THE CLIMATE SECURITY INDEX

A methodological note

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INITIATIVE ON
Climate Resilience

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CGIAR FOCUS Climate Security

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1. Introduction

Climate variability is widely impacting natural and human systems. One of the many impacts is its potential threat to human security. The role of climate variability as a possible cause of violent conflict has been coming to the forefront of public and scientific debates. In this so-called Climate Security Nexus, climate variability acts as a multidirectional threat multiplier, aggravating existing vulnerabilities of people and communities.

Climate-related conflict is likely to emerge in regions that are vulnerable to climate variability and lack resilience and coping mechanisms to absorb, adapt and recover for the changing climate. Often, they are also characterized by high levels of poverty, political inequality, and dependence on renewable resources, especially agricultural production.

Water, land and food systems are at the core of climate security (Laederach et al., 2021, Liebig et al., 2022). Therefore, researchers began calling for more emphasis on studying the role of agriculture in conflict development several years ago (Meierding, 2013). The resilience of agricultural and food systems is fundamental in understanding and tackling climate security risks. This view is even shared by scholars who question the relationship between climate variability and conflict (Abrahams et al. 2017).

Despite increasing attention towards the CSN, knowledge about which geographies are or might be at risk for climate-related insecurity, and what the underlying factors and their interactions are is scarce. This is partly due to a lack of data sources, availability or coverage, but also due to methodological challenges. Yet, data and analytical tools considering the complex interplay of climate, socio-economic vulnerabilities and conflict are needed to systemically understand the CSN (Madurga Lopez et al., 2021).

Measures such as composite indicators, used for ranking and benchmarking are highly popular in many domains that require user-friendly information to be aggregated for decision-making. While there are some novel advances in existing indices, most of the conflict/peace measures do either not include climate-related variables, or do not allow for assumptions on the underlying relationships among the used indicators. In other words, most measures do not take into account the complex interlinkages of the CSN (Fig. 1, Annex).

In this methodological note, we propose a quantitative framework to develop a Climate and Security Index (CSI), for measuring and monitoring climate security vulnerability. Primarily meant for long-term planning and decision making for resilience building, it incorporates a broad range of drivers of the climate-security nexus, including those from climatic, conflict, socioeconomic, agricultural, and contextual (i.e., mitigating factors, adaptive capacity) dimensions, to indicate climate-security risks at subnational level. Emphasizing the role of water, land and food systems, a systemic approach, based on innovative modeling tools is envisioned, to account for the underlying relationships within the CSN.

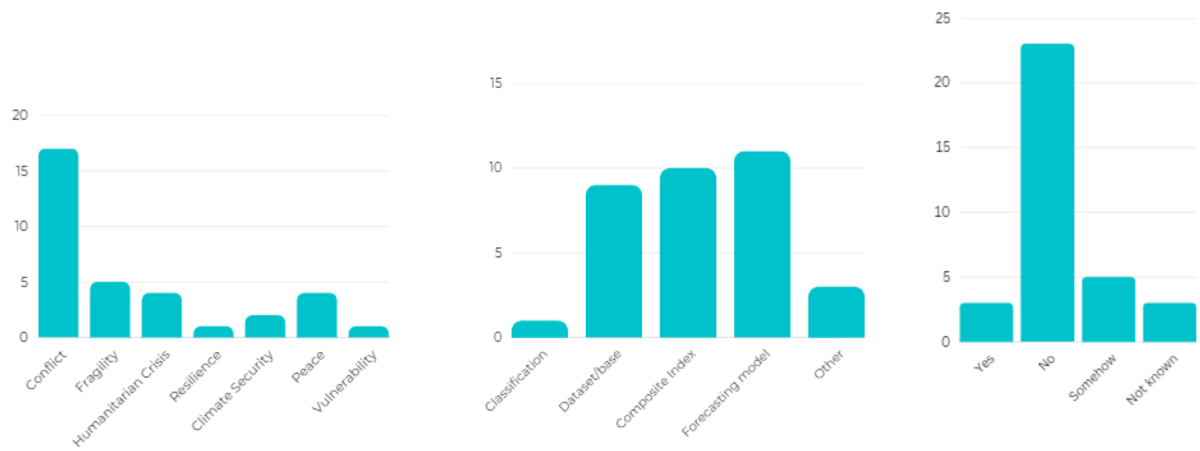

Figure 1. Measured concepts (left), types (middle) and its focus on climate security (right) of the 33 reviewed measurements and indicators. Most of them focused on concepts around conflict, were based on composite indexing or forecasting models, and did not focus on climate security.

2. Methodological framework

To support policymakers for taking contextualized and climate security-sensitive decisions for policies, programs, or finance, and for ultimately mitigating ongoing or future conflicts, the CSI framework should enable users (academics and policymakers) to easily identify which geographics are or might be at risk for climate-driven instability. Users should be provided with an understanding of which factors are the most important in defining the CSN in different contexts, and how they are related to each other. Furthermore, users should be able to compare CSI values across different geographic locations, as well as different time points.

We will first discuss common tools for building indices, and then provide an overview of a potential framework to develop a CSI that meets the above-mentioned requirements.

Common tools for building indices

Composite indicators have become incredibly popular in a variety of study areas and have attracted the interest of international organizations, global policymakers, and the media alike (Greco et al., 2019). However, there has been much criticism of their use, particularly with regard to the creation of aggregate indices. Such an index, according to opponents, is statistically meaningless and insufficient to fully capture complex phenomena (Sharpe, 2004). Numerous weaknesses in the methodological framework itself have also been criticized, particularly in connection with the weighting, aggregation and robustness stages. Since understanding the complex linkages among drivers of the CSN is one of the main objectives of the CSI, a composite index based on weighting and aggregation would not fulfill the requirements for its construction.

Other measures, such as the Global Conflict Risk Index, rely on regression-based approaches to build an index (Halkia et al., 2020). However, even if non-linear models are applied, a standard regression framework would hardly fit the structure of the data while accounting for all the complex links between the driving factors. For instance, the number of the interaction terms would grow exponentially. Further, such a model mainly focuses on (linear) relationships and measuring "average treatment effects". Since the CSI intends to capture and describe relationships between all drivers of the CSN rather than specifying a single outcome variable in dependence of a set of predictors, a standard regression framework is also considered unsuitable.

The previous point is also relevant to the common emphasis on conflict as an outcome variable. Although conflict and instability are key components of the CSI idea, we would like to move away from frameworks that exclusively anticipate or predict conflict. First, our goal is not to anticipate conflict or, more generally, to predict a particular outcome variable; rather, we want to draw attention to multiple factors that interact with or potentially contribute to conflict. Identifying these factors would be a starting point for mitigating conflict and, ideally, for managing it. Under the CSI framework, conflict is used as a variable to validate and calibrate the methodological components, but it is not our primary focus.

While analytical tools devised for forecasting purposes might be useful to derive quite accurate predictions and study the relative contribution of the different input features in producing such estimates, they are not well-suited to explore the interconnections between the features and incorporate theoretical insights about such relationships. By including multiple methods, the CSI allows for this type of complementary analysis, which is much necessary to inform policymakers on how to design interventions addressing specific drivers, and how these interventions might produce spillover effects across the system.

Second, a number of analyses and studies have shown that prediction is still highly controversial in academic conflict research (Bazzi et al;, 2022, Muggah and Whitlock, 2022, Cederman and Weidmann, 2017). Although significant efforts have been made, no early warning system has proven to be a reliable tool for policymaking, and attempts to predict and address conflict outbreaks have often performed worse than expected (Muggah and Whitlock, 2022; O'brien, 2010).

Suggested approach

What we suggest instead is a more comprehensive approach (Fig. 2). Our CSI it is not just a single measure, but an overall and innovative framework to evaluate the multiple aspects of the CSN. While its three methodological components (Bayesian networks, machine learning algorithms for forecasting, and Gaussian processes) can be combined to provide an overall picture of the climate security risk for a country, the modular approach allows users to only focus on one of them to answer specific questions. As shown in figure 2, the framework considers multiple dimensions of the CSN, such as agriculture and socioeconomic vulnerabilities, climate and environment, mitigating and conflict factors, in the form of time-series data. We are interested in measuring structural features of these dimensions. For instance, the volatility of commodity prices or the likelihood of extreme weather events. These structural features enter as inputs for the three complementary methodologies embedded in the CSI framework, which are devised to provide specific insights. As an example, the use of sparse Bayesian networks is meant to provide a picture of the long-term structural relationships between the CSN dimensions, allowing policymakers to design informed policy interventions that account for such linkages. The methodologies proposed will be calibrated and validated using a taxonomy of (violent) conflict, which is how our approach incorporates this fundamental aspect of the CSN as a key component. From the three methods, we will also derive individual metrics that can easily convey the insights provided by the

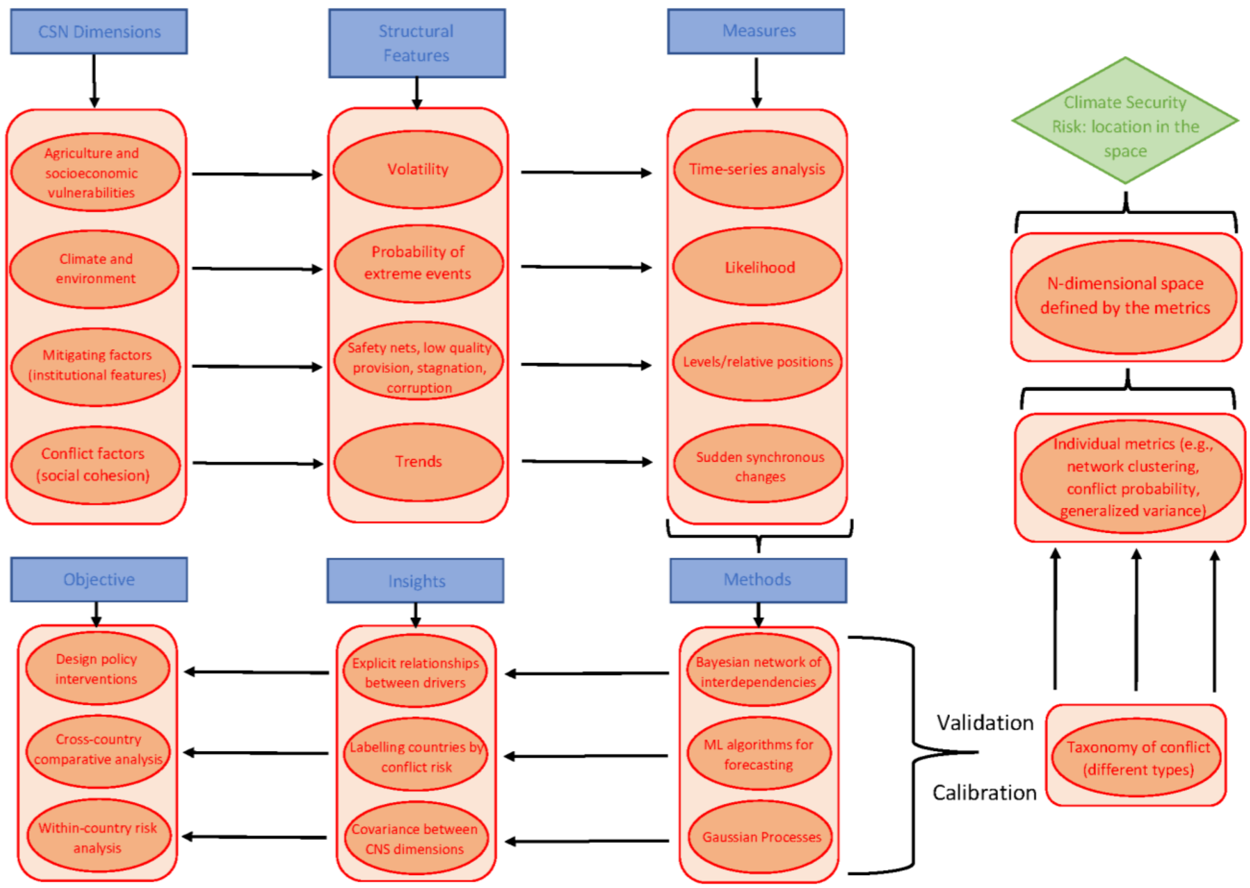

Figure. 2. Analytical framework for building the climate security index.

techniques (e.g., in the case of the network analysis, the global clustering coefficient can be considered). These metrics can later be employed to define the axes of a n-dimensional space in which the scenario (i.e., the country) considered can be located according to its relative score along the different metrics. Such a space will facilitate the presentation of the results while allowing for straightforward cross-country comparisons. Finally, a single measure that describes such location (e.g., the norm of the vector in the space) can be determined to provide a comprehensive view of the climate security risk in the case at hand. Hence, the framework does not only result in an accessible frontend for policymakers, but it also allows for deeper analyses that can shed light on specific features of the CSN.

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4. Annex

NAME	MEASUREMENTTYPE	MEASUREOF	DESCRIPTION	METHOD	BY	CSSENSITIVE?	STATECOVERAGE
GLOBAL PEACE INDEX (GPI)	Composite index	Peace	Ranks 163 independent states and territories according to their level of peacefulness (concept of negative peace, i.e. absence of violence and fear of violence"). Measures the state of peace across three domains: the level of Societal Safety and Security, the extent of Ongoing Domestic and International Conflict, and the degree of Militarisation.	**Weighted arithmetic mean**. Scores for each indicator are normalised on a scale of 1-5. 7 of the 22 indicators are scored qualitatively by the Economist Intelligence Unit's country analysts. Indicators are aggregated by weighted arithmetic mean into dimension indices according to the expert weightings; the 'internal' and 'external' peace dimensions are then aggregated by weighted arithmetic mean into the overall index. Index metric: 1-5 scale, 1 = most peaceful, 5 = least peaceful	Institute for Economics and Peace (IEP)	No	163 states
POSITIVE PEACE INDEX (PPI)	Composite index	Peace	First statistically derived index measuring Positive Peace according to the definition "the attitudes, institutions and structures that create and sustain peaceful societies."	Eight-part taxonomy, further classified in three groups: Attitudes, Institutions and Structures, of the factors associated with peaceful societies derived from the data series that had the strongest correlation with internal peacefulness as measured by the GPI (24 indicators in total).	Institute for Economics and Peace (IEP)	No	163 states

ECOLOGICAL THREAT REGISTER (ETR)	Composite index	Resilience	Ranks countries least likely to cope with extreme ecological shocks. It analyses risk using 8 indicators related to water risk, food insecurity, natural disasters, and rapid population growth.	1. All indicators are normalised on a one to five scale, with a higher score representing a higher threat level. This calculation is conducted at the sub-national ADMIN1 level. 2. The overall ETR score is calculated as the average of the individual ecological threats. This is the sub-national administrative unit ETR score. The average of the sub-national ETR scores aggregated to the country level represents the overall threat a country faces.	Institute for Economics and Peace (IEP)	No	178 states
INFORM RISK INDEX	Composite index	Humanitarian crisis	Global, open-source risk assessment for humanitarian crises and disasters. It can support decisions about prevention, preparedness and response.	Index based on concept of Hazards & exposure (events that could occur and exposure to them, Vulnerability (the susceptibility of communities to those hazards) and Lack of coping capacity (lack of resources available that can alleviate the impact)	Joint initiative of the Inter Agency Standing Committee, the European Commission and humanitarian and development organisations worldwide.	Somehow	191
FRAGILE STATES INDEX (FSI)	Composite index	Fragility	Measures and ranks the risk of states for instability or risk of violence. Based on a conflict assessment system framework, using twelve conflict risk indicators from quantitative, qualitative, and expert validation sources, to measure the condition of a state at any given moment. The indicators provide a snapshot in time that can be measured against other snapshots in a time series to determine whether conditions are improving or worsening.	Content analysis software scans 115,000 online English-language publications worldwide, including digitised news and magazine articles, essays, reports and speeches for indicator subject matter; this is incorporated with quantitative data from the sources listed; aggregated data are normalised and scaled from 0-10 to obtain final scores for the 12 social, economic and political/military indicators. The total score is the	The Fund For Peace	No	178 states

				sum of the 12 indicators. Index metric: 0-120 scale 0 = most stable			
STATE FRAGILITY INDEX AND MATRIX	Composite index	Fragility	The 2010 State Fragility Index rates 164 countries on state fragility and monitors change in fragility over time.	In the 2010 State Fragility Index, fourteen indicators are derived from expert data and public statistics measuring effectiveness and legitimacy, with four sectors each (security, political, economic, and social). Categories are ranked 0-3: 0-no fragility 1-low fragility 2-medium fragility 3-high fragility with all categories weighted equally.	Center for Systemic Peace	No	167 states
INFORM SEVERITY INDEX	Composite index	Humanitarian crisis	Improved way to objectively measure and compare the severity of humanitarian crises and disasters globally. It can help us develop a shared understanding of crisis severity and ensure all those affected get the help they need.	INFORM Severity index = Impact of the crisis × Conditions of people affected + Complexity of the crisis. Weighed composite index.	Inter-Agency Standing Committee Reference Group on Risk, Early Warning and Preparedness; European Commission	No	
INTERNAL VIOLENCE INDEX (IVI)	Composite index	Conflict	The Internal Violence Index (IVI) aims to compare the amount of violence at country level for 130 developing countries.. The IVI is a composite indicator composed of 4 clusters - internal armed conflict, criminality, terrorism, and political violence.	It is based on quantitative variables only, in contrast to the existing subjective indicators of fragility. Primary data for the 9 variables come from different open source databases (UCDP/PRIO, IDMC, UNODC, GTD, CNTS). Most of the	Fondation pour les Etudes et Recherches sur le Developpement	No	130 countries

				variables relate to the period 2008-2012.	International (FERDI)		
UPPSALA CONFLICT DATABASE PROGRAM (UCDP)	Datasets/Database	Conflict	UCDP offers a web-based system for visualising, handling and downloading data, including ready-made datasets on organized violence and peacemaking.	Data collection on conflict events categorized as fatal organized violence	Uppsala Conflict Database Program (UCDP)	No	Global
CORRELATES OF WAR PROJECT (COW)	Datasets/Database	Conflict	COW seeks to facilitate the collection, dissemination, and use of accurate and reliable quantitative data in international relations.	Data collection on international politics and national capabilities over time since 1816	Project lead by Jeff Carter (Appalachian State University) and Scott Wolford (University of Texas)	No	
ARMED CONFLICT LOCATION & EVENT DATA PROJECT (ACLED)	Datasets/Database	Conflict	Database on armed conflicts and organized violence, in which information on several aspects of armed conflict such as conflict dynamics and conflict resolution is available. Ongoing data collection for civil war, with aCollects real-time data from news feeds on the locations, dates, actors, fatalities, and types of all reported political violence and protest events across Africa, the Middle East, Latin America and the Caribbean, East Asia, South Asia, Southeast Asia, Central Asia and the Caucasus, Europe, and the United States.	Model is an ensemble of 7 separate machine learning models. It uses historical ACLED data for each actor and event type combination to predict outcomes. Such data includes the number of events, the number of fatalities, the number of unique locations and other actors active in a given location. The model is tuned to incorporate each of the underlying machine learning models to produce the most accurate prediction.	ACLED. Non-profit, non-governmental organization incorporated in Wisconsin.	No	Global
DATA - PEACE RESEARCH INSTITUTE OSLO	Datasets/Database	Peace			Peace Research Institute Oslo (PRIO)	No	

SITUATIONAL AWARENESS GEOSPATIAL ENTERPRISE (SAGE)	Datasets/Data base	Conflict	An incident and event database developed in 2018 used to identify trends and indicators for early warning.	SAGE features an incident monitoring database used by UN military, police and civilians in UN peace operations. Since structured data is stored and categorized, it can be analyzed using machine learning.	United Nations Department of Peacekeeping Operations (UN DPKO)	No	
CONFLICT BAROMETER	Datasets/Data base	Conflict	The HIIK dataset is based on information gathered in its CONTRA database	Data collection on conflict items, conflict intensity and status as well as conflict types	Heidelberg Institute for International Conflict Research	No	Global
ACLED CONFLICT PULSE	Forecasting model	Conflict	The Conflict Pulse is ACLED's actor prediction and modeling tool. Use the dashboard below to track predicted trends in conflict actor behavior a week into the future or to explore historical predictions.	Model predicts whether or not there will be an increase in the number of events for a given actor and event type as compared to the previous week, basing this prediction off of a number of factors.	ACLED. Non-profit, non-governmental organization incorporated in Wisconsin.	No	
EARLY WARNING PROJECT'S STATISTICAL RISK ASSESSMENT	Forecasting model	Conflict	Applies qualitative and quantitative forecasting methods to identify countries where risks of mass atrocities are high.	An annual statistical risk assessment of 160 countries based on assessing historical episodes (1945-present) and training a model (logistic regression with elastic-net regularization) of roughly 20 variables to predict onset risks. More than 30 variables as input for logistic regression model with "elastic-net" regularization are used. Detailed method here.	Simon-Skjodt Center for the Prevention of Genocide, United States Holocaust Memorial Museum; Dickey Center for International Understanding, Dartmouth College	No	160 states

VIEWS	Forecasting model	Conflict	Tracks four types of political violence including state-non-state actors, between nonstate actors, violence against civilians, and forced displacement. Brings together three distinct but interrelated research projects: the political Violence Early-Warning System (ViEWS), and the interdisciplinary conflict impacts projects Societies at Risk and ANTICIPATE	Applies a blended approach including Bayesian and regression methods to generate early warnings for specific actors across geographic areas, one month in advance. Geographically focused on Africa. For each type of violence, the system generates a monthly probabilistic assessment of the likelihood that 25 or more battle-related deaths will occur in a given country and month over a rolling three-year window, and the predicted risk that at least one such fatality will occur per 0.5×0.5 decimal degree PRIO-GRID cell (approximately 55x55km each) and month. The system also generates a combined forecast of the risk that the thresholds above will be reached in a given country-month or PRIO-GRID-month from either one of the three types of violence.	Uppsala University & PRIO	Somehow	Africa
INTEGRATED CRISIS EARLY WARNING SYSTEM (ICEWS)	Forecasting model	Conflict	Comprehensive automated system to monitor, assess and forecast national and subnational crisis (e.g., conflict, ethnic/religious violence, rebellion/insurgency)	Mixed method approach using 100 data sources and 250 newsfeeds parsed using Jabari technology and BBN Serif NLP technology. Includes iData (who did what to whom and when), iTrace (news mining), iCast (forecasting) and iSENT (sentiment). Uses a CAMEO ontology.	DARPA and the Office of Naval Research, maintained by Lockheed Martin	?	?
CONTINENTAL EARLY WARNING SYSTEM (CEWS)	Forecasting model	Conflict	Intended to anticipate and prevent conflict and provide timely information according to specific metrics	Observation and monitoring unit collects data and analysis and regional units linked to 'SitRoom'	African Union with MoU connecting Regional Economic Communities	?	?

					such as SADC, ECOWAS		
[CONFLICT EARLY WARNING AND RESPONSE MECHANISM (CEWARN)]()	Forecasting model	Conflict	Assesses regional situations that could potentially lead to violence, develops case scenarios, shares analyses and prepares response options.	CEWARN divides incidents into four categories: armed clashes, raids, protest demonstrations, and other crimes. The mechanism consists of 50 indicators from open sources and SitRoom reports. CEWARN's early warning model relies on feld observation data through the regular monitoring of socio-economic, political and security related developments and trends as well as monitoring the occurrence of violent incidents in its areas of operation. The data based on forty-seven diverse variables inform the mechanism's predictive model.	IGAD (Intergovernmental Authority on Development) member countries: Djibouti, Ethiopia, Kenya, Somalia, Uganda, Sudan and Eritrea.	No	Djibouti, Ethiopia, Kenya, Somalia, Uganda, Sudan and Eritrea?
[ATROCITY FORECASTING PROJECT]()	Forecasting model	Conflict	Deploys multiple quantitative forecasting models to improve insight on causes of political instability and conflict leading to mass atrocities and genocide.	The Atrocity Forecasting Project applies machine learning-based forecasting techniques based on over 200 incidents recorded between 1946-2017.	Based in the Australian National University, the initiative issues periodic updates on risks for a specific interval (2015-20). The project also hosts periodic events.	No	Global

THE SENTINEL PROJECT EWS	Forecasting model	Conflict	Focuses on genocide prevention, though alert functions are still in development	Draws on open sources, including social media to monitor potential genocidal events in selected sites. Currently developing a database that will facilitate automated data collection from open sources.	Based in Canada and outputs include reports and visualizations.	?	i.e., Myanmar, Central African Republic, Democratic Republic of Congo, Iraq, Kenya, South Sudan and Uganda.
GLOBAL CONFLICT RISK INDEX (GCRI)	Forecasting model	Conflict	Index of the statistical risk of violent conflict in the next 1-4 years and is exclusively based on quantitative indicators from open sources. With the assumption that structural conditions in a country are linked to the occurrence of violent conflict	The GCRI uses a linear regression model including historical data to train the model. Its creators at the EC JRC first determined the predictive value of the 24 variables regarding conflict onsets in the past 20 years. They then applied the results to the final model and derived the weights for the indicators from their significance regarding the model performance.	Joint Research Centre (JRC) of the European Commission (EC)	Somehow	

CONFLICT FORECAST OF THE GLOBAL EARLY WARNING TOOL	Forecasting model	Conflict	The Global Early Warning Tool uses a machine learning-based methodology to forecast conflict over the next 12 months. The aim of the Global Tool is to help relevant actors identify conflict hotspots before violence erupts and understand the local context.	Machine learning-based methodology to forecast conflict (defined as organized violence resulting in at least 10 fatalities over a 12 month period), up to a year in advance using a random forest model. When applied to reserved test data, the model captures 86% of future conflicts.	Water, Peace and Security (WPS) partnership is a collaboration between the Netherlands Ministry of Foreign Affairs, the German Agency for International Cooperation (GIZ) and a consortium of six partners: Deltares, The Hague Centre for Strategic Studies (HCSS), IHE Delft (lead partner), International Alert, Wetlands International and World Resources Institute (WRI). Read more about Our Partners.	Yes
REVISED CLASSIFICATION OF FRAGILITY AND CONFLICT	Classification	Fragility	The FCS functions primarily as a tool to help the WBG adapt its approaches, policies, and instruments in difficult and complex environments. The WBG also uses it for monitoring and accountability around its support	The list is based on publicly available global indicators* followed by an internal review; and is updated every year on July 1st to reflect changes in country situations.	World Bank Group	No

SITUATIONS (FCS)			for the most vulnerable and marginalized communities.				
CLIMATE SECURITY VULNERABILITY MODEL OF THE COMPLEX EMERGENCIES DASHBOARD	Other	Climate Security	Online mapping platform to enable policymakers and researchers to visualize Strauss Center's Complex Emergencies and Political Stability in Asia (CEPSA) datasets on climate vulnerability, conflict, national disaster preparation, and international climate and disaster aid, along with related external datasets on other security concerns like food access and forced migration.	the CEPSA dashboard brings together raw data and modeling, mapping, and qualitative analysis to provide a data-driven framework for analyzing the convergence of security vulnerabilities and responses	Complex Emergencies and Politial Instability in Asia (CEPSA) Programm at the University of Texas-Austin	Yes	South and Southeast Asia
ENVIRONMENTAL AND CLIMATE STRESS INDEX OF STRATA: EARTH STRESS MONITOR	Other	Climate Security	Strata aggregates spatial data for climate, environmental, and peace and security stress indicators. It combines these with data layers on population exposure and socioeconomic vulnerability to produce hotspot maps that highlight where the climate, environmental and security stresses overlap, and where they coincide with populations vulnerable to these stresses.	The combination of data layers is based on the convergence of evidence approach, developed by the European Commission’s Joint Research Center. With this approach, each indicator is assigned a threshold value, above which the indicator is considered to be “red flagged”, i.e. at a “level of concern”. The hotspot map shows the sum of all the red flags across the chosen indicators, weighted by the population exposure and vulnerability.	United Nations Environment Programme (UNEP), the University of Edinburgh, and Earth Blox	Yes	
UNIVERSAL VULNERABILITY INDEX (UVI)	Composite index	Vulnerability			The Commonwealth	No	
CRISISWATCH	Datasets/Database	Conflict			International Crisis Group	No	

POLITICAL STABILITY INDEX	Composite index	Stability	The 2010 Political Instability Index assesses 165 countries on how susceptible they are to social unrest.	The Political Instability Index is based on four factors: (1) the level of development as measured by the infant mortality rate; (2) extreme cases of economic or political discrimination against minorities (according to assessments and codings by the Minorities at Risk Project); (3)"a bad neighborhood" (if a country has at least four neighbors that suffered violent conflicts) and; (4) regime type (intermediate regimes that are neither consolidated democracies nor autocratic regimes combined with the existence in these regimes of intense factionalism in domestic politics, as coded by the Polity Project on democracy). There are 15 indicators in all—12 for the underlying and 3 for the economic distress index.	The Economist Intelligence Unit	No	165 countries
PEACE AND CONFLICT INSTABILITY LEDGER	Datasets/Data base	Fragility	The 2012 Peace and Conflict Instability Ledger ranks 163 countries based on their projected risk of political instability or armed conflict over a three-year period (2010-2012). It focuses in particular on violent events like war and genocide.	The Peace and Conflict Instability Ledger includes 5 indicators across social, economic, political, and security dimensions based on expert data and public statistics measuring institutional consistency (the extent to which the institutions which make up a political system are uniformly autocratic or democratic); economic openness; infant mortality rates; militarization; neighborhood security.	University of Maryland	No	163 countries

COUNTRY INDICATORS FOR FOREIGN POLICY: FAILED AND FRAGILE STATES	Datasets/Data base	Fragility	The Country Indicators for Foreign Policy examines state fragility using a combination of extensive structural data and dynamic events monitoring to prove and overall pictures of state fragility. Its 2012 report provides a global fragility ranking for 2011 for 197 countries. The Country Indicators for Foreign Policy on Failed and Fragile States is accompanied by a yearly report.	The Country Indicators for Foreign Policy bases its rankings on 75 indicators of state fragility and robustness, which are organized in six categories: governance, economics, security and Crime, human development, demography, and environment.	Carleton University, The Norman Paterson School of International Affairs	No	197 countries