CENTRAL AFRICAN REPUBLIC FLOOD SUSCEPTIBILITY & RISK

ANALYSIS METHODOLOGY

INTRODUCTION

The Central African Republic rainy season is intense due to the equatorial country's tropical climate. These rains have historically caused destruction of shelters, obstructed transportation routes, and increased incidence of diseases like cholera and malaria. Unfortunately, due to climate change, flood events are predicted to increase in frequency, magnitude and seasonality globally [9]. Floods are among the most frequent and costly natural disasters in terms of human and economic loss [10]. Mitigating the effect of natural disasters on vulnerable populations is becoming ever more relevant in humanitarian crisis intervention due to the looming climate crisis - particularly in countries like Central African Republic where livelihoods are largely dependent on subsistence agriculture.

This country-wide analysis aims to provide humanitarian actors with an improved understanding of the exposure of vulnerable populations to flooding in Central African Republic. Though this analysis does not represent comprehensive hydrological predictions, it can serve as a means to inform humanitarian programming relating to flood risk and preparedness.

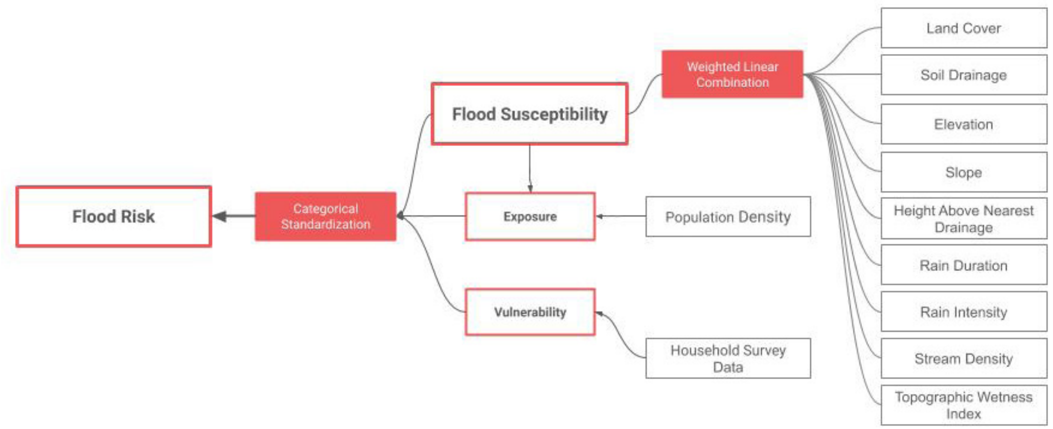
RATIONALE

The objective of this analysis is to identify areas in Central African Republic (CAR) that are the most and least susceptible to flooding. Though there are existing maps of the extent and impact of past flooding events in the country, there are none highlighting the susceptibility to future flooding at the level of detail of this analysis and which use the chosen methodological approach.

UNEP GRID, GLOFAS Forecasting and ThinkHazard! have information on flood potential globally. These resources respectively assess potential riverine flooding not flash flooding, lack clarity for novice audiences, and lack granular sub-prefecture detail.

The analysis utilizes free and open datasets to gauge flood susceptibility and in-situ survey data to estimate flood risk to vulnerable populations.

WORKFLOW



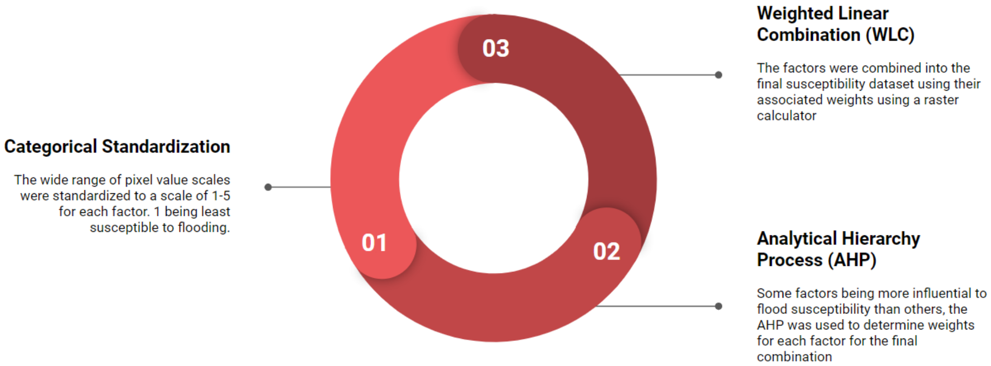
DATASETS

Source	Variable(s)	Resolution	Period
Africa SoilGrids	Soil Drainage	~250 m	1960 - 2016
CHIRPS Daily: InfrarRed Precipitation w/ Station Data v2	Rain Intensity, Rain Duration	~0.05 arc degrees	1990-2020
World Wildlife Fund (WWF) HydroRivers v1.0	Drainage Density	vector	2019
European Space Agency (ESA) Climate Change Initiative (CCI) Africa	Landcover	~20 m	2016
Japan Aerospace Exploration Agency (JAXA) Advanced Land Observing Satellite (ALOS) Digital Surface Model (DSM)	Elevation, Slope, Drainage Density	~30 m	2019
The University of Tokyo - MERIT Hydro	Height above Nearest Drainage	~90 m	2019
Africa Soil Information Service (AfSIS)	Topographic Wetness Inex	~90m	2010-2017
Facebook Central African Republic: High Resoultion Population Density	Risk - Exposure	20 m	2018
REACH Initiatives Central African Republic Multi-Sectoral Needs Assessment	Risk- Vulnerability		2019
Eurpoean Joint Research Centre and Global Flood Awareness System Flood Hazard	Accuracy Assessment		2016
United Nations Environment Programme- Global Assessment Report Flood Hazard	Accuracy Assessment		2015

FLOOD SUSCEPTIBILITY

Flood susceptibility mapping is informed by multiple physical parameters that collectively contribute to the likelihood of floods. Using geographical location as a commonality between datasets, GIS platforms enable the combination of contributing flood factors into one single dataset representing susceptibility across the study area. This method leverages modelling capabilities of Google Earth Engine, ArcGIS, RStudio and QGIS to assess flood susceptibility based on a variety of satellite images and ancillary datasets.

Nine criteria representing different topographical, physical and hydrological characteristics of the region were used. The modeling process can be summarized in three steps:



CATEGORICAL STANDARDIZATION

All input datasets have varying scales and units of measurement. In order to calculate susceptibility as a cumulative score of all factors, they were each standardized to the same scale. The pixel values were reclassified into the same categorical scale from one to five- one being least, and five being most likely to flood. This was done using the natural breaks classification method for the continuous datasets. For landcover, classes were ranked based the degree of imperviousness [11]. Soil drainage was classified according to the designated drainage quality.

FACTORS USED

- Elevation
- Slope
- Topographic Wetness Index (TWI)
- Rainfall Intensity (Ave. Max. Annual)
- Rainfall Duration (Ave. Max. Annual)
- Drainage Density
- Height Above Nearest Drainage (HAND)
- Land-cover
- Soil Drainage

ANALYTICAL HIERARCHY PROCESS

WLC using AHP provides a consistent method of judgment of diverse criteria, reducing bias through weight normalization. "AHP uses hierarchical structures to represent a problem and, then, develop priorities for alternatives based on the judgment of the user based on paired comparisons. Evaluation criteria and their weights must be determined according to their importance" [9]. The pairwise comparison chart was used to obtain the weights, which were calculated based on rankings determined by relative influence of each factor on flooding. In order to build the pairwise comparison chart, academic papers which applied the AHP technique for flood were referenced. This approach was used so that the hierarchy and relative influence of criteria matches that of expert opinions.

Pairwise Comparison Chart

	TWI	Elevation	Slope	HAND	Soil Drainage	Rain Intensity	Rain Duration	Land Cover	Stream Density	Final Weight
TWI	1	1.00	2.00	0.75	3.00	2.00	2.00	1.33	1.00	0.133
Elevation	1.00	1	3.00	0.75	3.00	3.00	3.00	5.00	1.00	0.177
Slope	0.50	0.33	1	0.50	3.00	2.00	3.00	2.00	0.33	0.088
HAND	1.33	1.33	2.00	1	4.00	5.00	5.00	4.00	3.00	0.236
Soil Drainage	0.33	0.33	0.33	0.25	1	0.50	0.50	1.00	0.33	0.043
Rain Intensity	0.50	0.33	0.50	0.20	2.00	1	1.50	0.50	1.00	0.066
Rain Duration	0.50	0.33	0.50	0.20	0.67	1.00	1	0.50	1.00	0.055
Land Cover	0.75	0.20	1.00	0.25	1.00	2.00	2.00	1	0.33	0.072
Stream Density	1.00	1.00	3.00	0.33	3.00	1.00	1.00	3.00	1	0.129

WEIGHTED LINEAR COMBINATION

The weighted linear combination (WLC) was adopted to produce the final flood susceptibility map. This method used the ArcGIS Raster Calculator tool to aggregate all the weighted factor rasters to produce the final output.

```
Flood Susceptibility = (Land cover * 0.072) + (Soil Drainage* 0.043) + (Elevation * 0.177) + (Slope* 0.087) + (TWI* 0.133) + (HAND * 0.236) + (Stream Density* 0.129) + (Rain Duration * 0.055) + (Rain Intensity* 0.066)
```

Due to technical limitations, the end product of this analysis is a map representing flood susceptibility rather than risk. Risk implies consequential basis of analysis, and can be defined as demarcating "the areas under potential consequences where consequences can be those affecting human life, having economic effects or causing environmental changes for instance" [2]. With such definition, the final result of this analysis, which depends on natural factors (rather than social or economic ones), will be indicative of flood susceptibility rather than risk.

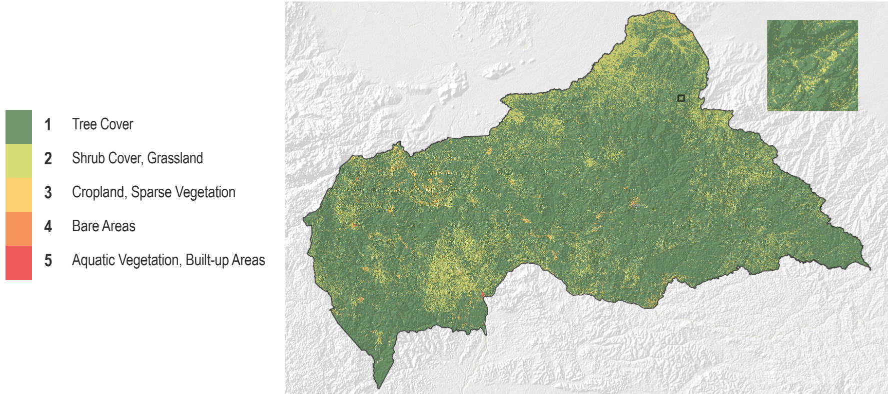
DATA PROCESSING & ANALYSIS

Nine criteria were considered in this susceptibility analysis. Their datasets were either readily available for download online, or derived through spatial analysis from existing datasets, and satellite images. The data processing was done mostly in Google Earth Engine (GEE) and on ArcGIS Pro. Following the processing of all of the datasets individually, they were combined using the Weighted Linear Combination (WLC) technique in ArcGIS Pro. The reasoning and processing of each factor is detailed here.

LANDCOVER

This factor is important when considering runoff, as the composition of the landscape, whether natural or man-made, affects infiltration [1]. Land cover can directly or indirectly influence evapotranspiration and surface runoff as well [2].

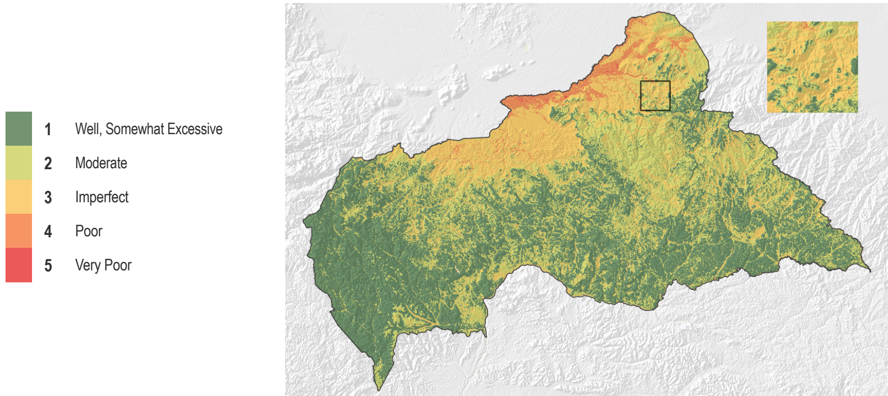
A 2016 20m resolution African landcover dataset produced by the ESA was used.



SOIL DRAINAGE

Soil quality influences runoff potential through infiltration rates, and therefore the magnitude of inundation resulting from intense rainfall.

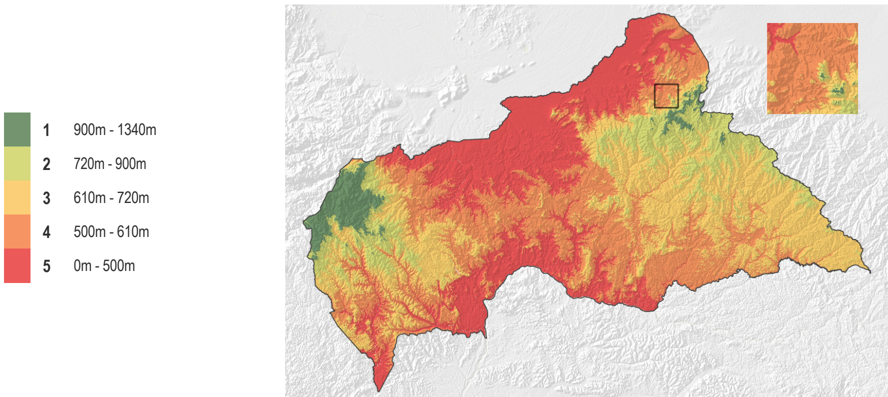
The ISRIC soil drainage dataset classifies drainage based on soil organic matter, soil texture and structure with a machine learning algorithm [3].



ELEVATION

Floods are typically identified in low elevations because rainfall on higher elevations accumulates downhill due to gravitational forces.

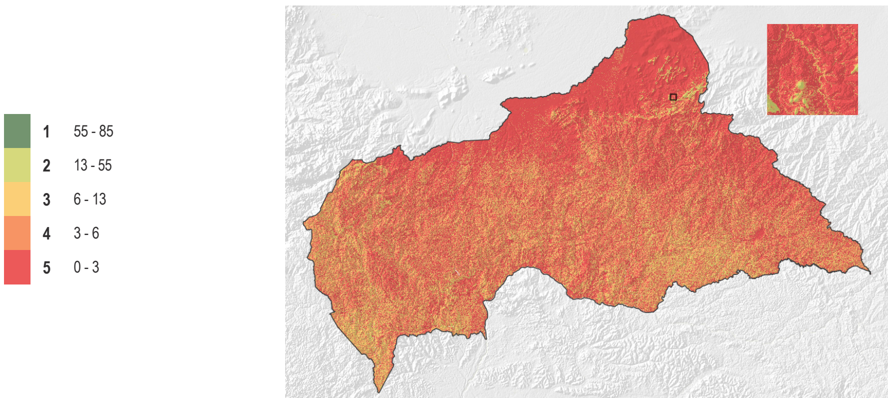
The ALOS World 3D-30m digital elevation model (DEM) was acquired to represent this criteria - provided by Google Earth Engine.



SLOPE

Floods caused by extraordinary rainfall events are the result of accumulated runoff. Steep slopes are less likely to be inundated during intense rainfall because the water drains down-slope, where flooding is more likely to occur in flat areas[4].

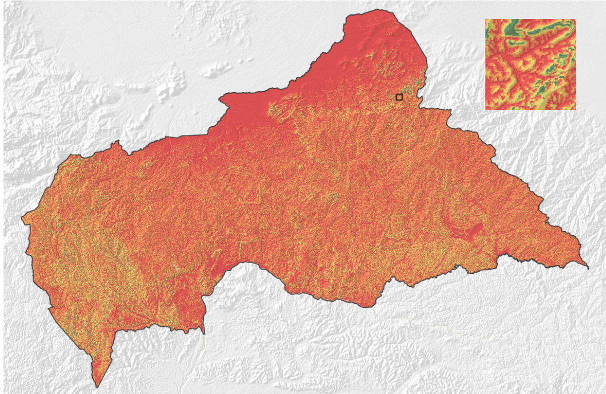
This slope factor was calculated in degrees, derived from the DEM in QGIS.



HEIGHT ABOVE NEAREST DRAINAGE (HAND)

This is a proxy for hydrological drainage networks, incorporating topography and gravitational potentials in a manner that normalizes terrain heights. It captures local topographic heterogeneities, fundamental for flood hazard mapping [5]. Representative of fluvial flood hazard ratter than hydrologically isolated pluvial flood hazard [6].

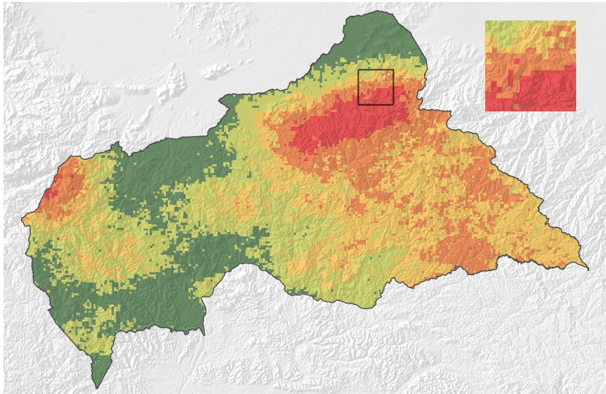
This data was made available by the University of Tokyo MERIT Hydro global hydrography dataset.



RAINFALL DURATION

Prolonged rainfall is a characteristic associated with flooding. Areas experiencing long periods of rainfall are more susceptible to flooding

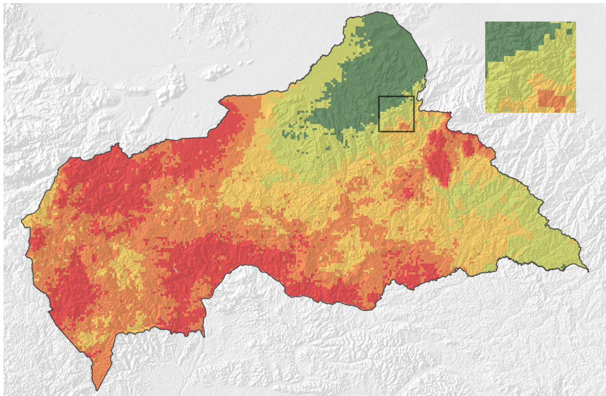
Daily rainfall data available on GEE was analysed within the GEE cloud computing platform to derive the average longest period of consecutive days of rainfall per year from 1984 to 2017. Code*



RAINFALL INTENSITY

Floods are often caused by intense rainfall events. Areas experiencing high amounts of rainfall are more susceptible to flooding.

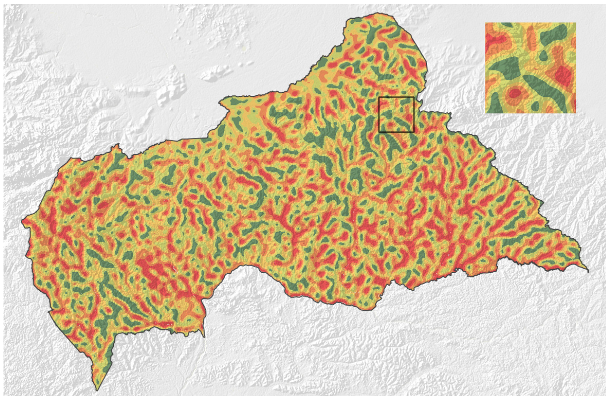
Daily rainfall data available on GEE was analysed within the GEE cloud computing platform to derive the average of maximum annual rainfall per year from 1984 to 2018. Code*



STREAM DENSITY

Flood plains, low-lying areas near river banks, are susceptible to flood. Drainage density influences water output and sediment accumulation. Low density is associated with higher permeability and more vegetation, making the area less susceptible [2].

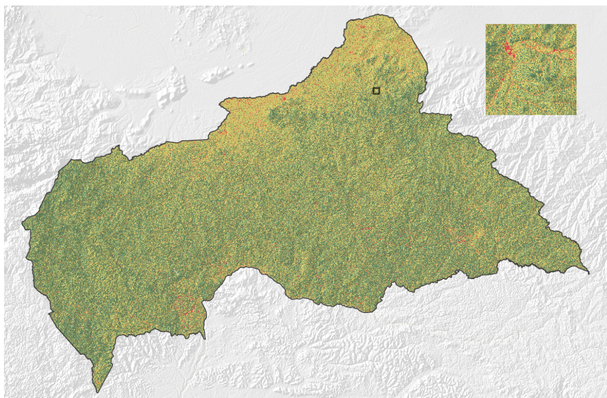
The drainage network from the HydroSheds dataset was used to derive the drainage density via number of vertices using heat map in QGIS.



TOPOGRAPHIC WETNESS INDEX

TWI is a runoff model that exploits slope, elevation, flow accumulation and flow direction to determine the capability of a land surface to accumulate water [7]. It accounts for the probability of localized flash-flood events [8].

The dataset was provided by AfSIS and NASA for the African continent at a 90m resolution.

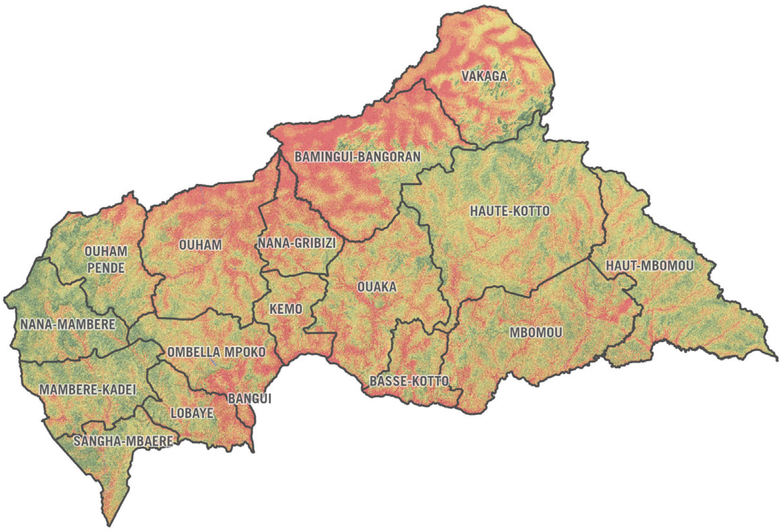


RESULT

The nal result of the calculations is an image where each pixel has continuous values ranging from 1 to 5 as a representation of the susceptibility to ooding in each location. The output is signi cantly impacted by the weights, however, the compounding values retain information about the degree of relative susceptibility.

Classes were rede ned to equal interval classes designating pixels as very low, low, medium, high, or very high ood susceptibility.

- 1 Very Low
- 2 Low
- 3 Meduim
- 4 High
- 5 Very High



FLOOD RISK

Flood risk incorporates human impact analysis into this study which is intended to inform flood preparedness. In this case, risk was calculated using measures of flood hazard (susceptibility), exposure, and vulnerability. This method leverages the flood suscpeitbility dataset created in this analysis, population raster data and the 2019 REACH Multi-Sectoral Needs Assessment (MSNA) data.

RISK = HAZARD + EXPOSURE + VULNERABILITY

HAZARD

The hazard parametergauges the relative probablilty of a disasterous flood event occuring in a given area. Flood liklihood is provided through our measure of flood susceptibility through weighted linear combination. The final nation-wide flood susceptibility dataset was masked to exclude uninhabited areas, to derrive the average flood susceptibility score per administarative area.

EXPOSURE

The estimated number of people who reside in high and very high flood risk areas was used as the exposure parameter for the flood risk score. Exposure is a measure of a given area's predisposition to disruption by a flooding event due to its location [12].

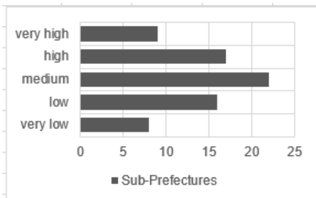
VULNERABILITY

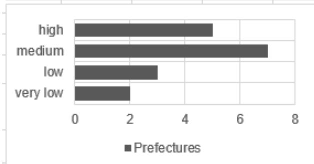
The communities with less capacity to cope and adapt to flood disaster are considered to be vulnerable in our caluclation of flood risk. Proportion of the following populations were utilized in a composite vulnerability score:

- People lacking structural resiliency (% living in emergency/transitional shelter or no shelter)
- People with low financial resilience (% average monthly income level less than 50,000 XAF)
- People with food insecurity (% with unacceptable FCS score)
- Unaccompanied and seperated youth
- Children (% of children under 18)
- Elderly people (% of adults over 59 years old)
- Disabled people (% with mental or physical disability)
- Internally Displaced People in sites (CCCM Data, March 2020)

COMPOSITE METHODS

The vulnerability factor considers many measures of community needs and conditions. Administrative units were scored on their realative vulnerability by simply taking the sum of proportions larger than 50% and again for larger than 75 %. Example: in Lobaye Prefecture, 63% of the population are children, adding a 1 to the score, and the proportion of people with low financial resilience is 75.3%, therefore 1 is added to the proportion being above 50% and another is added for being above 75%.





Quantile thresholds for the data distribution of the hazard and exposure factors were used to standardize values to a score of 1-4. The resulting scores for vulnerability hazard and exposure were then added together for a composite risk score. The numeric risk scores were converted into five classes designating prefectures and sub-prefectures as risk score very low, low, medium. high, very high.

See table of results in Appendix 1.

ACCURACY ASSESSMENT

An accuracy assessment was conducted by comparing the flood susceptibility model against 1) global flood risk datasets and against 2) actual flood inundation. The results of this validation reveal that our flood susceptibility model accurately delineate areas that are more prone to flood.

GLOBAL FLOOD RISK COMPARISON

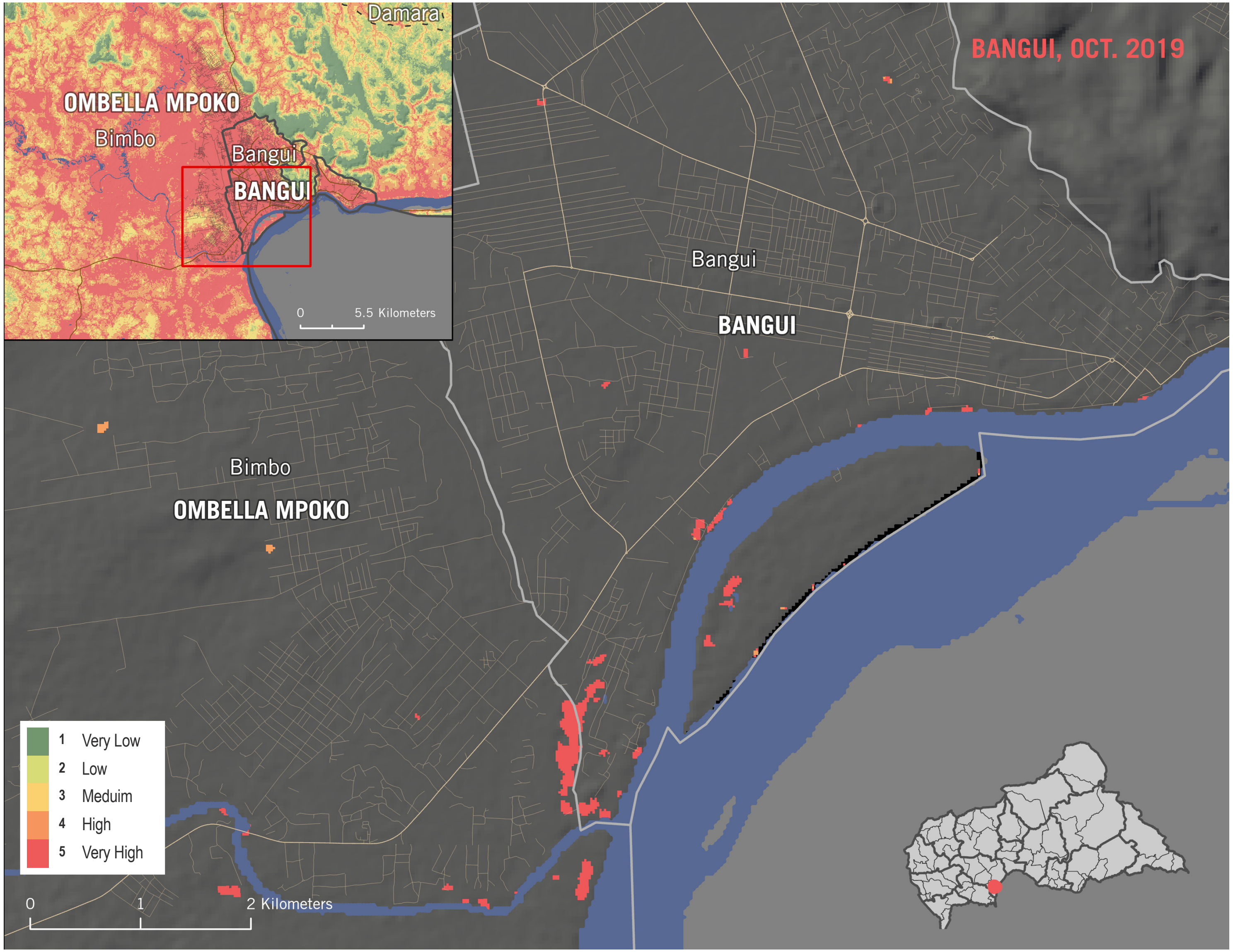
Two global riverine flood risk datasets, both measuring 500 year return period were provided by the Joint Research Centre (JRC), European Comission and the United Nations Office for Disaster Risk Reduction (UNISDR) Global Assessment Report (GAR) Atlas.

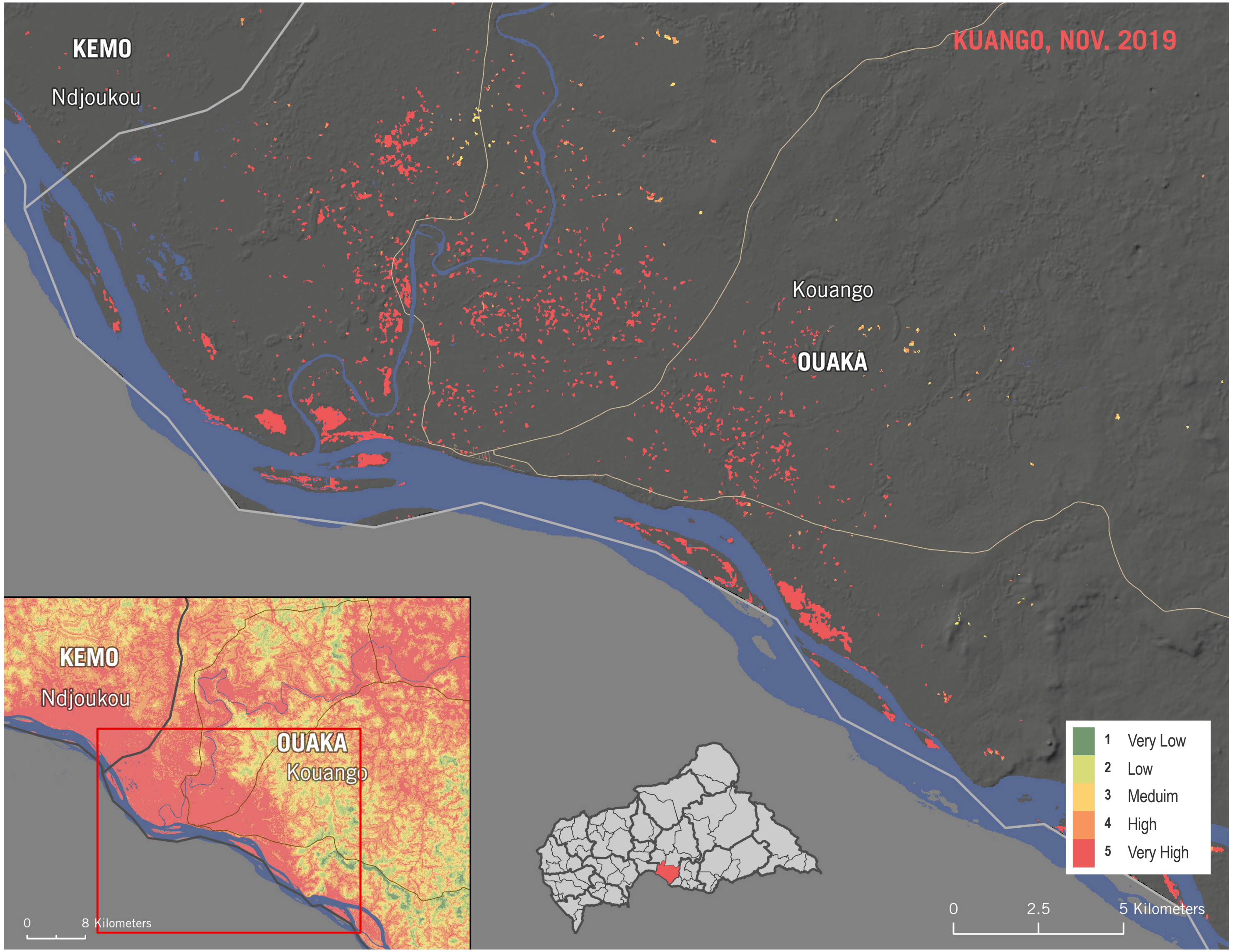
Areas designated as 500-year flood return zones in both the JRC and GAR global flood datasets were utilized as footprints to extract spatially associated regions of the REACH CAR flood susceptibility dataset. Results show that 90% of areas designated as flood-return areas were classified as high or very highly susceptible to flooding in our model.

Note the flood susceptibility analysis conducted in this research accounts for both fluvial and pluvial flood event types. Comparison to the global flood risk datasets is validation of the riverine flood susceptibility inherent in the analysis, and not the pluvial flood susceptibility.

INUNDATION COMPARISON

Two flood events were chosen, based on the availability of optical satellite data and on the extent of the event: October and November 2019 which devastated Bangui and Kuango respectively.





The validation against actual flood inundation was done by first acquiring footprint of the floods using a Google Earth Engine script Developed by IN-SPIDER [13]. The script classifies areas as either flooded, or not using synthetic aperture radar (SAR) satellite imagery and user input of 'before' and 'after' flood dates.

The resulting footprints from Baungi October 23rd 2019 and Kouango November 17th, 2019 were then used as a mask to extract the spatially associated flood susceptibility values. The results of this extraction are presented in the accuracy assessment maps.

RESULTS

The tables below show the percentage of each flood susceptibility class observed in the inundation footprint. It is apparent through this comparison that our flood susceptibility model aligns closely with actual inundation. The comparison against global riverine flood risk is not as significant, but is still confirming agreement.

Susceptibility Class	Bangui Oct. 2019	Kuango Nov. 2019	GAR	JRC
VERY LOW	0.04%	0.01%	0.78%	0.07%
LOW	0.14%	0.05%	5.02%	0.44%
MEDIUM	4.41%	1.53%	13.86%	2.81%
HIGH	13.26%	5.53%	31.26%	30.65%
VERY HIGH	82.14%	92.88%	49.08%	66.02%

NOTICE

This interpretation of flood susceptibility is not predictive. The analysis indicates areas more or less susceptible to flooding based on physical land features and rainfall and has not been corroborated with hydrological models.

The analysis highlights areas which are more likely to experience flooding and have potential to be more severely impacted in the case of flood. Such areas should undergo an in-depth hydrological assessment prior to preventative measures involving infrastructure construction.

Recommended areas of improvement for future work relating to this exploratory research:

- An automation of the calculated flood risk to account for updates in household assessment data
- Collaborating with hydrological experts to determine unique and precise fuzzy membership transformation methods for factors rather than natural breaks
- Additional flood events in various regions of the country to further validate the accuracy of the flood susceptibility component of this analysis

Please consider that this exploratory analysis was not verified by hydrological experts when consulting these outputs for strategic humanitarian planning. The data, designations and boundaries contained in these images are not warranted to be error-free and do not imply acceptance by the REACH partners, associated, donors referenced.

ABOUT REACH

REACH is a joint initiative that facilitates the development of information tools and products that enhance the capacity of aid actors to make evidence-based decisions in emergency, recovery and development contexts. By doing so, REACH contributes to ensuring that communities affected by emergencies receive the support they need. All REACH activities are conducted in support to and within the framework of inter-agency aid coordination mechanisms. For more information, please visit our website at **www.reach-initiative.org**, contact us directly at **reach.mapping@impact-initiatives.org** or follow us on Twitter at **@REACH_info**.

Download static flood susceptibility maps by prefecture at the REACH Resource Centre

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Appendix 1

Prefecture	Sub-Prefecture	Vulnerability Score	Susceptibility/Hazard Score	People in High/Very High Flood Risk Area %	People in High/Very High Flood Risk Area #	FINAL RISK SCORE
Ombella M'Poko		1	4.20	74%	320,360	high
	Boali	1	4.01	70%	19,298	medium
	Bogangolo	3	3.32	54%	5,066	medium
	Bossembélé	2	3.20	35%	13,308	low
	Damara	2	4.20	82%	29,708	high
	Yaloké	2	2.45	14%	5,564	very low
Lobaye		3	3.59	53%	161,627	low
	Boda	2	3.69	60%	33,036	medium
	Boganangone	3	2.25	5%	1,774	low
	Boganda	3	2.73	27%	4,322	low
	Mbaïki	3	3.87	58%	100,873	medium
	Mongoumba	3	4.11	80%	21,509	very high
Mambéré-Kadéï		2	2.87	27%	122,092	very low
	Amada-Gaza	3	2.41	11%	2,410	low
	Berbérati	2	2.72	25%	43,211	very low
	Carnot	3	3.31	40%	46,522	medium
	Dédé-Mokouba	3	3.21	35%	8,958	medium
	Gadzi	2	2.49	11%	7,757	very low
	Gamboula	2	3.11	32%	10,799	low
	Sosso-Nakombo	3	2.18	9%	1,593	low
Nana-Mambéré		2	2.06	9%	21,026	very low
	Abba	2	2.37	18%	5,307	very low
	Baboua	2	1.85	6%	3,087	very low
	Baoro	2	2.18	5%	1,787	very low
	Bouar	1	2.10	11%	11,251	very low
Sangha-Mbaéré		3	3.65	59%	74,824	medium
	Bambio	2	3.66	58%	8,812	low
	Bayanga	3	3.70	60%	7,665	high
	Nola	3	3.64	59%	58,339	medium
Ouham Pendé		3	2.77	24%	116,132	low
	Bocaranga	3	2.28	10%	7,884	low
	Bossemtélé	2	2.12	8%	1,852	very low
	Bozoum	3	3.00	31%	16,623	low
	Koui	3	2.23	3%	810	low
	Ngaoundaye	3	2.53	17%	18,315	low
	Paoua	3	3.28	38%	74,619	medium
Ouham		2	4.08	74%	334,110	medium
	Batangafo	2	4.50	92%	72,290	high
	Bossangoa	2	3.82	59%	87,645	medium
	Bouca	3	4.26	80%	53,463	very high
	Kabo	3	4.60	99%	49,898	very high
	Markounda	3	4.28	89%	20,113	very high
	Nana-Bakassa	3	3.85	69%	39,385	high
	Nangha Boguila	3	3.45	45%	12,423	medium
Kémo		3	4.13	70%	106,957	high
	Dékoa	3	3.27	35%	16,344	medium
	Mala	3	3.69	60%	10,873	medium
	Ndjoukou	3	4.42	94%	34,306	very high
	Sibut	3	4.39	89%	45,505	very high
Nana-Gribizi		2	4.04	72%	101,176	medium
	Kaga-Bandoro	2	4.19	78%	93,186	high
	Mbrès	2	3.44	49%	9,517	low
Ouaka		3	3.80	65%	240,230	medium

* Risk calculation excludes the vulnerability component, due to a lack of household data

	Bakala	3	4.25	81%	4,825	very high
	Bambari	3	3.80	67%	113,843	high
	Grimari	3	4.01	70%	40,636	high
	Ippy	3	3.58	53%	23,743	medium
	Kouango	3	3.86	65%	58,372	high
Bamingui-Bangoran		2	3.99	70%	41,846	medium
	Bamingui	3	4.63	93%	8,482	very high
	Ndélé	2	3.85	66%	33,320	medium
Haute-Kotto		2	4.19	81%	91,422	high
	Bria	3	4.34	86%	76,393	very high
	Ouadda		3.72	65%	12,248	medium*
	Yalinga		3.46	45%	2,843	medium*
Vakaga		2	4.39	91%	59,101	high
	Birao	2	4.46	93%	56,025	high
	Ouanda-Djallé		3.70	63%	3,062	medium*
Basse-Kotto		3	3.73	63%	198,780	medium
	Alindao	4	3.70	62%	51,867	high
	Kembé	2	3.43	48%	20,834	low
	Mingala		3.57	53%	18,322	low*
	Mobaye	3	3.95	74%	56,098	high
	Satéma	1	4.38	82%	30,241	high
	Zangba	3	3.74	61%	24,161	high
Mbomou		1	4.12	79%	163,962	medium
	Bakouma	1	3.96	70%	15,374	medium
	Bangassou	2	4.09	76%	68,779	medium
	Gambo	1	4.09	78%	12,313	medium
	Ouango	1	4.42	90%	56,510	high
	Rafai	3	4.11	77%	12,333	high
Haut-Mbomou		4	3.43	57%	47,450	low
	Bambouti		1.78	0%	0	low*
	Djéma		3.11	32%	5,876	low*
	Obo	2	3.55	65%	28,587	medium
	Zémio	3	3.37	49%	9,500	medium
Bangui		2	4.80	98%	1,234,991	high
	Bangui	1	4.80	98%	1,234,991	high

* Risk calculation excludes the vulnerability component, due to a lack of household data