2.5 Vulnerable Populations

Marion Borderon[1], Antoinette Ludwig[2], and Stéphanie Brazeau[2]
[1]*Department of Geography and Regional Research, University of Vienna, Vienna, Austria;* [2]*Public Health Risk Sciences Division, National Microbiology Laboratory, Public Health Agency of Canada, Saint-Hyacinthe, Canada*

Context

Human vulnerability to diseases is the key measure of the potential impacts of a given change on the well-being of human populations. Human *vulnerability* is most often defined by the complex interaction between the *susceptibility* of an individual, community, or population, their *exposure* to a threat (i.e. the hazard), and their capacity for *resilience* (Turner, 2010). *Exposure* can be expressed by the presence or proximity of and the potential contact between the hazard and susceptible populations (Blaikie *et al.*, 1994; Cutter, 1996). *Susceptibility* can include immune capacity, behavior, or perception of a person or a community facing a threat (Fritzsche *et al.*, 2014). *Coping capacity* constitutes resilience, expressed in a public health context as the human ability to face a threat and develop coping skills to protect or to recover from diseases. These capacities depend on many factors and dynamics (Gallopin, 2006), including socio-demographic and economic factors such as education, age, and income; institutional factors such as prevention messages, access to clinics, and trained medical staff; and technological factors such as access to media and prevention tools and geospatial analysis capabilities (Birkmann, 2006). Sociodemographic data that could help identify the vulnerability of human populations in spatial terms include elements such as: population distribution, density, age, and gender; education and income; and specific public health-related information that often varies from country to country. In some studies of vector-borne diseases that are transmitted human to human (as in the example of malaria given below) the relationships of risk, exposure, susceptibility, and resilience are somewhat changed so that *risk* comprises the mostly entomological component (exposure) as well as the human population components of susceptibility and resilience combined together as *vulnerability* (Haines *et al.*, 2006).

Examples of recent research

Since vulnerability of human populations to vector-borne disease is influenced by complex biophysical, social, and human behavioral factors, the assessment of its spatial and temporal dynamics and associated environmental and anthropogenic patterns requires sophisticated mapping and modeling techniques.

As an example of empirical studies that offer options for mapping vulnerable populations, Cleckner and Allen (2014) demonstrated that a dasymetric mapping technique could be used successfully to map spatial patterns of vulnerable human populations to mosquito vector exposure. They refined vulnerable population data available at the level of census districts to a finer spatial scale by using satellite imagery data, thus narrowing down the areas where relief programs needed to be focused. In the same vein, Gadiaga *et al.* (2021) have developed an integrated housing quality-based typology of the neighborhoods in Dakar, Senegal, by combining the 2013 census data with remotely sensed land cover and land use data at a very high resolution. The derived housing quality indices appear to be relevant proxies of spatial variations of crude mortality rate and could therefore be considered as a guide for public health interventions in cities where accurate and detailed health data remain limited. Van Wesenbeeck *et al.* (2016) linked susceptibility survey data for human populations collected at the household level with agro-ecological data obtained from satellite image analysis at a large spatial scale for regions in East and West Africa. The satellite data analysis aimed at locating areas where ecosystem sensitivity to the effects of climate change was the highest. Bantis *et al.* (2017) mapped the spatio-temporal patterns of disabled people during a major storm event in the UK in 2013. They used the data of automatic transportation fare collection to track the variation in time and space of the human population that was using London's transport network. This information included age categories of people using the network, thus allowing for the determination of movement – or lack thereof – of users more susceptible during emergency situations, such as the elderly, disabled people, and children.

Many empirical studies exist on the relevance of using EO data in characterizing populations and places most vulnerable to health risks (Weng *et al.*, 2014). Recently, Parselia *et al.* (2019) published a scoping review of the use of EO data in epidemiological modeling of malaria, dengue, and West Nile virus. The review shows that EO data are rarely combined with demographic data and, when they are, it is often only to consider population density. However, epidemiological models gain in accuracy if they integrate information on the characteristics of the populations exposed to the entomological threat. It is the vulnerability of these populations to this threat that determines the risk level of a disease outbreak.

Challenges and questions

The spatio-temporal representation of human vulnerability is a challenging task. At a technical level, the challenge is related to appropriately matching spatial detail of the different information sources during risk map integration exercises, as mismatches can cause inaccuracies and sometimes loss of spatial cohesion. At a conceptual level and in terms of data sourcing, the challenge lies in selecting and skillfully utilizing EO data to supplement or refine socio-demographic information that could be provided by census surveys or relevant individual and household surveys. Pertinent questions that address these challenges are:

- To what extent are EO and geospatial data suitable for developing the relationship with physical-environmental features and human factors in addressing vulnerability issues? Which EO and other geospatial data sources can be advantageous for mapping or monitoring conditions, patterns, or dynamics of susceptible population?
- How can one improve the integration of different geospatial data layers extracted from EO or other sources to capture the spatial-temporal variation of human vulnerability?

Responses and options

Below are key comments and suggestions from experts regarding critical geospatial data on vulnerable populations:

- In general, EO can provide baseline information on the location of the population, including identifying rural and urban areas; detailed and up-to-date EO data can provide evidence of hard-to-reach "invisible" populations, such as those that are dislocated and/or migratory.
- EO can provide frequent and detailed data to determine habitable vs. non-habitable areas in disaster situations for a variety of environments.
- Risk and sensitivity maps of communities and populations should incorporate public health-related elements that contextualize census data, EO data in combination with 3D settlement data, and vegetation data (if relevant to the disease).
- Multi-temporal EO analyses and change detection methods should be used.

From *Anopheles* to humans: reconstructing the risk of malaria infection in Dakar, Senegal

In this example, the definitions of risk and vulnerability are those for a human-to-human transmitted vector-borne disease, i.e. risk comprises entomological hazard plus vulnerability as the human population aspects of susceptibility and coping capacity. For malaria infection to occur, three components need to interact: the parasite, the vector, and the human host. The identification of areas where these three components can easily interact is essential in the fight against malaria and the improvement of programs for the prevention and control actions and to guide interventions toward controlling the disease.

Studying the risk of malaria infection in urban spaces requires detailed and high-quality information on the presence of vector-competent mosquitoes, on the individual behaviors of the human hosts, and on the parasites. The provision and utilization of such information comes at a significant cost. In resource-poor countries, researchers and public health practitioners often have limited resources and often inadequate data on prevalence and incidence of the disease, including poor representation of the actual population affected (Programme National de Lutte contre le Paludisme, 2008; Diallo *et al.*, 2012). In addition, relevant geospatial data are limited and often non-existent.

With the development and more widespread application of GIS and satellite imagery, and more diversified sources of ecosystem-related geospatial information ecosystems, it is feasible to extract key environmental variables related to mosquitoes and their breeding sites. The combination of such information with socio-demographic census data or health surveys enables researchers to reconstruct and study the spatial variability of malaria infection risk (Borderon, 2016).

For the city of Dakar, Senegal, multi-temporal satellite imagery, census data, and results from social and health surveys have been integrated into a GIS with the goal of identifying potential exposure of urban neighborhoods and populations to epidemic risk of malaria (Fig. 2.5.1). Epidemic risk has been defined as the combination of two key indicators of malaria infection: the presence of the *Anopheles* spp. vectors, and social vulnerability of individuals or populations regarding the exposure to these vectors. Prevalence data collected during Project ACTUPALU were used to validate the risk model and produce a risk map (Borderon and Oliveau, 2017).

Expected outcomes and impacts

What does this map do? The risk map associates each district of the city with a profile of exposure to the disease, highlighting areas of potential outbreaks. At an urban scale, the mapping results contribute to the identification of areas of social-ecological vulnerability and reveal a possible risk pattern of malaria transmission for different types of sub-urban areas.

This risk model was created from the combination of three indicators:

1. An estimate of the human biting rate (HBR) of mosquitoes.
2. An estimate of the precise population density and dilution effect on biting rates.
3. An estimate of the social vulnerability of the population.

These indicators have been produced and aggregated at the Census District (CD) level according to a conceptual vulnerability and risk framework adapted from Taubenböck *et al.* (2008) (Fig. 2.5.2). The CD represents the smallest administrative unit of approximately 1000 inhabitants within the metropolitan area of Dakar.

The risk concept derives from two parameters: hazard and vulnerability. In the case of this study, the hazard is the HBR (bites/person/night), representing the probability of being bitten by a mosquito vector. The notion of exposure – often implicitly related to the studied hazard – has been added by taking into account the population density: the higher the density, the more the effects of bites are theoretically shared among the population. The combination of these two parameters gives an approximation of the probability of being bitten, all things being equal. However, the probability of individuals or populations being bitten can vary dramatically according to education, resources, or demographic characteristics, among other factors.

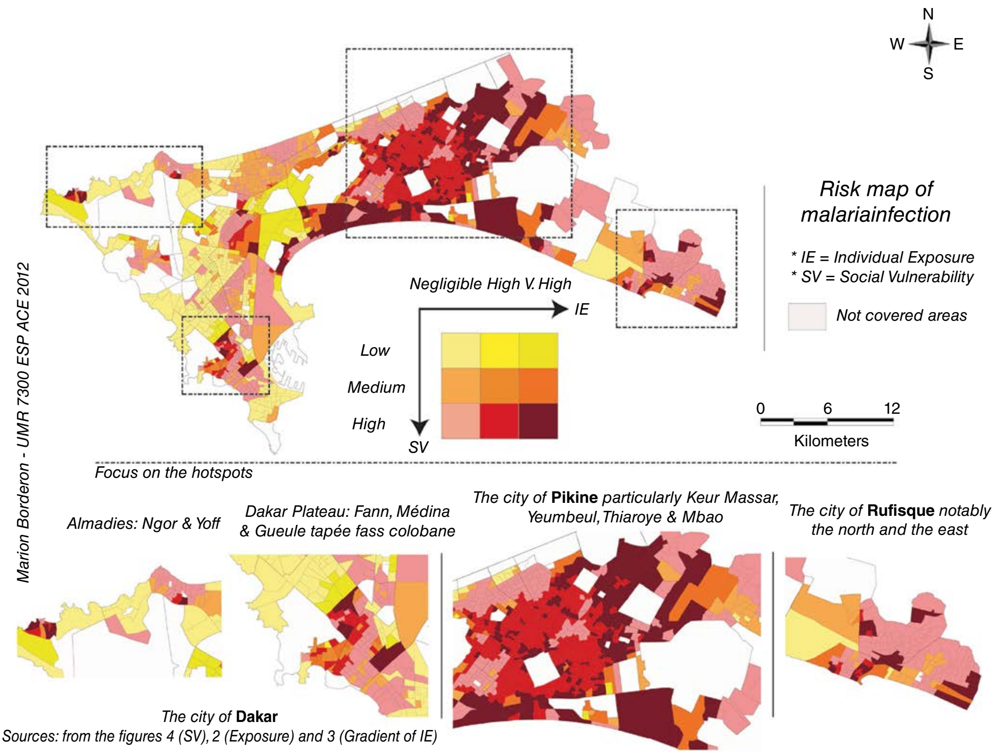

Fig. 2.5.1. Empirical risk model of malaria infection in Grand Dakar, Senegal.

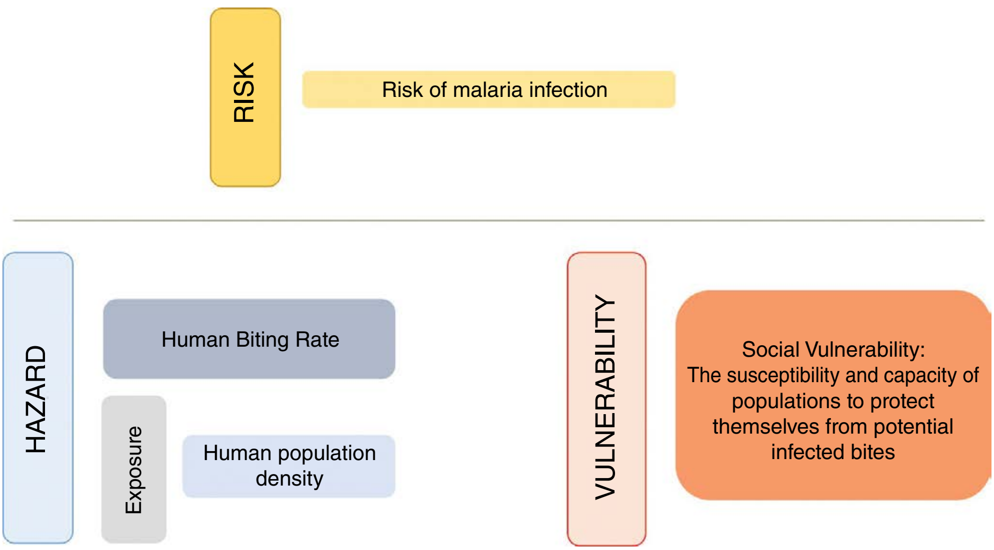

Fig. 2.5.2. Conceptual framework applied to the risk of malaria infection. (From: Taubenböck *et al*., 2008.)

In the multivariate map (Fig. 2.5.1), risk is represented as a linear combination or aggregation of hazard and vulnerability. Nine different combinations of risk have been developed. Individual exposure (IE) to mosquitoes is divided into three categories: negligible, high, and very high. The social vulnerability ranking also entails three categories (low, medium, and high); it assumes that the higher the social vulnerability is, the lower the protection against the bites will be and the lower the likelihood of available health care service will be.

The color intensity scheme of the map points to the potential hotspots of malaria infection, thus identifying areas that deserve special attention during the rainy season, especially if there is little or no medical support for households by institutions or aid programs.

Two weak points deserve to be considered regarding this mapping approach. One involves the selection of thresholds for continuous variables and assumptions on mobility. The scientific literature on malaria infections contains little knowledge on the existence of thresholds whereby the probability of being bitten varies as a function of population density. The thresholds used are thus arbitrary detection thresholds. The second point involves the initial assumption that the hosts are bitten where they live and that the model is static, representing a general situation. This means two things: the mobility of people and periods spent outside the area are not considered, and the effects of seasonal/environmental conditions are not taken into account.

Why use EO data? When working on diseases such as malaria, researchers often face a lack of quality data required for optimal targeting of the intervention and monitoring (Ceccato *et al.*, 2017; Quattrochi *et al.*, 2017). Data from satellite imagery with useful spatial and temporal resolution can help fill the gap and are becoming more readily available. EO data can be particularly helpful for characterizing relevant landscape features or urban environments. Although socio-economic or demographic data are rarely derived directly from EO, they can be combined or extrapolated to produce useful information, such as the malaria infection risk index in the above-mentioned work.

Who are the end users? Ideally, malaria risk maps and their subcomponents – hazard and vulnerability maps – become valuable tools for practitioners and policy makers who wish to obtain useful information on the potential hotspots of risk of malaria infection in urban environments. The information would allow them to identify vulnerable populations and address their needs, identify uneven capacity for preparedness and response, and reduce pre-existing risk. In the context of vector-borne diseases in low- and middle-income countries (LMICs), this knowledge, combined with geospatial information products developed with the help of remotely sensed data and GIS, can enable decision makers to better allocate limited resources in the fight against epidemics. Since vector-borne diseases are linked to climate and environmental conditions as well as human and societal characteristics, the integration of climate data and environmental information combined with socio-demographic data sets becomes an essential task for governmental and intergovernmental institutions with responsibilities for public health.

Technical considerations for producing risk and vulnerability maps

This section highlights the technical considerations necessary for the production of the different subcomponents of the risk map.

What EO data are needed? Assessing the risk of malaria infection requires a combination of data and skills and relies on interdisciplinary studies. Core aspects of the work are illustrated in Fig. 2.5.3. The integrated assessment of risk of malaria infection in Dakar required several sources of quantitative information, as listed in Table 2.5.1. A more detailed description of EO data used for the HBR model is given below. EO data and derived information products are integrated into hazard modeling of HBR estimates and identification and characterization of the human vulnerability to malaria infection.

EO data for estimating the HBR

A tele-epidemiology approach was used to estimate the density of the main mosquito vector of malaria in Dakar, *Anopheles gambiae* sl. The approach involved in the production of the vulnerability map depicted in Fig. 2.5.4 followed three major steps: (i) intensive ground measurements

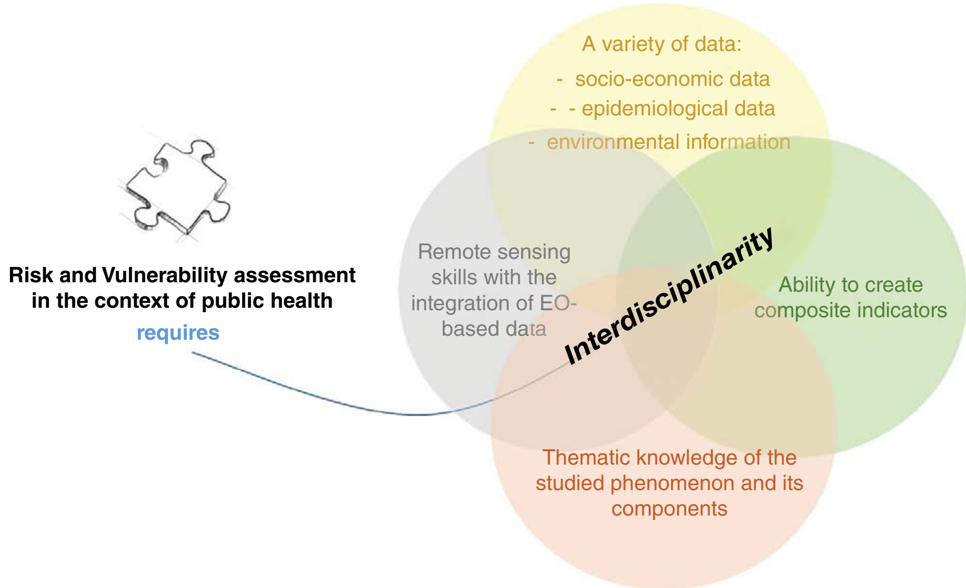

Fig. 2.5.3. The inherent interdisciplinarity of assessing risk and vulnerability.

Table 2.5.1. Preliminary data sources for Dakar metropolitan area and census districts (CDs).

Type	Area coverage	Time frame	Source
Socio-economic and demographic variables	2000 CDs	2002 (published in 2006)	Census ANSD
Predicted HBR	1476 CDs	1994–1997–2008–2010	Laboratoire d'aérologie
Prevalence (data used for risk model validation)	112 CDs	2008	ANR ActuPalu
Multi-temporal land use and land cover analysis	Dakar metropolitan area	1988–2008	Centre de Suivi Ecologique (CSE)

ANR, Agence Nationale de la Recherche; ANSD, Agence Nationale de Statistique et de la Démographie.

(*Anopheles* larval habitats and HBR); (ii) selection of satellite data for mapping and extracting environmental and meteorological information; and (iii) use of statistical models taking into account the spatio-temporal variability of the data.

The models were developed by a team of researchers at the Department of Infectiologie de Terrain de l'Institut de Recherche Biomédicale des Armées (IRBA) in Marseille (Machault *et al.*, 2012).

High-resolution SPOT-5 satellite images of Dakar and surroundings were acquired for the summer rainy season to coincide with the fieldwork during 26 September 2007, 24 September 2008, and 28 September 2009; a dry season image was captured on 11 May 2009. This multi-temporal, atmospherically corrected data set included three spectral bands at 2.5-m spatial resolution (green, red, and near infrared) and one short-wave infrared band at10-m spatial resolution (Machault *et al.*, 2012). A digital elevation model (DEM) at a spatial resolution of 90 m was available from the Shuttle Radar Topography Mission (SRTM 4.1).

In order to characterize the hazard component for a better HBR estimate one needs to consider the net population density in the built-up areas of a city. In Dakar, population densities are often calculated on the basis of CD data. However, since CDs are not completely covered by built-up areas, a more realistic measure can be applied in the form of dasymetric mapping. The principle of

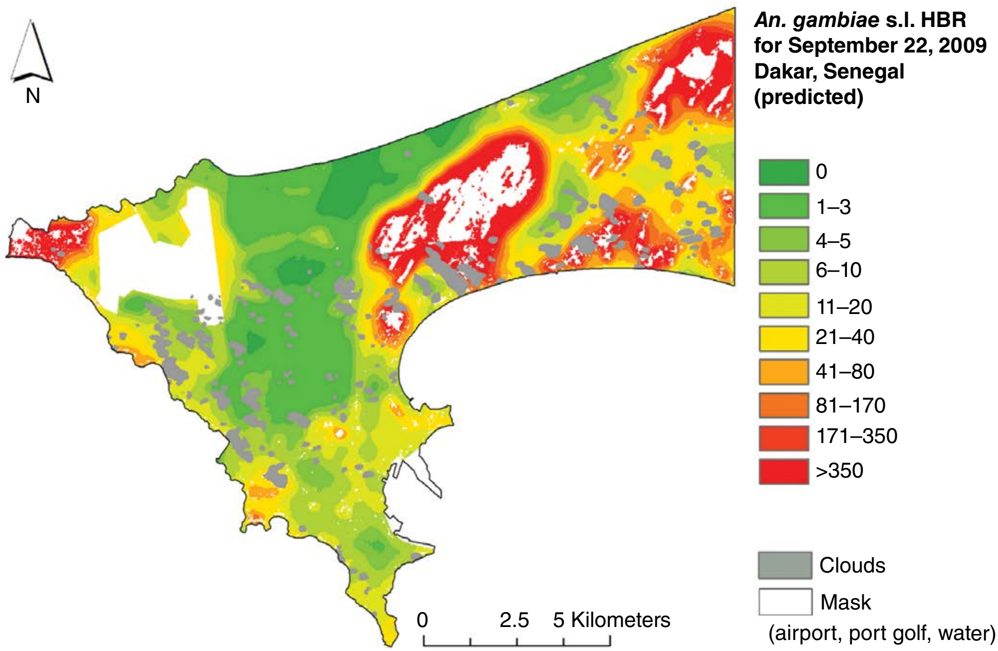

Fig. 2.5.4. Vulnerability of populations in terms of predicted *Anopheles gambiae* sl. number of bites per person per night for 22 September 2009. (From: Machault *et al*., 2012.)

dasymetric mapping is to adjust human population density exclusively to the space where people actually live (Mennis, 2003). Dasymetric mapping recalculates the actual – or net – population density by excluding areas of vegetation, water, bare soil, and roads. Figure 2.5.5 shows the urban net density for Dakar (Borderon *et al*., 2014).

EO data for estimating human vulnerability characteristics: The actual risk map (Fig. 2.5.1) reflects the interaction between hazard and vulnerability of the population. In the context of this study, social vulnerability has generally been defined as the set of characteristics of a group or individuals in terms of their capacity to anticipate, cope with, and resist the impact of natural hazards like malaria infection. Following the Social Vulnerability Index approach,[1] a social vulnerability metric was implemented for mapping in the metropolitan area of Dakar (Borderon, 2016; Fig. 2.5.6).

What resources are needed? Assessing complex environmental and social phenomena associated with the geospatial assessment of malaria infection risk requires the integration of EO data with demographic, socio-economic, and other data. It is recognized that the exposure to hazard alone is insufficient to predict impact, because the populations affected are heterogeneous and vulnerable to impact in different ways (De Sherbinin, 2017). Common issues often identified in the literature with respect to data integration revolve around data quality and scale.

Data availability and the choice of scale: Since vulnerability assessments rely on a variety of data sources, reliable access to these data sets is essential and policies for data sharing embedded in a spatial data infrastructure are required to provide reliable and consistent results. Once the database is built, one of the challenging issues is the choice of a common scale for data integration. This choice should ideally be related to the "scale of action" at which phenomena or features of interest can best be observed, rather than by the scale of available data. For instance, small-scale data sets can be resampled at higher resolution. Fritzsche *et al.* (2014) and OECD (2008) discussed different aggregation methods in detail. Data integration also requires familiarity with the science behind the data sets and their composition. As an example, many remote sensing data analyses involve highly refined methods for measuring and assessing the impact

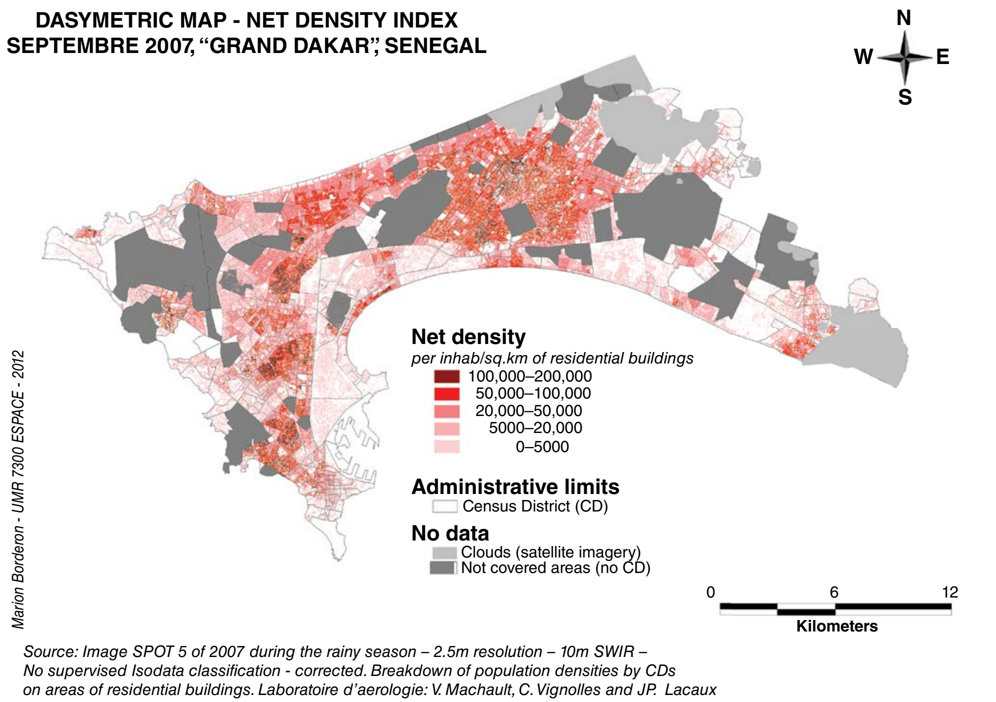

Fig. 2.5.5. The estimation of urban net density in Dakar.

of errors in their measurements through classification accuracies and standard errors, whereas most spatial socio-economic data do not come with corresponding error bars for the estimates contained in them. Hence, characterizing the validity and accuracy of derived products can be challenging (De Sherbinin, 2017).

Data management and analysis: Recently, computer processing, data storage facilities, and access to remotely sensed products have become more ubiquitous and user-friendly. Moderate- and high-resolution satellite imagery is often available free of charge. However, there is still a significant need for assistance in the process of technology transfer. This applies especially for the public health sectors of many countries that seek to employ effective geospatial assets against the threat of malaria with the help of EO data analysis.

Perspectives

What future developments are needed? Integrative vulnerability assessments require some methodological advances. The difficulty of coupling the dynamic disease modeling approaches and their uncertainty to assess population vulnerability is often evident in projects modeling the risk of malaria infection and transmission. More transparency is needed at each stage of the decision process when it comes to combining modeling and visualizing the data. Systematic validation of the produced model is another requirement. In the context of malaria, this could be achieved, in part, by the development of new frameworks for modeling routine malaria surveillance data and by the integration of other malaria-related metrics.

What are the opportunities for EO? EO data, products derived from them, and other geospatial data from available databases and surveys offer several opportunities for the development of risk and vulnerability maps with high spatial and temporal resolution:

- *To better understand the relationship between diseases and the environment and climate.* Satellites provide raw data that are continuously archived and cover large areas

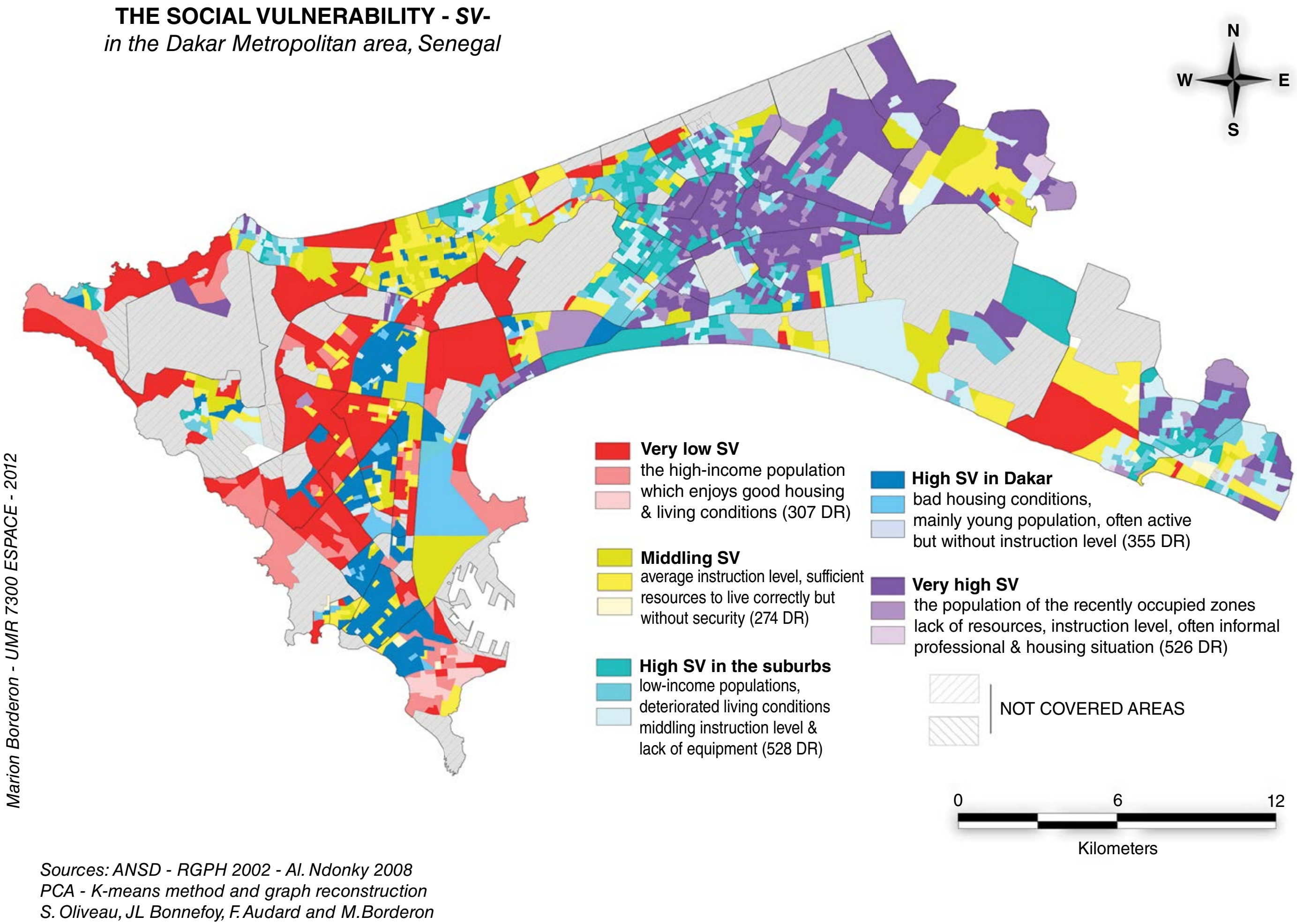

Fig. 2.5.6. The Social Vulnerability Index for Dakar, Senegal.

of the Earth. Sources for satellite-generated climate or environmental data that can help assess the exposure of population to a climate-related disease are varied and some are freely available online. A list of useful sources is included in Quattroci *et al.* (2017).

- *To assess precisely who is at risk and where.* Population data sets from surveys or census data can be combined with EO data to produce dasymetric maps. Dasymetric mapping is a method to disaggregate census data to finer scales by integrating satellite-based data and land cover data; the result provides a more realistic impression about the population distribution than using arbitrary administrative boundaries such as census tracts.
- *To better understand the relationship between diseases and demographic and socio-economic characteristics of the population.* Some programs combine EO data with population census data and surveys to provide high-resolution multi-temporal population maps. These maps offer estimates of population size and distribution as well as other related characteristics for data-limited environments. For instance, the *WorldPop* population mapping program is based on peer-reviewed methodologies and currently provides the spatial demographic data sets of choice for over 100 government agencies in low-income and lower-middle-income countries in Africa and Asia.
- *To help measure the accessibility of health care or the health situation of some marginalized populations* (not present in the classical data sets) or a population in a post-crisis situation where key baseline data are not available. Satellite-based information could help to establish baseline data for population surveys in the absence of household lists or systematic civil registration. EO products can support selection of representative samples of populations in the absence of census-type data on households (Kondo *et al.*, 2014).

Current EO product developments in the public health sector: The integrative assessment of risk and vulnerability in the context of public health has been applied and improved over the past 30 years. Some examples of new products and approaches utilizing EO in the public health sectors of vulnerable countries reflect well on current developments.

Example of bottom-up population mapping from WorldPop

Where census data are outdated or unreliable, *WorldPop* has been collaborating with the Bill and Melinda Gates Foundation and Oak Ridge National Laboratories to develop approaches to estimating population distributions at high spatial resolution through a combination of satellite-derived feature extractions and household surveys. Initial outputs are available on the *WorldPop* website with some outputs already available for Nigeria in their vaccination tracking system.[2]

The *Flowminder Foundation* offers examples of the collection, aggregation, integration, and analysis of anonymous mobile operator, satellite, and household survey data.[3] The following is an extract from the three applications of their work related to public health:

Disaster response	"We pioneered the use of de-identified data from mobile operators to follow population displacement. With this data we support relief agencies in delivering the right supplies to the right people at the right time."
Socio-economic analysis	"Traditional surveys in low- and middle-income countries produce estimates only for large areas. Using new statistical methods, satellite and mobile data we produce estimates of poverty and key social indicators at a resolution of 1km^2."
Precision epidemiology	"Most infectious diseases spread through human movements. We integrate large numbers of data sources, including data from mobile phone operators to model and predict spread of infectious diseases."

Notes

[1] http://artsandsciences.sc.edu/geog/hvri/sovi (accessed 4 January 2022).
[2] https://www.worldpop.org/methods (accessed 4 January 2022).
[3] http://www.flowminder.org/ (accessed 4 January 2022).

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