(4-method)))&*x(:,i).
  end loop.
 end if.
 do if (method = 0 or method = 1).
  loop i=1 to k.
    compute x(:,i) = resid&*x(:,i).
  end loop.
 end if.
 do if (method = 5).
   loop i=1 to k.
    compute x(:,i) = sqrt(mse)&*x(:,i).
  end loop.
 end if.
do if (method = 4).
 compute mn = make(n,2,4).
 compute pr3 = n-df2.
 compute mn(:,2) = (n*h)/pr3.
 compute ex=rmin(mn).
```

```
  loop i=1 to k.
    compute x(:,i) = (resid&/(1-h)&**(ex/2))&*x(:,i).
  end loop.
 end if.
compute hc = invXtX*t(x)*x*invXtX.
compute hcn=(n/(n-k))*t(x)*x.
do if (method = 1).
  compute hc = (n/(n-k))&*hc.
  do if (newey=1).
  compute hc=hcn.
  compute matsum2=make(k,k,0).
    loop Lp = 1 to lag.
      compute sum=(1-(Lp/(lag+1))).
      compute matsum=make(k,k,0).
      loop ts=(Lp+1) to n.
        compute mat=(resid(ts,1)*resid((ts-Lp),1))*(t(x2(ts,:))*x2((ts-Lp),:)+t(x2((ts-Lp),:))*
    x2(ts,:)).
        compute matsum=matsum+mat.
      end loop.
      compute matsum2=matsum2+(sum*matsum).
    end loop.
    compute nwy=(n/(n-k))*matsum2.
    compute nwy=hc+nwy.
    compute hc=invxtx*nwy*invxtx.
  end if.
end if.
compute F = (t(t(L)*b)*inv(t(L)*hc*L)*((t(L)*b)))/pr.
compute pf = 1-fcdf(f,pr,df2).
compute r2 = (tss-ess)/tss.
compute pf = {r2,f,pr,df2,pf}.
do if (method < 5 and newey = 0).
print method/title = "HC Method"/format F1.0.
end if.
print dv/title = "Criterion Variable"/format A8.
print pf/title = "Model Fit:"/clabels = "R-sq" "F" "df1" "df2" "p"/format F10.4.
compute sebhc = sqrt(diag(hc)).
compute te = b&/sebhc.
compute p = 2*(1-tcdf(abs(te), n-nrow(b))).
compute oput = {b,sebhc, te, p}.
do if (method < 5 and newey=0).
  print oput/title = 'Heteroscedasticity-Consistent Regression Results'/clabels
        = "Coeff" "SE(HC)" "t" "P>|t|"/rnames = iv/format f10.4.
end if.
do if (method = 1 and newey=1).
```

```
  print oput/title = 'Regression Results with Newey-West Standard Errors'/clabels
        = "Coeff" "N-W SE" "t" "P>|t|"/rnames = iv/format f10.4.
  print lag/title="Lag specified:"/format=F3.0.
  print/title="Note: The Newey-West option assumes the data are sorted as a time series ".
  print/title="      with the earliest time at the top and latest time at the bottom."/space=0.
  do if (lag=0).
    print/title="      With lag=0, Newey-West standard errors are equivalent to HC1."/space=0.
  end if.
end if.
do if (method = 5).
print oput/title = 'OLS Regression Results Assuming Homoscedasticity'/clabels
       = "Coeff" "SE" "t" "P>|t|"/rnames = iv/format f10.4.
end if.
compute iv2 = t(iv).
do if (!covmat = 1).
print hc/title = 'Covariance Matrix of Parameter Estimates'/cnames =
      iv/rnames = iv2/format f10.4.
end if.
do if (!test > 0 and !test < pr).
 compute L2 = make(pr-!test+!const,!test,0).
 compute L = {L2;L((pr+1-!test+!const):(pr+!const),(pr-!test+1):(pr))}.
 compute F = (t(t(L)*b)*inv(t(L)*hc*L)*((t(L)*b)))/!test.
 compute pf = 1-fcdf(f,!test,df2).
 compute pf = {f,!test,df2,pf}.
 print pf/title = "Setwise Hypothesis Test"
    /clabels = "F" "df1" "df2" "p"/format F10.4.
 compute iv = t(iv((pr+1-!test+!const):(pr+!const),1)).
 print iv/title = "Variables in Set:"/format A8.
end if.
END MATRIX.
RESTORE.
!ENDDEFINE.

HCREG dv=Conflict_count/iv=Polity2 numbeProtectedWithOutIUCN GDP InfantMortality
    log_population/method=3
  /covmat=1/const=1/lag=1.

restore.
```

Daryanto test for heteroskedasticity

```
/*Breusch-pagan test for heteroskedasticity.
/*macro created by Ahmad Daryanto*/.
DEFINE BPK (iv = !charend('/')
/dv = !charend('/')
/robse = !charend('/')!default(3))
SET MXLOOPS = 10000001.
SET PRINTBACK = OFF.
MATRIX.
get mat/variables=!dv !iv  /names=nms /MISSING=OMIT.
compute n=nrow(mat).
*dv in original metrix.
compute Y=mat(:,1).
*==============================================.
*         OLS Regression of Raw Data .
*==============================================.
compute n=nrow(mat).
compute ones=make(n,1,1).
compute Y=mat(:,1).
compute X={ones,mat(:,2:ncol(mat))}.
compute b=(inv(sscp(X)))*t(X)*Y.
compute k=ncol(X).
*===computing standard error of b, t value and p-value of OLS ==.
compute e=Y-X*b.
compute e2=e(:,1)&*e(:,1).
compute sser=csum(e2).
compute mse=(1/(n-k))*sser.
compute vb=mse*inv(sscp(X)).
compute sb=sqrt(diag(vb)).
compute tb=b/sb.
compute dff=n-k.
compute F=tb&*tb.
compute pF=1-fcdf(F,1,dff).
compute pF=1-fcdf(F,1,dff).
   *--95% CI--.
compute LB=b-1.96*sb.
compute UB=b+1.96*sb.
compute olsout={b,sb, tb,pF,LB,UB}.
*for output with robust std error HC0.
do if (!robse=0).
   compute  vbh=inv(sscp(X))*t(X)*mdiag(e2)*X*inv(sscp(X)).
end if.
* HC1.
do if (!robse=1).
```

```
compute  vbh=inv(sscp(X))*t(X)*mdiag(e2)*X*inv(sscp(X)).
    compute vbh=vbh*N/(N-k).
end if.
*HC2.
do if (!robse=2).
compute hat=X*inv(sscp(X))* t(X).
compute dhat=e2&/(ones-diag(hat)).
compute vbh=inv(sscp(X))*t(X)*mdiag(dhat)*X*inv(sscp(X)).
end if.
*HC3.
do if (!robse=3).
compute hat=X*inv(sscp(X))* t(X).
compute hat2=(ones-diag(hat))&*(ones-diag(hat)).
compute dhat=e2&/hat2.
compute vbh=inv(sscp(X))*t(X)*mdiag(dhat)*X*inv(sscp(X)).
end if.
*HC4.
do if (!robse=4).
compute hat=X*inv(sscp(X))* t(X).
compute fours=make(n,1,4).
compute mh={fours,n*diag(hat)/k}.
compute dummy=rmin(mh).
compute hat2=(ones-diag(hat))&**dummy.
compute dhat=e2&/hat2.
compute vbh=inv(sscp(X))*t(X)*mdiag(dhat)*X*inv(sscp(X)).
end if.
    compute sbh=sqrt(diag(vbh)).
    compute tbh=b/sbh.
    compute dff=n-k.
    compute Fh=tbh&*tbh.
    compute pFh=1-fcdf(Fh,1,dff).
    compute pF=1-fcdf(Fh,1,dff).
     *--95% CI--.
   compute LBh=b-1.96*sb.
   compute UBh=b+1.96*sb.
   compute olsouth={b,sbh, tbh,pFh, LBh, UBh}.
*end of calculation.
print/title=" written by Ahmad Daryanto".
compute temp=t(nms(:,1)).
print/title="Original Regression model:".
print temp/title="Dependent variable"/format=A8.
*===Preparing input ANOVA table.
*computing mean square regression.
compute meanY=ones*t(csum(Y)/n).
```

```
compute e_reg=X*b-meanY.
compute ssreg=csum(sscp(e_reg)).
compute sumsq=T({ssreg,sser}).
compute dfa=T({k-1,n-k}).
compute mse_a=sumsq/dfa.
compute Fval=(ssreg/(k-1))/(sser/(n-k)).
Compute pF_a=1-fcdf(Fval,k-1,n-k).
compute F_a=T({Fval,-999}).
compute pFa=T({pF_a,-999}).
*--computing R-square.
Compute total=sser+ssreg.
Compute Rsq=ssreg/total.
print Rsq/title="R-square"/format=F9.3.
*--OLS output.
compute nmvars = t(nms(1,2:ncol(mat))).
compute nmvars = {"constant"; nmvars; "interact"}.
compute cnms={"b","se", "t", "sig", "95%LB", "95%UB"}.
print olsout/title ="OLS outputs"/rnames=nmvars/cnames=cnms/format=F9.3.
*--OLS output associated with robust standard errors.
compute nmvars = t(nms(1,2:ncol(mat))).
compute nmvars = {"constant"; nmvars; "interact"}.
print olsouth/title ="OLS outputs with heterocedasticity-robust standard "+
   "errors:"/rnames=nmvars/cnames=cnms/format=F9.3.
do if (!robse=0).
print/title="* Note: standard error is HC0 variant (Eicker-Huber–White standard errors), not
              "+
   "recommended for sample sizes < 250 (Long and Ervin, 2000)".
end if.
do if (!robse=1).
print/title="* Note: standard error is HC1 variant".
end if.
do if (!robse=2).
print/title="* Note: standard error is HC2 variant".
end if.
do if (!robse=3).
print/title="* Note: standard error is HC3 variant".
end if.
do if (!robse=4).
print/title="* Note: standard error is HC4 variant".
end if.
*--ANOVA table.
print {sumsq,dfa, mse_a,F_a,pFa} /space=3
  /title '------- ANOVA TABLE  --------'
  /clabel "SS" "df" "MS" "F" "Sig"
```

```
  /rlabel "Model" "Residual"
  /format f10.3 .
/*============================================.
/*Breusch-Pagan test for heteroskedasticity
/*============================================.
compute var_e=sscp(e)/n.
*residuals are scaled.
compute g=e2/var_e.
compute bp=(inv(sscp(X)))*t(X)*g.
compute ep=g-X*bp.
compute e2p=ep(:,1)&*ep(:,1).
compute sserp=csum(e2p).
compute msep=(1/(n-k))*sserp.
compute vbp=msep*inv(sscp(X)).
compute sbp=sqrt(diag(vbp)).
compute tbp=bp/sbp.
compute dff=n-k.
compute Fp=tbp&*tbp.
compute pFp=1-fcdf(Fp,1,dff).
    *--95% CI--.
compute LB=bp-1.96*sbp.
compute UB=bp+1.96*sbp.
compute olsout={bp,sbp, tbp,pFp, LB, UB}.
print/title="================================================".
print/title="Breusch-Pagan and Koenker test".
print/title="================================================".
print/title="The tests use the scaled residuals from the original OLS above with no adjustment
            to "+
   "standard errors.".
print olsout/title ="OLS outputs"/rnames=nmvars/cnames=cnms/format=F9.3.
*--Computing LM statistics .
compute meanY=ones*t(csum(g)/n).
compute e_regp=X*bp-meanY.
compute ssregp=csum(sscp(e_regp)).
Compute total=sserp+ssregp.
Compute Rsqp=ssregp/total.
print Rsqp/title="R-square"/format=F9.3.
compute F=(ssregp/(k-1))/(sserp/(n-k)).
Compute pF=1-fcdf(Fval,k-1,n-k).
*--ANOVA table.
compute F_a=T({F,-999}).
compute pF_a=T({pF,-999}).
compute sumsq=T({ssregp,sserp}).
compute msep=sumsq/dfa.
```

```
print {sumsq,dfa, msep,F_a,pF_a} /space=3
  /title '------- ANOVA TABLE  --------'
  /clabel "SS" "df" "MS" "F" "Sig"
  /rlabel "Model" "Residual"
  /format f10.3 .
/* test statisticsby Breusch-Pagan.
compute np=ncol(mat)-1.
Compute LMb=0.5*ssregp.
compute sigb=1-chicdf(LMb,np).
/* test statisticsby Koenker.
Compute LMk=n*Rsqp.
compute sigk=1-chicdf(LMk,np).
compute LM=T({LMb,LMk}).
compute sig=T({sigb,sigk}).
print{LM,sig}
  /title '------- Breusch-Pagan and Koenker test statistics and sig-values --------'
  /clabel "LM"  "Sig"
  /rlabel "BP" "Koenker"
  /format f10.3 .
print/title="Null hypothesis: heteroskedasticity not present (homoskedasticity).".
print/title="If sig-value less than 0.05, reject the null hypothesis.".
print/title="Note: Breusch-Pagan test is a large sample test and assumes the residuals to be "+
   "normally distributed.".
END MATRIX.
!ENDDEFINE.
BPK dv = Conflict_count
/iv = Polity2 numbeProtectedWithOutIUCN GDP InfantMortality lag_Confl_c
            log_population
/robse = 3.
```

Graphs

```
* Chart Builder.
GGRAPH
  /GRAPHDATASET NAME="graphdataset" VARIABLES=Populationtotal Conflict_count
            MISSING=LISTWISE
    REPORTMISSING=NO
  /GRAPHSPEC SOURCE=INLINE.
BEGIN GPL
  SOURCE: s=userSource(id("graphdataset"))
  DATA: Populationtotal=col(source(s), name("Populationtotal"))
  DATA: Conflict_count=col(source(s), name("Conflict_count"))
  GUIDE: axis(dim(1), label("Populationtotal"))
  GUIDE: axis(dim(2), label("Conflict_count"))
  ELEMENT: point(position(Populationtotal*Conflict_count))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATASET NAME="graphdataset" VARIABLES=Populationtotal
            MISSING=LISTWISE REPORTMISSING=NO
  /GRAPHSPEC SOURCE=INLINE.
BEGIN GPL
  SOURCE: s=userSource(id("graphdataset"))
  DATA: Populationtotal=col(source(s), name("Populationtotal"))
  GUIDE: axis(dim(1), label("Populationtotal"))
  GUIDE: axis(dim(2), label("Frequency"))
  ELEMENT: interval(position(summary.count(bin.rect(Populationtotal))),
    shape.interior(shape.square))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATASET NAME="graphdataset" VARIABLES=ZRE_1 ZPR_1
            MISSING=LISTWISE REPORTMISSING=NO
  /GRAPHSPEC SOURCE=INLINE.
BEGIN GPL
  SOURCE: s=userSource(id("graphdataset"))
  DATA: ZRE_1=col(source(s), name("ZRE_1"))
  DATA: ZPR_1=col(source(s), name("ZPR_1"))
  GUIDE: axis(dim(1), label("Standardized Residual"))
  GUIDE: axis(dim(2), label("Standardized Predicted Value"))
  ELEMENT: point(position(ZRE_1*ZPR_1))
END GPL.
```

```
DATASET ACTIVATE DataSet1.
* Chart Builder.
GGRAPH
  /GRAPHDATASET NAME="graphdataset" VARIABLES=GDP MISSING=LISTWISE
            REPORTMISSING=NO
  /GRAPHSPEC SOURCE=INLINE.
BEGIN GPL
  SOURCE: s=userSource(id("graphdataset"))
  DATA: GDP=col(source(s), name("GDP"))
  GUIDE: axis(dim(1), label("GDP growth per year"))
  GUIDE: axis(dim(2), label("Frequency"))
  ELEMENT: interval(position(summary.count(bin.rect(GDP))),
            shape.interior(shape.square))
END GPL.

COMPUTE GDP_log=LN(GDP).
EXECUTE.

* Chart Builder.
GGRAPH
  /GRAPHDATASET NAME="graphdataset" VARIABLES=Dummy_PA
    MEAN(Conflict_count)[name="MEAN_Conflict_count"] MISSING=LISTWISE
            REPORTMISSING=NO
  /GRAPHSPEC SOURCE=INLINE.
BEGIN GPL
  SOURCE: s=userSource(id("graphdataset"))
  DATA: Dummy_PA=col(source(s), name("Dummy_PA"), unit.category())
  DATA: MEAN_Conflict_count=col(source(s), name("MEAN_Conflict_count"))
  GUIDE: axis(dim(1), label("Total Number of Protected Areas"))
  GUIDE: axis(dim(2), label("Mean Conflict_count"))
  SCALE: linear(dim(2), include(0))
  ELEMENT: interval(position(Dummy_PA*MEAN_Conflict_count),
            shape.interior(shape.square))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATASET NAME="graphdataset" VARIABLES=Dummy_PA
    VALIDN(Conflict_count)[name="VALIDN_Conflict_count"] MISSING=LISTWISE
            REPORTMISSING=NO
  /GRAPHSPEC SOURCE=INLINE.
BEGIN GPL
  SOURCE: s=userSource(id("graphdataset"))
  DATA: Dummy_PA=col(source(s), name("Dummy_PA"), unit.category())
```

```
  DATA: VALIDN_Conflict_count=col(source(s), name("VALIDN_Conflict_count"))
  GUIDE: axis(dim(1), label("Total Number of Protected Areas"))
  GUIDE: axis(dim(2), label("Valid N Conflict_count"))
  SCALE: linear(dim(2), include(0))
  ELEMENT: interval(position(Dummy_PA*VALIDN_Conflict_count),
        shape.interior(shape.square))
END GPL.
```