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# The Global Conflict Risk Index (GCRI) Regression model: data ingestion, processing, and output methods

GCRI
Global Conflict Risk Index

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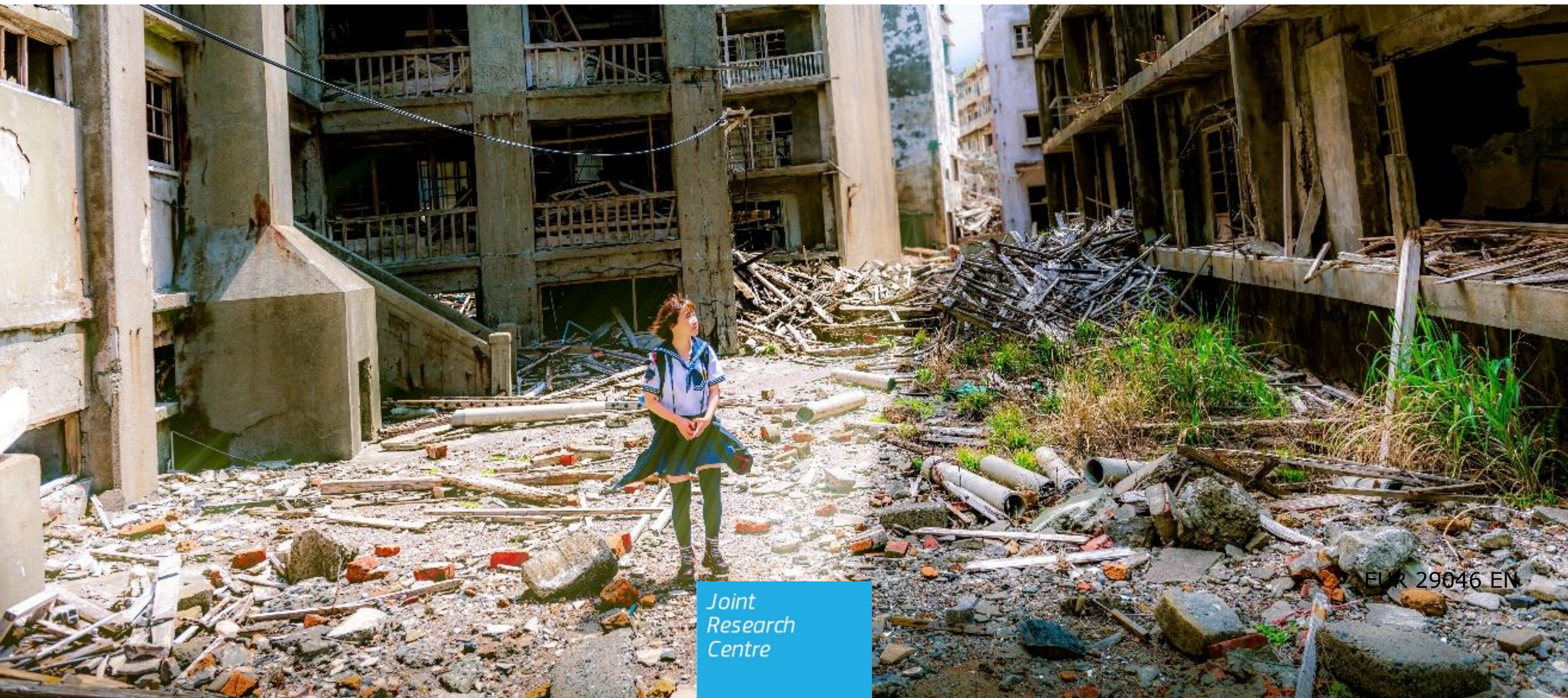
2017



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# The Global Conflict Risk Index (GCRI) Regression model: data ingestion, processing, and output methods

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# Abstract

The GCRI is a quantitative conflict risk model, developed by the JRC and based solely on open source data, providing quantitative input to the EU early warning framework, one input to the EU Conflict Early Warning System (EWS), developed by the European External Action Service (EEAS) in close partnership with the European Commission to enhance the EU's conflict prevention capacities. The GCRI distinguishes between three types of violent conflict a state may experience: civil war over national power, subnational conflicts over secession, autonomy, or resources, and conflicts in the international sphere. While the latter are not currently modelled by GCRI, for the first two the index quantifies the probability and the intensity respectively of national and subnational conflicts occurring in the next one to four years. Relying on historical data and a statistical model that includes political, socio-economic, environmental and security variables, it assesses the level and likelihood of future conflicts

The GCRI is composed of two statistical models: the regression model and the composite model. Both models are based on twenty-four individual variables. This report presents the work done between February 2017 and September 2017, specifically focused on improving the documentation on the regression model.

The present report describes on the one hand the regression model, including the input data and the model itself. On the other hand, it presents the statistical significance test, and the matrix of confusion, performed in order to get a highly detailed analysis of the performances of the model. The results of these analyses are presented in chapter 4 and 5.

This report is part of a series of technical documents produced in 2017 aiming at improving the GCRI models with greater transparency and robustness. It is not a validation of the GCRI, but a contribution to exploit its potential.

# 1. Introduction

The Global Conflict Risk Index (GCRI) has been designed to give policy makers a global risk assessment based on quantitative data. It quantifies the probability and the intensity of national and subnational conflicts occurring in the next one to four years.

The GCRI, inspired by quantitative conflict risk models, is made of two statistical models: the regression model and the composite model. Both models are based on twenty-four individual variables, all relatively stable, in that little change is to be expected from year to year. The data used are all freely accessible by any user on the Internet.

While the composite model assesses the risk-of-conflict at country level using weighted average method, the regression model applies to the twenty-four variables logistic and linear equations. The logistic equations are used to calculate the probability of a conflict whereas the linear ones are used to predict its intensity. The variables and the composite model are described in detail in the technical report *"Conflict Risk Indicators: Significance and Data Management in the GCRI"* (doi. 10.2760/44005).

This report describes the regression model, dividing it in four parts. The first section provides an overview on the input data (2), the second presents in detail how the predictions are obtained and the output data (3), the third shows the statistical significance test and its application to the model (4), and the last one describes the confusion matrix and its application to the model (5).

This report refers to the work done between February 2017 and September 2017 specifically focused on improving the documentation of the regression model. While the work presented here shows great advances in reliability and reproducibility, there is still great potential for improvements.

# 2. Input Data

This section provides all the relevant information on the variables used in the regression model.

The risk assessment is based on economic, social, political, geographical and environmental factors, studied through 24 variables. The data used are extracted from 14 different datasets, which are all freely accessible by any user on the Internet. Table 2 provides details about the data provider, the dataset used, and the URL where on can download the data. Table 3 presents some descriptive statistics: the original range of the data distribution, the thresholds imposed, the transformation done and years covered by each original dataset. While some of the datasets used are complete, others contain missing data for specific years and/or specific countries. In order to overcome the lack of data and be able to compute the model, the missing data are imputed (replacing missing data with substituted values). In the imputation system adopted, data is taken from either the closest known historical data (desk research is conducted for finding precise information which would then justify the substituted value), or, if not possible, from regional averages, or from similar countries. The imputation is included in the data construction phase, making the data a single and complete dataset ready for statistical analysis. For more information on the data management, please refer to the technical report "*Conflict Risk Indicators: Significance and Data Management in the GCRI*" (doi. 10.2760/44005).

| Indicator | Source | Name of dataset | Name of original indicator(s) | URL |
|---|---|---|---|---|
| **Regime type** | Center for Systemic Peace | Polity IV Annual Time-Series, 1800-2015 | PARCOM, EXREC | http://www.systemicpeace.org/inscrdata.html |
| **Lack of democracy** | Center for Systemic Peace | Polity IV Annual Time-Series, 1800-2015 | POLITY2 | http://www.systemicpeace.org/inscrdata.html |
| **Government effectiveness** | World Bank | Government Effectiveness: Estimate | GE.EST | http://databank.worldbank.org/data/reports.aspx?source=worldwide-governance-indicators |
| **Level of repression** | Political Terror Scale Project | PTS Data | Highest of the three indicators in the set (PTS_A, PTS_H, PTS_S) | http://www.politicalterrorscale.org/Data/Download.html |
| **Empowerment rights** | CIRI Human Rights Data Project | CIRI Data | NEW_EMPINX | http://www.humanrightsdata.com/p/data-documentation.html |
| **Recent internal conflict** | HIIK; UCDP/PRIO | Battle related deaths, One-sided violence, Non-state conflict, Conflict Barometer 2016 | Highest casualty estimates | http://ucdp.uu.se/downloads/<br>http://hiik.de/de/daten/ |
| **Neighbours with HVC** | HIIK; UCDP/PRIO | Battle related deaths, One-sided violence, Non-state conflict, Conflict Barometer 2016 | Highest casualty estimates | |
| **Years since HVC** | HIIK; UCDP/PRIO | Armed Conflict Dataset, Conflict Barometer 2016 | Conflicts of intensity level 2 | |
| **Corruption** | World Bank | Control of Corruption: Estimate | CC.EST | http://databank.worldbank.org/data/reports.aspx?source=worldwide-governance-indicators |
| **Ethnic Power Change** | ETH Zurich | EPR Core Dataset | Recording of dataset, see variable page | http://www.icr.ethz.ch/data/epr |

*Table 1 - Variable sources (first part)*[1]

[1] All datasets have been accessed on September 15th, 2017.

| | | | | |
|---|---|---|---|---|
| **Ethnic compilation** | ETH Zurich | EPR Core Dataset | Recording of dataset, see variable page | http://www.icr.ethz.ch/data/epr |
| **Transnational ethnic bonds** | CIDCM Center for International Development &Conflict Management | Marupdate_20042006 | GC10 | http://www.mar.umd.edu/mar_data.asp |
| **Homicide rate** | World Bank | World Development Indicators | Intentional homicides (per 100,000 people) | http://data.worldbank.org/indicator/VC.IHR.PSRC.P5 |
| **Infant mortality** | World Bank | World Development Indicators | Mortality rate, under-5 (per 1,000 live births) | http://data.worldbank.org/indicator/SH.DYN.MORT |

| Indicator | Source | Name of dataset | Name of original indicator(s) | URL |
|---|---|---|---|---|
| **GDP per capita** | World Bank | World Development Indicators | GDP per capita, PPP (constant 2011 international $) | http://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD |
| **Income inequality** | Harvard Dataverse Network | The Standardized World Income Inequality Database | Net inequality | https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/11992 |
| **Openness** | Word Bank | World Development Indicators | Foreign direct investment, net inflows (BoP, current US$) | http://data.worldbank.org/indicator/BX.KLT.DINV.CD.WD |
| | | | Foreign direct investment, net inflows (% of GDP) | http://data.worldbank.org/indicator/BX.KLT.DINV.WD.GD.ZS |
| | | | Exports of goods and services (% of GDP) | http://data.worldbank.org/indicator/NE.EXP.GNFS.ZS |
| **Food security** | FAO | Food security indicators | Average dietary energy supply adequacy | http://www.fao.org/economic/ess/ess-fs/ess-fadata/en/ |
| | | | Domestic food price index | |
| | | | Prevalence of undernourishment | |
| | | | Domestic food price volatility | |
| **Unemployment** | World Bank | World Development Indicators | Unemployment, total (% of total labour force) (modelled ILO estimate) | http://data.worldbank.org/indicator/SL.UEM.TOTL.ZS |
| **Water stress** | World Resources Institute | Aqueduct Country and River Basin Rankings (Raw country scores) | tdefm | http://www.wri.org/resources/data-sets/aqueduct-country-and-river-basin-rankings |
| **Oil producer** | World Bank | World Development Indicators | Fuel exports (% of merchandise exports) | http://data.worldbank.org/indicator/TX.VAL.FUEL.ZS.UN |
| **Structural constraints** | BTI: The Bertelsmann Stiftung | BTI 2016 | Structural constrains (Q13.1) | http://www.bti-project.org/en/index/ |

| | | | | |
|---|---|---|---|---|
| **Population size** | UN DESA/ Population Division | Annual population by single age - Both Sexes. | Sum of all ages | http://esa.un.org/unpd/wpp/Download/Standard/Interpolated/ |
| **Youth bulge** | UN DESA/ Population Division | Annual population by single age - Both Sexes. | Sum of ages 15-24 divided by sum of ages 25+ | http://esa.un.org/unpd/wpp/Download/Standard/Interpolated/ |

*Table 2 - Variable sources (second part)*[2]

[2] All datasets have been accessed on September 15th, 2017.

| Indicator | Original range | Threshold Min | Threshold Max | Transformation (Before rescaling) | Years covered |
|---|---|---|---|---|---|
| Regime type | Parcomp -88 to 5 | NA | NA | See variable details. | 1800-2015 |
| | Exrec -88 to 8 | NA | NA | | 1800-2015 |
| Lack of democracy | -10 to 10 | - | - | None | 1800-2015 |
| Government effectiveness | -2.49 to 2.43 | - | - | None | 1996-2015 |
| Level of repression | 1 to 5 | - | - | None | 1976-2015 |
| Empowerment rights | 0 to 14 | - | - | None | 1981-2011 |
| Recent internal conflict | NA | NA | NA | None | 1989-2015 (PRIO), 2016 (HIIIK) |
| Neighbours with HVC | NA | NA | NA | None | 1989-2015 (PRIO), 2016 (HIIIK) |
| Years since HVC | NA | NA | NA | None | 1946-2015 (PRIO), 2016 (HIIK) |
| Corruption | -2.06 to 2.58 | -2 | 2 | None | 1996-2015 |
| Ethnic power change | - | - | - | See variable details. | 1946-2013 |
| Ethnic compilation | - | - | - | See Table XX | 1946-2013 |
| Transnational ethnic bonds | 0 to 3 | - | - | None | 2004-2006 |
| Homicide rate | 0 to 139.13 | 1 | 50 | Log | 1995-2014 |
| Infant mortality | 1.9 to 332.9 | - | - | Log | 1989-2015 |
| GDP per capita | 246.7 to 137164 | - | - | Log | 1990-2015 |
| Income inequality | 14.06 to 67.21 | - | - | None | 1960-2015 |
| Openness | Foreign: -29679425810 to 3.065354e+12 | 100k | 15billion | Log | 1989-2015 |
| | Foreign 2: -82.89 to 466.6 | **1** | 15 | Log | 1989-2015 |
| | Export: 0.005 to 230 | 3 | 200 | Log | 1989-2015 |
| Food security | Nourishment: 5 to 80.8 | 5 | 35 | None | 1990-2014 |
| | Volatility: 0 to 210.4 | - | 20 | None | 1990-2014 |
| | Diet: 68 to 165 | 75 | 150 | None | 1990-2014 |
| | Price level: 1 to 11.69 | - | 10 | None | 1990-2014 |
| Unemployment | 0.1 to 39.3 | 2 | - | None | 1991-2014 |

| | | | | | |
|---|---|---|---|---|---|
| Water stress | 0.58 to 4.43 | 0.58 | 4.44 | None | NA |
| Oil producer | 0 to 99.97 | 1 | - | Log | 1989-2015 |
| Structural constraints | 1 to 10 | - | - | None | 2006-2016 |
| Population size | 0 to 1.38 billion | 6 | 12.5 | Log | 1989-2016 |
| Youth bulge | 0.10 to 0.42 | 0.12 | 0.39 | None | 1989-2016 |

*Table 3 - Descriptive statistics*

# 3. Regression model

Conflict studies use mostly regression analysis when they want to find a casual relation between the risk of conflict and structural indicators (see e.g. Beck et al., 2000; Bennett and Stam, 2000; Goldstone et al., 2000; Elbadawi and Sambanis, 2002). Based on economic, social, environmental and political data, the regression model used for the GCRI gives an insight into the probability and intensity of conflict at country level. The present chapter describes the model and its outputs.

The regression models described in this chapter are the same generalized linear model (glm) and linear model (lm) described in the two previous JRC technical reports on the GCRI[3], as well as for the model assumption, the dimension and the related notation.

The regression model is based on equations composed of the variables and respective coefficients. This chapter contributes to the detailed description of the GCRI regression model by explaining how the regression model operates (3.1), what the equations are (3.2), and how the coefficients are calculated (3.3).

## 3.1. The three phases of the regression model

Figure 1 presents the three different phases that characterize the regression model. Specific statistical methods, i.e. linear and logistic regression, are applied on the input data in order to obtain the output in the form of 8 different scores.

[3] "*The Global Conflict Risk Index (GCRI) A Quantitative Model, Concept and Methodology*" (2014), and "*The Global Conflict Risk Index (GCRI) Manual for data management and product output, Version 5, Code documentation and methodology summary*" (2016).

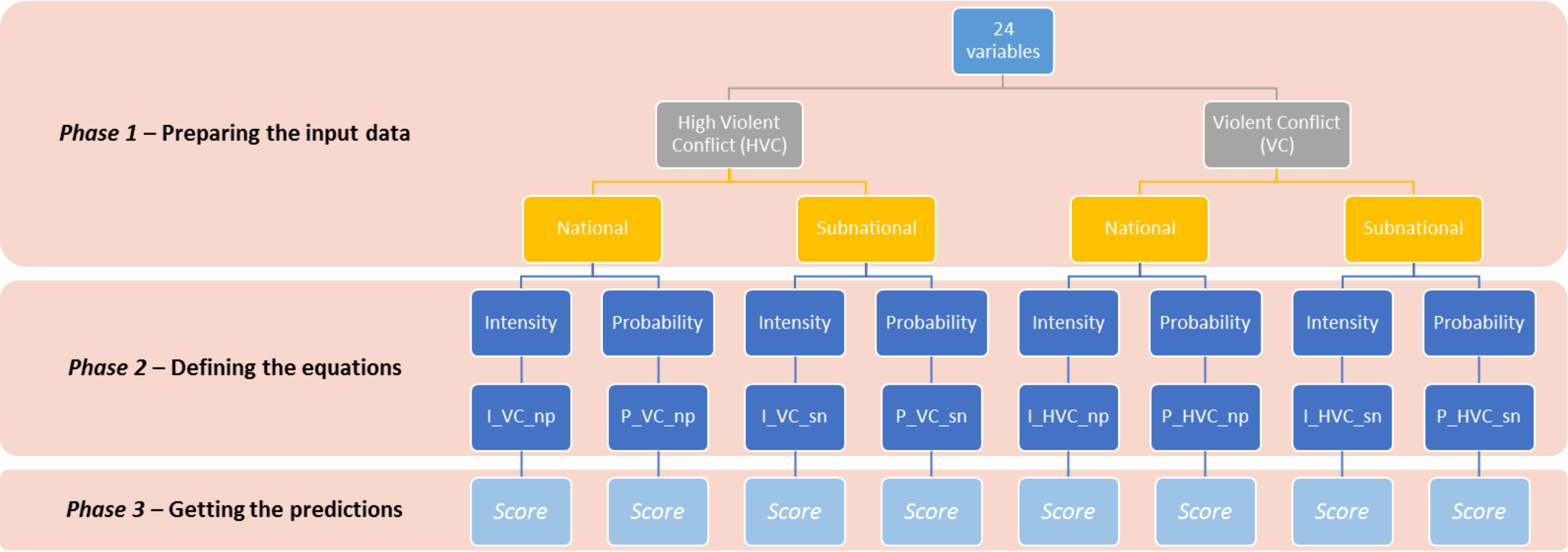

*Figure 1 - The regression model*

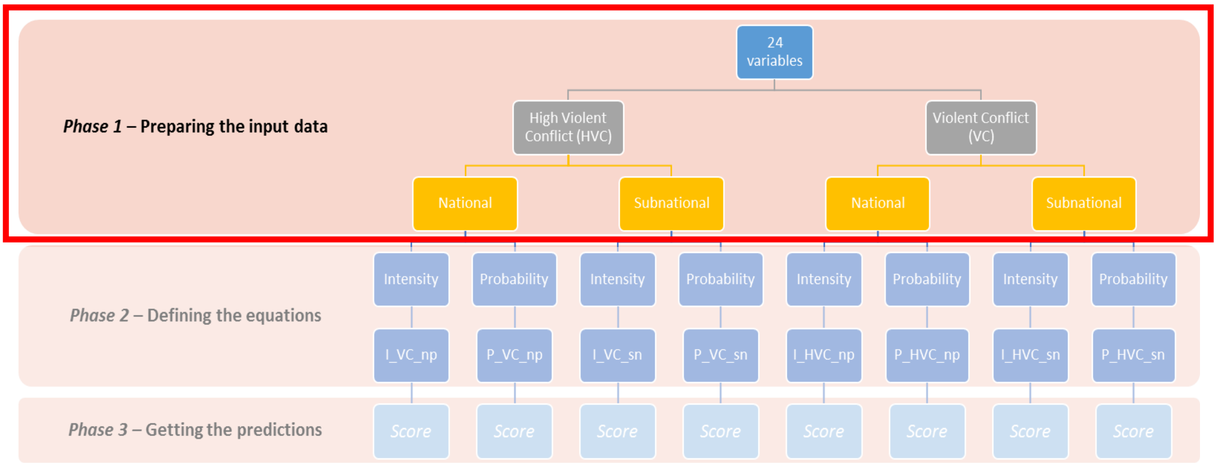

*Figure 2 - The regression model, Phase 1*

## Phase 1 – Preparing the input data

The input data for the regression model are the 24 variables described in Table 1 and Table 2 (p.4 and p.7). The preparation of the input data involves several steps. First of all, the raw data are computed, by imputing data (if necessary) and rescaling the values from 0 to 10 (the meaning of the rescaled values differs according to the variable[4]). Once the first step of the preparation is completed, the second step can start, which consist in further categorisations (Highly violent and violent conflicts; National and subnational conflicts), as described below.

### Type of conflict

Conflicts are categorized according to their type: High Violent Conflict (HVC) or Violent Conflict (VC). This differentiation is made by applying threshold on the variable "Recent Internal Conflict" whose values scale from 0 to 10 (no conflict to high violent conflict). A conflict is classified in the "High Violent Conflict (HVC)" category, if the country/year score for this specific variable is equal or higher than 8. On the other hand, a conflict is classified in the "Violent Conflict (VC)" category when the threshold applied is of 5. Then a lag[5] is calculated, in order to analyse the change of the conflict situation in the next 4 years. More specifically, given a country/year, the highest value among the scores of the 4 following years is taken.

[4] The meanings of the rescaled values are described in the technical report "*Conflict Risk Indicators: Significance and Data Management in the GCRI*" (doi. 10.2760/44005).

[5] A lag refers to a difference in time between an observation and a previous observation. (Eurostat Statistics Explained, Glossary. Available at: http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Lag. Retrieved on 26/07/2017)

### Dimension

For each type of conflict (HVC and VC), we look at the two different dimensions of conflict: national and subnational, based on the input data.

### Dataset

As a result of the previous calculations, other variables are added into the dataset used:
- the lag of conflict intensity at the national level (based on the variable "Recent internal conflict");

- the lag of conflict intensity at the subnational level (based on the variable "Recent internal conflict");

- the maximum value between the intensity at the national and subnational levels (based on the variable "Recent internal conflict");

- the value of the variable "Neighbouring with HVC";

- the value of the variable "Years since HVC".

The dataset for running the regression model is complete after applying all these calculations to the raw data. The table below provides an overview on all variables used in the regression model once the preparation of the input data is completed.

| | | |
|---|---|---|
| Economic, social, political, geographical and environmental factors | Regime Type | REG_U |
| | Lack of Democracy | REG_P2 |
| | Government Effectiveness | GOV_EFF |
| | Level of Repression | REPRESS |
| | Empowerment Rights | EMPOWER |
| | Corruption | CORRUPT |
| | Ethnic Power Change | ETHNIC_NP |
| | Ethnic Compilation | ETHNIC_SN |
| | Transnational Ethnic Bonds | DISPER |
| | Homicide Rate | HOMIC |
| | Infant Mortality | MORT |
| | GDP per capita | GDP |
| | Income Inequality | INEQ_SWIID |
| | Openness | ECON_ISO |
| | Food Security | FOOD |
| | Unemployment | UNEMP |
| | Water Stress | WATER |
| | Oil Production | FUEL_EXP |
| | Structural Constraints | STRUCT |
| | Population Size | POP |

| | Youth Bulge | | YOUTHBOTH |
|---|---|---|---|
| Maximum value between the intensity at the national and subnational levels | | CON_INT | |
| Value of the intensity in neighbouring countries in HVC | | CON_NB | |
| Value of years since HVC | | YRS_HVC | |
| Intensity at the National level | | Intensity_Y_NP | |
| Lag applied on the intensity at the National level | | Intensity_Y4_NP | |
| Intensity at the Subnational level | | Intensity_Y_SN | |
| Lag applied on the intensity at the Subnational level | | Intensity_Y4_SN | |
| | ***Applied threshold of:*** | | |
| Boolean conditions HVC | ***8*** | Intensity National (Boolean) | HVC_Y_NP |
| | ***8*** | Lag of Intensity National (Boolean) | HVC_Y4_NP |
| | ***8*** | Intensity Subnational (Boolean) | HVC_Y_SN |
| | ***8*** | Lag of Intensity Subnational (Boolean) | HVC_Y4_SN |
| Boolean conditions VC | ***5*** | Intensity National (Boolean) | VC_Y_NP |
| | ***5*** | Lag of Intensity National (Boolean) | VC_Y4_NP |
| | ***5*** | Intensity Subnational (Boolean) | VC_Y_SN |
| | ***5*** | Lag of Intensity Subnational (Boolean) | VC_Y4_SN |

*Table 4 - Variables used in the regression model*

**Phase 2 – Defining the equations**

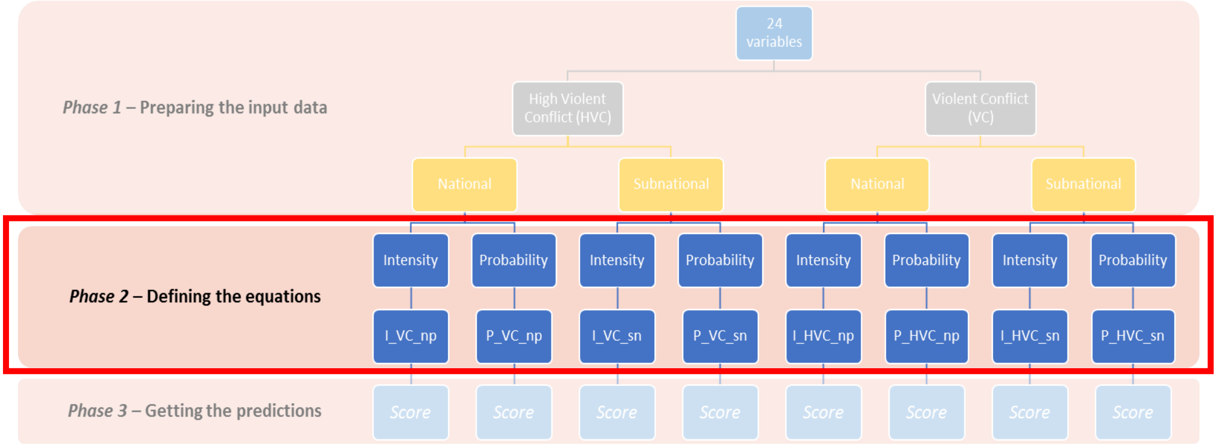

*Figure 3 - The regression model, Phase 2*

Based on the two categorisations, HVC and VC, National and Subnational, the scope of the assessment is therefore on the four cases listed below:

1) Probability and intensity of conflict in HVC at the subnational level;

2) Probability and intensity of conflict in HVC at the national level;

3) Probability and intensity of conflict in VC at the subnational level;

4) Probability and intensity of conflict in VC at the national level.

Two different equations are used to calculate the probability and the intensity, which means that, for each of the four cases presented above, two equations are hence needed. Therefore, 8 equations in total are required to assess the probability and intensity of conflict, and describe the full conflict panorama.

- The **intensity** of a conflict is predicted using a linear model lm, which has the following mathematical notation:

  $$I = a_0 + a_1X_1 + \dots + a_nX_n$$

  Where I is the intensity of the conflict, $a_0$, $a_1$, $a_2$, .. $a_n$ are the coefficients and $X_1$, $X_2$, … $X_n$ are the variables we consider in the model.

- The **probability** of a conflict is predicted using a logistic regression, which uses the generalized linear model glm and is mathematically defined as follows:

$$p = \frac{e^{Y}}{1 + e^{Y}} \quad ; \quad Y = a_0 + a_1x_1 + .. + a_nx_n$$

  Where p is the probability of a conflict, $a_0$, $a_1$, $a_2$, .. $a_n$ are the coefficients and $X_1$, $X_2$, … $X_n$ are the variables we consider in the model.

A schematic overview of the 8 equations, used to run the models, is presented in Table 5.

| **Name of the equation** | **Type of conflict** | **Dimension** | **Probability or Intensity** |
|---|---|---|---|
| P_HVC_NP | HVC | NP | PROBABILIY |
| P_HVC_SN | HVC | SN | PROBABILIY |
| P_VC_NP | VC | NP | PROBABILIY |
| P_VC_SN | VC | SN | PROBABILIY |
| I_HVC_NP | HVC | NP | INTENSITY |

| | | | |
|---|---|---|---|
| I_HVC_SN | HVC | SN | INTENSITY |
| I_VC_NP | VC | NP | INTENSITY |
| I_VC_SN | VC | SN | INTENSITY |

*Table 5 - The eight equations of the regression model*

## Phase 3 – Getting the predictions

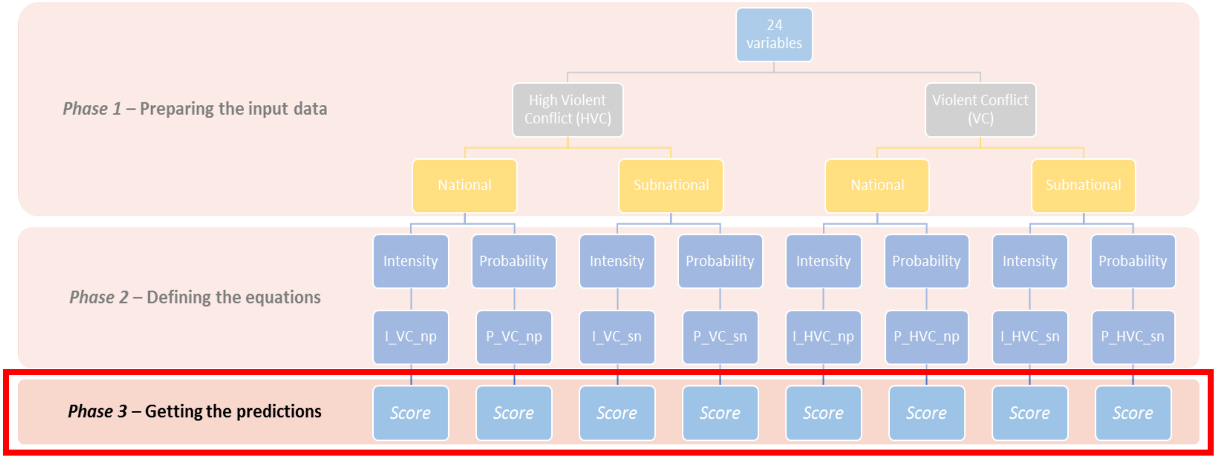

*Figure 4 - The regression model, Phase 3*

A "fitting" of the regression model is conducted so as to obtain the coefficients and intercept of the equations. For this, we use the two models (glm and lm) that consist of equations, while the quantities appearing in the equations are classified as variables. The fitting uses selected series of data from 1989 to 2011, named the "Dataset for fitting", which was inherited from previous phase of development. In order to ensure comparability throughout the years, this series is still being used. While all data from 1989 to 2011 are used for calculating the probability, a selection is made for calculating the intensity. In fact, a filter is applied on the dataset (equal to 1, as presented in the column "Filter" in the table below), in order to analyse only the cases experiencing a conflict. The output of the process is a statistical set of information which includes the coefficients and the intercept.

| **Name of the equation** | **Filter** | **Probability or Intensity** |
|---|---|---|
| P_HVC_NP | None | PROBABILIY |
| P_HVC_SN | None | PROBABILIY |

| | | |
|---|---|---|
| P_VC_NP | None | PROBABILIY |
| P_VC_SN | None | PROBABILIY |
| I_HVC_NP | HVC_Y4_NP==1 | INTENSITY |
| I_HVC_SN | HVC_Y4_SN==1 | INTENSITY |
| I_VC_NP | VC_Y4_NP==1 | INTENSITY |
| I_VC_SN | VC_Y4_SN==1 | INTENSITY |

*Table 6 - Filters applied on the dataset*

The calculations to obtain the predictions are performed using the equations and the coefficients and intercept obtained thanks to the “fitting” process. The outputs are scores of the intensity and probability. The following sections describe in detail the equations and the elements composing it.

## 3.2. Equations

All the 8 equations are composed of the same variables, except for *ETHNIC_NP* that is used only for the National dimension and *ETHNIC_SN* that is used only for the subnational one. We present in the sub-sections below the explicit equations and the associated coefficients. As described in section 3.1 (p.10) on input data preparation, conflicts are categorized according to their type (high violent conflict or violent conflict) and dimension (national and subnational). The first sub-section describes the equations associated with the conflict type “High Violent Conflict”, whereas the second sub-section describes the equations associated with the conflict type “Violent Conflict”.

### 3.2.1. High Violent Model Equations

This sub-section introduces the equations for calculating the probability and intensity of conflict, and the quantities appearing in the equations. In this sub-section, it applies specifically to each of the two dimensions “National” and “Subnational”, inside the conflict type “High Violent Conflict”. The quantities appearing in the equations presented below are the variables (in black) and associated coefficients (in orange). The coefficients are described in detailed in section 3.3 (p.20).

**High Violent Conflict (HVC), National Dimension, Intensity (I_HVC_NP)**

To calculate the Intensity for *National Conflict* (I_HVC_NP), the equation is:

I_HVC_NP = -1.108*REG_U+ -0.358*INEQ_SWIID+ -0.399*GDP_CAP+ 0.203*REG_U*INEQ_SWIID+ 0.036*INEQ_SWIID*GDP_CAP+ 0.158*REG_U*GDP_CAP + -0.029*REG_U*INEQ_SWIID*GDP_CAP+ 0.054*REG_P2+ -0.205*GOV_EFF+ -0.094*EMPOWER+ 0.027*REPRESS+ 0.033*CON_NB+ -0.003*YRS_HVC+ 0.031*CON_INT+ -0.144 *MORT+ -0.036 *DISPER+ -0.101 *HOMIC+ -0.056 *ETHNIC_NP+ 0.185 *FOOD+ 0.059*POP+ -0.094*WATER+ -0.051 *ECON_ISO+ 0.006 *FUEL_EXP+ 0.122*STRUCT+ -0.007*UNEMP+ 0.312*YOUTHBBOTH+ 0.275*CORRUPT+ 9.574

## High Violent Conflict (HVC), National Dimension, Probability (P_HVC_NP)

To calculate the Probability for *National Conflicts* (P_HVC_NP):

P_HVC_NP = EXP($\gamma$) / (1+EXP($\gamma$))

$\gamma$ = -1.166*REG_U+ -1.685*INEQ_SWIID+ -1.302*GDP_CAP+ 0.219*REG_U*INEQ_SWIID+ 0.181*INEQ_SWIID*GDP_CAP+ - 0.134*REG_U*GDP_CAP + -0.026*REG_U*INEQ_SWIID*GDP_CAP + 0.024*REG_P2+ 0.310*GOV_EFF+ -0.105*EMPOWER+ 0.152*REPRESS+ 0.069*CON_NB+ 0.171*YRS_HVC+ 0.229*CON_INT+ 0.214*MORT+ -0.075*DISPER+ 0.104*HOMIC+ -0.037*ETHNIC_NP+ -0.089*FOOD+ 0.110*POP+ 0.052*WATER+ 0.110*ECON_ISO+ 0.067*FUEL_EXP+ 0.448*STRUCT+ -0.098*UNEMP+ 0.468*YOUTHBBOTH+ 0.034*CORRUPT+ -4.881

## High Violent Conflict (HVC), Sub National Dimension, Intensity (I_HVC_SN)

To calculate the Intensity for *Subnational Conflict* (I_HVC_SN):

I_HVC_SN = -0.016*REG_U+ -0.132*INEQ_SWIID+ 0.078*GDP_CAP+ 0.001*REG_U*INEQ_SWIID+ -0.006*INEQ_SWIID*GDP_CAP+ -0.009*REG_U*GDP_CAP+ 0.002*REG_U*INEQ_SWIID*GDP_CAP + -0.006*REG_P2+ 0.039*GOV_EFF+ 0.022*EMPOWER+ -0.009*REPRESS+ -0.008 *CON_NB+ 0.026*YRS_HVC+ -0.009*CON_INT+ 0.136*MORT+ -0.041*DISPER+ 0.014*HOMIC+ 0.053*ETHNIC_SN+ 0.063*FOOD+ 0.056*POP+ 0.018*WATER+ -0.015*ECON_ISO+ 0.004*FUEL_EXP+ -0.128*STRUCT+ 0.052*UNEMP+ -0.043*YOUTHBBOTH+ 0.037*CORRUPT+ 8.435

## High Violent Conflict (HVC), Sub National Dimension, Probability (P_HVC_SN)

To calculate the Probability for *Subnational Conflicts* (P_HVC_SN):

P_HVC_SN = EXP($\gamma$) / (1+EXP($\gamma$))

$\gamma$ = 1.010*REG_U+ 0.477*INEQ_SWIID+ 0.647*GDP_CAP+ -0.198*REG_U*INEQ_SWIID+ -0.146*INEQ_SWIID*GDP_CAP+ - 0.194*REG_U*GDP_CAP + 0.038*REG_U*INEQ_SWIID*GDP_CAP + 0.008*REG_P2+ 0.439*GOV_EFF+ 0.06*EMPOWER+ 0.221*REPRESS+ -0.008*CON_NB+ -0.050*YRS_HVC+ 0.308*CON_INT+ 0.281*MORT+ -0.065*DISPER+ 0.147*HOMIC+ 0.257*ETHNIC_SN+ 0.062*FOOD+ 0.478*POP+ -0.125*WATER+ -0.053*ECON_ISO+ -0.144*FUEL_EXP+ -0.221*STRUCT+ 0.241*UNEMP+ -0.231*YOUTHBBOTH+ -0.139*CORRUPT+ -11.738

### 3.2.2. Violent Model Equations

This sub-section introduces the equations for calculating the probability and intensity of conflict, and the quantities appearing in the equations. In this sub-section, it applies specifically to each of the two dimensions "National" and "Subnational", inside the conflict type "Violent Conflict". The quantities appearing in the equations presented below are the variables (in black) and associated coefficients (in orange).

**Violent Conflict (VC), National Dimension, Intensity (I_VC_NP)**

To calculate the Intensity for *National Conflict* (I_VC_NP):

I_VC_NP = -1.238*REG_U+ -1.088*INEQ_SWIID+ -1.009*GDP_CAP+ 0.189*REG_U*INEQ_SWIID+ 0.119*INEQ_SWIID*GDP_CAP+ 0.171*REG_U*GDP_CAP+ -0.026*REG_U*INEQ_SWIID*GDP_CAP + 0.073*REG_P2+ -0.057*GOV_EFF+ -0.092*EMPOWER+ 0.015*REPRESS+ -0.022*CON_NB+0.112*YRS_HVC+0.123*CON_INT+0.084*MORT+ -0.032*DISPER+ 0.020*HOMIC+ -0.042*ETHNIC_NP+ -0.030*FOOD+ 0.024*POP+ -0.140*WATER+ 0.015*ECON_ISO+ 0.065*FUEL_EXP+ 0.266*STRUCT+ -0.076*UNEMP+ 0.330*YOUTHBBOTH+ 0.353*CORRUPT+8.331

**Violent Conflict (VC), National Dimension, Probability (P_VC_NP)**

To calculate the Probability for *National Conflicts* (P_VC_NP):

P_VC_NP = EXP($\gamma$) / (1+EXP($\gamma$))

$\gamma$ = 0.324*REG_U+ -0.538*INEQ_SWIID+ -0.192*GDP_CAP+ 0.016*REG_U*INEQ_SWIID+ 0.028*INEQ_SWIID*GDP_CAP+ - 0.093*REG_U*GDP_CAP + 0.006*REG_U*INEQ_SWIID*GDP_CAP + -0.025*REG_P2+ 0.587*GOV_EFF+ -0.126*EMPOWER+ 0.155*REPRESS+ 0.164*CON_NB+ 0.125*YRS_HVC+ 0.210*CON_INT+ 0.239*MORT+ -0.075*DISPER+ 0.042*HOMIC+ -0.012*ETHNIC_NP+ -0.066*FOOD+ 0.181*POP+ 0.211*WATER+ 0.003*ECON_ISO+ 0.053*FUEL_EXP+ 0.420*STRUCT+ 0.002*UNEMP+ 0.196*YOUTHBBOTH+ -0.263*CORRUPT+ -10.06

**Violent Conflict (VC), Sub National Dimension, Intensity (I_VC_SN)**

To calculate the Intensity for *Subnational Conflict* (I_VC_SN):

I_VC_NP = 0.872*REG_U+ 0.446*INEQ_SWIID+ 0.777*GDP_CAP+ -0.175*REG_U*INEQ_SWIID+ -0.110*INEQ_SWIID*GDP_CAP+ -0.157*REG_U*GDP_CAP+ 0.032 REG_U*INEQ_SWIID*GDP_CAP + 0.021*REG_P2+ 0.238*GOV_EFF+ 0.059*EMPOWER+ 0.040*REPRESS+ -0.025*CON_NB+ 0.001*YRS_HVC+ 0.151*CON_INT+ -0.036*MORT+ -0.057*DISPER+ 0.051*HOMIC+ 0.098*ETHNIC_SN+ -0.017*FOOD+ 0.310*POP+ -0.075*WATER+ -0.070*ECON_ISO+ -0.075*FUEL_EXP+ -0.112*STRUCT+ 0.217*UNEMP+ -0.160*YOUTHBBOTH+ 0.076*CORRUPT+0.275

**Violent Conflict (VC), Sub National Dimension, Probability (P_VC_SN)**

To calculate the Probability for *Subnational Conflicts* (P_VC_SN):

P_VC_SN = EXP(γ) / (1+EXP(γ))

γ = 1.074*REG_U+ 0.114*INEQ_SWIID+ -0.007*GDP_CAP+ -0.064*REG_U*INEQ_SWIID+ -0.004*INEQ_SWIID*GDP_CAP+ -0.148*REG_U*GDP_CAP + 0.020*REG_U*INEQ_SWIID*GDP_CAP + -0.081*REG_P2+ 0.052*GOV_EFF+ -0.084*EMPOWER+ 0.178*REPRESS+ -0.009*CON_NB+ -0.035*YRS_HVC+ 0.285*CON_INT+ 0.396*MORT+ 0.072*DISPER+ 0.033*HOMIC+ 0.244*ETHNIC_SN+ 0.002*FOOD+ 0.289*POP+ 0.018*WATER+ -0.039*ECON_ISO+ 0.009*FUEL_EXP+ 0.025*STRUCT+ -0.100*UNEMP+ 0.091*YOUTHBBOTH+ 0.164*CORRUPT+ -8.547

## 3.3. Coefficients

The coefficients give a specific weight to the variables they are associated to. The coefficients are either positive (it corresponds to a reinforcing effect) or negative (it corresponds to a hindering effect). As described in the section 3.2 (p.17) presenting the equations, the coefficients are one of the two quantities appearing in the equations for calculating the probability and intensity of conflict, together with the variables. The following sub-sections list the coefficients used in the equations. The coefficients used for the conflict type "High violent conflict" are presented in the first sub-section whereas the coefficients used for the conflict type "Violent conflict" are presented in the second sub-section.

### 3.3.1. High Violent Model Coefficients

This sub-section introduces the coefficients used for calculating the probability and intensity of conflict. As shown in the tables below, the coefficients are associated to specific variables. In this sub-section, it applies specifically to each of the two dimensions “National” and “Subnational”, inside the conflict type “High Violent Conflict”.

**High Violent Model Coefficients National Dimension**

The coefficients used for calculating the probability of conflict are listed on the left side of the tables (*NP HVC Prob*), and the coefficients used for calculating the intensity of conflict are listed on the right side of the tables (*NP HVC Intensity*).

| NP HVC Prob | | NP HVC Intensity | |
|---|---|---|---|
| **(Intercept)** | -4.8815 | **(Intercept)** | 9.5742 |
| **REG_U** | -1.1670 | **REG_U** | -1.1083 |
| **INEQ_SWIID** | -1.6856 | **INEQ_SWIID** | -0.3588 |
| **GDP_CAP** | -1.3024 | **GDP_CAP** | -0.3992 |
| **REG_P2** | 0.0246 | **REG_P2** | 0.0540 |
| **GOV_EFF** | 0.3109 | **GOV_EFF** | -0.2060 |
| **EMPOWER** | -0.1053 | **EMPOWER** | -0.0944 |
| **REPRESS** | 0.1526 | **REPRESS** | 0.0273 |
| **CON_NB** | 0.0694 | **CON_NB** | 0.0333 |
| **YRS_HVC** | 0.1717 | **YRS_HVC** | -0.0032 |
| **CON_INT** | 0.2291 | **CON_INT** | 0.0312 |
| **MORT** | 0.2148 | **MORT** | -0.1444 |
| **DISPER** | -0.0758 | **DISPER** | -0.0367 |
| **HOMIC** | 0.1047 | **HOMIC** | -0.1014 |
| **ETHNIC_NP** | -0.0374 | **ETHNIC_NP** | -0.0566 |
| **FOOD** | -0.0898 | **FOOD** | 0.1851 |
| **POP** | 0.1102 | **POP** | 0.0600 |
| **WATER** | 0.0530 | **WATER** | -0.0941 |
| **ECON_ISO** | 0.1108 | **ECON_ISO** | -0.0514 |
| **FUEL_EXP** | 0.0677 | **FUEL_EXP** | 0.0061 |
| **STRUCT** | 0.4485 | **STRUCT** | 0.1225 |
| **UNEMP** | -0.0985 | **UNEMP** | -0.0079 |
| **YOUTHBBOTH** | 0.4688 | **YOUTHBBOTH** | 0.3122 |
| **CORRUPT** | 0.0340 | **CORRUPT** | 0.2759 |

|  |  |  |  |
|---|---|---|---|
| REG_U:INEQ_SWIID | 0.2192 | REG_U:INEQ_SWIID | 0.2040 |
| REG_U:GDP_CAP | 0.1348 | REG_U:GDP_CAP | 0.1585 |
| INEQ_SWIID:GDP_CAP | 0.1818 | INEQ_SWIID:GDP_CAP | 0.0361 |
| REG_U:INEQ_SWIID:GDP_CAP | -0.0263 | REG_U:INEQ_SWIID:GDP_CAP | -0.0293 |

*Table 7 - High Violent Model Coefficients National Dimension*

### High Violent Model Coefficients Sub National Dimension

The coefficients used for calculating the probability of conflict are listed on the left side of the tables (*SN HVC Prob*), and the coefficients used for calculating the intensity of conflict are listed on the right side of the tables (*SN HVC Intensity*).

| SN HVC Prob |  | SN HVC Intensity |  |
|---|---|---|---|
| (Intercept) | -11.7387 | (Intercept) | 8.4356 |
| REG_U | 1.0105 | REG_U | -0.0168 |
| INEQ_SWIID | 0.4779 | INEQ_SWIID | -0.1322 |
| GDP_CAP | 0.6470 | GDP_CAP | 0.0788 |
| REG_P2 | 0.0081 | REG_P2 | -0.0063 |
| GOV_EFF | 0.4392 | GOV_EFF | 0.0392 |
| EMPOWER | 0.0620 | EMPOWER | 0.0226 |
| REPRESS | 0.2214 | REPRESS | -0.0097 |
| CON_NB | -0.0088 | CON_NB | -0.0089 |
| YRS_HVC | -0.0509 | YRS_HVC | 0.0262 |
| CON_INT | 0.3080 | CON_INT | -0.0091 |
| MORT | 0.2813 | MORT | 0.1364 |
| DISPER | -0.0658 | DISPER | -0.0416 |
| HOMIC | 0.1479 | HOMIC | 0.0145 |
| ETHNIC_SN | 0.2573 | ETHNIC_SN | 0.0538 |
| FOOD | 0.0621 | FOOD | 0.0635 |
| POP | 0.4784 | POP | 0.0569 |
| WATER | -0.1255 | WATER | 0.0181 |
| ECON_ISO | -0.0532 | ECON_ISO | -0.0155 |
| FUEL_EXP | -0.1443 | FUEL_EXP | 0.0048 |
| STRUCT | -0.2211 | STRUCT | -0.1288 |
| UNEMP | 0.2417 | UNEMP | 0.0522 |
| YOUTHBBOTH | -0.2312 | YOUTHBBOTH | -0.0435 |
| CORRUPT | -0.1391 | CORRUPT | 0.0372 |

| | | | |
|---|---|---|---|
| REG_U:INEQ_SWIID | -0.1987 | REG_U:INEQ_SWIID | 0.0014 |
| REG_U:GDP_CAP | -0.1950 | REG_U:GDP_CAP | -0.0092 |
| INEQ_SWIID:GDP_CAP | -0.1463 | INEQ_SWIID:GDP_CAP | -0.0067 |
| REG_U:INEQ_SWIID:GDP_CAP | 0.0387 | REG_U:INEQ_SWIID:GDP_CAP | 0.0028 |

*Table 8 - High Violent Model Coefficients Sub National Dimension*

### 3.3.2. Violent Model Coefficients

This sub-section introduces the coefficients used for calculating the probability and intensity of conflict. As shown in the tables below, the coefficients are associated to specific variables. In this sub-section, it applies specifically to each of the two dimensions "National" and "Subnational", inside the conflict type "Violent Conflict".

**Violent Model Coefficients National Dimension**

The coefficients used for calculating the probability of conflict are listed on the left side of the tables (*NP VC Prob*), and the coefficients used for calculating the intensity of conflict are listed on the right side of the tables (*NP VC Intensity*).

| NP VC Prob | | NP VC Intensity | |
|---|---|---|---|
| (Intercept) | -10.0602 | (Intercept) | 8.3311 |
| REG_U | 0.3250 | REG_U | -1.2381 |
| INEQ_SWIID | -0.5386 | INEQ_SWIID | -1.0888 |
| GDP_CAP | -0.1929 | GDP_CAP | -1.0095 |
| REG_P2 | -0.0250 | REG_P2 | 0.0734 |
| GOV_EFF | 0.5877 | GOV_EFF | -0.0577 |
| EMPOWER | -0.1265 | EMPOWER | -0.0924 |
| REPRESS | 0.1550 | REPRESS | 0.0159 |
| CON_NB | 0.1640 | CON_NB | -0.0225 |
| YRS_HVC | 0.1257 | YRS_HVC | 0.1126 |
| CON_INT | 0.2106 | CON_INT | 0.1238 |
| MORT | 0.2400 | MORT | 0.0841 |
| DISPER | -0.0759 | DISPER | -0.0323 |
| HOMIC | 0.0424 | HOMIC | 0.0203 |
| ETHNIC_NP | -0.0126 | ETHNIC_NP | -0.0426 |
| FOOD | -0.0661 | FOOD | -0.0301 |
| POP | 0.1814 | POP | 0.0250 |

| | | | |
|---|---|---|---|
| **WATER** | 0.2120 | **WATER** | -0.1402 |
| **ECON_ISO** | 0.0039 | **ECON_ISO** | 0.0160 |
| **FUEL_EXP** | 0.0530 | **FUEL_EXP** | 0.0656 |
| **STRUCT** | 0.4203 | **STRUCT** | 0.2664 |
| **UNEMP** | 0.0029 | **UNEMP** | -0.0763 |
| **YOUTHBBOTH** | 0.1969 | **YOUTHBBOTH** | 0.3305 |
| **CORRUPT** | -0.2631 | **CORRUPT** | 0.3531 |
| **REG_U:INEQ_SWIID** | 0.0166 | **REG_U:INEQ_SWIID** | 0.1891 |
| **REG_U:GDP_CAP** | -0.0930 | **REG_U:GDP_CAP** | 0.1718 |
| **INEQ_SWIID:GDP_CAP** | 0.0280 | **INEQ_SWIID:GDP_CAP** | 0.1199 |
| **REG_U:INEQ_SWIID:GDP_CAP** | 0.0063 | **REG_U:INEQ_SWIID:GDP_CAP** | -0.0269 |

*Table 9 - Violent Model Coefficients National Dimension*

**Violent Model Coefficients Sub National Dimension**

The coefficients used for calculating the probability of conflict are listed on the left side of the tables (*SN VC Prob*), and the coefficients used for calculating the intensity of conflict are listed on the right side of the tables (*SN VC Intensity*).

| SN VC Prob | | SN VC Intensity | |
|---|---|---|---|
| **(Intercept)** | -8.5473 | **(Intercept)** | 0.2752 |
| **REG_U** | 1.0750 | **REG_U** | 0.8728 |
| **INEQ_SWIID** | 0.1146 | **INEQ_SWIID** | 0.4468 |
| **GDP_CAP** | -0.0076 | **GDP_CAP** | 0.7776 |
| **REG_P2** | -0.0814 | **REG_P2** | 0.0214 |
| **GOV_EFF** | -0.0523 | **GOV_EFF** | 0.2382 |
| **EMPOWER** | -0.0846 | **EMPOWER** | 0.0595 |
| **REPRESS** | 0.1784 | **REPRESS** | 0.0407 |
| **CON_NB** | -0.0091 | **CON_NB** | -0.0251 |
| **YRS_HVC** | -0.0356 | **YRS_HVC** | 0.0016 |
| **CON_INT** | 0.2855 | **CON_INT** | 0.1519 |
| **MORT** | 0.3964 | **MORT** | -0.0362 |
| **DISPER** | 0.0722 | **DISPER** | -0.0572 |
| **HOMIC** | 0.0340 | **HOMIC** | 0.0512 |
| **ETHNIC_SN** | 0.2446 | **ETHNIC_SN** | 0.0985 |
| **FOOD** | 0.0027 | **FOOD** | -0.0178 |
| **POP** | 0.2896 | **POP** | 0.3101 |
| **WATER** | 0.0187 | **WATER** | -0.0751 |

|  |  |  |  |
|---|---|---|---|
| ECON_ISO | -0.0399 | ECON_ISO | -0.0708 |
| FUEL_EXP | 0.0099 | FUEL_EXP | -0.0754 |
| STRUCT | 0.0256 | STRUCT | -0.1127 |
| UNEMP | -0.1009 | UNEMP | 0.2180 |
| YOUTHBBOTH | 0.0917 | YOUTHBBOTH | -0.1603 |
| CORRUPT | 0.1649 | CORRUPT | 0.0765 |
| REG_U:INEQ_SWIID | -0.1650 | REG_U:INEQ_SWIID | -0.1754 |
| REG_U:GDP_CAP | -0.1488 | REG_U:GDP_CAP | -0.1576 |
| INEQ_SWIID:GDP_CAP | -0.0044 | INEQ_SWIID:GDP_CAP | -0.1103 |
| REG_U:INEQ_SWIID:GDP_CAP | 0.0204 | REG_U:INEQ_SWIID:GDP_CAP | 0.0323 |

*Table 10 - Violent Model Coefficients Sub National Dimension*

## 4. Statistical significance test

In a multiple linear regression with p variables and n observations, we do have the dependent (or "predicted") variable y modelled as a linear combination of the x variables (covariates) and the β parameters (coefficients of the linear equation)[6]. The corresponding equation is as follows:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i \ \textbf{\textit{for}}\ i = 1, 2, \ldots, n$$ *(Equation 1)*

The t-test (or Student test) allows us to test the following null hypothesis for any parameter $\beta_j$ :

$$H_0\colon\ \beta_j = 0$$

The alternative hypothesis is

$$H_1\colon\ \beta_j \neq 0$$

[6] For a deeper introduction to the use of the linear model in the study of armed conflicts, see *Kauffmann, Mayeul. Méthodes statistiques appliquées aux questions internationales*, March 2009, 197 p., L'Harmattan, Paris

The null hypothesis is the hypothesis that the coefficient equals zero. The ability to assess this hypothesis and the alternative hypothesis contributes to the model's falsifiability and is a significant element of the scientificity of the approach[7].

It should be noted here that we do not know the true value of the $\boldsymbol{\beta_j}$ coefficient (because of, inter alia, measurement errors); we only have an estimate $\widehat{\boldsymbol{\beta}}_j$ of the j^th^ coefficient of equation $y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i \; \textbf{\textit{for}} \; i = 1, 2, \dots, n$ (Equation 1). The estimates $\widehat{\boldsymbol{\beta}}_j$ are reported in the first numeric column of the tables showing the estimated models below; the first row ("Intercept") corresponds to $\widehat{\boldsymbol{\beta}}_0$ (the constant part of the equation), while the following rows correspond to the $\boldsymbol{\beta_j}$ coefficients relevant to each covariate $\boldsymbol{j}$.

Small random variations in the dataset may lead to an estimate of the coefficient $\widehat{\boldsymbol{\beta}}_j$ which is slightly different from zero, but not significantly different enough to allow us to reject the null hypothesis that the true (unknown) $\boldsymbol{\beta_j}$ coefficient is indeed zero ; in this case, this is equivalent to saying that the $\boldsymbol{x_j}$ covariate has no significant impact on $\boldsymbol{y}$ (in our case, that a given GCRI component has no significant impact on the intensity of conflict in a particular model, assuming that this model is appropriate). If $\boldsymbol{H_0}$ is rejected, we then keep the alternative hypothesis that the parameter is most likely different from zero.

In the case of the linear models used to model the intensity of conflict, the test statistic is the t statistic, defined as the estimate of the parameter divided by its standard deviation (this is shown in tables below in the column "t value"). Under appropriate hypotheses, the test statistic t follows a Student's distribution with n - (p+1) degrees of freedom. If there was no uncertainty and if the covariates had no impact on y, then the t

[7] For a more thorough discussion of these concepts in view of Popper's epistemology, see Kauffmann, Mayeul, "Introduction" in Kauffmann, Mayeul (ed.) *Building and Using Datasets on Armed Conflicts*, May 2008, Amsterdam: IOS Press, 204 p. ISBN: 978-1586038472 http://ebooks.iospress.nl/volume/building-and-using-datasets-on-armed-conflicts

values would all be equal to zero. Because of uncertainty, a t value different from zero might still be compatible with the null hypothesis. The last column of the table, Pr(>|t|), also named the "p-value", measures the probability that we get a t value that far from zero (or even further from zero than the t value), given that the null hypothesis is assumed to be true. If this probability is very low (often, below 5% or 0.05) we use a decision rule which says that the null hypothesis should be rejected. If the p-value is higher than the threshold, then the null hypothesis cannot be rejected.

It should be emphasised that the p-value associated with the t-test is only a hint on the likelihood of the impact of a covariate on the dependent variable. In no way can a p-value of 0.05 be interpreted as: "the probability of incorrectly rejecting a true null hypothesis is 5 %" (such a probability has been measured to be greater than 23 % and typically close to 50 % by Sellke et al. (2001))[8] .

The interpretation of the four logistic models[9] below (modelling the probability of conflict) is similar to that of the linear models (for conflict intensity) if we look at the p-value. The test statistic, however, is different. In effect, it can be demonstrated that the estimate divided by its standard errors follows (under the null hypothesis) a normal distribution (not a Student distribution); in this case, the test statistic is named z. Hence, the p-value is Pr(>|z|) as shown in the last column of the tables related to the logistic models.

### Probability of VC_NP logistic model

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|

[8] Thomas SELLKE, M. J. BAYARRI, and James O. BERGER, "Calibration of p Values for Testing Precise Null Hypotheses", *The American Statistician*, February 2001, Vol. 55, No. 1, pp. 63-64. Available at http://www.cems.uvm.edu/~jbuzas/buzas/calibrating_p_values.pdf

[9] For a presentation of the Generalized Linear Model (of which the logistic model is a particular case) in the context of conflict modelling, and a review of several GLMs, see: Kauffmann, Mayeul, "Short Term and Event Interdependence Matter: A Political Economy Continuous Model of Civil War", in Peace Economics, Peace Science and Public Policy, Vol. 13, Issue 1, 2007, BE-Press (Berkeley), 19 p. See also: Kucera Jan; Kauffmann Mayeul; Duta Ana-Maria; Soler Ivette Tarrida; Tenerelli Patrizia; Trianni Giovanna; Hale Catherine; Rizzo Lauren; Ferri Stefano. Armed conflicts and natural resources - Scientific report on Global Atlas and Information Centre for Conflicts and Natural Resources. 2011. European Commission - Scientific and Technical Research Reports. ISBN 978-92-79-20498-2, pp. 23-28. Kauffmann, Mayeul, Gouvernance économique mondiale et conflits armés. Banque mondiale, FMI et GATT-OMC, Paris: l'Harmattan, May 2006, 330 p.

| | | | | |
|---|---|---|---|---|
| (Intercept) | -10.0602 | 2.2051 | -4.56 | 0.0000 |
| REG_U | 0.3250 | 0.3691 | 0.88 | 0.3787 |
| INEQ_SWIID | -0.5386 | 0.3885 | -1.39 | 0.1656 |
| GDP_CAP | -0.1929 | 0.3489 | -0.55 | 0.5804 |
| REG_P2 | -0.0250 | 0.0359 | -0.70 | 0.4869 |
| GOV_EFF | 0.5877 | 0.1122 | 5.24 | 0.0000 |
| EMPOWER | -0.1265 | 0.0419 | -3.02 | 0.0026 |
| REPRESS | 0.1550 | 0.0387 | 4.01 | 0.0001 |
| CON_NB | 0.1640 | 0.0200 | 8.22 | 0.0000 |
| YRS_HVC | 0.1257 | 0.0235 | 5.34 | 0.0000 |
| CON_INT | 0.2106 | 0.0245 | 8.61 | 0.0000 |
| MORT | 0.2400 | 0.0838 | 2.86 | 0.0042 |
| DISPER | -0.0759 | 0.0192 | -3.95 | 0.0001 |
| HOMIC | 0.0424 | 0.0355 | 1.19 | 0.2333 |
| ETHNIC_NP | -0.0126 | 0.0350 | -0.36 | 0.7180 |
| FOOD | -0.0661 | 0.0443 | -1.49 | 0.1355 |
| POP | 0.1814 | 0.0430 | 4.22 | 0.0000 |
| WATER | 0.2120 | 0.0427 | 4.97 | 0.0000 |
| ECON_ISO | 0.0039 | 0.0565 | 0.07 | 0.9452 |
| FUEL_EXP | 0.0530 | 0.0229 | 2.31 | 0.0207 |
| STRUCT | 0.4203 | 0.0607 | 6.92 | 0.0000 |
| UNEMP | 0.0029 | 0.0360 | 0.08 | 0.9348 |

| | | | | |
|---|---|---|---|---|
| YOUTHBBOTH | 0.1969 | 0.0665 | 2.96 | 0.0031 |
| CORRUPT | -0.2631 | 0.0965 | -2.73 | 0.0064 |
| REG_U:INEQ_SWIID | 0.0166 | 0.0678 | 0.25 | 0.8060 |
| REG_U:GDP_CAP | -0.0930 | 0.0577 | -1.61 | 0.1068 |
| INEQ_SWIID:GDP_CAP | 0.0280 | 0.0631 | 0.44 | 0.6572 |
| REG_U:INEQ_SWIID:GDP_CAP | 0.0063 | 0.0107 | 0.59 | 0.5557 |

*Table 11- Probability of VC_NP logistic model*

## Intensity of VC_NP linear model

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 8.3311 | 2.9236 | 2.85 | 0.0045 |
| REG_U | -1.2381 | 0.4856 | -2.55 | 0.0110 |
| INEQ_SWIID | -1.0888 | 0.5332 | -2.04 | 0.0416 |
| GDP_CAP | -1.0095 | 0.4492 | -2.25 | 0.0250 |
| REG_P2 | 0.0734 | 0.0491 | 1.49 | 0.1355 |
| GOV_EFF | -0.0577 | 0.1540 | -0.37 | 0.7082 |
| EMPOWER | -0.0924 | 0.0527 | -1.75 | 0.0801 |
| REPRESS | 0.0159 | 0.0527 | 0.30 | 0.7634 |
| CON_NB | -0.0225 | 0.0281 | -0.80 | 0.4237 |
| YRS_HVC | 0.1126 | 0.0273 | 4.12 | 0.0000 |
| CON_INT | 0.1238 | 0.0322 | 3.84 | 0.0001 |
| MORT | 0.0841 | 0.1207 | 0.70 | 0.4861 |
| DISPER | -0.0323 | 0.0254 | -1.27 | 0.2033 |

| | | | | |
|---|---|---|---|---|
| HOMIC | 0.0203 | 0.0533 | 0.38 | 0.7030 |
| ETHNIC_NP | -0.0426 | 0.0402 | -1.06 | 0.2895 |
| FOOD | -0.0301 | 0.0714 | -0.42 | 0.6737 |
| POP | 0.0250 | 0.0691 | 0.36 | 0.7177 |
| WATER | -0.1402 | 0.0588 | -2.38 | 0.0175 |
| ECON_ISO | 0.0160 | 0.0747 | 0.21 | 0.8309 |
| FUEL_EXP | 0.0656 | 0.0315 | 2.08 | 0.0375 |
| STRUCT | 0.2664 | 0.0849 | 3.14 | 0.0018 |
| UNEMP | -0.0763 | 0.0530 | -1.44 | 0.1501 |
| YOUTHBBOTH | 0.3305 | 0.1016 | 3.25 | 0.0012 |
| CORRUPT | 0.3531 | 0.1336 | 2.64 | 0.0085 |
| REG_U:INEQ_SWIID | 0.1891 | 0.0867 | 2.18 | 0.0295 |
| REG_U:GDP_CAP | 0.1718 | 0.0731 | 2.35 | 0.0190 |
| INEQ_SWIID:GDP_CAP | 0.1199 | 0.0822 | 1.46 | 0.1456 |
| REG_U:INEQ_SWIID:GDP_CAP | -0.0269 | 0.0134 | -2.01 | 0.0445 |

*Table 12 – Intensity of VC_NP linear model*

### Probability of VC_SN logistic model

| | **Estimate** | **Std. Error** | **z value** | **Pr(>\|z\|)** |
|---|---|---|---|---|
| (Intercept) | -8.5473 | 1.4543 | -5.88 | 0.0000 |
| REG_U | 1.0750 | 0.2613 | 4.11 | 0.0000 |
| INEQ_SWIID | 0.1146 | 0.2829 | 0.41 | 0.6853 |
| GDP_CAP | -0.0076 | 0.2598 | -0.03 | 0.9765 |

| | | | | |
|---|---|---|---|---|
| REG_P2 | -0.0814 | 0.0327 | -2.49 | 0.0128 |
| GOV_EFF | -0.0523 | 0.0973 | -0.54 | 0.5910 |
| EMPOWER | -0.0846 | 0.0369 | -2.29 | 0.0221 |
| REPRESS | 0.1784 | 0.0345 | 5.18 | 0.0000 |
| CON_NB | -0.0091 | 0.0159 | -0.58 | 0.5645 |
| YRS_HVC | -0.0356 | 0.0244 | -1.45 | 0.1457 |
| CON_INT | 0.2855 | 0.0232 | 12.33 | 0.0000 |
| MORT | 0.3964 | 0.0777 | 5.10 | 0.0000 |
| DISPER | 0.0722 | 0.0168 | 4.30 | 0.0000 |
| HOMIC | 0.0340 | 0.0312 | 1.09 | 0.2755 |
| ETHNIC_SN | 0.2446 | 0.0258 | 9.48 | 0.0000 |
| FOOD | 0.0027 | 0.0422 | 0.06 | 0.9497 |
| POP | 0.2896 | 0.0353 | 8.20 | 0.0000 |
| WATER | 0.0187 | 0.0371 | 0.50 | 0.6151 |
| ECON_ISO | -0.0399 | 0.0505 | -0.79 | 0.4288 |
| FUEL_EXP | 0.0099 | 0.0201 | 0.50 | 0.6204 |
| STRUCT | 0.0256 | 0.0498 | 0.51 | 0.6070 |
| UNEMP | -0.1009 | 0.0284 | -3.55 | 0.0004 |
| YOUTHBBOTH | 0.0917 | 0.0533 | 1.72 | 0.0852 |
| CORRUPT | 0.1649 | 0.0854 | 1.93 | 0.0535 |
| REG_U:INEQ_SWIID | -0.1650 | 0.0527 | -3.13 | 0.0017 |
| REG_U:GDP_CAP | -0.1488 | 0.0451 | -3.30 | 0.0010 |

| | | | | |
|---|---|---|---|---|
| INEQ_SWIID:GDP_CAP | -0.0044 | 0.0488 | -0.09 | 0.9276 |
| REG_U:INEQ_SWIID:GDP_CAP | 0.0204 | 0.0090 | 2.26 | 0.0240 |

*Table 13 – Probability of VC_SN logistic model*

### Intensity of VC_SN linear model

| | **Estimate** | **Std. Error** | **t value** | **Pr(>\|t\|)** |
|---|---|---|---|---|
| (Intercept) | 0.2752 | 1.5629 | 0.18 | 0.8603 |
| REG_U | 0.8728 | 0.2510 | 3.48 | 0.0005 |
| INEQ_SWIID | 0.4468 | 0.3077 | 1.45 | 0.1469 |
| GDP_CAP | 0.7776 | 0.2668 | 2.91 | 0.0036 |
| REG_P2 | 0.0214 | 0.0338 | 0.63 | 0.5277 |
| GOV_EFF | 0.2382 | 0.1071 | 2.22 | 0.0264 |
| EMPOWER | 0.0595 | 0.0371 | 1.61 | 0.1084 |
| REPRESS | 0.0407 | 0.0382 | 1.06 | 0.2879 |
| CON_NB | -0.0251 | 0.0175 | -1.44 | 0.1513 |
| YRS_HVC | 0.0016 | 0.0190 | 0.08 | 0.9332 |
| CON_INT | 0.1519 | 0.0208 | 7.29 | 0.0000 |
| MORT | -0.0362 | 0.0793 | -0.46 | 0.6483 |
| DISPER | -0.0572 | 0.0188 | -3.04 | 0.0024 |
| HOMIC | 0.0512 | 0.0366 | 1.40 | 0.1626 |
| ETHNIC_SN | 0.0985 | 0.0258 | 3.82 | 0.0001 |
| FOOD | -0.0178 | 0.0441 | -0.40 | 0.6871 |
| POP | 0.3101 | 0.0393 | 7.88 | 0.0000 |

| | | | | |
|---|---|---|---|---|
| WATER | -0.0751 | 0.0421 | -1.78 | 0.0749 |
| ECON_ISO | -0.0708 | 0.0540 | -1.31 | 0.1901 |
| FUEL_EXP | -0.0754 | 0.0216 | -3.49 | 0.0005 |
| STRUCT | -0.1127 | 0.0573 | -1.97 | 0.0494 |
| UNEMP | 0.2180 | 0.0361 | 6.03 | 0.0000 |
| YOUTHBBOTH | -0.1603 | 0.0638 | -2.51 | 0.0122 |
| CORRUPT | 0.0765 | 0.1007 | 0.76 | 0.4479 |
| REG_U:INEQ_SWIID | -0.1754 | 0.0505 | -3.48 | 0.0005 |
| REG_U:GDP_CAP | -0.1576 | 0.0396 | -3.98 | 0.0001 |
| INEQ_SWIID:GDP_CAP | -0.1103 | 0.0509 | -2.17 | 0.0304 |
| REG_U:INEQ_SWIID:GDP_CAP | 0.0323 | 0.0081 | 3.97 | 0.0001 |

*Table 14 –Intensity of VC_SN linear model*

**Probability of HVC_NP logistic model**

| | **Estimate** | **Std. Error** | **z value** | **Pr(>\|z\|)** |
|---|---|---|---|---|
| (Intercept) | -4.8815 | 2.8445 | -1.72 | 0.0861 |
| REG_U | -1.1670 | 0.5321 | -2.19 | 0.0283 |
| INEQ_SWIID | -1.6856 | 0.5443 | -3.10 | 0.0020 |
| GDP_CAP | -1.3024 | 0.4818 | -2.70 | 0.0069 |
| REG_P2 | 0.0246 | 0.0481 | 0.51 | 0.6090 |
| GOV_EFF | 0.3109 | 0.1579 | 1.97 | 0.0490 |
| EMPOWER | -0.1053 | 0.0557 | -1.89 | 0.0589 |
| REPRESS | 0.1526 | 0.0526 | 2.90 | 0.0037 |

| | | | | |
|---|---|---|---|---|
| CON_NB | 0.0694 | 0.0264 | 2.63 | 0.0087 |
| YRS_HVC | 0.1717 | 0.0261 | 6.58 | 0.0000 |
| CON_INT | 0.2291 | 0.0319 | 7.19 | 0.0000 |
| MORT | 0.2148 | 0.1111 | 1.93 | 0.0533 |
| DISPER | -0.0758 | 0.0261 | -2.90 | 0.0037 |
| HOMIC | 0.1047 | 0.0519 | 2.02 | 0.0436 |
| ETHNIC_NP | -0.0374 | 0.0413 | -0.91 | 0.3645 |
| FOOD | -0.0898 | 0.0652 | -1.38 | 0.1683 |
| POP | 0.1102 | 0.0621 | 1.77 | 0.0761 |
| WATER | 0.0530 | 0.0614 | 0.86 | 0.3880 |
| ECON_ISO | 0.1108 | 0.0748 | 1.48 | 0.1387 |
| FUEL_EXP | 0.0677 | 0.0312 | 2.17 | 0.0297 |
| STRUCT | 0.4485 | 0.0833 | 5.39 | 0.0000 |
| UNEMP | -0.0985 | 0.0531 | -1.85 | 0.0636 |
| YOUTHBBOTH | 0.4688 | 0.0955 | 4.91 | 0.0000 |
| CORRUPT | 0.0340 | 0.1424 | 0.24 | 0.8111 |
| REG_U:INEQ_SWIID | 0.2192 | 0.0936 | 2.34 | 0.0192 |
| REG_U:GDP_CAP | 0.1348 | 0.0796 | 1.69 | 0.0902 |
| INEQ_SWIID:GDP_CAP | 0.1818 | 0.0862 | 2.11 | 0.0350 |
| REG_U:INEQ_SWIID:GDP_CAP | -0.0263 | 0.0144 | -1.83 | 0.0677 |

*Table 15 – Probability of HVC_NP logistic model*

**Intensity of HVC_NP linear model**

| | **Estimate** | **Std. Error** | **t value** | **Pr(>\|t\|)** |
|---|---|---|---|---|
| (Intercept) | 9.5742 | 1.6529 | 5.79 | 0.0000 |
| REG_U | -1.1083 | 0.3092 | -3.58 | 0.0004 |
| INEQ_SWIID | -0.3588 | 0.3001 | -1.20 | 0.2327 |
| GDP_CAP | -0.3992 | 0.2596 | -1.54 | 0.1251 |
| REG_P2 | 0.0540 | 0.0279 | 1.93 | 0.0540 |
| GOV_EFF | -0.2060 | 0.0955 | -2.16 | 0.0319 |
| EMPOWER | -0.0944 | 0.0291 | -3.25 | 0.0013 |
| REPRESS | 0.0273 | 0.0316 | 0.87 | 0.3874 |
| CON_NB | 0.0333 | 0.0148 | 2.24 | 0.0257 |
| YRS_HVC | -0.0032 | 0.0143 | -0.23 | 0.8217 |
| CON_INT | 0.0312 | 0.0179 | 1.74 | 0.0823 |
| MORT | -0.1444 | 0.0737 | -1.96 | 0.0512 |
| DISPER | -0.0367 | 0.0160 | -2.30 | 0.0223 |
| HOMIC | -0.1014 | 0.0396 | -2.56 | 0.0110 |
| ETHNIC_NP | -0.0566 | 0.0192 | -2.95 | 0.0034 |
| FOOD | 0.1851 | 0.0449 | 4.12 | 0.0000 |
| POP | 0.0600 | 0.0420 | 1.43 | 0.1547 |
| WATER | -0.0941 | 0.0415 | -2.27 | 0.0241 |
| ECON_ISO | -0.0514 | 0.0430 | -1.20 | 0.2327 |
| FUEL_EXP | 0.0061 | 0.0172 | 0.35 | 0.7239 |
| STRUCT | 0.1225 | 0.0514 | 2.38 | 0.0179 |

| | | | | |
|---|---|---|---|---|
| UNEMP | -0.0079 | 0.0329 | -0.24 | 0.8097 |
| YOUTHBBOTH | 0.3122 | 0.0695 | 4.49 | 0.0000 |
| CORRUPT | 0.2759 | 0.1055 | 2.62 | 0.0094 |
| REG_U:INEQ_SWIID | 0.2040 | 0.0524 | 3.89 | 0.0001 |
| REG_U:GDP_CAP | 0.1585 | 0.0441 | 3.60 | 0.0004 |
| INEQ_SWIID:GDP_CAP | 0.0361 | 0.0452 | 0.80 | 0.4250 |
| REG_U:INEQ_SWIID:GDP_CAP | -0.0293 | 0.0077 | -3.81 | 0.0002 |

*Table 16 – Intensity of HVC_NP linear model*

### Probability of HVC_SN logistic model

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| (Intercept) | -8.5473 | 1.4543 | -5.88 | 0.0000 |
| REG_U | 1.0750 | 0.2613 | 4.11 | 0.0000 |
| INEQ_SWIID | 0.1146 | 0.2829 | 0.41 | 0.6853 |
| GDP_CAP | -0.0076 | 0.2598 | -0.03 | 0.9765 |
| REG_P2 | -0.0814 | 0.0327 | -2.49 | 0.0128 |
| GOV_EFF | -0.0523 | 0.0973 | -0.54 | 0.5910 |
| EMPOWER | -0.0846 | 0.0369 | -2.29 | 0.0221 |
| REPRESS | 0.1784 | 0.0345 | 5.18 | 0.0000 |
| CON_NB | -0.0091 | 0.0159 | -0.58 | 0.5645 |
| YRS_HVC | -0.0356 | 0.0244 | -1.45 | 0.1457 |
| CON_INT | 0.2855 | 0.0232 | 12.33 | 0.0000 |
| MORT | 0.3964 | 0.0777 | 5.10 | 0.0000 |

|  |  |  |  |  |
|---|---|---|---|---|
| DISPER | 0.0722 | 0.0168 | 4.30 | 0.0000 |
| HOMIC | 0.0340 | 0.0312 | 1.09 | 0.2755 |
| ETHNIC_SN | 0.2446 | 0.0258 | 9.48 | 0.0000 |
| FOOD | 0.0027 | 0.0422 | 0.06 | 0.9497 |
| POP | 0.2896 | 0.0353 | 8.20 | 0.0000 |
| WATER | 0.0187 | 0.0371 | 0.50 | 0.6151 |
| ECON_ISO | -0.0399 | 0.0505 | -0.79 | 0.4288 |
| FUEL_EXP | 0.0099 | 0.0201 | 0.50 | 0.6204 |
| STRUCT | 0.0256 | 0.0498 | 0.51 | 0.6070 |
| UNEMP | -0.1009 | 0.0284 | -3.55 | 0.0004 |
| YOUTHBBOTH | 0.0917 | 0.0533 | 1.72 | 0.0852 |
| CORRUPT | 0.1649 | 0.0854 | 1.93 | 0.0535 |
| REG_U:INEQ_SWIID | -0.1650 | 0.0527 | -3.13 | 0.0017 |
| REG_U:GDP_CAP | -0.1488 | 0.0451 | -3.30 | 0.0010 |
| INEQ_SWIID:GDP_CAP | -0.0044 | 0.0488 | -0.09 | 0.9276 |
| REG_U:INEQ_SWIID:GDP_CAP | 0.0204 | 0.0090 | 2.26 | 0.0240 |

*Table 17 – Probability of HVC_SN logistic model*

### Intensity of HVC_SN linear model

|  | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 0.2752 | 1.5629 | 0.18 | 0.8603 |
| REG_U | 0.8728 | 0.2510 | 3.48 | 0.0005 |
| INEQ_SWIID | 0.4468 | 0.3077 | 1.45 | 0.1469 |

| | | | | |
|---|---|---|---|---|
| GDP_CAP | 0.7776 | 0.2668 | 2.91 | 0.0036 |
| REG_P2 | 0.0214 | 0.0338 | 0.63 | 0.5277 |
| GOV_EFF | 0.2382 | 0.1071 | 2.22 | 0.0264 |
| EMPOWER | 0.0595 | 0.0371 | 1.61 | 0.1084 |
| REPRESS | 0.0407 | 0.0382 | 1.06 | 0.2879 |
| CON_NB | -0.0251 | 0.0175 | -1.44 | 0.1513 |
| YRS_HVC | 0.0016 | 0.0190 | 0.08 | 0.9332 |
| CON_INT | 0.1519 | 0.0208 | 7.29 | 0.0000 |
| MORT | -0.0362 | 0.0793 | -0.46 | 0.6483 |
| DISPER | -0.0572 | 0.0188 | -3.04 | 0.0024 |
| HOMIC | 0.0512 | 0.0366 | 1.40 | 0.1626 |
| ETHNIC_SN | 0.0985 | 0.0258 | 3.82 | 0.0001 |
| FOOD | -0.0178 | 0.0441 | -0.40 | 0.6871 |
| POP | 0.3101 | 0.0393 | 7.88 | 0.0000 |
| WATER | -0.0751 | 0.0421 | -1.78 | 0.0749 |
| ECON_ISO | -0.0708 | 0.0540 | -1.31 | 0.1901 |
| FUEL_EXP | -0.0754 | 0.0216 | -3.49 | 0.0005 |
| STRUCT | -0.1127 | 0.0573 | -1.97 | 0.0494 |
| UNEMP | 0.2180 | 0.0361 | 6.03 | 0.0000 |
| YOUTHBBOTH | -0.1603 | 0.0638 | -2.51 | 0.0122 |
| CORRUPT | 0.0765 | 0.1007 | 0.76 | 0.4479 |
| REG_U:INEQ_SWIID | -0.1754 | 0.0505 | -3.48 | 0.0005 |

| | | | | |
|---|---|---|---|---|
| REG_U:GDP_CAP | -0.1576 | 0.0396 | -3.98 | 0.0001 |
| INEQ_SWIID:GDP_CAP | -0.1103 | 0.0509 | -2.17 | 0.0304 |
| REG_U:INEQ_SWIID:GDP_CAP | 0.0323 | 0.0081 | 3.97 | 0.0001 |

*Table 18 – Intensity of HVC_SN linear model*

## 5. Statistical Metrics

In predictive analytics, a table of confusion (also called a confusion matrix) is a table with two rows and two columns that reports the number of false positives, false negatives, true positives and true negatives. This allows more detailed analysis than mere proportion of correct classifications (accuracy). Accuracy is not a reliable metric for the real performance of a classifier, because it will yield misleading results if the data set is unbalanced (that is, when the numbers of observations in different classes vary greatly).

Assuming the confusion matrix mentioned above, its corresponding table of confusion would be for the conflict class:

| | | Actual Y4 Conflict situation | |
|---|---|---|---|
| | | Conflict | Non-Conflict |
| Predicted Y4 Conflict situation | Conflict | True Positives (TP) | False Positive (FP) |
| | Non-Conflict | False Negatives (FN) | True Negatives (TN) |

However, since we have 2 models (HVC/VC) in 2 dimensions (NP/SN), we obtain in total 4 confusion matrix, as shown in the tables below.

| | | Actual Y4 HVC NP Conflict situation | |
|---|---|---|---|
| | | Conflict | Non-Conflict |
| Predicted Y4 HVC | Conflict | True Positives (TP) | False Positive (FP) |

| | | | |
|---|---|---|---|
| NP Conflict situation | Non-Conflict | False Negatives (FN) | True Negatives (TN) |

| | | Actual Y4 HVC SN Conflict situation | |
|---|---|---|---|
| | | Conflict | Non-Conflict |
| Predicted Y4 HVC SN Conflict situation | Conflict | True Positives (TP) | False Positive (FP) |
| | Non-Conflict | False Negatives (FN) | True Negatives (TN) |

| | | Actual Y4 VC NP Conflict situation | |
|---|---|---|---|
| | | Conflict | Non-Conflict |
| Predicted Y4 VC NP Conflict situation | Conflict | True Positives (TP) | False Positive (FP) |
| | Non-Conflict | False Negatives (FN) | True Negatives (TN) |

| | | Actual Y4 VC SN Conflict situation | |
|---|---|---|---|
| | | Conflict | Non-Conflict |
| Predicted Y4 VC SN Conflict situation | Conflict | True Positives (TP) | False Positive (FP) |
| | Non-Conflict | False Negatives (FN) | True Negatives (TN) |

In all the four confusion matrix, the meanings of TP, FP, FN, TN are the following:

- **TP** equivalent with hit. While considering the characteristics of each model, this means that the presence of conflict (Y4) was correctly predicted.
- **TN** equivalent with correct rejection. While considering the characteristics of each model, this means that the non-conflict (Y4) was correctly predicted.

- **FP** equivalent with false alarm. While considering the characteristics of each model, this means that the conflict (Y4) was not correctly predicted; the conflict did not occur.
- **FN** equivalent with miss. While considering the characteristics of each model, this means that the conflict (Y4) was not correctly predicted; the conflict occurred, although it was not predicted.

There are in addition the totals of Actual/real (Y4) situations/cases:

- **P** condition positive. The number of real positive cases in the data.
- **N** condition negatives. The number of real negative cases in the data.

**Terminology and derivations from a confusion matrix**

Sensitivity, recall, hit rate or true positive rate (TPR) measures the proportion of positives that are correctly identified:

$$TPR = \frac{TP}{P} = \frac{TP}{TP + FN}$$

Specificity or true negative rate (TNR) measures the proportion of negatives that are correctly identified:

$$TNR = \frac{TN}{N} = \frac{TN}{TN + FP}$$

Precision or positive predictive value (PPV) is the fraction of relevant positives instances among the retrieved instances:

$$PPV = \frac{TP}{TP + FP}$$

Negative predictive value (NPV) is the fraction of relevant negatives instances among the retrieved instances:

$$NPV = \frac{TN}{TN + FN}$$

Fall-out or false positive rate (FPR) is calculated as the ratio between the number of negative events wrongly categorized as positive (false positives) and the total number of actual negative events (regardless of classification):

$$FPR = \frac{FP}{N} = \frac{FP}{FP + TN} = 1 - TNR$$

Complementarily, the Miss rate or false negative rate (FNR) is the proportion of positives which yield negative test outcomes with the test, i.e. the conditional probability of a negative test result given that the condition being looked for is present.

$$FNR = \frac{FN}{P} = \frac{FN}{FP + TP} = 1 - TPR$$

Accuracy (ACC) has two definitions:

1. More commonly, it is a description of systematic errors, a measure of statistical bias; as these cause a difference between a result and a "true" value, International Organization for Standardization (ISO) calls this trueness.
2. Alternatively, ISO defines accuracy as describing a combination of both types of observational error above (random and systematic), so high accuracy requires both high precision and high trueness.

In simplest terms, given a set of data points from a series of measurements, the set can be said to be precise if the values are close to the average value of the quantity being measured, while the set can be said to be accurate if the values are close to the true value of the quantity being measured. The two concepts are independent of each other, so a particular set of data can be said to be either accurate, or precise, or both, or neither.

Following a more commonly used definition in the fields of science and engineering, the accuracy of a measurement system is the degree of closeness of measurements of a quantity to that quantity's true value.

$$ACC = \frac{TP + TN}{P + N} = \frac{TP + TN}{TP + TN + FP + FN}$$

**Mean squared error**

The MSE is a measure of the quality of an estimator—it is always non-negative, and values closer to zero are better.

In statistics, the mean squared error (MSE) or mean squared deviation (MSD) of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors or deviations—that is, the difference between the estimator and what is estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance of the estimator. Like the variance, MSE has the same units of measurement as the square of the quantity being estimated. In an analogy to standard deviation, taking the square root of MSE yields the root-mean-square error or root-mean-square deviation (RMSE or RMSD), which has the same units as the quantity being estimated; for an unbiased estimator, the RMSE is the square root of the variance, known as the standard deviation.

**Root mean squared error**

The root-mean-square deviation (RMSD) or root-mean-square error (RMSE) is a frequently used measure of the differences between values (sample and population values) predicted by a model or an estimator and the values actually observed. The RMSD represents the sample standard deviation of the differences between predicted values and observed values. These individual differences are called residuals when the calculations are performed over the data sample that was used for estimation, and are called prediction errors when computed out-of-sample. The RMSD serves to aggregate the magnitudes of the errors in predictions for various times into a single measure of predictive power. RMSD is a measure of accuracy, to compare forecasting errors of different models for a particular data and not between datasets, as it is scale-dependent.

Although RMSE is one of the most commonly reported measures of disagreement, some scientists misinterpret RMSD as average error, which RMSD is not. RMSD is the square root of the average of squared errors, thus RMSD confounds information concerning average error with information concerning variation in the errors. The effect of each error on RMSD is proportional to the size of the squared error thus larger errors have a disproportionately large effect on RMSD. Consequently, RMSD is sensitive to outliers.

| | METRICS_VC_NP | METRICS_VC_SN | METRICS_HVC_NP | METRICS_HVC_SN |
|---|---:|---:|---:|---:|
| MSE | 25.09 | 22.78 | 60.66 | 65.37 |
| RMSE | 5.01 | 4.77 | 7.79 | 8.08 |
| Sensitivity or TPR | 0.96 | 0.93 | 1 | 1 |
| Specificity or TNR | 0.49 | 0.40 | 0.39 | 0 |
| Precision or PPV | 0.26 | 0.33 | 0.12 | 0.09 |
| NPV | 0.98 | 0.94 | 1 | - |

|  |  |  |  |  |
|---|---|---|---|---|
| fall-out or FPR | 0.50 | 0.59 | 0.60 | 1 |
| FNR | 0.04 | 0.07 | 0 | 0 |
| accuracy | 0.57 | 0.53 | 0.44 | 0.091 |

## 6. Conclusion

In the present report, we have discussed on the one hand the input data for the regression model, how the predictions are obtained, as well as the output data. Based on the twenty-four variables, all relatively stable and freely accessible by any user the regression model operates through 3 phases so as to obtain the probability and intensity of conflict at the country level. On the other hand, the statistical significance test, as well as the confusion matrix, provides an in-depth analysis of the regression model. Further development should, in fact, focus on conducting an advanced evaluation of the coefficients and assessment of the model (using the step-wise method) in order to select the best possible combination of variables. Furthermore, future development would imply reviewing the dataset for fitting, because of updated datasets, as well as exploring possibilities for automatic and intelligent technics for updating the datasets for fitting.

The present report is part of a documentation work aiming at improving the GCRI models with greater transparency, but in no case at validating it. With this specific report on the regression model, we contribute to document a high-potential conflict risk modelling method.  The strength of the GCRI methodological approach lies in the diversity of sources used as input data, as well as the large number of variables included into the index. Thanks to this, we are more likely to get a comprehensive evaluation of conflict risk.

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