SCOPING FOR DETAIL

A review of global indicators to assess social vulnerability to water scarcity on a local level

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Colophon

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Abstract

Increasing impacts of natural hazards caused by water scarcity make better risk assessments even more valuable. The risk of water scarcity is based on three pillars: hazard, exposure and vulnerability. Research in regards to water scarcity events has made good progress in recent years. The global hazard and exposure assessments are capable of delivering local detail together with accuracy. Vulnerability assessments have proven to be a bottleneck: they are dependent on local data and cannot capture the complexity. Better global vulnerability assessments are needed to change to a proactive attitude to identify adequate mitigation measures, develop an early warning system and support the decision-making process.

This thesis explores the potential of global indicators to assess the social aspect of vulnerability focused on two relations: Human development and government capacity, agricultural activity/ productivity and technological development.

New methods based on the Average Light Index and Rural Population Density show promising results. Combined with more time and money consuming research by WorldPop and Croplands it has the potential to assess the social vulnerability on a local scale, thereby improving risk assessments.

Table of contents

List of definitions and abbreviations

ALI	-	Average Light Index
CCS	-	Climate Change School
IPCC	-	Intergovernmental Panel on Climate Change
MPI	-	Multivariable Poverty Index
RRS	-	Risk Reduction School
UNCCD	-	United Nations Convention to Combat Desertification
UNISDR	-	United Nations International Strategy for Disaster Reduction
WGI	-	Worldwide Government Indicators

Risk	-	Hazard x Exposure x Vulnerability
Water Scarcity	-	Water demand exceeds water availability (can be human induced)
Drought	-	Meteorological, agricultural, and/or hydrological water deficiency in comparison to what expected or “normal”

Introduction

In the first months of 2018, Cape Town was a frequent headline in the news; their water reservoir was shrinking, therefore dealing with water scarcity throughout the region. Cape Town is one of the many areas that are experiencing the effects of climate change through drought (Iceland et al., 2018). Drought is one of the least understood natural hazards and has shown a growing impact during events in the last century (Wang et al., 2014). Furthermore, the complexity of events intensifies since more sectors are affected (Wilhite et al., 2007) and droughts are predicted to be less equally distributed, thereby increasing the regional impacts (Spinoni et al., 2017).

The complexity of drought is caused by its diverse impact on the economy, environment and society. Drought puts pressure on the water and food security of animals and humans, covers large geographic areas and affects multiple sectors like agriculture and industry (Mishra & Sing, 2010). The risk of water scarcity is based on three pillars: hazard, exposure and vulnerability (Cardona et al., 2012). Past research has shown that hazard and exposure could be estimated in detail with global data and that the difficulties in predicting water scarcity are mostly related to the assessment of vulnerability (Gonzalez Tanago et al., 2016). These factors make it difficult to construct a universal definition of drought and its impacts (Wilhite et al., 2007; Lloyd-Hughes, 2014).

Assessing the vulnerability to water scarcity with global data is difficult due to the local variance of variables (Wilhite et al., 2007). Detailed maps concerning vulnerability are mostly based on local data. Maps based on global data often lack the scope, the detail or the number of variables needed to capture the complexity of vulnerability to water scarcity. Therefore most contemporary maps are not capable of an accurate assessment of vulnerable groups (Gonzalez Tanago et al., 2016; Carrao et al., 2016). This results in a reactive approach to counteract water scarcity. A change to a proactive attitude is needed to identify adequate mitigation measures, develop an early warning system and support the decision-making process (UNCCD, 2016; Gonzalez Tanago et al., 2016). By the use of remote sensing and the growing availability of census data, datasets are being created with high resolutions. These spatial datasets show a high potential in regards to vulnerability research.

Deltares has started to construct WaterLoupe: a dashboard for water scarcity risk assessments at a local scale. The aim of this research is to assist the construction of WaterLoupe by showing the possible uses of global datasets to identify the social vulnerability to water scarcity on a local scale. First, it is important to define what social vulnerability to water scarcity is. This definition will lead the way to promising indicators and datasets. Can they deliver a local scope?

At first, the definitions used and previous research are described to construct the framework upon the research is based. In the following section, the methods used to scope for detail are explained for each social vulnerability indicator. The results show the capability of contributing to a local assessment of social vulnerability to water scarcity of selected indicators. Furthermore, the next steps within social vulnerability research will be discussed based on the finding of this paper.

Background: Social vulnerability to water scarcity

As the UNCCD summarizes in their report ‘The ripple effect’ published in 2016, water scarcity or drought causes losses of agricultural production and livestock. Furthermore, the secondary impacts affect multiple sectors like energy, transportation, health and industry. The costs and uncertainties accompanied by the impacts of water scarcity have a negative effect on human security and conflicts (UNCCD, 2016). Rural livelihood systems are pressured by the destructive capacity of water scarcity events and their collapse has become a new driver of conflicts and migration patterns. The UNCCD seems to use a high estimation of the impacts of water scarcity and drought events for their statements in comparison to research conducted by Wilhite et al. (2007), Gleick (2014) and Burrows and Kinney (2016). They all state that the relationship between climate change and migration and conflict is apparent but too complex to show a direct correlation. However, they all support the need for a new approach in order to enhance water scarcity resilience and mitigate water scarcity risks.

The UNCCD established three main pillars to guide the way for a proactive approach: Improved monitoring and early warning systems, detailed vulnerability and risk assessment and corresponding mitigation measures. This approach will not only help to reduce the impacts of water scarcity but also aims to better understand the underlying processes. This research focusses on showing possible improvements to the detail of social vulnerability indicators and thereby assist the process of enhancing monitoring, improving assessments and eventually choosing the right local mitigation measures.

First, the significance of local assessment is underlined. Furthermore, it is important to clearly define vulnerability and the factors that influence the social aspect of vulnerability. Followed by the state of art and evaluation of research in regards to these factors, this will provide a solid foundation to review the application of higher detailed data sources.

Action vs. Reaction

Present day, most national policies in regards to water scarcity or drought events are reaction based (UNCCD, 2016). This is mostly due to two factors: the awareness of the impacts and dangers of these natural hazards are low and within the areas most affected the institutional capacities are not strong enough to foresee and plan for future stresses.

A recent study by Shackleton et al. in 2015 explains the barriers that cause these factors, stated by the UNCCD, in Sub Saharan Africa. Cognitive and psychological barriers are constructed by a disbelieve in future predictions of climate change or the role of religion (God’s will). Institutional and cultural barriers are caused by the power of the elite, corruption, new policies that are not conform the present norms “doing things different” and insufficient knowledge of the institutional requirements of new interventions or policies. Furthermore, informational and knowledge barriers are formed when the feeling arises that local knowledge no longer is sufficient and people cannot predict what to expect. Most of these barriers, as will be underlined in the next paragraph, can be traced back to factors of vulnerability like poverty, inequality, inequity, weak institutional capacity and low levels of development. The research of Shackleton et al. (2015) concludes that future research should focus on overcoming these barriers on a community level and that closer attention to the vulnerable is needed for successful adaptation.

A case study in Ontario, Canada showed similar outcomes: To further strengthen or optimize local institutional capacity it is important to personalise interventions (Ivey et al., 2004). Local assessments have the ability to capture local stakeholders knowledge and help to identify policy specific factors for each region. Thereby the problem of universal, but ineffective coping mechanism can be overcome. Furthermore, local research helps to understand local water systems and the dispersion of vulnerability, which enhances awareness and assists in creating local partnerships.

Local specialised assessments seem the way to go in order to better understand and identify vulnerable groups to water scarcity and make the change to a proactive view. What is the drawback? Local research is time-consuming and costs money. Two factors that are not readily available, especially in the most vulnerable areas. The use of detailed global datasets has the potential to ensure a universal method, but with local and region-specific results.

Vulnerability: Which school?

Research in regards to the vulnerability to water scarcity is guided by the definition of vulnerability used. Within vulnerability research, there are two main schools that have constructed clear definitions: the Risk Reduction School (RRS) and the Climate Change School (CCS) (Gonzalez Tanago et al., 2016). The RRS and CCS are closely related but differ on the reach of vulnerability. The definition used is dependent on the aim of the research (see table 1 for the differences in definition).

The CCS uses the following definition of vulnerability stated by the IPCC (2014): “The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts including sensitivity or susceptibility to harm and lack of capacity to cope and adapt.” This definition sees vulnerability as the projected outcome of an assessment. The aim is to mitigate for long-term stress since vulnerability is composed of sensitivity, exposure and adaptive capacity.

The RRS definition for vulnerability is clearly defined by the UNISDR (2016): “The conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards.” Vulnerability is seen as one step of the process, since risk is composed of hazard, exposure and vulnerability. This definition is aimed to reduce the risk of a natural hazard event (shocks). If there is water scarcity, who is vulnerable?

Table 1 - Differences in definitions between the RRS and CCS in regards to vulnerability

Differences	Risk Reduction School	Climate Change School
Objective	Identify risk reduction measures	How to face a progressive climate
Process/ Timescale	Shocks	Stresses
Spatial scale	Local to global consideration	Global awareness to local need
Functional scale	Ministry of the Interior/ Defence/ Development	Environment ministries and meteorologial services
Formula	Risk = Hazard x Exposure x Vulnerability	Vulnerability = Impacts - Adaptation
Uncertainty	Low to medium	Medium to very high

This research uses the definition proposed by the UNISDR since it gives the opportunity to isolate the social aspects of vulnerability as shown by the research of Carrao et al. (2016) and Faneca Sanchez et al. (2017). The definition of the IPCC mostly uses the variable of exposure to provide higher resolution assessments and thereby surpasses gaps that exist within the assessment of the socio-economic aspects of vulnerability. By using exposure as an individual variable as stated by the UNISDR, vulnerability is focused on the socio-economic features of sensitivity and adaptive capacity.

However, this choice of definition does not mean that the research is solely usable for the risk reduction of shocks. Due to its narrower definition, it unwinds the difficulties in the assessment of vulnerability, but in the end will be capable of giving more detailed and accurate predictions for the future (Romieu et al., 2010). Furthermore, it ensures the process to go from a local to a global consideration and is usually overseen by ministries that have more power (Interior, Defence or Development instead of Environment or Meteorology).

Social aspect of Vulnerability

In line with the framework of the UNISDR definition and the research of Carrao et al. there are three main categories of factors to consider that contribute to vulnerability: social, economic and infrastructural. Previous research shows that a differentiation of indicators between these factors can be difficult since they all influence each other and therefore the origin is not always clear. In order to define indicators for the social aspect of vulnerability the work of Carrao et al. (2016), Gonzalez Tanago et al. (2015, Naumann et al. (2014) and Brooks et al. (2005) are examined. Table 2 shows the different indicators mentioned in each paper to account for the social factor of vulnerability.

Table 2- Common Indicators used for social vulnerability categorised by assessment paper

Indicators social vulnerability			
Carrao et al.	Rural population Literacy rate Access to improved water sources Life expectancy Age structure Refugee population Government effectiveness Disaster prevention and preparedness	Gonzalez Tanago et al.	Agricultural land and water usage Population Education Economic rescources Employment Agricultural income Government presence/ programs Irrigation
Naumann et al.	Population below poverty level Literacy rate Life expectancy Government effectiveness Institutional capacity Access to improved water sources Refugees	Brooks et al.	Access to sanitation Literacy rate Maternal mortality Calorific intake Civil liberties and political rights Government effectiveness Life expectancy

The indicators show a lot of similarities with indicators used to assess human development like poverty, literacy rate, age structures, migration and life expectancy. Furthermore, the effectiveness of the government and its institutional capacity are mentioned in all papers. Also, indicators like rural population percentage, agricultural water usage and irrigation are used, to account for the impacts of water scarcity on the agricultural sector and therefore food security. The mentioned indicators accentuate two major relationships in accordance with the work of Smit & Wandel(2006) and Otto et al. (2017) on the social vulnerability of natural hazards:

- The interaction between human development and the capacity of the government.
- The influence of (technological) development in the agricultural sector.

Further investigations in this paper on the possibilities of using global datasets to indicate social vulnerability to water scarcity of socio-economic groups will focus on the above relationships. How can a detailed assessment be made with global data to assess Human Development, Government Capacity, Agricultural activity and Development?

State of Art

The following section will give an overview of previous research conducted within the field of the human development indicators poverty, age structure and migration. Followed by tested methods to assess a governments effectiveness and capability to adapt. To indicate the agricultural activity this paper will focus on previous research in regards to urban population density. Finally, methods to assess development in regards to the agricultural sector will be summarized.

Human Development

The research focused on human development has been dependent on census data. The gathering of census data has proven to be time and money consuming. Therefore it has not been readily available on a global scale. Furthermore, research using census data is dependent on the number of respondents in order to produce an accurate measure, which leads to a bottleneck for mapping beyond the administrative 1 level (county level). However recent advancements have been made by the rise of remote sensing. Combined with growing databases stocked with census data it unravels a promising picture.

Poverty

Still, the most common approach to measure poverty is to use income and consumption as indicators, but since this approach is based on census data it also resembles the weaknesses being not readily available and unreliable. A revise of the indicators of poverty can also help overcome these challenges as Pezzulo et al. outline in their 2014 final report of the Bill and Melinda Gates Foundation. Their use of the Multidimensional Poverty Index (MPI), based on deprivations and constructed by Alkire and Foster in 2011, gives them the detailed and accurate data needed. In combination with mobile phone data, national censuses and satellite images they are able to map poverty with a 90 to 97% certainty. Unfortunately, this approach still requires time and money and therefore data is only available for eight countries worldwide at worldpop.org.uk. Promising for the long run, but not feasible for now.

In order to fill the gap between long and costly detailed research and rough country wide predictions, concessions have to be made. However, research by Yu et al. in 2015 has shown that by only using Night Time Light data it is possible to map poverty with an 85% certainty on the county level in China. Data for other countries are not available till now, but this approach shows to have the ability to make a quick and reliable assessment of poverty.

Age Structures and Migration

In contrary to worldpop.org.uk's work on poverty mapping, their work in regards to age structures and migration is completed in the sense that they have readily available global maps. By combining the detailed population maps constructed by Stevens et al. (2015) and age/ sex structure data by Tatem et al. (2013) a detailed spatial dataset on age structures was constructed with a one by one kilometre grid. Sorichetta et al. (2016) provide migration maps based on observations. The migration maps only cover national migration, but international migrations maps are expected in the coming year.

Agriculture

Smallholder farming is the most apparent form of agriculture in the world and is the backbone for many vulnerable populations (Samberg et al., 2016). The so-called “green revolution” observed in Asia is also apparent in Africa: farms with 0.75 hectares up to a few tens of hectares producing up to 80% of the agricultural output and comprised of half the rural population (Mellor, 2014). These farms are generally not poor and are important in reducing local poverty by providing opportunities for the rural non-farm sectors. But what happens when rural farms don’t have the required space? Muyanga & Jayne discovered that the benefits of smallholder farming diminish when the rural population exceeds 500 people/km2 in Kenya: household income per adult and land intensification decline (2014). When the problem of defining rural and urban can be overcome, using these thresholds in combination with available detailed populations maps have the potential to highlight the vulnerability of farms.

Agricultural Development

The state of agricultural development is commonly related to the use of fertilisers and the measure of irrigation. Global data on Fertiliser consumption is even on a country level not complete (World Bank, 2015). In contrary to fertiliser usage, the research in regards to irrigation has made significant advancements. Thenkabail et al. were able to visualize irrigation and crop type use on a one by one kilometre grid (2012). By the use of remote sensing, they combined global spatial data from Landsat, MODIS, NPP-VIIRS, GDEM and LULC with national and sub-national statistics and in-situ observations. The map available at croplands.org has proved to be 90% accurate.

Government

Although there is a need for government capacity and efficiency indicators beyond the country level, they are not available as global datasets (Preston & Stafford Smith, 2009). Local stakeholders engagement and knowledge are still key to gather specific data. However, the variance in capacity between countries can be useful when conducting border crossing assessments (for instance at catchment level).

Methods: Scoping for detail

Remote sensing has proven to be of significant value to vulnerability research, but how does this unfold in practice? To further investigate the use of global datasets within local social vulnerability assessments this research will focus on the datasets shown in table 3.

Table 3 - Social vulnerability to water scarcity datasets

Map	Year	Reliability	Scope	Data Source/ Method
ALI	2013	85%	2nd Administrative Level	Yu et al.
Rural Population Density	2015	-	100m	Van Egmond
Age Structures	2015	80-88%	1km	Worldpop.org.uk
Irrigation + Crop Type	2013	90%	1km	Croplands.org
Worldwide Government Index	2014	-	Country	World Bank
Internal Migration	2005-2010	-	1st Aministrative Level	Worldpop.org.uk

These six datasets show the potential to give a detailed view beyond the administrative one level and will, therefore, be tested on two cases in Latin America: The Aburrá Valley near Medellin in Colombia and Bacia do Alto Tiete surrounding Sao Paulo in Brazil.

Average Light Index

Poverty will be mapped by the use of the Average Light Index (ALI) method explained by Yu et al. (2015). The ALI will be calculated with the following formula:

$$A = \frac{T}{N}$$

A = ALI

T = Total Night-time Light (TNL)

N = # pixels with radiance > 0

For the administrative 2 level, or county level, the sum of all night time light scores of the corrected version of NPP-VIIRS data (no fires and clouds) will be taken and divided by the number of pixels with a positive radiance. This produces the ALI that has proven to be 85% accurate when compared to a multidimensional poverty index. The Ali will be divided into five categories in accordance with Yu et al. (2015, table 4).

Table 4 - Poverty categories based on ALI values

ALI level	Range
very low	0 - 3
low	3 - 4
medium	4 - 6
high	6 - 15
very high	> 15

Rural Population Density

The rural population density will be based on the research of Stevens et al. (2015) and Muyanga & Jayne (2014). The global population dataset by Stevens et al. uses a random forest regression tree-based mapping approach. This enables them to incorporate census data and ancillary datasets within the available geospatial datasets on a 100m by 100m grid. The predictions of this model are then used as a weight for the redistribution of census counts at the country level.

To make the divide between urban and rural, the population map is calibrated with a map of the active urban areas in Latin America. This resulted in a threshold value of 1500 people per square kilometre. Furthermore, the rural population is categorized according to the numbers of Muyanga and Jayne (2014). Rural area with a population between 0 and 550 people/km2 shows a decrease in vulnerability due to higher productivity and income. Areas with a rural population above 550 people/km2 show an increased vulnerability.

Age Structures

To assess the age structures the global data of worldpop.org is used. Their dataset is constructed by Pezzulo et al. in 2015. Their research resulted in a detailed and contemporary age structure dataset by combining detailed population maps with national and subnational estimates of age and sex structures. For a count of the vulnerable population, ages between 0-15 and above 65 are accounted for according to Cutter et al. (2003).

Irrigation and Crop Type

Thenkabail et al. composed a dataset that included the spatial distribution of the five major global cropland types wheat, rice, barley, corn and soybeans (2012). Finally, they constructed an irrigation map by overlying the cropland type data over the irrigated and rainfed cropland map.

To assess the vulnerability of the croplands, the crop types are ranked based on water needs and type of irrigation. This results in seven categories with varying vulnerability as seen in table 5.

Table 5 - Vulnerability level in accordance to irrigation and crop type

Irrigation + Crop Type	Vulnerability
Ocean	
Irrigated - Wheat and Rice	
Irrigated - Mixed Crops 1	
Irrigated - Mixed Crops 2	
Rainfed - Wheat, Rice, Soybeans, Sugarcane	
Rainfed - Barley, Wheat	
Rainfed - Corn, Soybeans	
Rainfed - Mixed Crops	
Fractions of Mixed Crops	
Non Cropland	

Worldwide Government Indicators

Worldwide Government Indicators were derived from the WorldBank for each country within South America and correlated with their country shapefile to give an overview of national differences.

Internal Migration

Sorichetta et al. combined microdata based on census with corresponding administrative units to construct national migration patterns. By the use of migration push and pull factors for each administrative level, a predictive model for migration flows was established.

A netto migration count is calculated for each administrative unit by adding up the in- and outflow of each administrative unit, divided by their total population. The netto migration is divided into five categories based on standard deviation.

Results

The results for each indicator that can contribute to the assessment of social vulnerability will be described in the same order as the previous section. Every dataset is visualised by the use of maps to show the level of detail.

Average Light Index

The composition of the average light index for the countries Colombia and Brazil resulted in the maps shown in figure 1 and 2. The ALI has proven to correlate with a multivariable poverty index and is therefore used as a proxy for poverty. The maps show that is possible to use the night time light intensity maps and shapefiles of the administrative 2 level of each country to create the ALI. The maps show a unique value for each county.

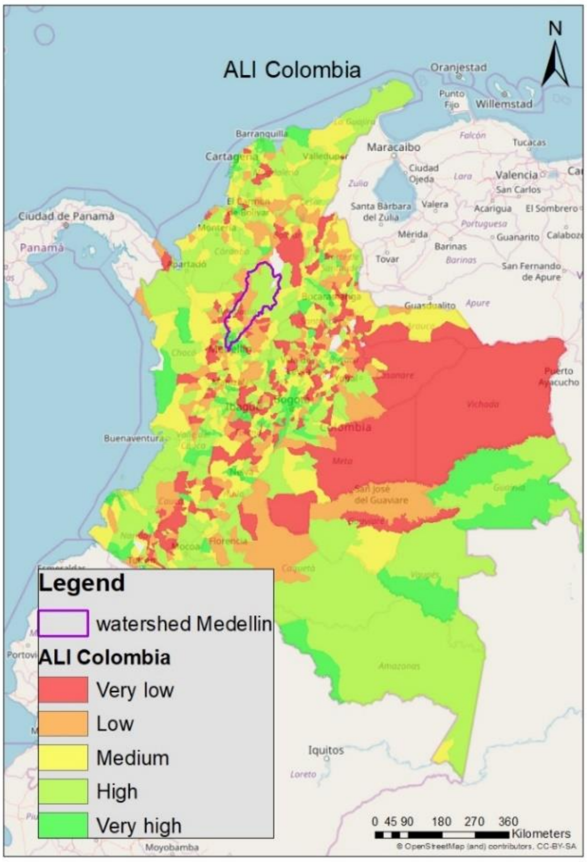

Figure 1 - Average Light Index at county level (Colombia)

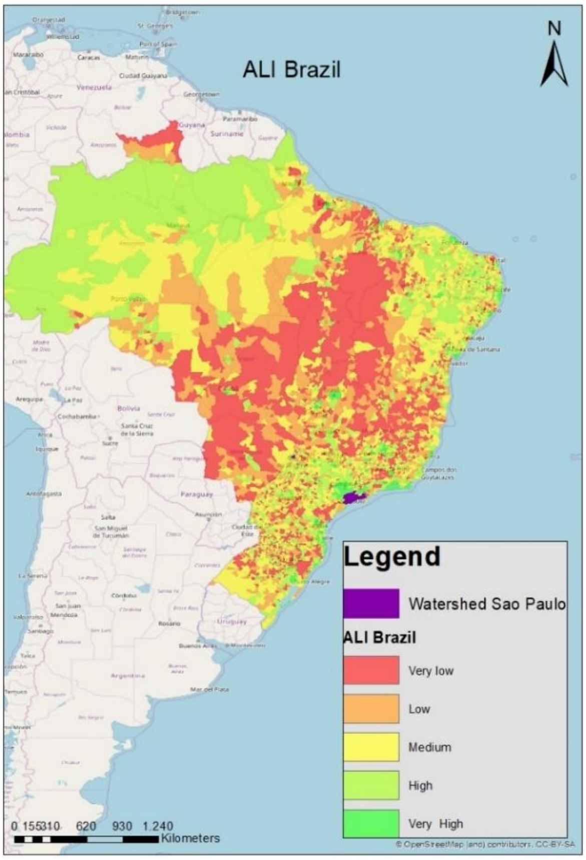

Figure 2 - Average Light Index at county level (Brazil)

The maps in figure 3 and 4 show the watersheds surrounding respectively Medellin and Sao Paulo. The map of Medellin shows a variation of average light index intensity. The county representing a very high ALI is the only dense urban area in this watershed. The watershed of Sao Paulo, on the other hand, shows a less diverse picture. The entire Metropolitan area surrounding Sao Paulo shows a high ALI value and only the outskirts represent different ALI classes.

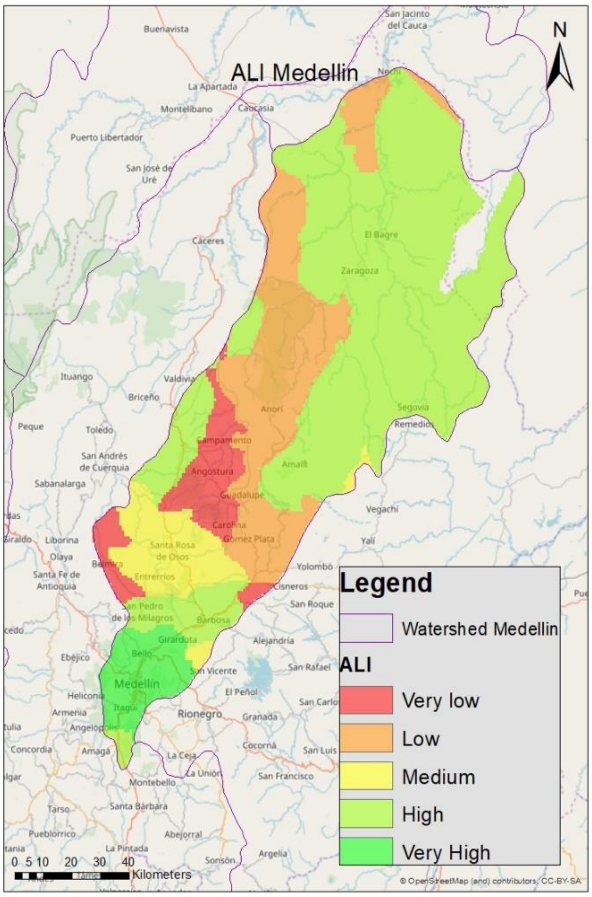

Figure 3 - Average Light Index at county level

(Medellin, Colombia)

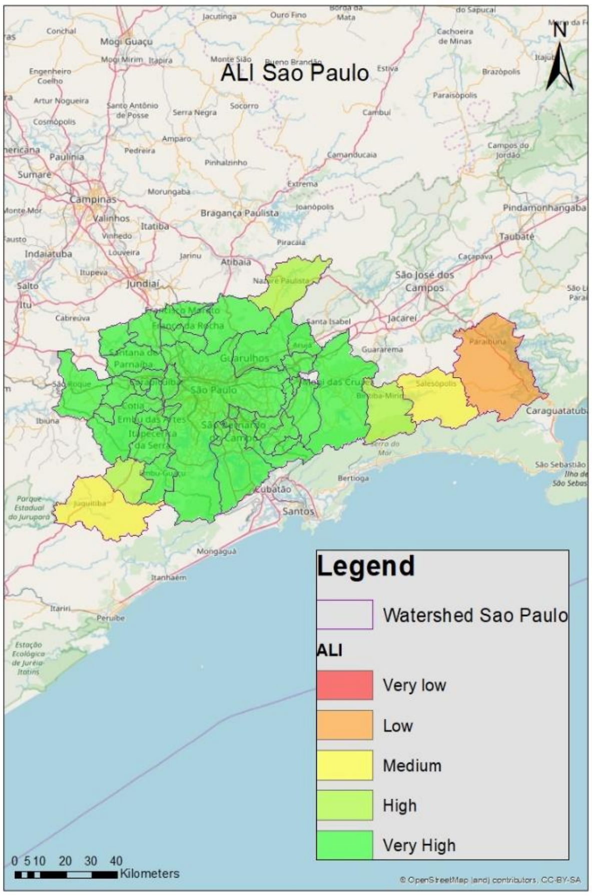

Figure 4 - Average Light Index at county level

(Sao Paulo, Brazil)

Rural Population Density

By using the population density map of Stevens et al. (2015) and the rural population threshold in regards to agricultural activity and productivity by Muyanga & Jayne (2014) rural population maps of the watersheds surrounding Medellin and Sao Paulo are constructed (figure 5 and 6). The map of Medellin shows large clusters of possibly vulnerable areas in comparison to Sao Paulo. Sao Paulo shows small clusters of a couple square kilometres each surrounding the outline of the city, were Medellin has clusters of up to 160 square kilometres. Furthermore, the watershed of Medellin shows no large variation in population density further away from the urban area . The watershed of Sao Paulo has a lot of small densely populated areas scattered around the map with more local variance in comparison with Medellin.

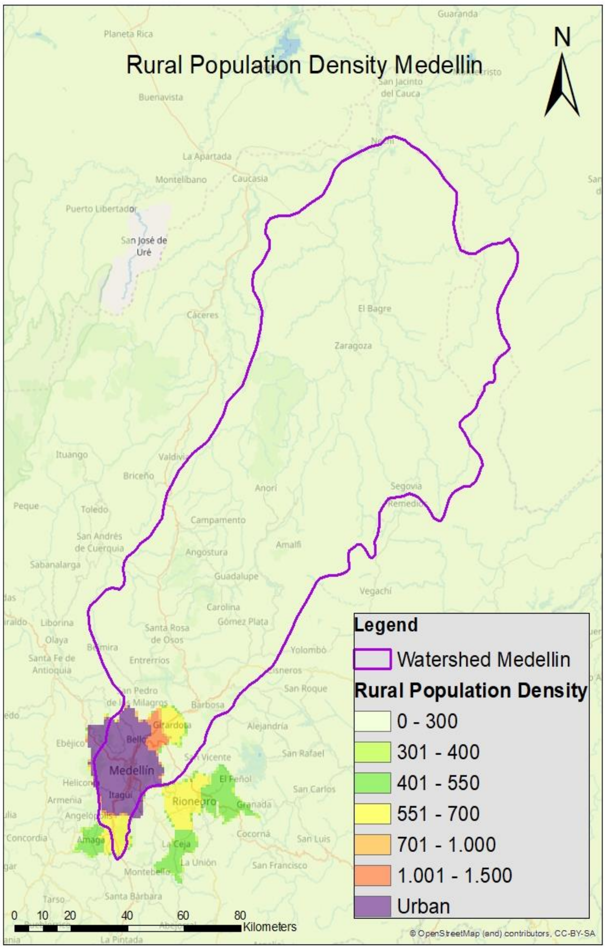

Figure 5 - Rural population density at 1km grid

(Medellin, Colombia)

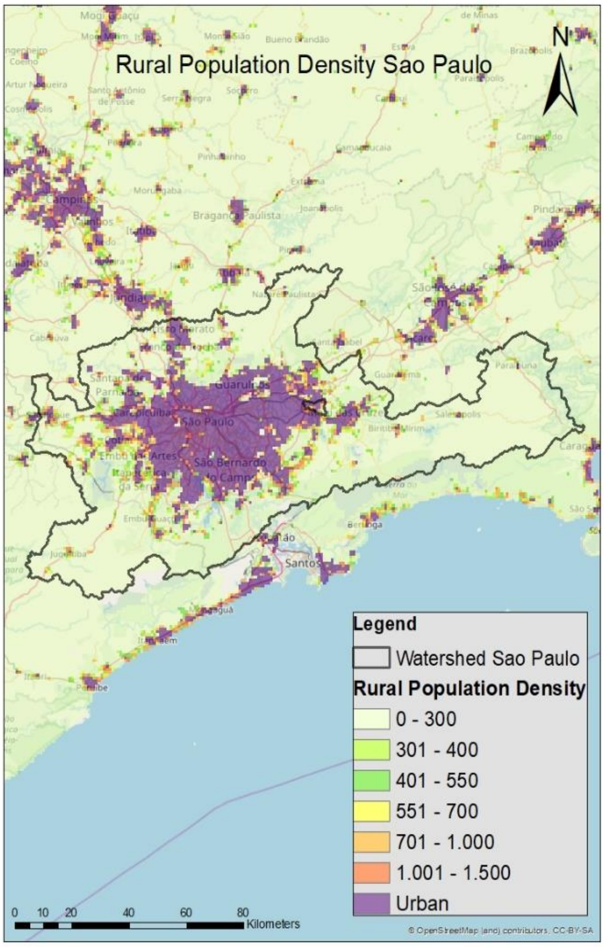

Figure 6 - Rural population density at 1km grid

(Sao Paulo, Brazil)

Age Structures

As can be seen in figure 7, the map shows the count of the vulnerable population of South America with a very high degree of detail (100m grid size). But when the counts are transcribed to the percentage of the total population, the map shows a different and varying level of detail as can be seen in figure 8. The actual age structures show a differentiation in detail that varies between the administrative 1 and 2 level.

Figure 7 - Vulnerable population count at 100m grid (South America)

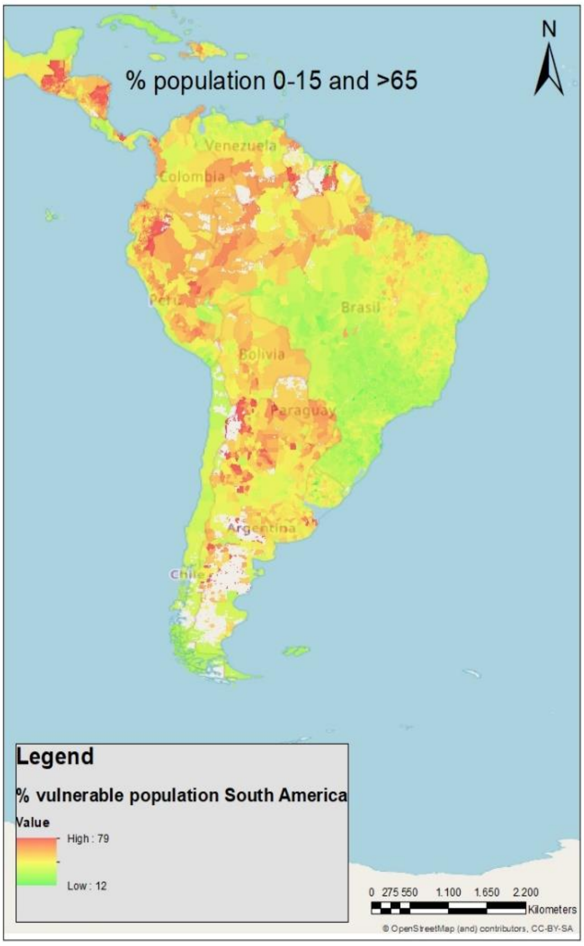

Figure 8 - Vulnerable population percentage (South America)

Figure 10 shows the percentage of vulnerable population in the watershed of Sao Paulo. The level of detail of Sao Paulo is bound to the administrative 2 level and is therefore capable of showing differences within the watershed. The map of Colombia shows detail up to the administrative 1 level (figure 9). Therefore it is not capable of showing noticeable differentiation within the watershed of Medellin.

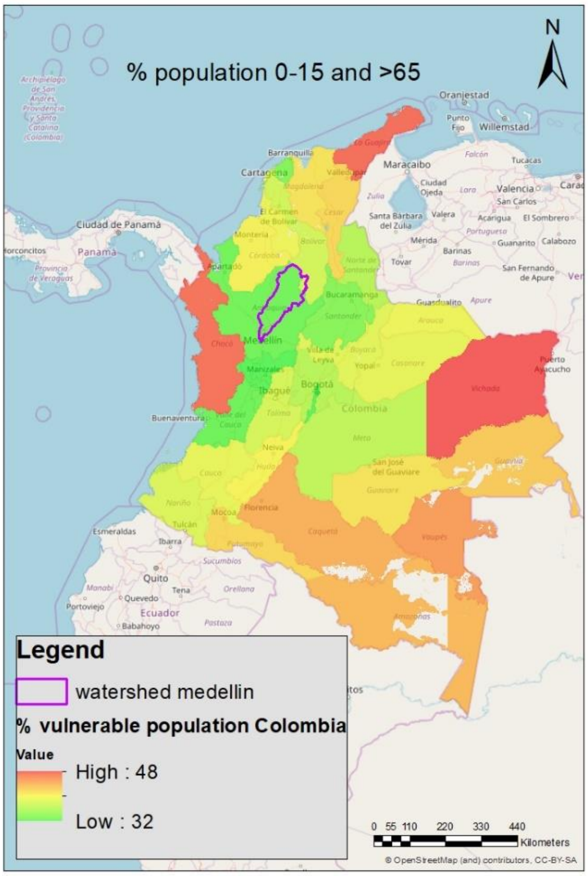

Figure 9 - Vulnerable population percentage at state level (Colombia)

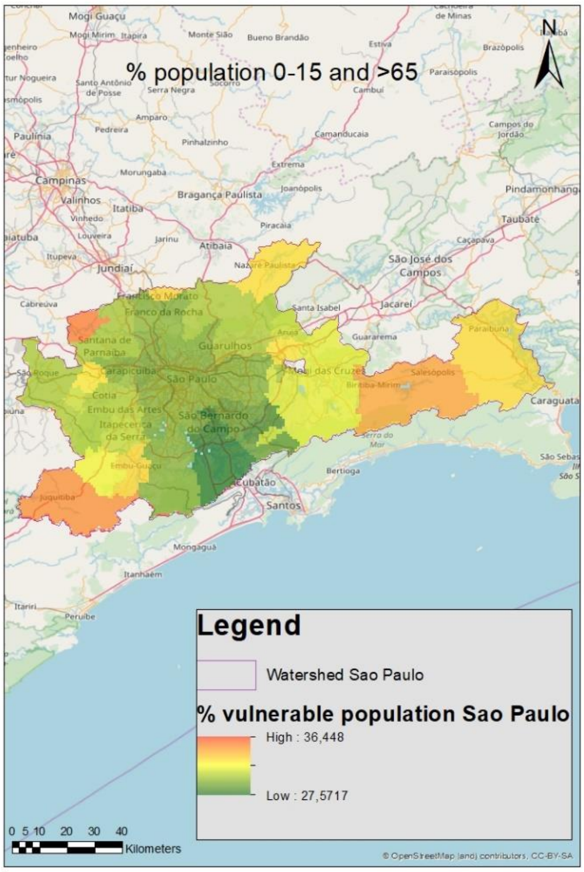

Figure 10 - Vulnerable population percentage at county level (Sao Paulo, Brazil)

Irrigation and Crop Type

Figure 11 and 12 show the maps that were created by using the irrigation and crop type data constructed and collected by Thenkabail et al. (2012). The maps for respectively Brazil and Colombia show a good level of detail throughout the countries with a large amount of rainfed (and therefore vulnerable) croplands.

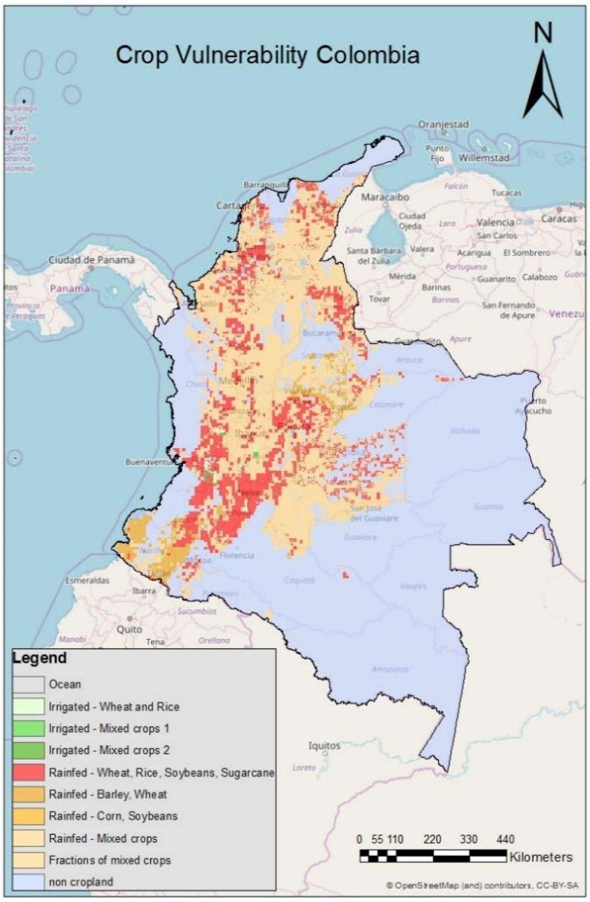

Figure 11 - Crop vulnerability at 1km grid (Colombia)

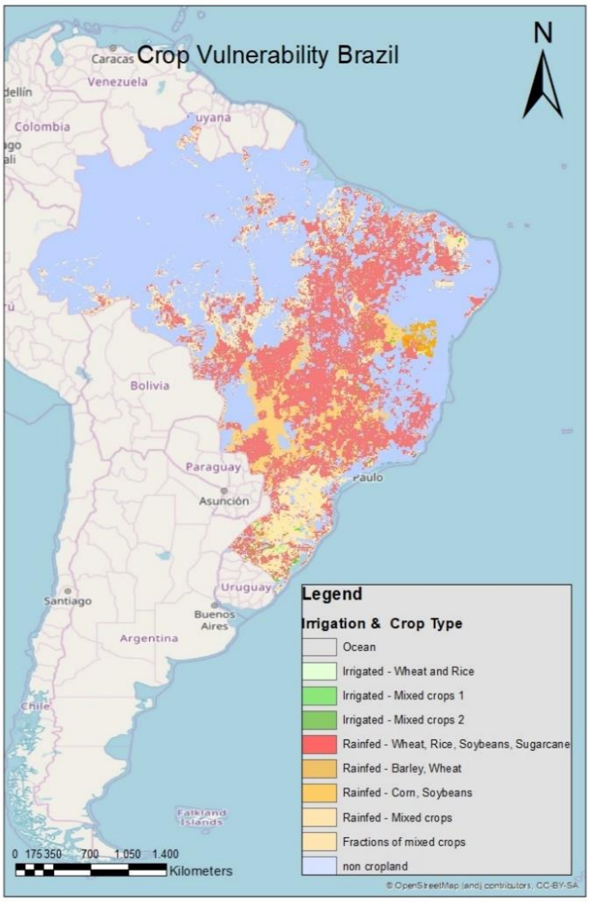

Figure 12 - Crop vulnerability at 1km grid (Brazil)

A closer look to the watersheds surrounding Medellin and Sao Paulo shows that the detail of these maps is possibly not equally distributed and not completely accurate (figure 13 and 14). The maps show a differentiation in detail between 1km and 10km size grids. Furthermore, the urban area of Medellin is seen as cropland and the whole metropolis of Sao Paulo is non-cropland. These observations bring doubt to the accuracy of these maps.

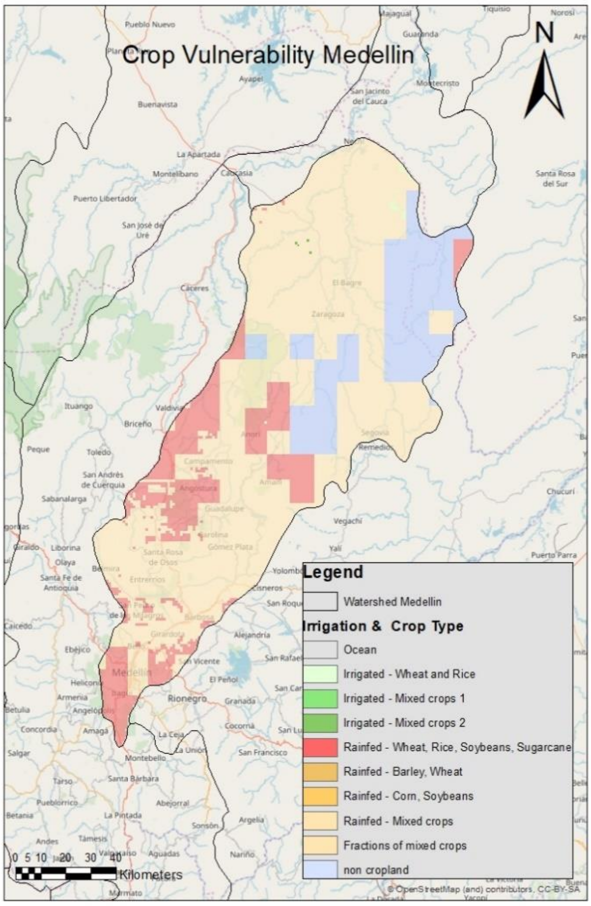

Figure 13 - Crop vulnerability at 1km grid (Medellin, Colombia)

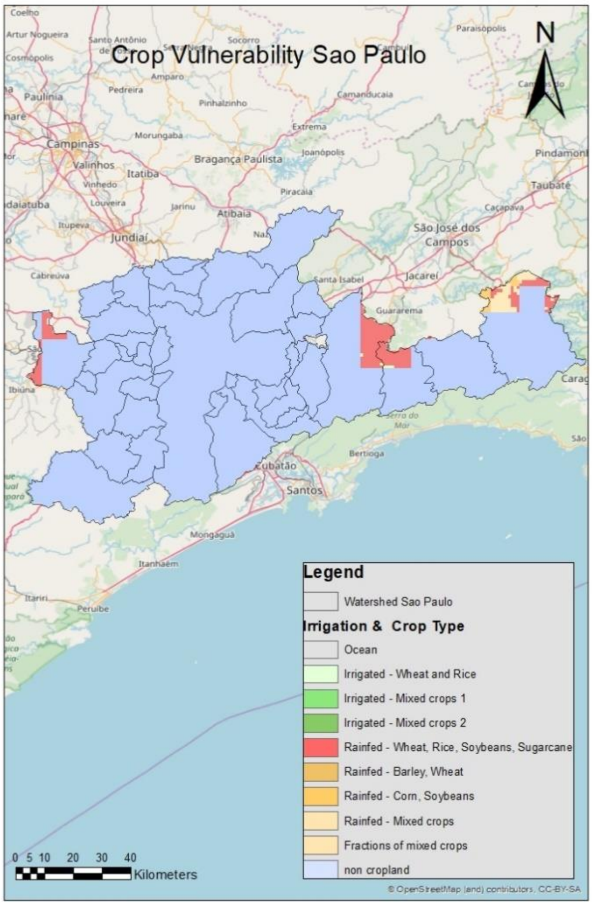

Figure 14 - Crop vulnerability at 1km grid (Sao Paulo, Brazil)

Worldwide Government Indicators

The Worldwide Government Indicators are used to measure the efficiency and capacity of governments. The WGI data is only available on the country level. As can be seen in figure 15, South America scores are low. Chili is the only country with a slightly positive score. The level of detail is limited for WGI, but it is capable of assessing differences in the government effectiveness and capacity between countries.

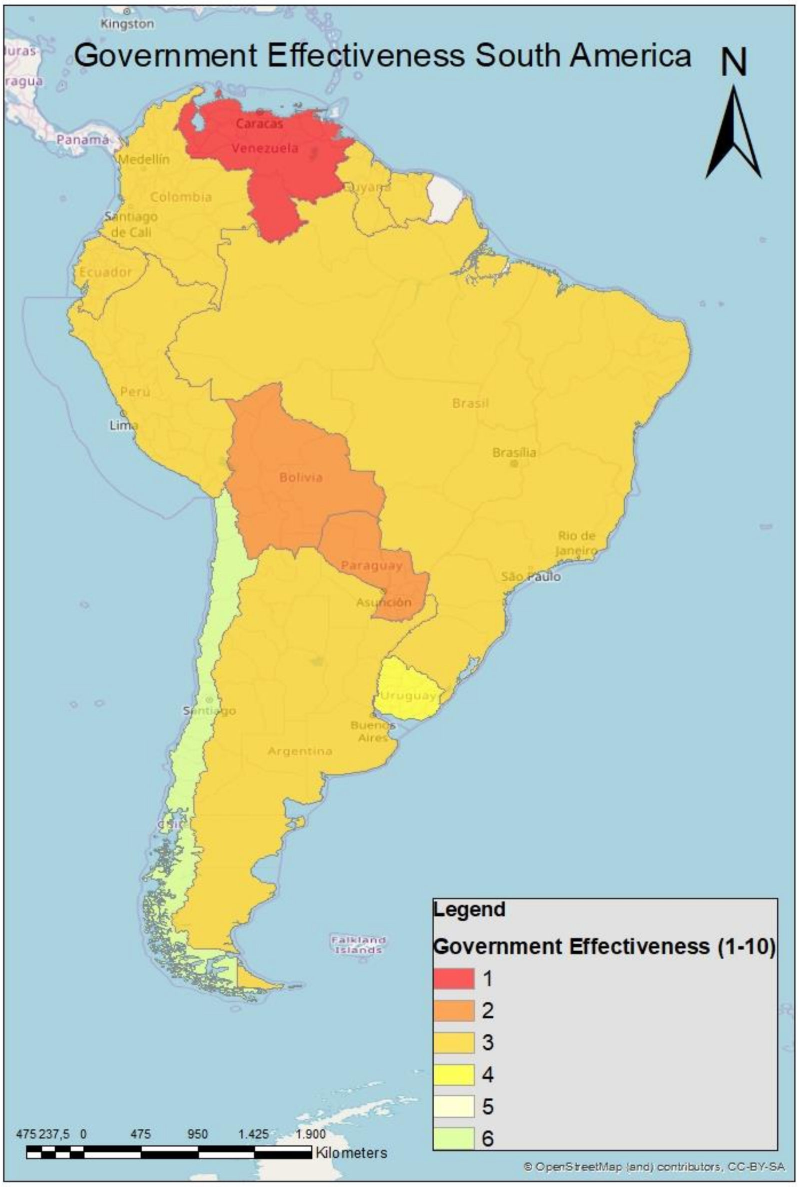

Figure 15 - Government effectiveness at country level

(South America)

Internal Migration

Figure 16 shows the internal netto migration of each administrative 1 unit in Colombia. These numbers don't take international migration into account and also don't have the detail to assess differences in vulnerability of the watershed surrounding Medellin.

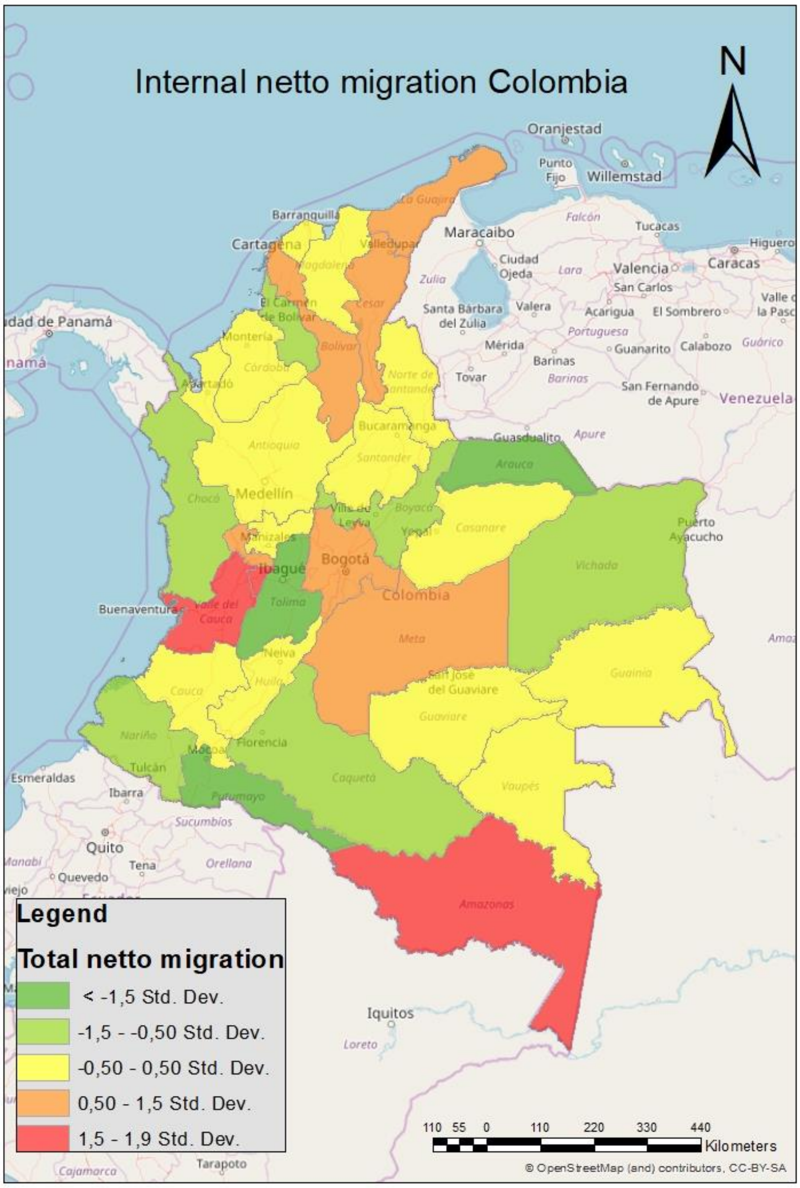

Figure 16 - Internal netto migration at state level (Colombia)

Discussion

The realisation and implementation of new methods made possible by techniques like remote sensing are showing great promise, but there is still a long way to go. This research shows progress has been made and sometimes very simple assumptions turn out to be a great indicator to help with the assessment of social vulnerability to water scarcity.

The Average Light Index is a great example of using a one-dimensional indicator for a complex factor of social vulnerability to water scarcity. With just the assumption that no light equals poverty, it has shown a high accuracy in regards to a Multivariable Poverty Index. Based on the map of the Sao Paulo district it seems that the ALI is affected by large urban areas with a very high Night Time Light intensity and the corresponding glow. This assumption can be tested in further research by comparing the scores to a Multivariable Poverty Index. The fact that the method only has been tested in China does not have to be a downfall since the research in China covers a large area with variation in county size, economic activity, population density, poverty and development. In other words, the method was 85% accurate in a country that shows aspects of both the Western - and the developing world. More verifications of this method will lead to a better understanding of the ALI. Furthermore, it could be made more accurate by the use of population density maps as Weidmann & Schutte have shown (2017).

Another simplified method is the use of the rural population density to assess the vulnerability of farmers. In order to improve this method, it is critical to better understand the dynamics of farming in relation to the population density. However, this does not mean that extensive research is needed. It is easy to get lost in data and research, but stakeholders engagement can provide helpful shortcuts. Local stakeholders knowledge should be capable of helping establishing thresholds for agricultural productivity. Adekunle & Fatunbi research from 2012 shows the potential of establishing agricultural research with a combination of 'hard' and 'soft' sciences.

To improve the knowledge about the measure of irrigation and the crop type used it seems important to develop global high-resolution land use maps like the CORINE dataset constructed for Europe. This can be used to make a better division between croplands and non-croplands and help the model to make better predictions.

Assessing the capacity of local governance seems a bridge too far. At this moment it still requires time-consuming and costly local research and promising new studies are lacking. In contrary, new upgraded migration maps are expected to come out at the end of the year with international migration at the administrative 1 level at worldpop.org.uk. This can really help to understand the migration flow dynamics and help in the assessment of vulnerable areas.

The composed detailed datasets already have proven to be useful. For example, the age structure map is being used in vulnerability research of Deltares in the Sao Paulo area.

The main question for further research should not be based on how much detail we can get and how high the accuracy can be. It is more important to focus on a good balance in regards to the final goal. Global vulnerability assessment is often used to give an indication of possible weak spots and are used as a guideline for further research. Therefore, a rapid assessment with a slight degree of accuracy lost should not be an issue, but instead, be greeted with open arms.

Conclusion

This research aimed to give an insight into the possibilities of assessing social vulnerability to water scarcity on a local scale. By analysing previous social vulnerability research and using the definition of the UNISDR that sees vulnerability as a step within a risk assessment this paper focusses on two major relationships in regards to social vulnerability: The interaction between human development and the capacity of the government and the influence of (technological) development on the agricultural sector.

The results show that it is possible to calculate ALI values for each individual county by using night time light intensity maps. ALI values have proven to be accurate as an indicator of poverty when compared to multivariable poverty indicators. Therefor ALI can be used to assess the social vulnerability of the poor.

Furthermore, the option of using rural population density maps is explored and this resulted in density maps with a grid size of 1km. With accurately calculated threshold values, these maps show the potential to assess the social vulnerability of farmers.

The age structures maps gathered from worldpop.org show varying detail. When the count of the vulnerable population is transcribed into a percentage of the total population it is clear that the datasets are still heavily reliant on the availability of census data. The scope of this social vulnerability indicator is therefore dependent on the location of the assessment.

The social vulnerability of farmers can also be indicated by their crop use and irrigation method. The combined irrigation and cropland maps show a great level of detail with a 1km grid size. There are a couple of discrepancies within the datasets since the city of Medellin is shown as cropland. This can be explained by the land use and land cover maps used that do not have a 1km level of detail.

In addition, worldwide government indicators can be used to assess the government effectiveness, but will only be of use when assessing the vulnerability of a watershed covering multiple countries. Furthermore, the datasets that cover migration do not have the ability yet to help assessing social vulnerability to water scarcity.

This thesis shows that new methods are capable of constructing or improving datasets for indicators that can determine the social vulnerability to water scarcity. These indicators address the social factors of the vulnerability of citizens which accentuate the poor and farmers.

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