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19/10/2020

Visualizing Climate Change

EXAM 3

Mapping Agriculture and Food Security Vulnerability in the Democratic Republic of the Congo

SECTION 1 – THE DATA

The aim of this project is to avail of spatial visual representations as a tool to map agriculture and food security vulnerability in the Democratic Republic of the Congo (DRC), to aid key stakeholders in the identification of vulnerable regions and hotspots within the country. In my project, I define vulnerability similarly to the IPCC's (2014:1048) report, where it is described as "the propensity or predisposition to be adversely affected". This project can be seen as a baby-step towards using geographic visualizations, to assess vulnerability in the DRC, in a manner that is analogous to that of Wiréhn et al (2016). However, compared to these researchers and their tool AgroExplore, this project does not extend to the point of opening up the "black-box" of composite indices through multiple indicators and interactivity, but rather attempts, using a limited number of available datasets, to generate a composite index of vulnerability that is very broad in its definition and that relies only on some of the multitude of climate, socio-economic and climate related aspects required to generate a solid agricultural and food security composite index.

I avail of four datasets: one showing projected temperature change between the RCP85 scenario (2080-2099) and current climate trends; one showing projected change in precipitation between the RCP85 scenario (2080-2099) and current climate trends; one presenting sub-national Multidimensional Poverty Index (MPI) scores for the DRC in 2017; one showing the geographical distribution of maize crops and yield trends between 1989-2008. Together, these four datasets are agglomerated to map vulnerable hotspots in the DRC. The choice of datasets was made based on merely this question: given generating a vulnerability composite index can rely on a substantial number of datasets (see Wiréhn et al, 2016), what are sufficiently generic datasets that still capture key dimensions of vulnerability for agriculture and food insecurity, within the limited number of sufficiently-detailed datasets available? I thus picked two datasets that would indicate me which areas are most exposed to climate change effects in terms of temperature and precipitation, two key dimensions to assess impact on crops (although not the only ones, flooding, severe weather events can also be incorporated, but I limited myself to those given limitations in data availability). I then picked a dataset giving me a sub-national level overview of poverty of populations, of which I have used the MPI as a key variable. Finally, I used Ray's (2013) dataset on Yield Trends for maize between 1961-2008 to measure the ongoing agricultural productivity across the country, which is overall stagnating. I deemed that combining these datasets would give me a very basic, but sufficiently broad assessment of agricultural vulnerability (although I would have loved to incorporate more data on soil degradation, migration, land use and conflicts).

DATASETS

1. Annual mean precipitation change between baseline and RCP85 2080-2099: cmip5_anomaly_pr_annual_mean_multi-model-ensemble_rcp85_2080-2099.nc; https://learn.arcgis.com/en/projects/explore-future-climate-projections/world-climate-data.htm;
2. Annual mean temperature change between baseline and RCP85 2080-2099: cmip5_anomaly_tas_annual_mean_multi-model-ensemble_rcp85_2080-

2099.nc; https://learn.arcgis.com/en/projects/explore-future-climate-projections/world-climate-data.htm

3. Multidimensional Poverty Index: https://data.humdata.org/dataset/democratic-republic-of-the-congo-mpi
4. Maize Crop Yield Trends: http://www.earthstat.org/yield-trends-changes-maize-soybean-rice-wheat/

For regional borders I have used a shapefile containing the DRC administrative areas division: https://datacatalog.worldbank.org/dataset/democratic-republic-congo-administrative-boundaries-2017

METADATA

Here below I present some metadata for my datasets:

Focus	Measure	Time span	Format	Source	Key Variable
Rate of Yield Change for Maize	-40 to 60 globally (percent/year)	1961 to 2008	Raster (.tif) (global level)	Ray (2013)	Entire file
RCP8.5 temperature change	Annual mean change in Celsius degree	Future = 2080–99 - Current = 1986–2005	netCDF (global level)	Amman et al (2018)	Entire file
RCP8.5 precipitation	Annual mean change in mm/h	Future = 2080–99 - Current = 1986–2005	netCDF (global level)	Amman et al (2018)	Entire file
Multidimensional Poverty Index	0 to 1 (low to high poverty)	2017-18	Tabular (.xslx) (sub-national level)	Alkire et al (2020)	Multidimensional Poverty Index (MPI = H*A)

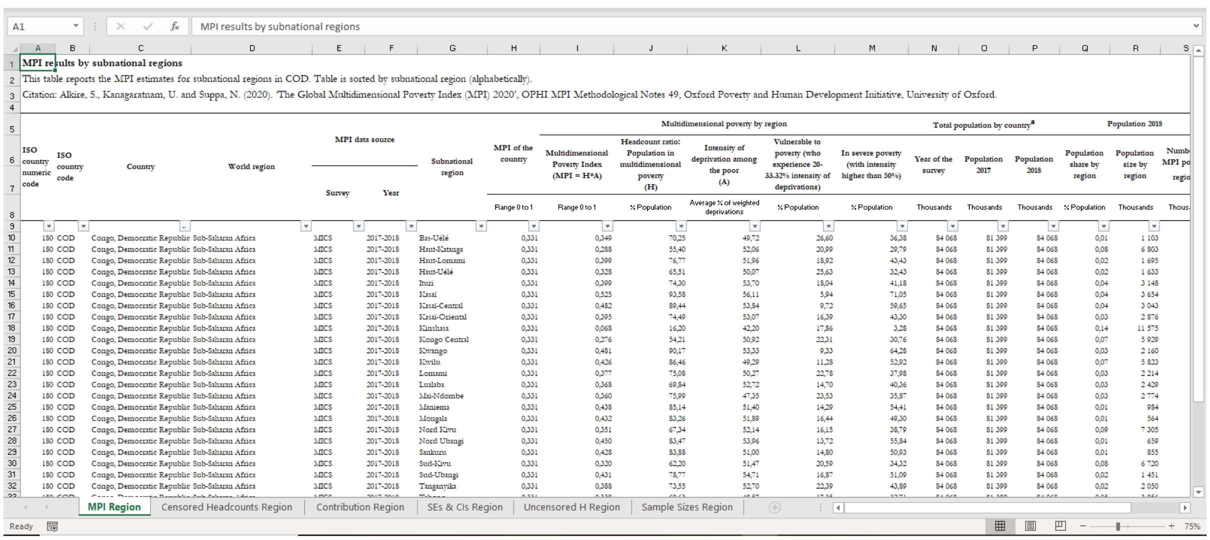
Additional information:
Cell size of raster file (will become relevant later)
-Precipitation and Temperature: 0.72/0.72
-Maize Crop Yield Trend: 0.0833333
-MPI: ~8000

SECTION 2 – THE PROCEDURE

VISUALISATION ONE (identifying hotspots by looking at distribution of crops across the country)

STEP 1: CLEANING OF XSLX FILE (MPI DATASET)

I had the issue that the .xslx file did not import in the format it came in, and I also had the problem that it contained a large number of variables I did generally not need. I cleaned up and rearranged the dataset, to get it into a format easily readable by ArcMap. Here below is my before/after of the MPI dataset. No values have been altered within the table, and the insertion of the column names as Excel headers helped later on in ArcMap. I then imported the data to my workspace.



MPI results by subnational regions

This table reports the MPI estimates for subnational regions in COD. Table is sorted by subnational region (alphabetically).

Citation: Alkire, S., Kanagaratnam, U. and Suppa, N. (2020). 'The Global Multidimensional Poverty Index (MPI) 2020', OPHI MPI Methodological Notes 49, Oxford Poverty and Human Development Initiative, University of Oxford.

ISO country numeric code	ISO country code	Country	World region	MPI data source		Subnational region	MPI of the country	Multidimensional poverty by region					Total population by country[a]			Population 2018	
				Survey	Year			Multidimensional Poverty Index (MPI = H*A)	Headcount ratio: Population in multidimensional poverty (H)	Intensity of deprivation among the poor (A)	Vulnerable to poverty (who experience 20-33.32% intensity of deprivations)	In severe poverty (with intensity higher than 50%)	Year of the survey	Population 2017	Population 2018	Population share by region	Population size by region
							Range 0 to 1	Range 0 to 1	% Population	Average % of weighted deprivations	% Population	% Population	Thousands	Thousands	Thousands	% Population	Thousands
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Bas-Uélé	0,331	0,349	70,25	49,72	26,60	36,38	84 068	81 399	84 068	0,01	1 103
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Haut-Katanga	0,331	0,288	55,40	52,06	20,99	29,79	84 068	81 399	84 068	0,08	6 803
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Haut-Lomami	0,331	0,399	76,77	51,96	18,92	43,43	84 068	81 399	84 068	0,02	1 695
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Haut-Uélé	0,331	0,328	65,51	50,07	25,63	32,43	84 068	81 399	84 068	0,02	1 633
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Ituri	0,331	0,399	74,30	53,70	18,04	41,18	84 068	81 399	84 068	0,04	3 148
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Kasaï	0,331	0,525	93,58	56,11	5,94	71,05	84 068	81 399	84 068	0,04	3 654
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Kasaï-Central	0,331	0,482	89,44	53,84	9,72	59,65	84 068	81 399	84 068	0,04	3 043
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Kasaï-Oriental	0,331	0,395	74,49	53,07	16,39	43,30	84 068	81 399	84 068	0,03	2 876
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Kinshasa	0,331	0,068	16,20	42,20	17,86	3,28	84 068	81 399	84 068	0,14	11 575
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Kongo Central	0,331	0,276	54,21	50,92	22,31	30,76	84 068	81 399	84 068	0,07	5 929
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Kwango	0,331	0,481	90,17	53,33	9,33	64,28	84 068	81 399	84 068	0,03	2 160
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Kwilu	0,331	0,426	86,46	49,29	11,28	52,92	84 068	81 399	84 068	0,07	5 823
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Lomami	0,331	0,377	75,08	50,27	22,78	37,98	84 068	81 399	84 068	0,03	2 214
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Lualaba	0,331	0,368	69,84	52,72	14,70	40,36	84 068	81 399	84 068	0,03	2 429
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Mai-Ndombe	0,331	0,360	75,99	47,35	23,53	35,87	84 068	81 399	84 068	0,03	2 774
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Maniema	0,331	0,438	85,14	51,40	14,29	54,41	84 068	81 399	84 068	0,01	984
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Mongala	0,331	0,432	83,26	51,89	16,44	49,30	84 068	81 399	84 068	0,01	564
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Nord Kivu	0,331	0,351	67,34	52,14	16,15	38,79	84 068	81 399	84 068	0,09	7 305
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Nord Ubangi	0,331	0,450	83,47	53,96	13,72	55,84	84 068	81 399	84 068	0,01	659
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Sankuru	0,331	0,428	83,88	51,00	14,80	50,93	84 068	81 399	84 068	0,01	855
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Sud-Kivu	0,331	0,320	62,20	51,47	20,59	34,32	84 068	81 399	84 068	0,08	6 720
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Sud-Ubangi	0,331	0,431	78,77	54,71	16,87	51,09	84 068	81 399	84 068	0,02	1 451
180	COD	Congo, Democratic Republic	Sub-Saharan Africa	MICS	2017-2018	Tanganyika	0,331	0,388	73,55	52,70	22,39	43,89	84 068	81 399	84 068	0,02	2 050

	ISO cou	ISO cou	Country	World region	Survey	Year	Subnational	Multidi	Headcc	In severe poverty percentage (with intensity higher than 50%)	Population share percentage by region 2018	Popula	Number of MPI poo
2	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Bas-Uele	0,349	70,25	36,38	0,01	1 103	
3	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Equateur	0,348	74,78	34,00	0,02	2 006	
4	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Haut-Katanga	0,288	55,40	29,79	0,08	6 803	
5	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Haut-Lomami	0,399	76,77	43,43	0,02	1 695	
6	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Haut-Uele	0,328	65,51	32,43	0,02	1 633	
7	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Ituri	0,399	74,30	41,18	0,04	3 148	
8	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Kasaï	0,525	93,58	71,05	0,04	3 654	
9	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Kasaï-Central	0,482	89,44	59,65	0,04	3 043	
10	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Kasaï-Oriental	0,395	74,49	43,30	0,03	2 876	
11	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Kinshasa	0,068	16,20	3,28	0,14	11 575	
12	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Kongo Central	0,276	54,21	30,76	0,07	5 929	
13	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Kwango	0,481	90,17	64,28	0,03	2 160	
14	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Kwilu	0,426	86,46	52,92	0,07	5 823	
15	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Lomami	0,377	75,08	37,98	0,03	2 214	
16	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Lualaba	0,368	69,84	40,36	0,03	2 429	
17	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Maï-Ndombe	0,360	75,99	35,87	0,03	2 774	
18	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Maniema	0,438	85,14	54,41	0,01	984	
19	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Mongala	0,432	83,26	49,30	0,01	564	
20	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Nord Kivu	0,351	67,34	38,79	0,09	7 305	
21	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Nord Ubangi	0,450	83,47	55,84	0,01	659	
22	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Sankuru	0,428	83,88	50,93	0,01	855	
23	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Sud-Kivu	0,320	62,20	34,32	0,08	6 720	
24	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Sud-Ubangi	0,431	78,77	51,09	0,02	1 451	
25	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Tanganyika	0,388	73,55	43,89	0,02	2 050	
26	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Tshopo	0,338	69,63	32,71	0,05	3 956	
27	180	COD	Congo, Der	Sub-Saharan Afri	MICS	2017-2018	Tshuapa	0,486	88,65	61,61	0,01	657	
28													
29													
30													

Sheet1

Average: 802,4504961 Count: 364 Sum: 146045,9903 100%

STEP 2: INTERPOLATION OF netCDF FILES, NORMALIZATION and EXTRACTION BY MASK

To create raster layers from the two NetCDF files, I imported them into ArcMap and distributed the data points for precipitation and temperature (separately) longitudinally and latitudinally. I was thereafter able to use interpolation (Kirging) as a way to generate continuous values for each raster cell. Following the creation of two raster files containing precipitation and temperature change from the RCP85 scenario, I normalized the two layers, as well as the crops yield one, to spread the values across a comparative range of 0 to 100. The normalization was done using the Raster Calculator, where I input the formula:

("raster"-min("raster"))/(max("raster")-min("raster"))*100

After normalizing the three layers, I extracted the relevant geospatial information for my project, which meant all cell values within the country borders of the DRC. I thus used my border shapefile to retain only the values of interest and remove the global raster layers from my workspace.

STEP 3: JOINING MPI DATASET TO SHAPEFILE and CONVERSION TO RASTER

To create the composite vulnerability index, I essentially had to make all layers compatible for aggregation. In my case, that meant getting all layers in the format of raster data. To get the MPI data to raster, I first joined the data to the administrative borders shapefile (merging by region name), then I used the symbology to visualize the MPI index score of each region, and finally converted the layer to raster. Crucially, when converting to raster, I had to choose a cell size for my file. At first, I tried the same size of the netCDF files, 0.72, but the procedure took my entire remainder PC memory, and thus I chose to follow the suggested cell size value of ~8000.

STEP 4: RESAMPLING

To aggregate the various raster layers and generate a composite vulnerability index, I first had to ensure that all rasters contained data at the same cell size. That meant changing the cell size for the precipitation, temperature and crop yield datasets, which I did using the Resample tool. I thus changed them to the same cell size of the MPI dataset. That did not change the look of the raster layers in my ArcMap.

STEP 5: RE-NORMALIZATION

The last step to ensure that aggregating my layers is meaningful and understandable was to re-normalize my layers data ranges to be within 0 and 100. That step was needed because upon extraction by mask the data values displayed were no longer on a 0 to 100 scale, but between the min-max value within the DRC. To me, that made it less intuitive, thus I re-normalized the layers, which crucially meant that the vulnerability score generated in the final step will be relative to the inner DRC, as opposed to the wider global scale. Put simply, it means that a 0 vulnerability score equals the lowest possible combination of values within each indicator based on the minimum values covered by the DRC. For example, the lowest possible temperature change capture by the RCP8.5 scenario for the globe could be 0.5degrees, but when looking within the DRC the minimum change value might instead be 0.8degrees. Another option would have been to build an index whose 0 value would equal the lowest possible combination of values of the indicators at the global level, but to me that was irrelevant given the vulnerability assessment is planned for stakeholders looking internally within the DRC.

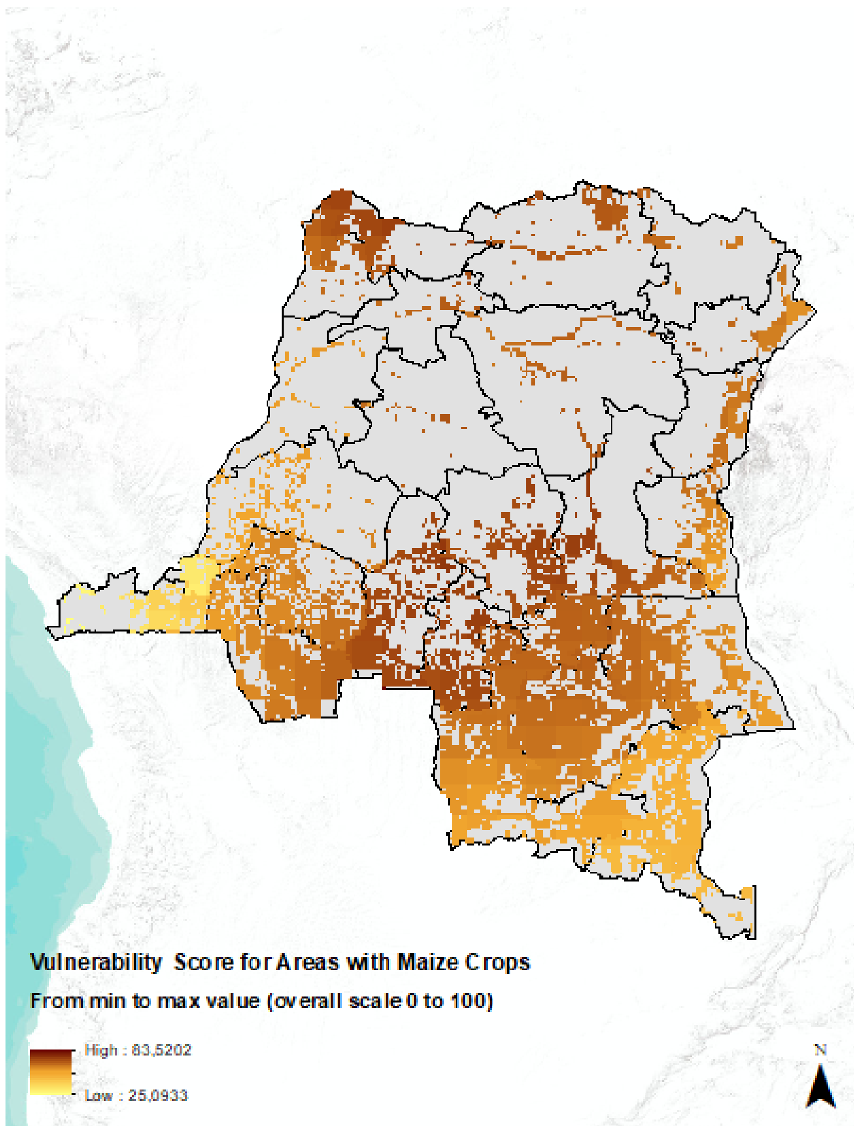
STEP 6: GENERATE VULNERABILITY SCORE FOR EACH CELL

I now essentially have four raster layers with identical cell sizes, borders and scales (0 to 100). I used the Raster Calculator once again to generate the vulnerability score at the cell level. The formula used was:

vulnerability_score = (raster1 + raster2 + raster3 + raster4)/4

The output is a raster layer that contained values from ~25 to ~83, showing me the aggregated vulnerability score for each cell. Crucially, however, that meant not having values for each cell within the country, as the crop layer only had cells for where crops are existent. I deemed that okay given looking at vulnerability in agricultural and food security terms makes sense in relation to where agricultural productivity at least exists. Here beside is my output map.

The scale of the range is kept at the min/max of my vulnerability score, however the potential range of values could have been between 0 and 100. I was unfortunately unsuccessful in changing the range to a 0 to 100 scale for the raster layer, although I managed to do it in my second visualization, as I will explain below. The map shows the level of vulnerability at the cell level for all those locations where crops were measured within the crop yield dataset. This map allows viewers to precisely assess the level of vulnerability at a micro level.



VISUALISATION TWO (identifying the most vulnerable regions):

The aim of my second map is to expand the identification of vulnerability from hotspots to the regional level. To do this, I was able to avail of the same procedure as above, and simply expand upon it as I will explain here below:

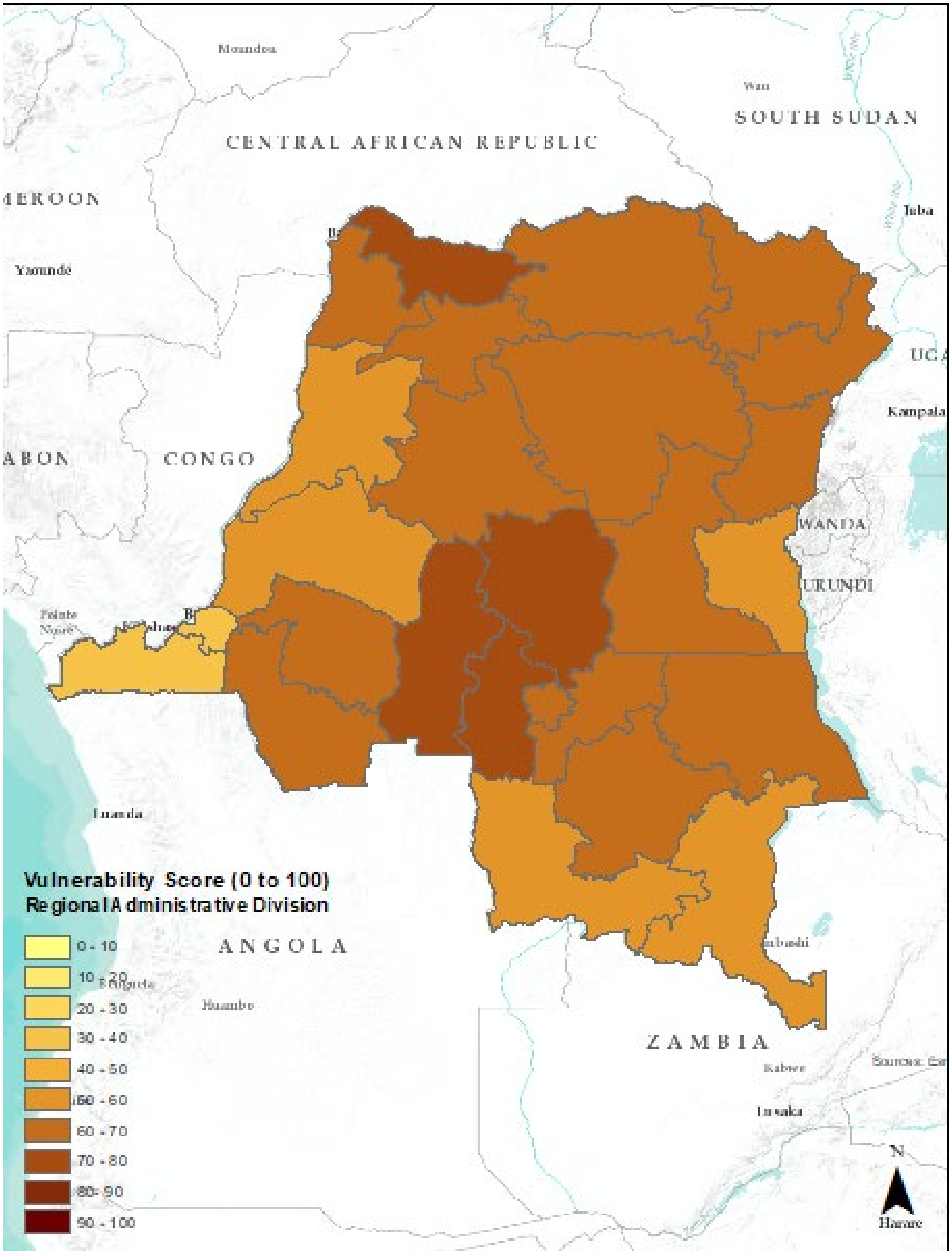
STEP 1-6: same as above

STEP 7: CALCULATE VULNERABILITY SCORE FOR EACH REGION

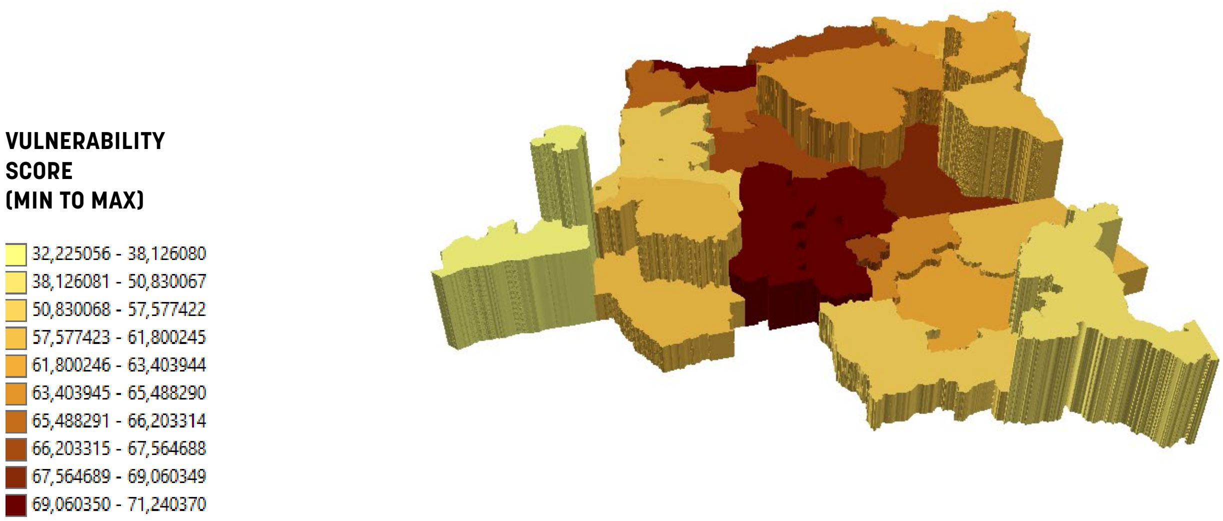
To calculate a regional vulnerability score for each region, I used the Zonal Statistics as a Table tool, and put as zonal input my administrative borders data, and the raster vulnerability score layer as my statistical information data source. The output was a table with a MEAN score for each region. One thing to bear in mind is that the number of cells varied substantially across regions, that is, some regions do not have as many crops as other. Thus, results might look inflated or somewhat incompatible. One consideration, however, is that one non-heavily productive region might fully depend on its few crops, and the vulnerability score as it is shows reliably the vulnerability for the region as a whole.

STEP 8: IMPORTING AN EXTERNAL RANGE OF VALUES TO VISUALISE CLASS BREAKS FROM 0 TO 100

One final issue I had was that I wanted my color palette to be a classification of 10 equally divided breaks, starting at 0 and finishing at 100, which are minimum and maximum possible values for the vulnerability score. By default, ArcMap visualized my data from the min to the max value within the variable. To solve the issue, I created a fake dataset with values ranging between 0 and 100, imported it into ArcMap, joined it to the shapefile, and imported its classification into the symbology for the vulnerability scores, thus enabling me to create more classes than what the data actually covers. To clarify, there are no regions in the lightest or darkest shade, simply because there are no regions with a vulnerability score below 20 or higher than 90, but I thought including them in the legend was important to show vulnerability in an objective and non-misleading manner.


Moundou
Wau
SOUTH SUDAN
CENTRAL AFRICAN REPUBLIC
Juba
Yaoundé
Kampala
CONGO
Luanda
Vulnerability Score (0 to 100)
Regional Administrative Division
0 - 10
10 - 20
20 - 30
30 - 40
40 - 50
50 - 60
60 - 70
70 - 80
80 - 90
90 - 100
ANGOLA
Huambo
ZAMBIA
Kabwe
Lusaka
N
Harare

I concluded the project by visualizing, in ArcScene, how the regional vulnerability score looks against population size by region (in thousands), which was another variable in the MPI dataset. Although it is hard to interpret the map when static, we can clearly see that some not so vulnerable, relative to others, have very high populations, and that, on the contrary, some not so populous regions have very high vulnerability scores.



VISUAL ATTRIBUTES

Given the plotted variable is the same, I have chosen one color palette and applied it to both visual representations. Given the vulnerability score is a sequential scale of non-diverging values, I have chosen a color scheme deemed appropriate for colorblind individuals as well, using an orange hue, which felt appropriate as a choice for vulnerability (Brewer 2020). One remark is that the same color palette is used between my two graphics despite the range differing – one shows the full 0 to 100 scale, and one the min-max values. Remarks are made in the legend title to clarify this.

The equal division of classes makes the ranges easily interpretable to the audience, although it can result in a homogeneously looking map depending on the underlying data distribution.

SECTION 3 – THE NARRATIVE

The DRC provides an interesting case study for vulnerability assessment given the country is rich of resources and is home to a large part of the Congo Basin tropical forests (which accounts for 18% of the world's forests), however its population has battled with internal and external conflicts in the past decade, it has high poverty rates (62%), and is subject to widespread diseases (malaria and Ebola to name just two) (USAID 2018). Ray (2013), upon assessing crop yield trends at a global level, shows that the yield of the major crop type in the DRC, maize, is stagnating within the nation. Future projections of an increasing population and climate change effects, which are set to damage the stability of the nation's eco- and agricultural systems through highly damaging weather events, warmer temperatures, flooding and dry spells, suggest that the DRC will face insurmountable challenges in feeding its already poor population (Boko et al 2017). The aim of this project is to provide an overview to key stakeholders (politicians and NGOs), on which areas are likely to become vulnerable hotspots in the possible realization of the IPCC's RCP85 future climate scenario for the upcoming century. The motivation for this project comes from, as Rød and colleagues pointed out (2015), the importance to look at subnational level to make assessment of vulnerability and climate change effects. To create an index of vulnerability, I chose datasets capturing the climate, the socio-economic, and the agricultural productivity dimensions, and agglomerated them to generate a geographically precise identification of hotspots in the DRC, as well as regional means to portray differences in needs for individuals regions. There is generally very superficial exploration of in-depth climate assessments for the DRC, partly due to historically poor data collection (USAID 2018), making the task of obtaining precise estimations and accurate projections quite challenging. Nonetheless, I used the best data available (often with a global focus) to make inferences on sub-national scores at the DRC.

Limitations to the project include elements highlighted by Wiréhn et al (2016), such as the usage of datasets on the basis that they were the ones available, the inability to open up the black box by incorporating interactivity or the visualization of the performance of each indicator alone, but simply looking at the composite aggregated level. In that sense, viewers are unable to infer what contributes to higher or lower vulnerability scores, but rather they can get a basic generalization of the vulnerability of an area or region.

Wordcount: 2434 words

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