GCERF
Preventing Violent Extremism

Technical Report on the Creation of the GCERF Entry and Prioritisation Index

1. Background

GCERF developed a multi-indicator indices tool using spatial analysis to create risk and vulnerability profiles of areas where GCERF currently works or where it plans to work in the future. The tool demonstrates through choropleth maps the geographic areas in which communities are likely to be most vulnerable to the influence of violent extremist groups and more susceptible to recruitment. The spatial analysis was conducted at the level of a 1km^2 grid covering the entire area of Nigeria.

2. Index overview

The overall Index on Community Risks, Vulnerability and Susceptibility to Extremist Group Recruitment is composed of three pillars and 12 sub-pillars, as follows:

- Pillar 1: Environmental fragility
    - Sub-pillar 1.1: Natural hazards
    - Sub-pillar 1.2: Food insecurity
    - Sub-pillar 1.3: Agricultural instability
- Pillar 2: Social structure instability
    - Sub-pillar 2.1: Underemployment rate
    - Sub-pillar 2.2: Inaccessibility of basic services
    - Sub-pillar 2.3: Political grievances
    - Sub-pillar 2.4: Discrimination
    - Sub-pillar 2.5: Violence and conflict
    - Sub-pillar 2.6: Social inequality
    - Sub-pillar 2.7: Crime rate[1]
- Pillar 3: Information sources
    - Sub-pillar 3.1: Sentiment towards extremist groups
    - Sub-pillar 3.2: Information uniformity

Each of the pillars is constructed from its corresponding sub-pillars using principal components analysis (PCA) to derive weights. The weights are used for geometric aggregation of the sub-pillars to each main pillar. The overall index is constructed from all 12 sub-pillars using PCA with

[1] Crime data was only available at state level and was therefore not modelled at the 1km level.

geometric aggregation. One proposed sub-pillar on the crime rate was only available at the state level. It was therefore used only for calculating the Social Structure Instability pillar and the overall Index but was not modelled at the 1km level of resolution.

3. Data collection

To calculate the overall index and its pillars and sub-pillars at $1km^2$ level, we collected geospatial data layers from the following secondary sources listed in Table 1. The various types of data include satellite imagery, estimated raster, geolocated survey microdata, social media, and crowdsourced GIS data.

Table 1. Geospatial data layers collected to construct the GCERF Entry and Prioritisation Index

Source	Type	Time
NASA/ESA	Satellite imagery	2000-2020
WorldPop	Estimated raster	2016
Spatially Interpolated Data on Ethnicity (SIDE)	Estimated raster	2013
The Institute for Health Metrics and Evaluation (IHME)	Estimated raster	2017
Living Standards Measurement Study (LSMS)	Survey microdata	2018
Demographic and Health Surveys (DHS)	Survey microdata	2018
Afrobarometer	Survey microdata	2017
Financial Inclusion Insights (FII) survey	Survey microdata	2017
OpenStreetMap	Crowdsourced GIS data	2021
The Armed Conflict Location & Event Data Project (ACLED)	Geotagged news reports	2016-2021
International Organization for Migration (IOM)	Geotagged event data (aggregated to LGA level)	2015-2021
Nigeria Bureau of Statistics	Census data (state level)	2017
Twitter	Social media records containing names of key VE groups/persons.	2019-2021

4. Data processing and modelling

The goal of data processing and modelling was to generate a $1km^2$ grid data layer for each component indicator of each sub-pillar. We used different methods to create these $1km^2$ data layers depending on the type of data. These component indicators were next aggregated to the sub-pillar level using PCA weighting with geometric aggregation.[2] Table 2 describes in detail the component indicators used to calculate each sub-pillar.

The general approach to calculating data layers is described below for different types of data:

- For all satellite imagery layers except for landcover, we applied the calculation of Standardised Precipitation Index (SPI) based each grid's historical data and focused on the last five years as the timeframe. Specifically, we modified the SPI for precipitation and evapotranspiration using the absolute value, and negated value, respectively, to indicate variability in precipitation and tendency to land degradation.
- For estimated raster layers, we cropped and resampled them so that they match the spatial extent and $1km^2$ resolution of our desired output.
- For crowdsourced GIS data, geotagged report/event data and social media records, we assigned to each $1km^2$ grid cell the distance between it and the nearest point of interest, and then weighted the distance by a spatial autocorrelation factor (Moran's I). We did this based on the assumption that a particular incident's impact on the population in a grid cell is proportional to its distance to the cell, whether it is positively or negatively correlated.
- For survey microdata, we used a machine-learning approach to estimate the value of survey indicators for each $1km^2$ grid cell using machine learning interpolation based on the national representativeness of the survey samples. Specifically, we adopted a spatial Bayesian regression modelling approach to calculate 17 geospatial layers from survey data covering demographic characteristics, agriculture and nutrition, and social and political perceptions.

Table 2 shows the comprehensive list of 42 individual indicators used in the construction of the index as well as their calculation steps. Relative to the other indicators, the modelling process for the survey indicators is described in less detail due to space limitations.

Table 2. List of individual geospatial indicators used for sub-pillar construction

GCERF Entry and Prioritisation Index	Pillar	Sub-Pillar	Indicator	Data source	Data type	Time	Indicator values for each 1km grid cell	Calculation of derived variable to be used for sub-pillar component
	1. Environmental fragility	1. Natural hazards	Seasonal and decadal variability of precipitation (flooding and droughts)	NASA/ESA - Standardised Precipitation Index (calculated from CHIRPS)	Satellite imagery	1981-2021	Standard deviation: Range from -3 (driest) to 3 (wettest)	Absolute value of the standard deviation from the median of the standardised normal distribution of the **precipitation** values of the same time period (month by default) over last 40 years. Larger value -> more variability.
			Land degradation & desertification	NASA/ESA - Evapotranspiration (MOD16A2)	Satellite imagery	2000-2020	Standard deviation: Range from -3 (driest) to 3 (wettest)	Reversed standard deviation from the median of the standardised normal distribution of the evapotranspiration values of the same time period (month by default) over last 20 years. Larger value -> increasing desertification.

[2] For details on this approach to index construction, see the *Handbook on Constructing Composite Indicators* published by the Organization for Economic Cooperation and Development (OECD). Available online at https://www.oecd.org/sdd/42495745.pdf

1 Community Risks, Vulnerability and Susceptibility to Recruitment			Temperature change	NASA/ESA - Land surface temperature/ emissivity (MOD11A1)	Satellite imagery	2000-2020	Standard deviation: Range from -3 (coldest) to 3 (hottest)	Standard deviation from the median of the standardised normal distribution of the **temperature** values of the same time period (month by default) over last 20 years. Larger value -> rising temperature.
		2. Agricultural instability	Shrinking farmland	NASA/ESA - Land cover (MCD12Q1)	Satellite imagery	2001-2020	An integer score between 0 and 19	Count of occurrence if landcover type = farmland over past 19 years
			Distance to roads	WorldPop	Estimated raster	2016	Distance in km	Resample to 1km level and calculate inverse
			Distance to population centers	OpenStreetMap	Crowdsourced GIS data	2021	Distance in km	Distance from each grid centre to the nearest population centre
			Population density	WorldPop	Estimated raster	2020	Population count	Resample to 1km level
			Food production or other agriculture output	NASA - crop net primary production (npp) (MOD17A2)	Satellite imagery	2001-2020	Standard deviation: Range from -3 (least productive) to 3 (most productive)	Standard deviation from the median of the standardised normal distribution of **crop production** the same time period (month by default) over last 19 years.
			Extent of grazing land	NASA/ESA - Land cover (MCD12Q1)	Satellite imagery	2001-2020	An integer score between 0 and 20	Count of occurrence if landcover type = grassland over past 19 years
			Extent of lake surface	NASA/ESA - Land cover (MCD12Q1)	Satellite imagery	2001-2020	An integer score between 0 and 20	Count of occurrence if landcover type = waterbodies over past 19 years
			Locust infection	EU Vito DevCocast greenness (NDVI)	Satellite imagery	2014-2021	Standard deviation: Range from -3 (least vegetated) to 3 (most vegetated)	Standard deviation from the median of the standardised normal distribution of the **greenness** values of the same time period (month by default) over last 7 years.
		3. Food insecurity	% of households adopting negative coping mechanisms (cutting down meals)	LSMS - ph_sec12: s12q8d, s12q8i	Survey microdata	2018	Percentage	% of households in each survey sampling point that reported cutting down on meals from LSMS; Implement spatial model to generate high resolution layer
			% of households with food insecurity/malnutrition prevalence	LSMS - fies_mod_rx: Probability of being moderately/severely food insecure >= 50%	Survey microdata	2018	Percentage	% of households in each survey sampling point being moderately/severely food insecure from LSMS; Implement spatial model to generate high resolution layer
			# of child under 5 mortality rate (per 1,000 live births)	GHDx	Estimated raster	2017	Percentage	GeoTIFF raster files for pixel-level (5km) estimates of death counts under-5 (**0-5 years old mortality**); resample to 1km grid
	2. Social structure instability	4. Underemployment rate	% of people ages between 15 and 35 unemployed	FII - Unemployed in the past 12 months	Survey microdata	2017	Percentage	% of people in each survey sampling point that reported **unemployed** from FII; Implement spatial model to generate high resolution layer
		5. Inaccessibility of basic services	% of school age children **not attending** primary/secondary/tertiary school	GHDx	Estimated raster	2017	Percentage	% of people in each survey sampling point that reported no education or preschool as highest education from DHS; Implement spatial model to generate high resolution layer

			% of school age children only attending religious madrasa education	FII - DG4	Survey microdata	2017	Percentage	% of people in each survey sampling point that reported **Koranic school** as highest education from FII; Implement spatial model to generate high resolution layer
			% of households with limited access to water (availability, accessibility, quality)	GHDx	Estimated raster	2017	Percentage	GeoTIFF raster files for pixel-level estimates of **drinking water** percent (percent of people with the given type of access) at the 5x5 km-level. 5 available layers: - Access to any improved water sources - Access to non-piped improved water sources - Access to piped water - Reliance on surface water - Reliance on unimproved water sources **Recommend definition: % of people with limited access to any water source or only reliance on unimproved water source (unprotected well and spring, river, lake, canal, dam, surface water)**
			Prevalence of communicable diseases	GHDx - HIV prevalence GHDx - Malaria GHDx - Lower Respiratory Infection	Estimated raster	2017 2019 (Malaria)	Prevalence (%)	- GeoTIFF raster files for pixel-level estimates of HIV prevalence among adults ages 15-49 at the 5x5 km-level - GeoTIFF raster files for pixel-level estimates of malaria prevalence among ages 0-10 at the 5x5 km-level - GeoTIFF raster files for pixel-level estimates of LRI prevalence among children under 5 at the 5x5 km-level
			% of households with limited access to electricity	DHS	Survey microdata	2020	Percentage	% of household in each survey sampling point that reported limited access of **electricity** from DHS; Implement spatial model to generate high resolution layer
			% of households with limited access to basic services (mobile, internet, bank)	DHS - mobile, computer, bank account	Survey microdata	2020	Percentage	% of household in each survey sampling point that reported limited access to the following: mobile phone, computer or bank account from DHS; Implement spatial model to generate high resolution layer
			Distance to health facilities	OpenStreetMap	Crowdsourced	2021	Distance in km	Distance to health facilities - Open street map from HDX
			Distance to schools	OpenStreetMap	Crowdsourced	2020	Distance in km	Distance to school - Open street map from HDX
		6. Political grievances	Rule of law perceptions	Afrobarometer	Survey microdata	2017	Score	Composite score for Afrobarometer survey questions on application of law and trust in legal institutions (42d, 42e, 42f, 43l) using the four variables that had the highest Chronbach Alpha score, which indicates correlation between the selected questions -Standardise each questions' score into [0,1] and calculate mean score. Closer to 1 indicates weaker adherence to the rule of law -Implement spatial model to generate high resolution layer
			Corruption perceptions	Afrobarometer	Survey microdata	2017	Score	Composite score for Afrobarometer survey questions on corruption (Qq 44, 45) -Calculate Cronbach's alpha to check the reliability between the selected questions -Standardise questions' score into [0,1] and calculate mean score. More closer to 1, stronger adherence to corruption. -Implement spatial model to generate high resolution layer
			% of people who report not having confidence and trust in the national government, public authorities	Afrobarometer	Survey microdata	2017	Score	Composite score for Afrobarometer survey questions on trust in various government institutions (q. 43) -Calculate Cronbach's alpha to check the reliability between the selected questions -Standardise questions' score into [0,1] and calculate mean score. -Implement spatial model to generate high resolution layer
		7. Social inequality	Political rights and freedoms perceptions	Afrobarometer	Survey microdata	2017	Score	Composite score for Afrobarometer survey questions on freedoms (q. 19a-e) Implement spatial model to generate high resolution layer

			Income inequality	DHS	Survey microdata	2018	Score	Wealth index (score) at each survey sampling point from DHS; - Calculate variance in cluster level - Implement spatial model to generate high resolution layer
			Gender inequality	FII	Survey microdata	2017	Percentage	% of women employed in each 1km grid from FII; Implement spatial model to generate high resolution layer
		8. Discrimination	Perceived religious discrimination	Afrobarometer	Survey microdata	2018	Score	Afrobarometer data on religious discrimination (Q86B) -Standardise questions' score into [0,1] and calculate mean score in cluster level -Implement spatial model to generate high resolution layer
			Perceived ethnic discrimination	Afrobarometer	Survey microdata	2018	Score	Afrobarometer data on ethnic discrimination (Q86C) -Standardise questions' score into [0,1] and calculate mean score in cluster level -Implement spatial model to generate high resolution layer
			Religious diversity	SIDE	Estimated raster	2013	Score	Religious diversity: Following SIDE methodology, we first calculate the percentage of each religious group in each 1km grid, Next, we calculate a diversity score for each 1km grid that reflects the number and proportion of each group in each grid. For a grid that contains N groups, the score is calculated as the square sum of the proportions, then multiplied by N. Grids where one religion is dominant have a relatively low score compared to grids with a mix of different religious groups.
			Ethnic diversity	SIDE	Estimated raster	2013	Score	Ethnic diversity: Following SIDE methodology, we first calculate the percentage of each ethnic group in each 1km grid. Next, we calculate a diversity score for each 1km grid that reflects the number and proportion of each group in each grid. For a grid that contains N groups, the score is calculated as the square sum of the proportions, then multiplied by N. Grids where one ethnic group is dominant have a relatively low score compared to grids with a mix of different religious groups.
		9. Violence and conflict	Ethnic or communal violence including pastoralist and agriculturalist clashes	ACLED	Geotagged news reports	2016-2021	Score	Inversed distance of each 1 km grid to the location of nearest communal violent event, (**INTER1 or INTER2 = 4 or ASSOC_ACTOR_1 or ASSOC_ACTOR_2 containing keyword "Farmer" or "Pastoralist"**), weighted by the # of events at the location over last 5 years as well as a spatial sensitivity factor (Moran's I). Formula: score = (Total # of event at nearest point) / (Distance from the grid of calculation to the nearest point ^ absolute value of local Moran's I of nearest point). Will multiply by -1 if local Moran's I < 0. The final score will be normalised on [0,1].
			Concentration of government-initiated operations against VE groups	ACLED	Geotagged news reports	2016-2021	Score	Inversed distance of each 1 km grid to the location of nearest government-initiated battle against VE group (**INTER1 = 1 and INTER2 = 2**), weighted by the # of events at the location over last 5 years as well as a spatial sensitivity factor (Moran's I). Formula: score = (Total # of event at nearest point) / (Distance from the grid of calculation to the nearest point ^ absolute value of local Moran's I of nearest point). Will multiply by -1 if local Moran's I < 0. The final score will be normalised on [0,1].
			# of people killed and injured by terrorist attacks, security incidents	ACLED	Geotagged news reports	2016-2021	Score	Inversed distance of each 1 km grid to the location of nearest event with casualty (**INTER1 = 2 and FATALITIES > 0**), weighted by the # of casualties at the location over last 5 years as well as a spatial sensitivity factor (Moran's I). Formula: score = (Total # of fatalities at nearest point) / (Distance from the grid of calculation to the nearest point ^ absolute value of local Moran's I of nearest point). Will multiply by -1 if local Moran's I < 0. The final score will be normalised on [0,1].
			Insecurity (conflict hotspots, attacks, etc.)	ACLED	Geotagged news reports	2016-2021	Score	Inversed distance of each 1 km grid to the location of nearest VE group stronghold (**Event type: "Battles" or "Explosions/Remote violence" or "Violence against civilians"**), weighted by the # of events at the location over last 5 years as well as a spatial sensitivity factor (Moran's I). Formula: score = (Total # of event at nearest point) / (Distance from the grid of calculation to the nearest point ^ absolute value of local Moran's I of nearest point). Will multiply by -1 if local Moran's I < 0. The final score will be normalised on [0,1].
			Proximity to VE group strongholds	ACLED	Geotagged news reports	2020	Score	Inversed distance of each 1 km grid to the location of nearest VE group stronghold (**Sub-event type: "Non-state actor overtakes territory" or "Headquarters or base established"**), weighted by the # of events at the location over last 5 years as well as a spatial sensitivity factor (Moran's I). Formula: score = (Total # of event at nearest point) / (Distance from the grid of calculation to the nearest point ^ absolute value of local Moran's I of nearest point). Will multiply by -1 if local Moran's I < 0. The final score will be normalised on [0,1].

			# of internally displaced population (IDP)	IOM	Geotagged event data	2015-2021	Count	IOM IDP counts at each camp location, aggregated to LGA level
		10. Crime rate	% of people with previous record of criminal history	NBS	Census data	2017	Percentage	% of criminal cases - State level - Offences against persons/Offences against property/Offences against lawful authority
	3. Information sources	11. Sentiment towards extremist groups	active online VE ideology or under influence of VE online recruitment	Twitter (Filtered by country and keywords. Only focusing on tweets containing names of key VE groups/persons)	Social media	2019-2021	Score ranging from -1 (negative) to 1 (positive)	Inversed distance of each 1 km grid to the location of nearest city inferred from tweets corpus in Nigeria from 2018-2021, weighted by the sentiment score at the location as well as a spatial sensitivity factor (Moran's I). Formula: score = (Sentiment Score) / (Distance from the grid of calculation to the nearest point ^ absolute value of local Moran's I of nearest point). Will multiply by -1 if local Moran's I < 0. The final score will be normalised on [0,1].
		12. Information uniformity	Information diversity score	Afrobarometer	Survey microdata	2017	Score	Consumption of diverse sources of information calculated by adding the values for Question 12 in the Afrobarometer survey for each respondent and calculate the average for respondents in each sampling point; % of population in each survey sampling point that are above 15 years old and illiterate was used as a predictor of information diversity

5. Weighting and aggregation

We used principal components analysis (PCA) to calculate weights for each of the component indicators of each sub-pillar. PCA is a dimension-reduction technique used to analyse the correlations between variables to capture the information they have in common on an underlying quantity of interest.

PCA reveals the components of the covariance matrix that account for the highest possible variation in the set of variables using the smallest number of factors. These factors, or eigenvectors, are used for weighting the index components based on the amount of information each indicator provides about the overall index, pillar, or sub-pillar.

The first step in PCA is to check the correlation structure of the data. If the correlation between the indicators is strong, then it is likely they share common factors.

The second step is to identify the principal components (fewer than the number of individual indicators) representing the commonality between the indicators. Each component depends on a set of coefficients (loadings); each coefficient measures the correlation between the individual indicator and the component. Standard practice is to choose components that: (i) have associated eigenvalues larger than one; (ii) contribute individually to the explanation of overall variance by more than 10%; and (iii) contribute cumulatively to the explanation of the overall variance by more than 60%. We have followed all these three guidelines in our practice.

The third step is to rotate the components. The rotation is used to minimise the number of individual indicators that have a high loading on the same component. The idea behind transforming the factorial axes is to obtain a “simpler structure” of the components (ideally a structure in which each indicator is loaded exclusively on one of the retained components).

Rotation changes the component loadings and hence the interpretation of the components, while leaving unchanged the analytical solutions obtained ex-ante and ex-post the rotation.

The last step is to construct the weights from the matrix of component loadings after rotation, given that the square of component loadings represents the proportion of the total unit variance of the indicator which is explained by the component. A complete list of aggregated indices and weights of their corresponding components can be found in the appendix table ("Indicator weights" tab).

As the weights are derived for the indicators, geometric aggregation is used to compute a composite score of the sub-pillar/pillar/index. For a sub-pillar with n indicators, the aggregated score *S* is calculated as $S = \prod_{i=1}^{n} x_i^{w_i}$, where x_i and w_i refer to the value and weight of each indicator.

All indicators were normalised on a scale of [1, 100] prior to aggregation to avoid multiplication by zero. We use geometric aggregation instead of additive aggregation to avoid the undesirable implication of full compensability with the latter, which means lower association with the index value in some indicators can be compensated for by other indicators.

It should be noted that during the aggregation process, the polarity of some sub-pillars and indicators was reversed so that for all sub-pillars, the larger score implies more susceptibility to VE recruitment. This change is important to index aggregation and it primarily affects some indicators whose original data measure the resilience/general well-being of the society (e.g., employment rate and cropland count over the years).

Table 3 below shows specific indicator weights for each composite index derived from its PCA loadings. The components are ranked according to the percentage shown in the 'Weights' column, which indicates the extent to which they contribute information to the composite index during geometric aggregation.

For the overall index, the top contributing sub-pillars are information uniformity, agricultural instability, and inaccessibility of basic services, each accounting for approximately 12% of the overall index. State-level crime rate, with a weight less than 3%, contributes least to index construction.

These weights reflect internal consistency within the data used to construct each pillar and sub-pillar. This means that the weights express the importance of each component relative to the other components according to the correlations within the data, and do not account for the contribution of any external factors to the phenomenon measured. Also, the weights reflect national averages across the 1*1km grid. This means that weights are not calculated separately for each grid cell or other subnational units. It is thus important to consider local variation in the relative importance of index components by looking not just at the overall index, but also at the different pillars and sub-pillars in local areas of interest.

Table 3. Weight of components used for composite indices construction

Composite indices	Component indicators	Weights
Overall index - Community vulnerability to VE recruitment	Information uniformity (Sub-pillar 3.2)	12.2%
	Agricultural instability (Sub-pillar 1.3)	12.2%
	Inaccessibility to basic services (Sub-pillar 2.2)	11.7%
	Violence and conflict (Sub-pillar 2.5)	10.9%
	Political grievances (Sub-pillar 2.3)	10.4%
	Food insecurity (Sub-pillar 1.2)	9.2%
	Sentiment towards extremist groups (Sub-pillar 3.1)	8.1%
	Discrimination (Sub-pillar 2.4)	7.8%
	Underemployment rate (Sub-pillar 2.1)	5.5%
	Social inequality (Sub-pillar 2.6)	5.0%
	Natural hazards (Sub-pillar 1.1)	4.0%
	Crime rate (Sub-pillar 2.7)	2.9%
Pillar 1 - Environmental fragility	Food insecurity (Sub-pillar 1.2)	56.5%
	Agricultural instability (Sub-pillar 1.3)	24.3%
	Natural hazards (Sub-pillar 1.1)	19.2%
Sub-pillar 1 - Natural hazards	Land degradation & desertification	62.7%
	Seasonal and decadal variability of precipitation (flooding and droughts)	26.9%
	Temperature change	10.5%
Sub-pillar 2 - Agricultural instability	Locust infection	17.7%
	Extent of lake surface	16.1%
	Food production or other agriculture output	15.7%
	Extent of grazing land	14.8%
	Extent of farmland	14.6%
	Population density	9.4%
	Distance to roads	7.0%
	Distance to population centers	4.8%
Sub-pillar 3 - Food insecurity	% of households cutting down meals	39.7%
	% of households with food insecurity/malnutrition prevalence	35.6%
	# of child under 5 mortality rate (per 1,000 live births)	24.7%
Pillar 2 - Social structure instability	Violence and conflict (Sub-pillar 2.5)	22.9%
	Inaccessibility of basic services (Sub-pillar 2.2)	19.1%
	Discrimination (Sub-pillar 2.4)	18.0%
	Political grievances (Sub-pillar 2.3)	16.7%
	Social inequality (Sub-pillar 2.6)	9.6%
	Underemployment rate (Sub-pillar 2.1)	7.9%
	Crime rate (Sub-pillar 2.7)	5.8%
	% of school age children not attending school	14.0%

Sub-pillar 5 - Inaccessibility of basic services	Prevalence of communicable diseases	12.8%
	Distance to schools	12.0%
	% of school age children only attending religious madrasa education	11.2%
	% of households with limited access to basic services (mobile phone, internet, bank)	10.2%
	% of households with limited access to electricity	9.6%
	Prevalence of communicable diseases – HIV	8.8%
	Distance to health facilities	8.2%
	% of households with limited access to water (availability, accessibility, quality)	7.7%
	Prevalence of communicable diseases – Malaria	5.5%
Sub-pillar 6 – Political grievances	Rule of law perceptions	75.4%
	Corruption perceptions	16.9%
	% of people who report not having confidence and trust in the national government, public authorities	7.7%
Sub-pillar 7 - Social inequality	Political rights and freedoms perceptions	40.6%
	Gender inequality	35.1%
	Income inequality	24.3%
Sub-pillar 8 - Discrimination	Ethnic diversity	33.4%
	Perceived ethnic discrimination	29.8%
	Perceived religious discrimination	26.5%
	Religious diversity	10.3%
Sub-pillar 9 - Violence and conflict	Ethnic or communal violence including pastoralist and agriculturalist clashes	24.8%
	Insecurity (conflict hotspots, attacks, etc.)	20.2%
	# of internally displaced population (IDP)	18.8%
	Proximity to VE group strongholds	14.0%
	Concentration of government-initiated operations against VE groups	12.6%
	# of people killed and injured by terrorist attacks, security incidents	9.5%
Pillar 3 – Information sources	Sentiment towards extremist groups (Sub-pillar 3.1)	59.1%
	Information uniformity (Sub-pillar 3.2)	40.9%