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Cash in the City: The Case of Port-au-Prince

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Abstract: Following the 2010 devastating earthquake and subsequent cholera epidemic, Port-au-Prince's residents have been increasingly affected by food insecurity, socio-economic unrest including periods of complete lock-down, and gang violence. In light of the insecurity which limits the possibilities to collect the necessary information to target the vulnerable residents of Port-au-Prince, this paper aims at providing meaningful evidence to inform the remote targeting and delivery of a potential social assistance program. Putting together household and geospatial data, we compute a composite vulnerability indicator for the metropolitan area, offering a first snapshot of inequality and vulnerability within the city, and discuss the results' implications for social protection programming.

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Contents

I. Vulnerability in Haiti and Port-au-Prince

Progress in terms of social and physical vulnerability in Haiti has been hampered over the last decade following a devastating earthquake in 2010, a series of devastating natural disasters as well as socio-economic unrest. The latest official data indicate that 58.5 percent of the population was considered poor, or living at or below $1.90 per day in 2012.[2] More recent World Bank estimates indicate a marginal increase, with nearly 60 percent of the population being poor in 2020.[3] With a Gross Domestic Product (GDP) per capita of $1,149.50 and a Human Development Index ranking of 170 out of 189 countries in 2020, Haiti is the poorest country in the Latin America and the Caribbean region and among the poorest and most unequal countries in the world.

The country has a higher number of natural disasters per square kilometer than the average of the Caribbean countries, and is prone to hurricanes, cyclones, torrential rains, flooding, and earthquakes. On January 12th, 2010, the metropolitan area of Port-au-Prince was severely hit by a 7.0 magnitude earthquake whose epicenter was located just 25 km southwest of the capital city. This event was the most destructive event any country has experienced in modern times when measured in terms of the number of people killed as a percentage of the country's population,[4] with up to 250,000 dead or missing, and 1.5 million homeless.[5] The same year, a cholera epidemic hit Haiti, including Port-au-Prince, sickening 820,000 people and killing nearly 10,000.[6] Haiti has since endured a notable series of hurricanes and earthquakes over the last

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[2] Enquête sur les Conditions de Vie des Ménages après Séisme 2012. Institut Haitien de Statistique et Informatique (IHSI).

[3] World Bank. (2021). Haiti Overview, April 26, 2021. Available at: https://www.worldbank.org/en/country/haiti/overview

[4] Cavallo, E.A., Powell, A., and Becerra, O. (2010). Estimating the Direct Economic Damage of the Earthquake in Haiti. IADB.

[5] Lozano-Gracia, Nancy; Garcia Lozano, Marisa (2017). Haitian Cities: Actions for Today with an Eye on Tomorrow. World Bank, Washington, DC.

[6] Haiti cholera outbreak prompts fresh UN aid plea. BBC News. 12 November 2010. Retrieved September, 13 2020: https://www.bbc.com/news/world-latin-america-11743629

decade, including the most recent earthquake on August 14, 2021, killing 2,248 people and injuring 12,000 people in the Southern region of Haiti.[7]

The prevalence of acute food insecurity and malnutrition have worsened in recent years. In 2016, the World Food Programme found that 30 percent of households in Port-au-Prince were food insecure,[8] while the latest estimates in 2021 indicated that 46 percent of the population was facing acute food insecurity across Haiti.[9] Escalating security issues have also contributed to inconsistencies and disruptions in supplies reaching markets in Port-au-Prince.[10]

The population in Haiti has been rapidly urbanizing: in 1990, 29 percent of the population lived in urban areas. In 2020, that figure had risen to 57 percent, and it is projected to reach 75 percent by 2050 (Figure 1), one of the highest rates of change in the world. The country's urban population has increased by 5.2 percent annually throughout the second half of the 20th century, due to factors such as faulty agricultural policies and overexploitation of land deteriorating the rural economy and fueling a massive migration into urban areas of peasants seeking security, opportunities, and access to services. Cité Soleil[11] is considered one of the largest informal settlements in the Northern Hemisphere, with a population of 265,072 inhabitants reported in 2015[12] and unofficial estimates ranging from 200,000 to 400,000. At a relatively advanced stage of urbanization in 2020, urban population growth has decreased to 2.5 percent growth in the last 20 years.

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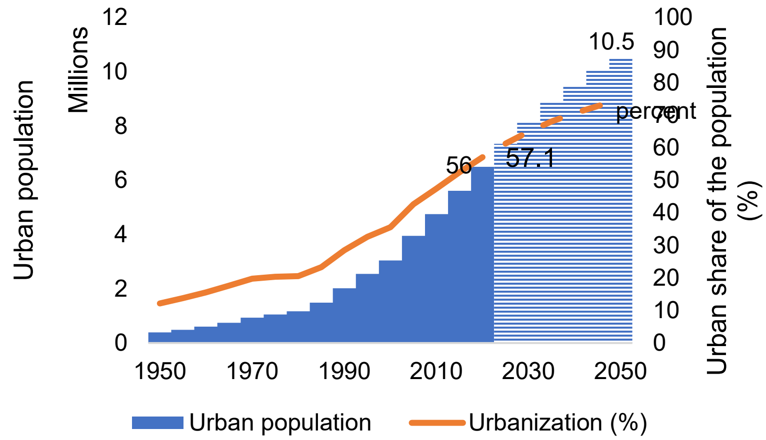
[7] https://www.bernama.com/en/news.php?id=2000560
[8] https://reliefweb.int/sites/reliefweb.int/files/resources/wfp286374.pdf
[9] https://www.ipcinfo.org/ipc-country-analysis/details-map/en/c/1152816/
[10] https://fews.net/central-america-and-caribbean/haiti/food-security-outlook/june-2021
[11] https://gho.unocha.org/haiti
[12] Institut Haïtien de Statistique et d'Informatique (IHSI). 2015.Population de 18 ans et plus ménages et densités estimés en 2015.

Figure 1. After 20 years of rapid urban population growth, urbanization is slowing down in Haiti[13]



Source: World Urbanization Prospects, 2018

With an estimated 24 percent of the Haitian population (circa 2.6 million) and 51 percent of all urban population residing in the Port-au-Prince Metropolitan Area (thereafter referred to as PAPMA),[14] the capital city represents the largest population hub in the country. Port-au-Prince is predicted to reach a population of about 5 million by 2050.[15] The area is marked by very high density-levels, reaching as high as 32,500 people per sq. km., much higher density than the center of African cities with similar levels of per capita income.[16] Port-au-Prince is also one of the largest cities in the world to exist without a central sewerage system.

Residents of the Port-au-Prince Metropolitan Area have faced a number of crises in recent years. 2018 witnessed the beginning of demonstrations known as "Peyi Lòk",[17] primarily in Port-au-Prince, arising from the release of results from a probe initiated by the Superior Court of Accounts

[13] Data from the UN's population division. https://population.un.org/wup/Download/
[14] According to the « Institut Haitien de Statistiques et de l'Informatique, *Population Totale, de 18 ans et plus, Ménages et Densités Estimés en 2015 », the* metropolitan area (including the cities of Port-au-Prince, Delmas, Cité Soleil, Tabarre, Carrefour and Pétion-Ville) represented 2,618,894 inhabitants while the overall population included 10,911,819 inhabitants.
[15] Port-au-Prince made up 27 percent (and 51 percent) of Haiti's total (and urban) population. Assuming PaP's population growth remains constant, it should reach about 5 million people by 2050.
[16] Lozano-Gracia, Nancy, Garcia Lozano, Marisa (2017).
[17] 'Peyi Lòk' refers to a lockdown form of protest whereby businesses, schools, and public transportation are generally halted, leading to shortages of food, gas, and other necessities.

and Administrative Disputes on the use of the Petro-Caribe fund.[18] Tensions further rose with the terms of most legislators ending in January 2020 without an election to replace them, and the assassination of the President in July 2021.

To further exacerbate this situation, the fragile country is also becoming a progressively violent one, and armed gangs are increasingly active, particularly in the Port-au-Prince area. Throughout 2020 violence against civilians in the country rose by nearly 35 percent compared to 2019.[19] Violence has been concentrated mostly in the impoverished neighborhoods of Port-au-Prince, which are divided and controlled by local gang lords. Civilians are often targeted and exploited by gangs, in particular, through kidnappings for ransom which have spiked since 2019. In 2021, armed clashes have increased further by about 15 percent compared to 2020 and the monthly frequency of abductions has nearly doubled,[20] leading Port-au-Prince to recently be characterized as the "kidnapping capital of the world".[21]

In parallel, the COVID pandemic and associated economic downturn have further compounded the socio-economic crisis, including through closures of businesses and school that had already been shut down previously during the Peyi Lok.

II. Programming social assistance in Port-au-Prince

The objective of this note is to inform efforts to reduce social and physical vulnerability in Port-au-Prince in three steps. First, we aim to update estimates of the population living in various areas of the PAPMA, given that the last census was conducted in 2003. Second, we develop and apply an urban vulnerability indicator to identify the most vulnerable areas of PAPMA based on existing data, including the 2019 ENUSAN dataset, 2017 World Bank flood risk data, and Million Neighborhoods data discussed further in the data section. Third, we discuss implications for

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[18] Petro-Caribe is an oil alliance involving 18 Caribbean member states and Venezuela. The CSCCA reports can be found at *https://www.cscca.gouv.ht/rapports_petro_caribe.php*
[19] Raleigh, C., Linke, A., Hegre, H., & Karlsen, J. (2010). Introducing ACLED: an armed conflict location and event dataset: special data feature. Journal of peace research, 47(5), 651-660. Data retrieved in 2021.
[20] https://acleddata.com/2021/02/02/ten-conflicts-to-worry-about-in-2021/#1612195820235-14ee80d6-2b08
[21] https://www.nytimes.com/2021/10/25/opinion/haiti-kidnapping-gangs.html

prioritizing and targeting of potential social assistance to households in selected areas based on the population estimates and urban vulnerability scores.

Since 2020, the COVID-19 pandemic and associated economic downturn saw unprecedented, large-scale social protection responses all over the world rapidly implemented to cope with the acute vulnerability of large segments of the population.[22] As urban areas were the ground zero of the COVID pandemic,[23] they were initially prioritized by governments in many countries for support during lockdown periods that resulted in lower earnings and difficulties in accessing food and services. The Government of Haiti implemented various programs to support its population via cash transfers and food distributions, with an intention to rely on the social registry SIMAST[24] to identify beneficiary households when feasible.[25]

Limited available information on target groups (including their size, needs and localization), lack of any major prior program, as well as a lack of a delivery chain to implement such a program in a context of high insecurity have been major challenges in responding at a large scale to the needs of the population of Port-au-Prince.

The social registry SIMAST[26] is a national-level database containing information on households' characteristics used to compute the Haitian Deprivation and Vulnerability Indicator (HDVI), a Proxy Means Test intended to be used by various stakeholders (including the Government, the UN, NGOs, and other development partners) to identify the most deprived and vulnerable households using 20 indicators across seven dimensions.[27] Since its inception in 2013, data

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[22] As of December 11, a total of 215 countries or territories have planned or implemented 1,414 social protection measures. Gentilini, Ugo; Almenfi, Mohamed; Orton, Ian; Dale, Pamela. 2020. *Social Protection and Jobs Responses to COVID-19: A Real-Time Review of Country Measures*. World Bank, Washington, DC.

[23] Contagious disease is among the demons of density, which have affected cities historically. This is particularly the case in poor neighborhoods, where density has turned into crowding. Glaeser, E. (2011). Triumph of the city: How urban spaces make us human. Pan Macmillan; Bhardwaj, G., Esch, T., Lall, S. V., Marconcini, M., Soppelsa, M. E., & Wahba, S. (2020). Cities, crowding, and the coronavirus: Predicting contagion risk hotspots. World Bank, Washington, DC.

[24] Système d'Information du Ministère des Affaires Sociales et du Travail.

[25] Limitations of the SIMAST include limited geographic coverage and outdated information

[26] See http://infopage.simast.info/

[27] The indicators were selected following a PMT methodology using the 2012 Survey on Living Conditions of Households after the Earthquake to identify factors contributing to variation in household consumption. The resulting index is based on a ranking across 4 categories clarified from a continuous score of 0-100 derived from the indicators.

collection for the SIMAST has expanded via census-sweep of entire communes with door-to-door surveying of all households. However, SIMAST's methodology harbors many constraints across Haiti, including inconsistencies in geographic selection and slow and expensive data collection. These constraints are further compounded in PAPMA due to difficulties associated with slum structures and lack of access to them, as well as security issues related to the presence and control of certain Port-au-Prince areas by gangs. This exclusion has de facto impeded two key uses of the SIMAST in PAPMA: 1) informing program design (by providing information on the number of households in need and their levels of needs) and 2) targeting assistance to those vulnerable households.

In light of the compounding crises and increasingly acute vulnerability of the population of PAPMA, given the current limitations in collecting the necessary SIMAST information to register inhabitants of Port-au-Prince in the social registry, meaningful evidence is needed to inform program design and targeting choices based on existing information. In pursuing this objective, it is important to note that, while SIMAST was unavailable, no new data were collected for the exercise at hand, which rather builds on using recently conducted household surveys, including or focusing on PAPMA (or parts of it), covering different dimensions of the potential risks faced by its inhabitants.

III. Port au Prince's hotspots of vulnerability

Defining Port au Prince Metropolitan Area

Estimating PAPMA's population is challenging for two reasons: city boundaries can be misleading, and no census has been conducted since 2003. The official administrative zones do not represent what could be considered urban today.[28] Over the last four decades, the metropolitan area has expanded dramatically (see comparison between 1986 and 2020 in Figure 2). The other

[28] See Roberts, M., Blankespoor, B., Deuskar, C., & Stewart, B. (2017). Urbanization and development: Is Latin America and the Caribbean different from the rest of the world? World Bank Policy Research Working Paper, World Bank, Washington, DC for a discussion on global definitions of urban areas.

challenging dimension is the outdated census data (last conducted almost twenty years ago), and the lack of surveys representative for official boundaries.

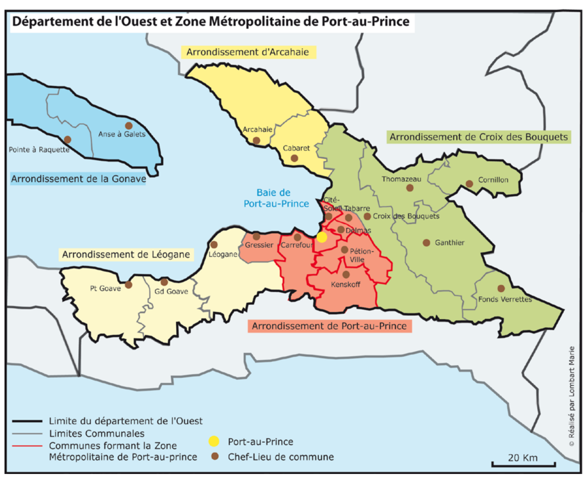
Figure 2. Port-au-Prince from space: 1986 vs. 2020

1986 **2020**

Source: NASA, 2020[29]

Figure 3 is a map of the administrative borders of the official Arrondissement of Port-au-Prince (in red), which is made of eight communes.[30]

Figure 3. Communes of the arrondissement "Ouest"



Source: Lombart et al. 2014.

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[29] https://earthobservatory.nasa.gov/images/146787/haitis-accidental-city

[30] The arrondissement of Port-au-Prince includes the following eight communes: 1. Port-au-Prince, 2. Carrefour, 3. Pétion-Ville, 4. Delmas, 5. Cité-Soleil, 6. Tabarre, 7. Kenskoff, 8. Gressier. These are further subdivided into 34 communal sections.

Starting with existing data, this note brings together existing methods of consistent urban population estimates and aims at reconciling PAPMA population estimates with anecdotal evidence. For example, large parts of the commune of Croix-des-Bouquets (split into 10 communal sections) have high average population density levels and are part of today's northeastern urban core. Although not officially considered part of Port-au-Prince in most population estimates, today, those zones are *de facto* part of greater Port-au-Prince, and should be included in this exercise.

Existing population estimates for Port-au-Prince vary widely, depending on the methodology used. There are broadly three main methodologies available: administrative data (based on the census), satellite imagery, and cellphone records. Although details on the methodology of the estimate are not available for each source, the differences are likely based on either discrepancy in the definition of PAPMA, in the assumed growth rates since the last census, sampling strategies or input data to the modeling.[31]

Looking at the series of official sources using administrative data, large differences appear based on which administrative areas are included in the estimate and which growth rates are applied to the outdated census (see Appendix). While the Government's official estimate of the urban core of Port-au-Prince was 2,618,894 in 2015, once the Croix-des-Bouquets is included, that estimate reaches 3,009,619 in the same year. More recent population estimates that extrapolate from the 2015 Government projections range from 2,913,183 (DHS) to 3,625,183 (UNFPA) for the metropolitan area in 2019.

Cellphone records have been used in Haiti to estimate population of PAPMA, notably for Haiti's 2017 *Urbanization Review,* which used individual cell-phone data from Digicel and estimated population for greater Port-au-Prince to reach approximately 3.5 million people in 2017.[32]

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[31] In particular, global population and built-up datasets have their limitations because they rely on remote sensing methods from imagery of varying quality, depending on year and location. Smaller built-up areas often go undetected, though estimates of population are notably more accurate there; in cities, population is often underestimated. But the growth in computing power, availability of satellite imagery, and expansion of geospatial analysis tools mean that better and more accurate models will expand and increase the capacity for enhanced planning and monitoring.

[32] Lozano-Gracia and Garcia Lozano (2017).

Our delimitation of PAPMA is meant to be as inclusive as possible in considering contiguous population density, as well as support an operational understanding ahead of targeting public assistance. We implement a two-phased approach.

First, we use a cutoff as defined by the Global Human Settlement (GHS) Urban Centre Database (also known as the Degree of Urbanization[33]) at the Joint Research Center of the European Commission, which defines urban areas cities based a certain level of contiguity in population density and built-up area. Built up area includes elements such as roads and rivers, and other spatial covariates attracting settlements. Population density is based on the Gridded Population of the World (GPW) at CIESIN.[34] In 2015, this methodology led to an estimated population of the metropolitan area of 2,801,925.[35] To match known administrative boundaries, we also include communes overlapping with defined urban boundaries. The 2020 WorldPop[36] raster data is then used to update the population of that area. The final delimitation is shown in Figure 4, leading to a total estimated population of 2,853,235 people in 2020.

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[33] The degree of urbanization is a common definition of urban and rural areas, departing from national definition and allows comparison across countries. https://ec.europa.eu/eurostat/web/degree-of-urbanisation/background

[34] Center for International Earth Science Information Network - CIESIN - Columbia University. 2018. Gridded Population of the World, Version 4 (GPWv4): Population Density, Revision 11. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/H49C6VHW.

[35] The degree of urbanization methodology relies on the GHS-POP dataset, which depicts the distribution of the population, expressed as the number of people in a 250m2 pixel. Residential population estimates are taken from CIESIN Gridded Population of the World (GPWv4) disaggregated from census or administrative units to grid cell, and then attributed to the built-up areas. The Urban Center database considers urban centers as contiguous 1-km grid cells with a density of at least 1,500 inhabitants, and a population of at least 50,000. See Florczyk, A. J., Melchiorri, M., Corbane, C., Schiavina, M., Maffenini, M., Pesaresi, M., ... & Zanchetta, L. (2019). Description of the GHS urban centre database 2015. Public Release and https://ghsl.jrc.ec.europa.eu/degurbaDefinitions.php.

[36] The WorldPop program provides high resolution (100m x 100m grid), open and contemporary data on human population distributions, allowing accurate measurement of local population distributions, high resolution maps of population counts and densities from 2000-2020. Tatem, A. (2017): WorldPop, open data for spatial demography. Sci Data 4(1). World Pop estimates uses a weighting layer obtained using a Random Forest (RF)-based dasymetric mapping approach to disaggregate population counts from administrative units into grid cells. Population counts are modeled relying on the last census, as well as a series of geospatial covariates, such as distance to urban areas, roads, distance to the coastline, nighttime lights, etc. See https://www.worldpop.org/tabs/gdata/html/6375/report_prj_2020_HTI.html for more information and Stevens, F. R., Gaughan, A. E., Linard, C. & Tatem, A. J. Disaggregating Census Data for Population Mapping Using Random Forests with Remotely-Sensed and Ancillary Data. PLoS ONE 10, e0107042 (2015).

Data

Although household data for Port-au-Prince is scarce, some relatively recent data is available across several communes in Port-au-Prince. While violence is an important factor in the life of the residents of PAPMA there is unfortunately no data suitable to be included as part of the analysis at this stage.[37] The following were chosen as they contain key aspects of vulnerability in an urban setting such as risk of flooding, crowding or lack of access to services.

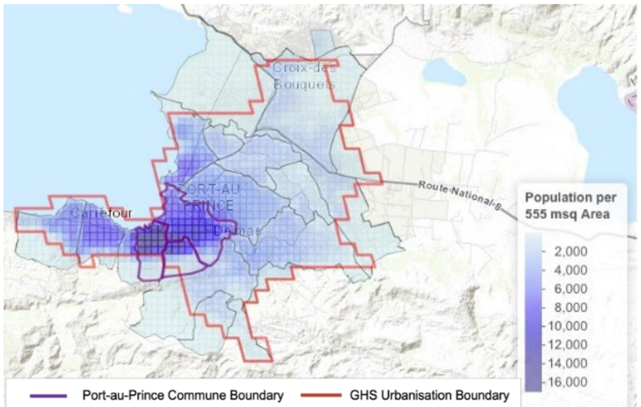
The **ENUSAN** (National Emergency Survey on Food and Nutrition Security[38]) was conducted in August and September 2019. It covers a total of approximately 3,150 households across seven communes nationwide.[39] Its questionnaire includes modules on the household composition, asset ownership, dwelling characteristics, access to services, food security, households' livelihood strategies as well as details on recently experienced shocks, amongst other modules. In the communes of Port-au-Prince, the survey is representative at the IPC zone level, each of the seven communes in PAPMA having 30 clusters with 15 households, and each household with individual GPS coordinates. The ENUSAN data are not available across the entirety of the city. As Figure 5 shows, interviews (blue dots) were concentrated in some areas matching residential land cover (shaded black) in 2016.

[37] Some other datasets, such as the SAMEPA, DHS, or ACLED, could not be used to construct the urban vulnerability index but were used for robustness checks. In the ACLED (Armed Conflict Location & Event Data) and DHS (Demographic and Health Survey) data individual observations could not be pinned down precisely enough geographically within PAMPA, while SAMEPA (Food Security, Livelihoods and Agricultural Production survey) had a significantly smaller sample and smaller questionnaire than ENUSAN.

[38] *Enquête Nationale d'Urgence sur la Sécurité Alimentaire et Nutritionnelle*

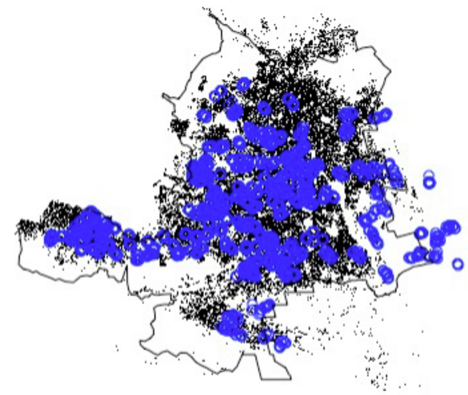
[39] Those communes are the communes of the arrondissement of Port-au-Prince - Port au Prince, Carrefour, Pétion-Ville, Delmas, Cite Soleil, Tabarre – and also the commune of Croix des Bouquets because it has become de facto an urban area of greater PAPMA.

Figure 4. Population Density of PAPMA per 0.005° Area



Source: Authors' calculations using WorldPop 2020 and GHS urban center Port au Prince boundary

Figure 5. Landcover vs. ENUSAN sampled household locations



Source: Authors' calculations using Port au Prince Land Cover Classification (2016), Background study for Lozano-Gracia and Garcia Lozano (2017).[40]

To optimize data coverage, the ENUSAN survey-based indicators were calculated at grids of three different sizes. The smallest has a side length of 0.005 degrees or 555m, the middle of 0.01 degrees or 1,110m, and the largest of 0.02 or 2,220m (Figure 6). If there were at least 5 households per grid cell at the smallest grid level, the average for those was computed, if not the next largest grid size was considered.[41] All indicators were then mapped to the smallest grid, even if computed at a larger scale. With this method complete data at the smallest cell is available for 38 percent of the population, and data is used at larger grid cell level to have a full dataset reaching 75 percent of the population. While this exercise is not representative from a statistical point of view, it offers the first snapshot of inequality and vulnerability across different indicators

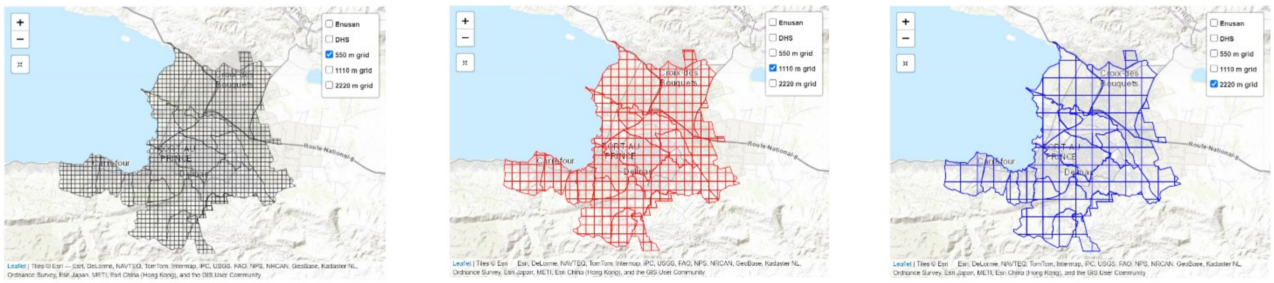
[40] Note: GPS coordinates at the household level. Most interviews were conducted in clusters of about 30 households. While many interviews were conducted in some concentrated areas, other areas are left out, which complicates accurate targeting.

[41] The smallest has a side length of 0.005 degrees or 555m, the middle of 0.01 degrees or 1,110m, and the largest of 0.02 or 2,220m. If there are at least 5 households per grid cell, the household vulnerability score was averaged at that grid size. If fewer than 5 households were surveyed at the smallest 555m grid level, the next largest grid of 1110m was used, and so on. If the largest 2,220m wide grid did not include enough observations, we did not represent the data. If an administrative border of a communal section runs through a grid, that border separates the grid into separate components in each of which the observations are averaged independently from one another to avoid operational implications from any extrapolation.

within the metropolitan area of Port au Prince. The survey data is further complemented by geospatial data sources.

Figure 6. Three different grids

Smallest: 555m side length | Mid-sized: 1,110m side length | Large: 2,220m side length



Source: Authors' calculations

Flood risk information stems from a World Bank exercise carried out in 2017 to produce a set of high-resolution flood hazard maps for Haiti. The work relies on soil and land use as well as rainfall data, using the LiDAR Digital Terrain Model (DTM) to produce flood hazard maps at a 10m resolution depth grid for three return periods: 5-year, 25-year and 100-year events.

Million Neighborhoods Data offers a characterization of the topology of access networks in cities based on OpenStreetMap. To measure street access, the analysis uses an index called the k-index or "block complexity". The exact interpretation of this value is the number of buildings an individual would pass from the least accessible building in a street block to the nearest external street access.[42] When the k-index is 2 or less it means that all buildings have direct access to streets, while values greater than 2 reflect blocks that are incrementally more inaccessible.

A Composite Urban Vulnerability Indicator (CUVI)

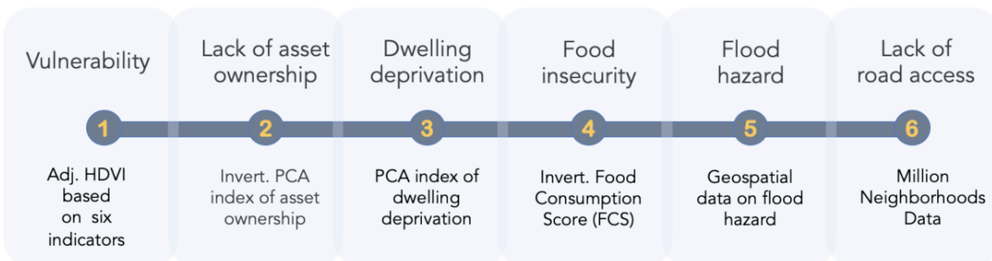
To be consistent with the current targeting approach, the CUVI methodology follows a framework similar to the HDVI. The CUVI is meant to be understood as a measure of the level of

[42] Brelsford, C., Martin, T., Hand, J., & Bettencourt, L. M. (2018). Toward cities without slums: Topology and the spatial evolution of neighborhoods. Science advances, Brelsford, C., Martin, T., & Bettencourt, L. M. (2019). Optimal reblocking as a practical tool for neighborhood development. *Environment and Planning B: Urban Analytics and City Science*, *46*(2), 303-321.

vulnerability, as such higher (lower) scores indicate higher (lower) vulnerability and are reflected in red (green) throughout the analysis. [43] However, to reflect the particularities of the urban context matter, indicators that capture vulnerabilities specific to cities were added.

The CUVI has six components as shown in Figure 7. Each of the component indicator is normalized and then weighted equally when combined in a single indicator. While the first component is closely related to the HDVI, the other five components proxy for other dimensions of vulnerability that are not covered in the HDVI but are of relevance in PAPMA.

Figure 7. CUVI components



Component 1: The HDVI indicators can be computed across PAPMA including 17 out of the 20 variables normally used for the HDVI.[44] Not all are relevant to the urban context, most indicators only show variation at the very top of the distribution, while the overwhelming majority of the variation across households stems from only 6 indicators – measures of (i) demographic vulnerability[45], (ii) overcrowding, (iii) inactive labor, (iv) lack of access to water, (v)

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[43] Grids ranking in the top quintile above 80 percent of all the grids in which households were surveyed (or grids with the better scores) are the darkest green. The bottom quartile ranking in the bottom 20 percent of grids in which households were surveyed (or grids with worse relative scores) are the darkest red. Grids in the middle 20 percent (ranking above the bottom 40 and below 60 percent) are yellow.

[44] See table in Appendix. The standard 20 variables include indicators on household demographics, health, education, labor conditions, food security, resources at home, and living conditions captured through the SIMAST surveys. The variables that could not be recreated using the alternative data are variable 2.1 on the presence of chronically ill at home, variable 3.1. on illiteracy, and variable 3.4. on children's school lag. Other indicators required adjustments where data was not available in the exact same format. One complication in construction indicator 1 (Household demographic composition) was that the ENUSAN-SAMEPA data did not include details on intra-household relations. It was therefore assumed that if there were both a male and a female adult aged 25 or older and 60 or younger, that the household is not "single-headed". For indicator 7, no data on education was available at the member level but only at the household head level, which is why the latter was used instead. Indicator 11 on unemployment was proxied for based on activity data.

[45] This indicator considers the number of children, the number of elderly and if the household is led by a single parent.

unemployment, and (vi) lack of access to lighting are reflected in Figure 8. The HDVI methodology was applied, and the existing weights were re-scaled such that they sum to one. Details on how those six deprivation indicators are defined can be found in the Appendix.

Component 2: The second component of the CUVI is an inverted PCA index of asset ownership. While the HDVI does not include asset ownership—likely because there is not enough variance in asset ownership in rural areas—this measure offers relevant data on vulnerability across households in PAPMA. The asset index relies on variables in the ENUSAN dataset on ownership of 11 assets (see appendix) and is shown on Figure 9.

Component 3: The third component of the CUVI is a PCA dwelling deprivation index (Figure 10). It measures if a household's dwelling floor and walls[46] are built with precarious materials.

Component 4: The inverted food consumption score (FCS) is based data on the types of food the household consumed, and their consumption frequency over the past 7 days. Figure 11 gives a snapshot of the food insecurity in 2019.[47]

Component 5: The fifth component is based on a World Bank funded national flood hazard mapping in 2017 using the freely available flood modelling software HEC-RAS for a 100-year return period. The flood models were developed by applying rainfall input data collected from Damien station just north of Port-au-Prince to a LiDAR-based Digital Terrain Model (DTM). Figure 12 gives a snapshot of relative flood hazard across different grid areas in 2017.

Component 6: Figure 13 reflects access to streets measured by "block complexity", reflecting the number of buildings an individual would pass from the least accessible building in a street block to the nearest external street access.[48] The red areas represent slums, which have very limited access to streets and hence services, while the green areas have the most access. Table 1

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[46] Roof material has very little variation in PAPMA, less than 1 percent of roofs are made of materials other than sheet metal or cement.

[47] The data was available for two points in time: 2019 (ENUSAN) and 2020 (SAMEPA) but 2019 had a larger sample size and was therefore chosen.

[48] Brelsford, C., Martin, T., Hand, J., & Bettencourt, L. M. (2018). Toward cities without slums: Topology and the spatial evolution of neighborhoods. Science advances, Brelsford, C., Martin, T., & Bettencourt, L. M. (2019). Optimal reblocking as a practical tool for neighborhood development. *Environment and Planning B: Urban Analytics and City Science*, *46*(2), 303-321.

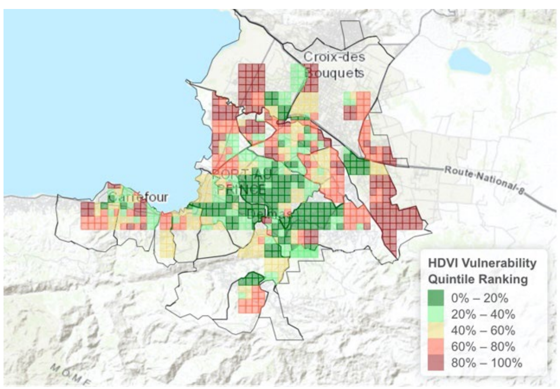
summarizes the pairwise correlations across the six components and shows the correlations with the final CUVI. More descriptive statistics of the CUVI, along with graphs of its distribution, can be found in the Appendix.

Table 1. Pairwise correlations of CUVI components

	CUVI	Component 1: Vulnerability / HDVI	Component 2: Lack of asset ownership	Component 3: Dwelling deprivation	Component 4: Food insecurity	Component 5: Flood hazard	Component 6: Lack of access to roads
CUVI	1.000						
Component 1: Vulnerability / HDVI	0.506	1					
Component 2: Lack of asset ownership	0.538	0.223	1				
Component 3: Dwelling deprivation	0.323	0.100	-0.090	1			
Component 4: Food insecurity	0.536	0.121	0.341	-0.009	1		
Component 5: Flood hazard	0.503	0.005	0.047	-0.017	0.051	1	
Component 6: Lack of access to roads	0.500	0.030	0.042	-0.045	0.051	0.372	1

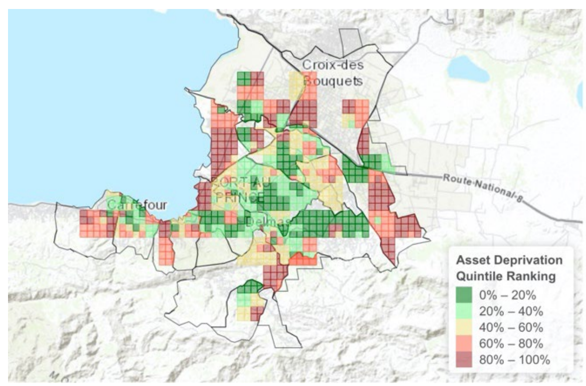
Source: Authors' calculations

Figure 8. CUVI Component 1: Vulnerability



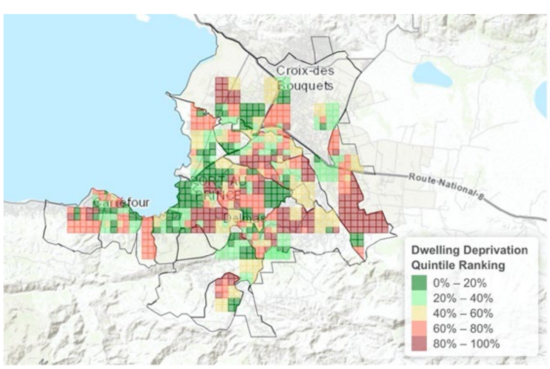
Source: Authors' calculations based on ENUSAN (2019).

Figure 9. CUVI Component 2: Lack of asset ownership



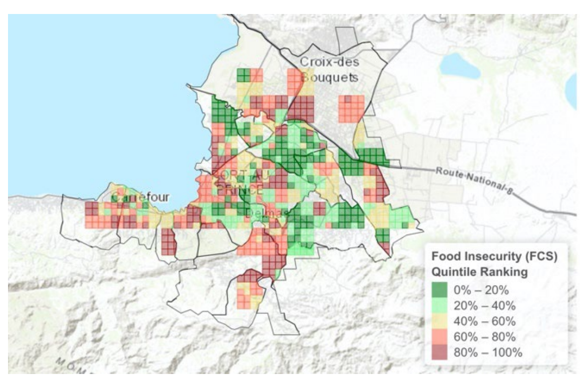
Source: Authors' calculations based on ENUSAN (2019).

Figure 10. CUVI Component 3: Dwelling deprivation



Source: Authors' calculations based on ENUSAN (2019)

Figure 11. CUVI Component 4: Food insecurity



Source: Authors' calculations based on ENUSAN (2019)

Figure 12. CUVI Component 5: Flood risk

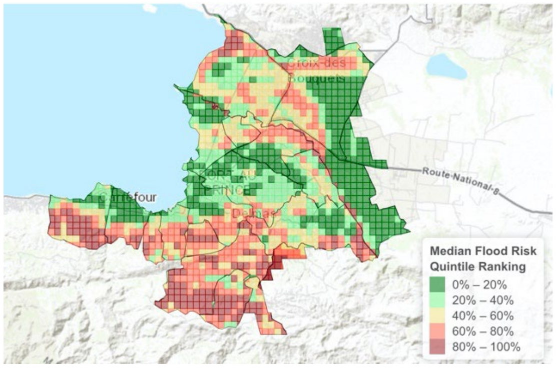
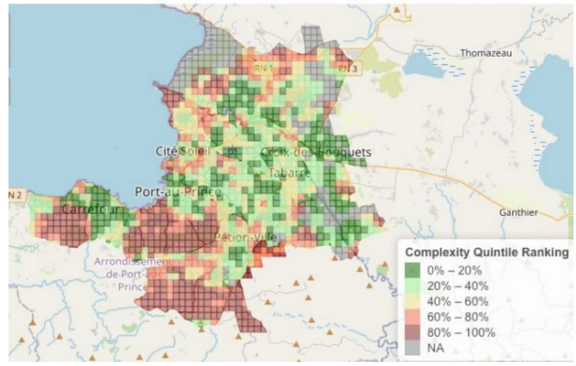


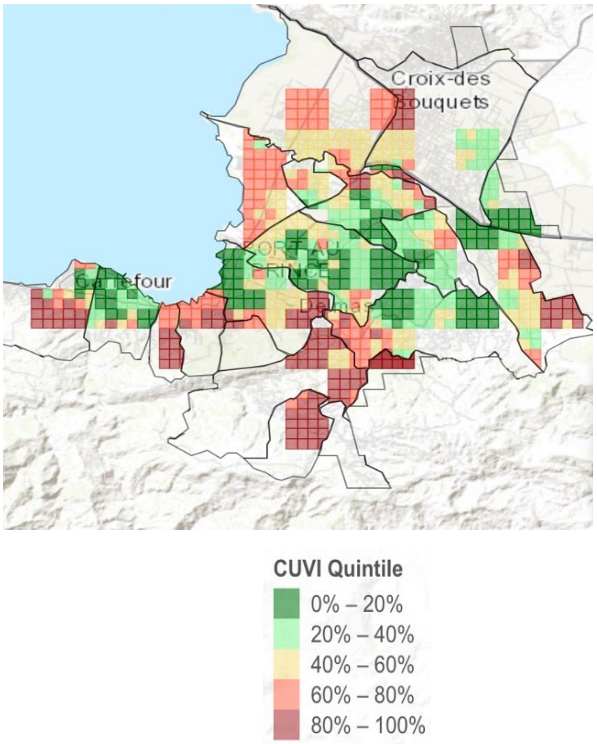
Figure 13. CUVI Component 6: Lack of road access



Bringing all components together leads to the Composite Urban Vulnerability Indicator (CUVI) shown in Figure 14. For reference, Figure 15 shows the communes with their communal sections in different colors for easier locating.[49]

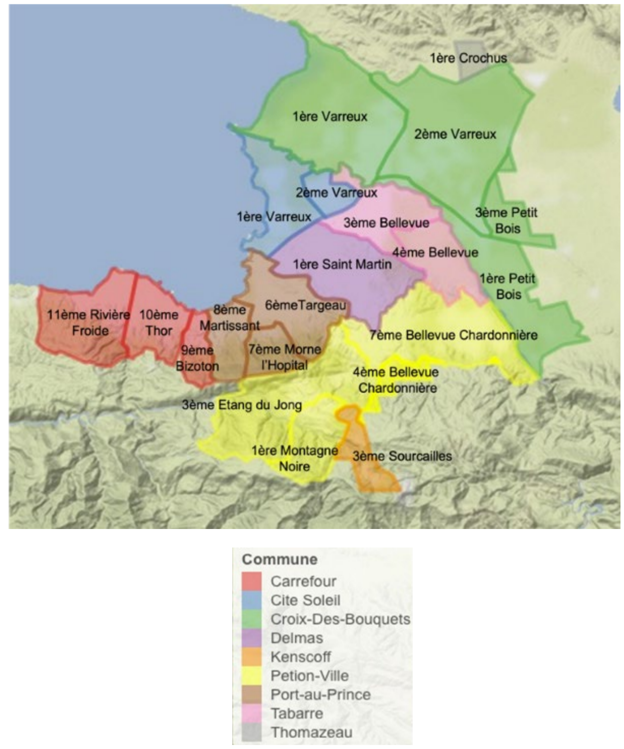
[49] Note that we added the commune of Croix-des-Bouquets (green) in the north-east of the city although it is not officially part of the arrondissement of Port-au-Prince because it falls within the criteria we use to define the PAPMA area in Section 2.1.

Figure 14. The Composite Urban Vulnerability Indicator



Source: Authors' calculations

Figure 15. Overview of the communes and sections within the metropolitan area



Source: Authors' calculations using CGNIS data

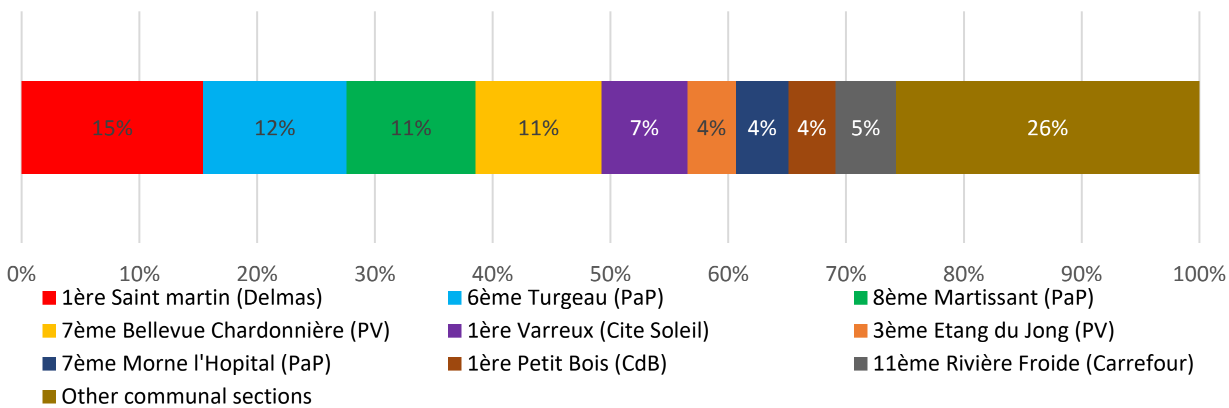
Vulnerability is the highest in the expected slum areas such as Martissant, Cite Soleil, west Carrefour, along the Grise river in the western part of the commune of Croix-de-Bouquets and along the Kenscoff route in the south. Less vulnerable areas in green include parts of the the Petion-Ville and Pacot areas, as well as sparsely populated north of the city, and the east part of Carrefour.

IV. Implications of the CUVI in terms of the vulnerability of the population

The grid cells and associated communal sections areas classified according to their CUVI vulnerability can be mapped to population levels to estimate the number of vulnerable individuals in the PAPMA.

Before discussing the vulnerability levels, it is important to note that despite numerous communal sections in PAPMA (29 with our definition), three quarters of the population lives in only 9 of these sections communales (see Figure 16). More so about half the population of PAPMA lives in 4 densely populated sections communales of Saint Martin in the commune of Delmas, Turgeau and Martissant in Port au Prince, and Bellevue Chardonnière in Pétion-Ville.

Figure 16. Population distribution in PAPMA

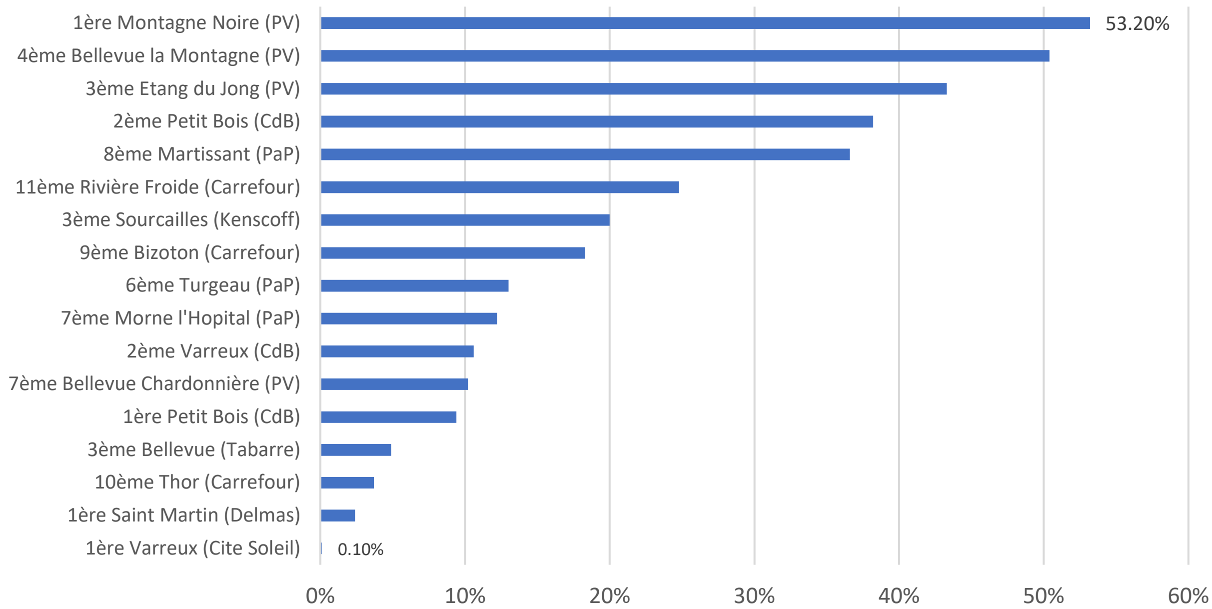


Source: Authors' calculations

Note: CdB is Croix-des-Bouquets, PaP is Port-au-Prince, PV is Pétion-Ville

The vulnerable population is estimated by categorizing individuals as vulnerable if they reside in the grid cells with the highest CUVI vulnerability status (the top quintile shown in dark red in Figure 14), thus focusing on the 14 percent most vulnerable PAPMA residents, representing 390,931 residents. Figure 17 displays the proportion of each communal section categorized as vulnerable, showing a range varying from 53.2 percent in Pétion-Ville to 0.1 percent in Cite Soleil. These estimates indicate that focusing on geographical targeting alone would likely result in large inclusion errors, which could potentially be avoided or reduced by complementing this analysis with a focused household-level targeting and ground truthing.

Figure 17. Share of population categorized as most vulnerable in each communal section

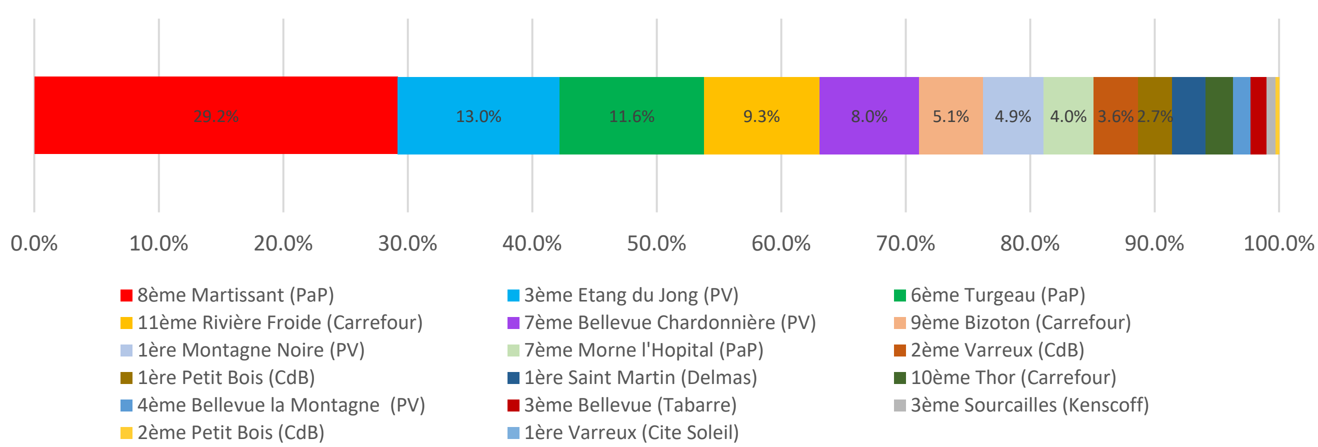


Source: Authors' calculations

Note: CdB is Croix-des-Bouquets, PaP is Port-au-Prince, PV is Pétion-Ville

Figure 18 shows the spatial distribution of those vulnerable populations in PAPMA, thus combining both the share of the population categorized as vulnerable and the overall share of the PAPMA population living in each communal section. More than 90 percent of the vulnerable population lives in 10 communal sections.

Figure 18. Distribution of most vulnerable population across PAPMA communal sections



Source: Authors' calculations

Note: CdB is Croix-des-Bouquets, PaP is Port-au-Prince, PV is Pétion-Ville

It is important to note here that while the CUVI provides some estimates of the size of the target population several steps would be required in order to actually identify and enroll households in such a program, and further targeting could improve accuracy with reduced inclusion errors. One option is to proceed with massive registration on the ground, with the known caveats of high costs, lengthy processes and dealing with the extremely complex security environment.

Another option that would allow for faster and more efficient enrollment would rely on a collaboration with telecom operators. Using the information on the prioritization of certain areas based on the CUVI, the telecom operators could provide an anonymized list of mobile phone subscribers living in the area could form the basis of a potential beneficiary registry. This list could be further refined by applying some filters based on call detail records (CDR) and/or satellite imagery data to limit inclusion errors, for instance by excluding smartphones, or by analyzing the CDR or roof materials to proxy poverty status. Identified beneficiaries can be reached out to through bulk SMS, audio messaging or radio campaigns, encouraging them to consent and self-register in the program (for instance through USSD). Telecom operators can then open mobile money accounts or leverage those already associated with beneficiaries' phone numbers to initiate transfers. This methodology was successfully implemented in Kinshasa as part of the COVID-19 social response.[50] Attention will need to be paid to offer an adequate communication strategy to share all relevant information and ensure take up.

One caveat with this approach is the need for vulnerable households to own a cellphone to access the benefit, and the need for the mobile payment ecosystem to be strong enough to support this type of transfer. Recent estimates indicate a nationwide average of two third of the population owning a cellphone in 2017[51], and according to the ENUSAN survey 84.2 percent of households in PAPMA owned one in 2019. While cellphone ownership is lower in the areas with the highest CUVI scores (81.8 percent) compared to the lowest (86.3 percent), it would still offer a remote

[50] See https://www.brookings.edu/blog/future-development/2021/09/08/cash-and-the-city-digital-covid-19-social-response-in-kinshasa/

[51] Findex data, 2017, see https://globalfindex.worldbank.org/#data_sec_focus

assistance delivery channel for the majority of the population. Outreach and communication efforts to encourage the purchase of SIM cards or cellphones (smartphones are not required) could further help narrow the excluded population. An assessment should however be conducted to ensure the infrastructure is in place for beneficiaries to either cash out their payment or use the mobile money directly with vendors, and that regulations, including Know-Your-Customer (KYC) are conducive to these processes (for instance if beneficiaries need formal identification to open mobile wallets or cash them out).

V. Discussion

Limitations and caveats

Building on available information, the CUVI intends to (1) define a methodology reflecting the specificity of the PAPMA while building on the existing methodology of SIMAST and (2) make the most use out of various data sources to inform programming and targeting of assistance. There are however important limitations and caveats to consider and that could be alleviated in further iterations.

First, the exclusion of certain areas and therefore some segments of the population. Large parts of Port-au-Prince are not covered by any of the surveys that were conducted since the last consumption survey in 2012, making a detailed vulnerability analysis in some areas impossible. The methodology allows for a coverage of 52 percent of the total PAPMA area, representing 76.2 percent of the population. With three quarters of the population covered we need to acknowledge that our estimates might be biased. For example, the CUVI only covers the northern coastal area of Martissant, a densely populated area that is notorious extremely vulnerable, including due to very intense gang activity.

Second, a number of assumptions are made when assigning ENUSAN surveyed household to the grid. The original survey was intended to be representative of the seven communes of PAPMA, sampling 15 household in 30 clusters for each. The precise GPS coordinates allowed us to assign households to a grid and trading off precision and coverage, a minimum of 5 households was chosen as a threshold for the first 4 components to be computed. The results should therefore be taken with caution.

Finally, this model could be significantly improved with more recent or different data sources given acute recent crises. In particular, up-to-date household data (such as SIMAST) or household survey data (such as ENUSAN) representative for the PAPMA would reflect recent deteriorations in the living conditions of PAPMA residents. There are a number of additional sources of data that would be of value for this model, for example the inclusion of service availability and quality information.

The dangers and costs associated with data collection on the grounds in PAPMA however call for some innovative techniques to be employed. Phone surveys, such as high-frequency, light surveys with a limited set of questions, could be used in gathering data. Another option is the use of Call Detail Records (CDR) data to refine both the estimates of the population living in an area (by analyzing the utilization of cellphone towers) and the estimates of vulnerability (discussed below). Another example is the use of satellite imagery to identify housing characteristics used to predict vulnerability, as has been done in Kenya.[52] Ground truth data can also be used to train machine learning algorithm to estimate the wealth of areas based on geographic characteristics, for instance that poorer areas tend to be characterized by certain terrain, roof materials or road quality, as was done in Togo.[53]

Implications for social assistance

Despite the caveats, the CUVI allows at the very least for a prioritization of areas in which high shares of the population are vulnerable. This is particularly useful to inform choices related to social assistance. Local authorities should be involved in designing and implementing a safety net program to ensure adequate ownership of the program and facilitation of its roll-out. In the case of Port-au-Prince, the approach could thus focus on collaborating with local authorities at the

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[52] See Abelson, Brian, Kush R. Varshney, and Joy Sun (2014). "Targeting direct cash transfers to the extremely poor." In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 1563-1572.

[53] https://www.poverty-action.org/study/using-mobile-phone-and-satellite-data-target-emergency-cash-transfers-togo

communal section level to leverage their knowledge of the constituents and relevant stakeholders. With more than half a million predicted vulnerable individuals in PAPMA, efforts could focus on the 10 communal sections in which more than 90 percent of these individuals reside to estimate a budget needed in those areas.

There are two main objectives a cash transfer could have: improve the livelihoods of the most vulnerable to alleviate chronic poverty and food insecurity, and to smooth consumption and promote recovery in response to a shock household may face. As described above both modalities are relevant in the context of Port-au-Prince but correspond to different timelines of implementation: the first would focus on regular, smaller transfers, while the latter will usually focus on very few, larger payments to help in the short term.

Based on the experience from previous programs in Haiti the benefit amount for a regular, monthly cash transfer could correspond to 20% of the minimum food basket (estimated at 123 USD per month in urban areas for a family of five),[54] or 24.6 USD per household. The budget associated with a transfer corresponding to 20% of the minimum food basket would reach 1,755,982 USD per month, or about 21.1 million USD per year, as detailed in Table 2. For an emergency cash transfer the amount could correspond to 70% of the minimum food basket,[55] or 86.1 USD, distributed once, corresponding to a total budget of 6 million USD. It is important to note that these budgets only reflect the sum of transfers and would need to include additional administrative costs related to the implementation of such a program, of the order of 5 to 10% of the transfers.

[54] The minimum expenditure basket (MEB) for food is computed to reflect the needs for 2,100 kcal calories per day per person for a family of 5 over one month. The MEB was defined by the Cash Working Group in 2019 and price data collected in December 2021

[55] Previous COVID-19 response emergency cash transfers implemented by WFP, including through the WB MDUR project, represented 70% of the minimum food basket. The Cash Working Group recommended transfers representing 75% of the minimum food basket following the earthquake in August 2021 in the South.

Table 2. Estimated annual budget for a transfer to the vulnerable population in the 6 prioritized communal sections

	A	B	C	D
	Vulnerable Population	Vulnerable Households (A/5)	Transfer costs for one year of monthly cash transfers representing 20% of minimum food basket transfer (B*24.6*12)	Transfer costs for one-time cash transfer representing 70% of the minimum food basket (B*86.1)
8ème Martissant (PaP)	114,159	22,832	$6,739,947	$1,965,818
3ème Etang du Jong (PV)	50,769	10,154	$2,997,402	$874,242
6ème Turgeau (PaP)	45,287	9,057	$2,673,744	$779,842
11ème Rivière Froide (Carrefour)	36,374	7,275	$2,147,521	$626,360
7ème Bellevue Chardonnière (PV)	31,235	6,247	$1,844,114	$537,867
9ème Bizoton (Carrefour)	19,988	3,998	$1,180,092	$344,193
1ère Montagne Noire (PV)	18,962	3,792	$1,119,516	$326,526
7ème Morne l'Hopital (PaP)	15,599	3,120	$920,965	$268,615
2ème Varreux (CdB)	13,942	2,788	$823,136	$240,081
1ère Petit Bois (CdB)	10,592	2,118	$625,352	$182,394
Total	356,907	71,381	$ 21,071,789	$6,145,939

Source: Authors' calculations

Note: CdB is Croix-des-Bouquets, PaP is Port-au-Prince, PV is Pétion-Ville

VI. Conclusion

Over the last decade, despite large amounts of aid, the vulnerability of Haiti's population has been worsened by a series of devastating disasters, an increase in violence, and political crises. The COVID-19 pandemic has compounded these crises, making it imperative to be able to provide support to extremely vulnerable populations across the country, including the Port-au-Prince Metropolitan Area. With increasing urbanization of the population and deteriorating living standards in this area the need is pressing to define options to target, enroll and provide assistance to urban beneficiaries of social assistance.

In the absence of social registry data for PAPMA, we estimate the population size and build a Composite Urban Vulnerability Index (CUVI) based on various sources of reliable information to estimate the size of the most vulnerable population in PAPMA. Leveraging experiences in other countries, including DRC and Togo, we identify options to prioritize the most vulnerable areas, for instance through piloting remote end-to-end delivery of transfers, starting with geographic (hotspot analysis) targeting, followed by further refining of the beneficiary lists based on CDR or satellite data, enrollment through automated processes via SMS, and, finally, payment through mobile wallets. These options would be relevant both for regular cash transfer programs and also for ad-hoc shock response efforts. Recent history demonstrates how pressing and necessary this issue is in PAPMA.

Beyond PAPMA this analysis could also be expanded nationwide, whether using survey data, CDR or satellite imagery. Mapping vulnerability will allow for an identification of particularly vulnerable areas, which should be prioritized for SIMAST expansions as well as potential safety net expansions.

While this analysis sheds light on a large segment of the Haitian population, the work underlines the need for more information to be gathered to accurately capture the vulnerability of the population. We identify various options to include other data sources, including the use of satellite imagery or phone surveys, as well as the possibility to take other factors into account to improve the CUVI in future iterations. One key aspect of vulnerability in PAPMA that could for example not be accounted for in the current framework is the issue of violence, which may affect households through a variety of channels, including difficulties in accessing goods and services.

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Appendix

Appendix A. Population estimates for Port-au-Prince

This table shows the various population estimates of Port-au-Prince or Haiti as a whole.

Table 1. Port-au-Prince population estimates

	Source	Included area	Estimate	Year	Method	Remarks
1	Government	Port-au-Prince, Metropolitan area	2,618,894	2015	Census	Urban areas in PaP Arrondissement
2	Government	Port-au-Prince	2,759,991	2015	Census	All of PaP
3	Government	Port-au-Prince + Croix-des-Bouquets	3,009,619	2015	Census	All of PaP + C-d-B
4	ENUSAN	Port-au-Prince	N/A	2018/2019	Unclear how weights are used	
5	UNFPA	Port-au-Prince	3,625,183	2019	Based on census applying own growth rates	Does not include C-d-B but all of PaP arrondissement
6	DHS	Port-au-Prince, "Metropolitan area"	2,913,941	2017	Based on Census using growth rates as suggested by countrymeters	All of PaP but not C-d-B
7	World Bank Urbanization Review	Port-au-Prince "Metropolitan area"	3,500,000	2017	Use Digicell cellphone data to estimate grid of city	Includes all densely populated areas incl. some sections of Canaan
8	WorldPop	Port-au-Prince	~3M	2021	Random-forest based dasymmetric redistribution	
8	GHS (Global Human Settlement Layer)	Port-au-Prince (1km grid)	2,801,925	2015	Combines built up environment & census	Based on density level
9	Macrotrends	Port-au-Prince	2,844,000	2021	Extrapolation based on 2015 census	Unclear how PaP is defined
10	World Bank	Only Haiti	11,123,000	2019	Uses UN population division figures	Only available for Haiti overall
11	UN Population Division	Only Haiti	11,126,000	2021	Models population growth based on 2015 census	Only available for Haiti overall

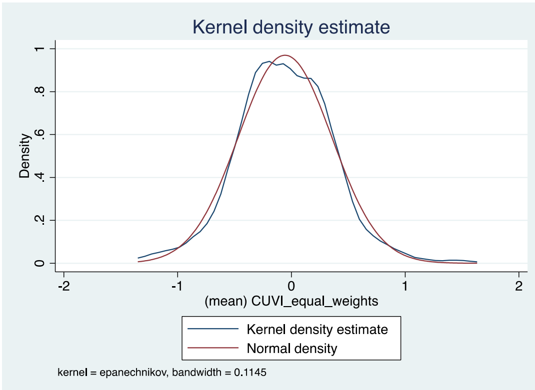
Source: Authors' compilation.

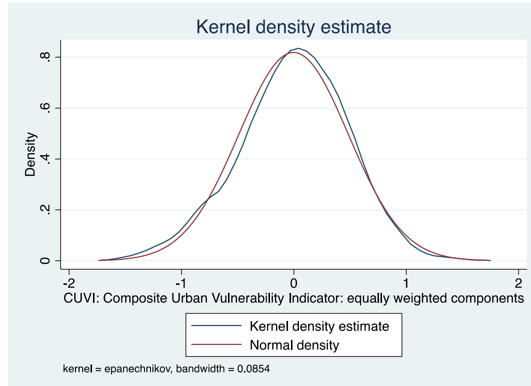
Appendix B. Distribution of the survey-based components: grid vs household

The figures below plot the kernel density function of the survey-based components of the CUVI at both the grid level (left) and the household level (right) and compare them to a normal distribution. Both distributions closely follow those of a normal distribution. There are no clear signs of bunching.

Figure 1. CUVI distribution (grid level)

Figure 2. CUVI distribution (household level)





Source: Authors' calculations

Appendix C. CUVI Component I: HDVI equivalent indicator

The standard HDVI includes 20 indicators from 7 dimensions, which are demographic vulnerability, health, education, labor conditions, food security, resources at home, and access to dwelling services. The HDVI seeks to not only identify deprived households, but also the depth of deprivation.

While SIMAST data is not available in Port-au-Prince, we use the ENUSAN data to calculate the equivalent indicators – some of which are slightly adapted, as shown in the following table.

Table 2. Overview of indicators included in the adjusted HDVI

Dimension	HDVI	Adjusted HDVI
Demographic vulnerability	1.1 Household demographic composition	Included but slight adjustments required
	1.2 Presence of children under 5 years old	Included
Health	2.1 Presence of disabled or per. injured	Included
	2.2 Chronically ill at home	Data unavailable
Education	3.1 Illiteracy	Data unavailable
	3.2 Absence of at least basic school	Included but slight adjustments required
	3.3 School non-attendance	Included
	3.4 School lag	Data unavailable
Labor conditions	4.1 Inactivity	Included
	4.2 Unemployment	Included but slight adjustments required
	4.3 Child labor	Included
Food security	5.1 Hunger	Included
	5.2 Absence of food	Included
	5.3 Restricted consumption of food	Included
Resources at home	6.1 Absence of remittances	Included
	6.2 Deprived material of floors, ceilings and	Included
	6.3 Overcrowding	Included
Access to dwelling services	7.1 Deprived lighting access	Included
	7.2 Deprived access to water	Included
	7.3 Deprived sanitation conditions	Included

Source: Authors' compilation

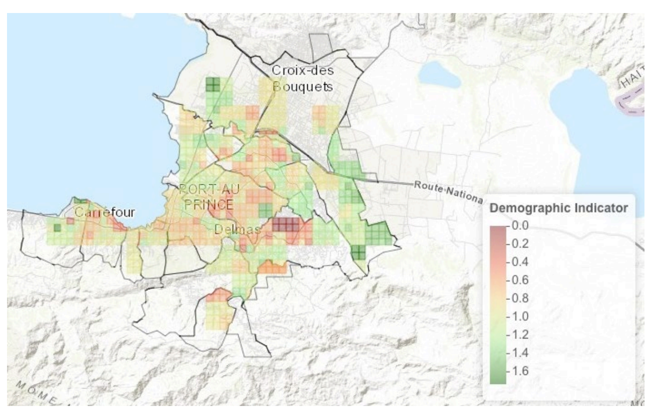
The adjusted HDVI built for PAPMA covers all seven dimensions and 17 out of 20 indicators. Not all HDVI components, however, show relevant variation in the metropolitan area of Port-au-Prince. But the first six indicators explain most differences across households in the capital. Those cover demographic vulnerability, overcrowding, inactivity and unemployment, as well as indicators on deprived lighting and water access.

Indicator	Mean	Min	p25	p50	p75	Max
Demographic vulnerability	0.93	0.00	0.00	1.63	1.73	1.73
Overcrowding	0.85	0.06	0.38	0.76	1.13	2.65
Inactivity labor	0.75	0.00	0.00	0.71	1.15	2.67
Water access	0.58	0.00	0.16	0.16	1.25	1.41
Unemployed	0.56	0.00	0.00	0.71	1.00	2.00
Lighting access	0.52	0.00	0.23	0.23	1.41	1.41
Dwelling	0.25	0.00	0.00	0.00	0.00	1.73
Absence of remittances	0.20	0.00	0.00	0.00	0.00	1.63
Hunger	0.15	0.00	0.00	0.00	0.00	3.16
Children under 5	0.14	0.00	0.00	0.00	0.00	1.51
Lack of basic education	0.13	0.00	0.00	0.00	0.00	1.00
Absence of food	0.12	0.00	0.00	0.00	0.00	3.16
Sanitary access	0.12	0.00	0.00	0.00	0.00	1.41
Disabled or perm injured	0.09	0.00	0.00	0.00	0.00	2.24
Restricted cons.	0.08	0.00	0.00	0.00	0.00	3.16
Not attending school	0.06	0.00	0.00	0.00	0.00	2.04
Child labor	0.00	0.00	0.00	0.00	0.00	1.22

Source: Authors' calculations

Note that the vulnerability indicators here are the final, unweighted indicators, and therefore do not correspond directly to the original composition explained below. The six indicators that we choose to incorporate in the CUVI are defined as follows:

Figure 3: Demographic vulnerability

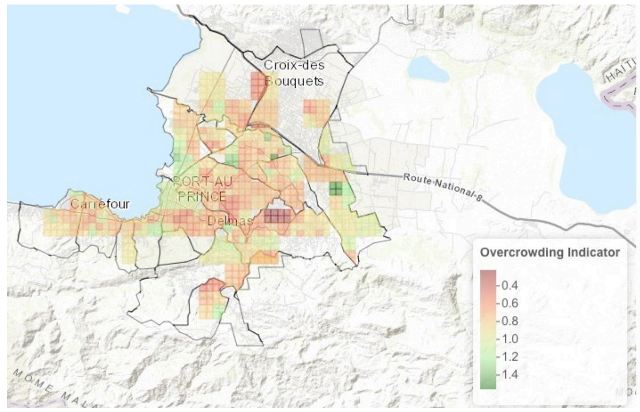


Demographic vulnerability: As per the HDVI, we created five mutually exclusive dichotomous variables according different household types classified as vulnerable: single-headed with children, with children, single headed with children and at least one elderly over 65, with children and at least one elderly over 65.[56]

Source: Authors' calculations based on ENUSAN (2019)

Overcrowding: The total number of household members divided by the total number of rooms available in the household.

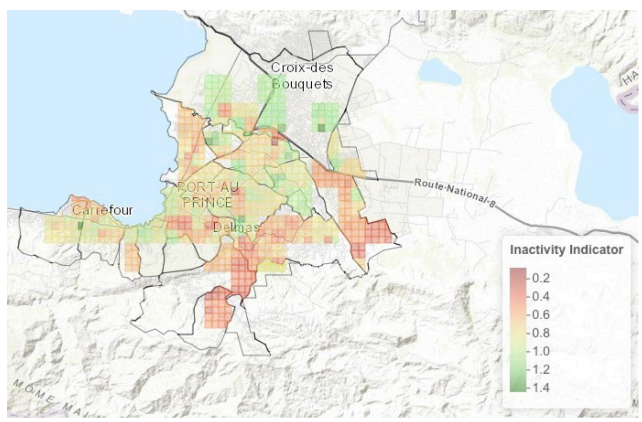
Figure 4. Overcrowding



Source: Authors' calculations based on ENUSAN (2019)

Inactivity: The indicator consists of the total number of household members who fall within the inactive category. Those include members that consider themselves as inactive, are students, retired, pensioners, rentiers, working in household only, disabled or other.

Figure 5. Inactivity

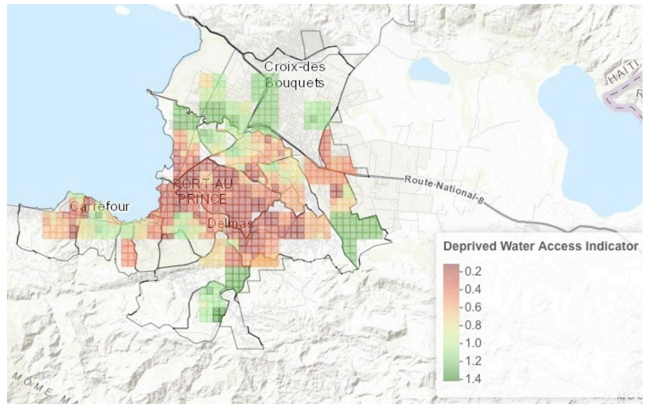


Source: Authors' calculations based on ENUSAN (2019)

[56] Note that those categories are not necessarily mutually exclusive. If more than one type applies for a household, we choose the one with the more deprived score. Since the ENUSAN data did not include details on intra-household relationships, it was assumed that the household is not single headed if both women and men of the age 18-60 live in the household. Scores are as follows: single-headed with children (2.8165), with children (3), single headed with children and at least one elderly over 65 (1.5703), with children and at least one elderly over 65 (0.6126)

Deprived access to water: Composite measure of access to water for drinking and other purposes. If the household uses drinking water other than water from a bottle, bag or gallon, it gets a score of 1 (deprived). If the household does not use water provided by the national water and sanitation company, or from a public fountain or from an artesian aquifer it gets a score of 1.[57]

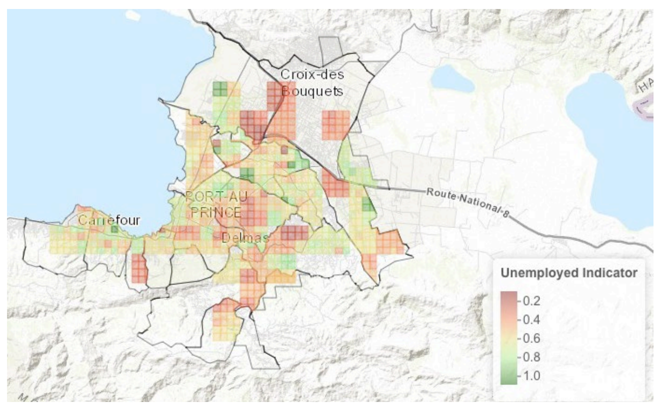
Figure 6. Deprived access to water



Source: Authors' calculations based on ENUSAN (2019)

Unemployment: The indicator consists of the total number of household members who are unemployed. Those include members that consider themselves as not working at all despite being of working age, 18 or older but less than 65 years old.

Figure 7. Unemployment

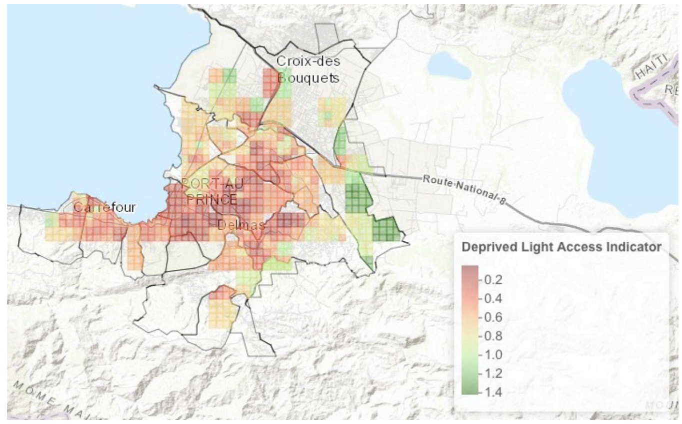


Source: Authors' calculations based on ENUSAN (2019)

[57] The weights for drinking and other purposes deprivation, respectively, are 0.8851 and 0.1149. The sum is therefor is multiplied by 2 such that the maximum deprivation score can be 2.

Deprived access to lighting: Composite measure of lighting deprivation based on the energy source utilized for artificial lighting and for cooking. We create two variables: (1) is a dummy that takes the value 1 if the household either does not dispose of any artificial lighting source, or uses candles, batteries, or kerosene (2) is a dummy that is equal to 1 if the household uses wood, straw or charcoal to cook in PAPMA.[58]

Figure 8. Depriving access to lighting



Source: Authors' calculations based on ENUSAN (2019)

Appendix D. CUVI Component II: Asset index

We add PCA asset index as components to the CUVI that we build using ENUSAN data. The index includes information on the following asset ownership variables:

Table 4: Asset Deprivation Indicator

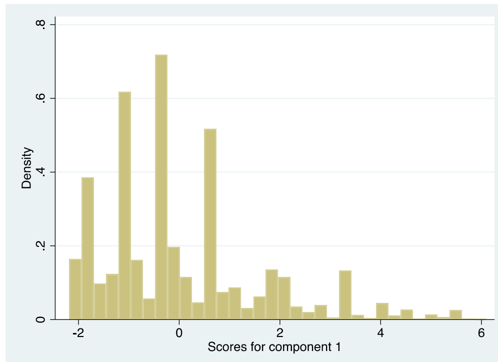
Indicator	Specific variable included in PCA
Assets	Solar panel, Generator, Mobile phone, Personal vehicle, TV, Computer/laptop, Fridge/Freezer, Radio, Storage facility, Axe, Billhook.

Source: Authors' compilation

Each variable of either PCA is constructed in binary form, where a value of 1 indicates that the household does own at least one item of the asset and 0 that it does not. We then invert the final PCA indicator such that a higher score means more less asset ownership rather than higher ownership. We standardize the inverted indicator before adding it to the CUVI. We also run

[58] Variable (1) is then weighted with a score of 0.8363 and variable (2) with 0.1636, and their sum is multiplied by 2 such that the maximum deprivation score is equal to 2. The artificial lighting score therefore is weighted more heavily in the overall lighting access variable.

robustness checks using DHS 2016 data and check for consistency with the ENUSAN 2019 data. We also create PCA indices including access to services data together with the dwelling data. Both robustness checks confirm the trends we see with the assets PCAs.



Source: Authors' calculations

Appendix E. CUVI Component III: Dwelling index

We add another PCA index as the third component to the CUVI. This index measures the household's deprivation in terms of its dwelling's characteristics and building materials. It assesses if a household's dwelling is vulnerable in the sense that its building materials for floors and walls are weak.

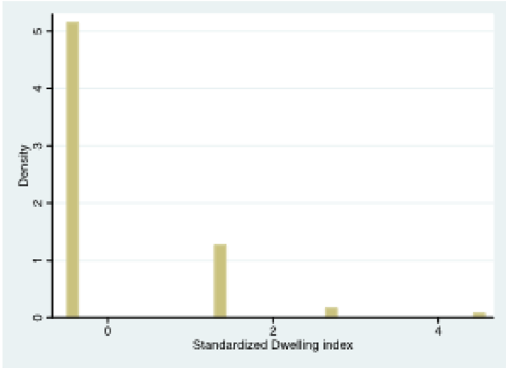
Table 3. Dwelling deprivation indicator

Indicator	Specific variable included in PCA
Dwelling	Deprivation of floor material → floor made with wood, earth or remains Deprivation of walls material → walls made of wood planks, earth, metal sheets, cards/plastic or other primitive covers

Source: Authors' compilation

Each variable of either PCA is constructed in binary form, where a value of 1 indicates that the household does face a dwelling characteristic that is considered deprived. We then standardize the indicator before adding it to the CUVI. We also run robustness checks using DHS 2016 data and check for consistency. We also create PCA indices including access to services data together with the dwelling data. Both robustness checks confirm the trends we see with the dwelling PCAs.

Figure 10: PCA based on dwelling deprivation



Source: Authors' calculations

Appendix E. CUVI Component IV: Food consumption score data

The standard methodology for the FCS was applied for both the ENUSAN and SAMEPA based indicators, with the standard weighting. Both datasets include the same questions but were asked at different points in time, which allows for a snapshot of trends in food security. A household's food security is ranked as "poor" if the score is lower than 35, "acceptable" if lower than 50, and "non-poor" if above 50. Although we plot both the ENUSAN-based and SAMEPA-based data, we decide to include only the ENUSAN data, both for consistency and because it has the much larger sample size than the SAMEPA. The ENUSAN-based FCS has a median of 48.1 and mean of 49 with a standard deviation of 9.2.

Figure 11. FCS based on ENUSAN data (2019)

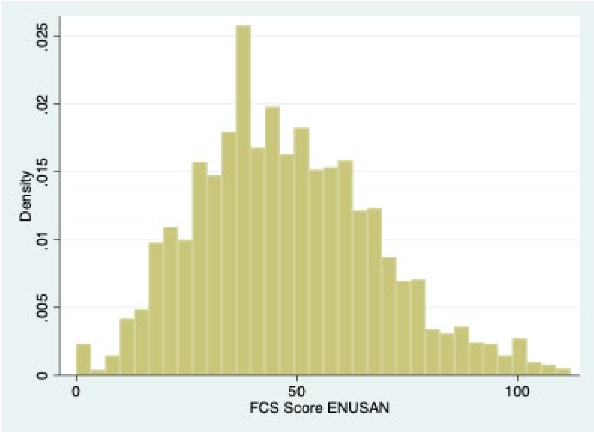
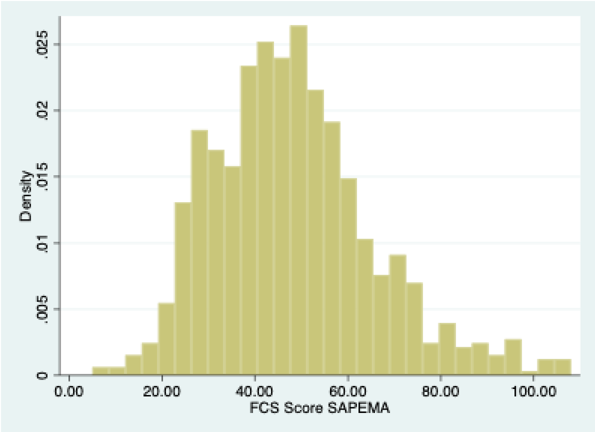


Figure 12. FCS based on SAMEPA data (2020)



Source: Authors' calculations based on ENUSAN (2019) and SAMEPA (2020)

Figure 13. Ranked ENUSAN-based Food Security Score per 555 sqm Area by Quintile (2019)

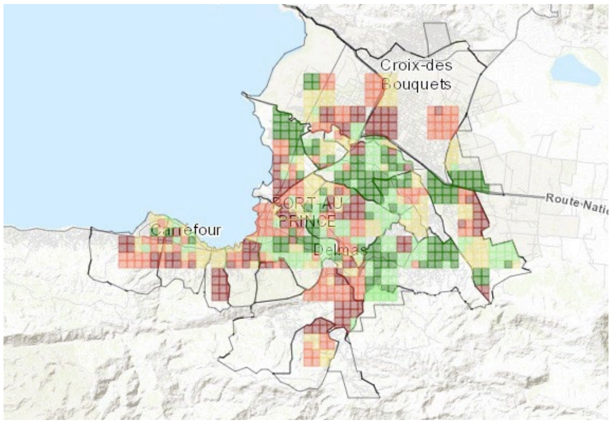
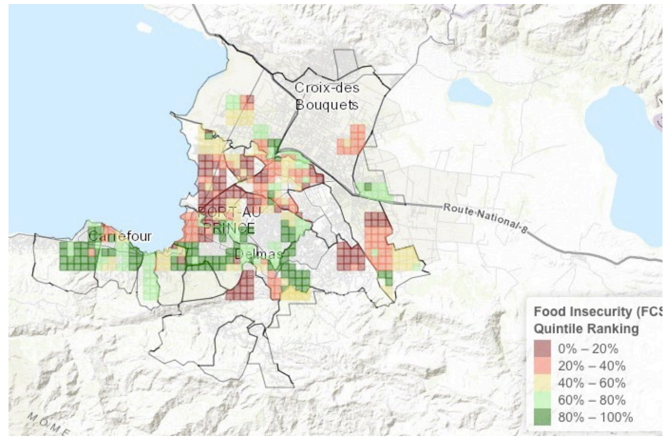


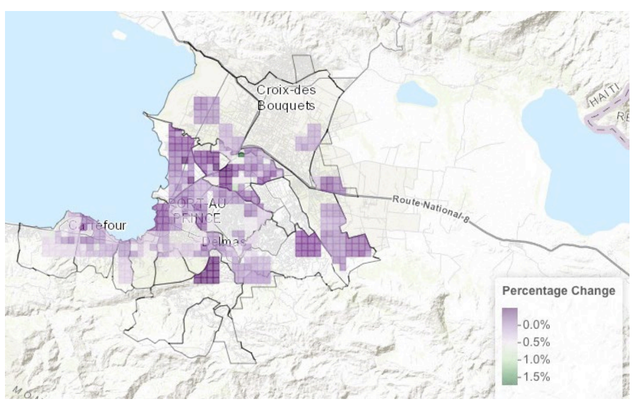
Figure 14. Ranked SAMEPA-based Food Security Score per 555 sqm Area by Quintile (2020)



Source: Authors' calculations based on ENUSAN (2019) and SAMEPA (2020)

Where there is data from both ENUSAN and SAMEPA, Figure 15 shows the mean percentage change in the FCS from when variables were collected in the ENUSAN survey in 2019 to when variables were collected in the SAMEPA survey in 2020. The median and average values of percentage change are 3.7 percent and 5.2 percent, respectively. The data implies that most households have a FCS that has stayed the same or gotten marginally better in the period between 2019 and 2020.

Figure 15. Percentage Change in Food Security Score from 2019 ENUSAN to 2020 SAMEPA



Source: Authors' calculations based on ENUSAN (2019) and SAMEPA (2020)

As for the PCA index, we invert the FCS data such that a higher score implies less food security, i.e. more deprivation. We standardize scores before adding them to the CUVI.

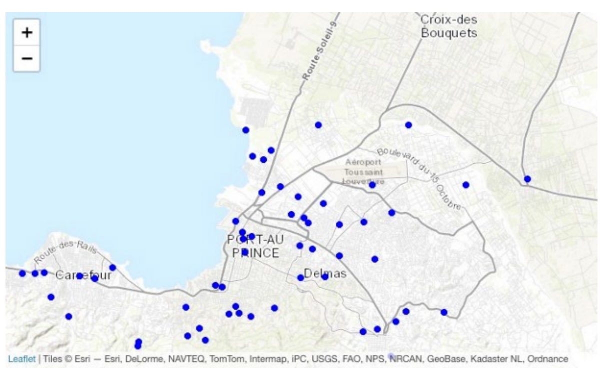
Appendix F. Details on other data sources for PAPMA

Two other household surveys were conducted in PAPMA within the past five years, but both did not provide relevant, additional data to ENUSAN.

The **SAMEPA** (*Sécurité Alimentaire, les Moyens d'Existence et la Production Agricole* or Food Security, Livelihoods and Agricultural Production survey) from 2020 is a phone-based follow up survey of the ENUSAN. It covers a total of about 3,000 households in PAPMA, of which 1,900 could be successfully matched within the relevant communes of the ENUSAN database. It includes many of the same modules and additionally asks households a few questions about their understanding of, and coping with, the COVID-19 pandemic.

The **DHS** (Demographic and Health Surveys) from 2016/2017 covers a total of 2,100 households across the relevant communes. Its questionnaire is more focused on health outcomes. It also includes details on the composition of each household, its education, its assets and access to services. The DHS assigns each household surveyed to a GPS location at the center cluster of households encompassing approximately 30 households within up to a 2 km radius each. The DHS centroid locations are marked in blue in the below figure. The move of coordinates and insufficient coverage made it less useful for this exercise.

Figure 16. DHS cluster-level coordinates



Note: GPS coordinates at the cluster level. For interviewed households to remain anonymous, the cluster-level coordinates were randomly moved by up to 2km from the true location.

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ABSTRACT

Following the 2010 devastating earthquake and subsequent cholera epidemic, Port-au-Prince's residents have been increasingly affected by food insecurity, socio-economic unrest including periods of complete lock-down, and gang violence. In light of the insecurity which limits the possibilities to collect the necessary information to target the vulnerable residents of Port-au-Prince, this paper aims at providing meaningful evidence to inform the remote targeting and delivery of a potential social assistance program. Putting together household and geospatial data, we compute a composite vulnerability indicator for the metropolitan area, offering a first snapshot of inequality and vulnerability within the city, and discuss the results' implications for social protection programming.

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