2 Earth Observation and Public Health Priority: Applications and Research Areas by Theme

This section presents six applications of Earth Observation (EO) to public health issues. There are also two tables in Appendix B that can guide the reader on the classes of resolution used to categorize EO systems and on EO systems and their spatial, spectral, and temporal resolution.

2.1 Mosquito-borne Diseases

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Context, state of knowledge, challenges, and responses

The World Health Organization (WHO) has highlighted identification and monitoring of vector populations as an important component of global vector-borne disease surveillance efforts.[1] (WHO, 2012, 2015) EO data could play a crucial role in identifying risk locations for mosquito-borne diseases globally on the basis of habitat and climate variables. Were EO data to have sufficiently high spatial and temporal resolution, applied research could develop weather-based and environment-based forecasting of high-risk locations and time periods for mosquito-borne diseases using statistical models. Furthermore, EO data may contribute to monitoring the evolution of risk. EO data are also useful for measuring or mapping a range of environmental parameters that help determine mosquito vector occurrence and abundance and the rate of development of mosquito-borne parasites and pathogens in mosquito vectors. These parameters include rainfall, extent of standing water, temperature, and land use and land cover.

Examples of recent research

For more than two decades, extensive research has been conducted into the use of EO data as a tool to inform responses to mosquito-borne diseases (Hay *et al.*, 1998a; Kalluri *et al.*, 2007; Kotchi *et al.*, 2019). Main objectives include identifying risk areas at various spatial scales (Rogers *et al.*, 2002), identifying seasonality in risk in different locations (Hay *et al.*, 1998b), and forecasting impending outbreaks or peaks in disease risk (Ceccato *et al.*, 2005). EO data have been used in a number of ways for these purposes. In its simplest form, EO data analysis for identifying different habitats can consist of classifying imagery into relevant landscape classes. In a case study on dengue, Machault *et al.* (2014) developed dynamic risk maps at the housing level on a daily basis for the vector mosquito *Aedes aegypti* in the French Antilles. The study identified EO data with very high spatial resolution of 0.5 m as a suitable source to produce land use classes for a spatio-temporal statistical model. Catry *et al.* (2016) fused radar and optical satellite imagery and derived land cover classifications for studying the eco-epidemiology of vector-borne diseases in tropical South America. Their study demonstrated that relevant land cover maps and wetland classifications could be generated on a weekly basis using multi-temporal cloud-penetrating C-band synthetic aperture radar (SAR) Sentinel-1A satellite data in combination with optical Sentinel-2 data and L-band SAR Advanced Land Observing Satellite-1 (ALOS) (Fig. 2.1.1).

In many parts of the world, there is insufficient ground-truthed information to reliably classify EO data as habitat that is either suitable or unsuitable for mosquito-borne disease transmission. Climate and habitat conditions must be suitable year-round for mosquito populations and pathogen transmission cycles to persist. Frequently used EO data processing techniques include ecological niche modeling, principal components analysis or Fourier processing, followed by discriminant analysis; supplemented with human case surveillance data, these techniques can be used to identify habitats that are predictive for mosquito-borne disease transmission (Rogers *et al.*, 2002; Moua *et al.*, 2021).

High levels of morbidity and mortality from mosquito-borne diseases, such as malaria, are often associated with areas where transmission of mosquito-borne diseases is unstable. This includes specific transition zones between regions where the pathogens are endemic and where environmental conditions preclude their transmission (Ewing *et al.*, 2021). The underlying reason is mostly immunological: people in transition zones are less likely to have been infected and to be immune to new infections. In researching these transition zones, EO data sets can be useful in several ways. First, they have sufficient resolution to identify these transition areas (Bejon *et al.*, 2010). Second, EO data can identify land management practices, such as irrigation, that render conditions suitable for mosquito-borne disease transmission in landscapes otherwise hostile to the vectors or transmission (Baeza *et al.*, 2013). Third, detailed EO data can identify urban environments where disease transmission may be very different from transmissions occurring in rural areas (Tatem and Hay, 2004; Ferraguti *et al.*, 2021).

While much of this research has taken place in an academic setting, there are increasing

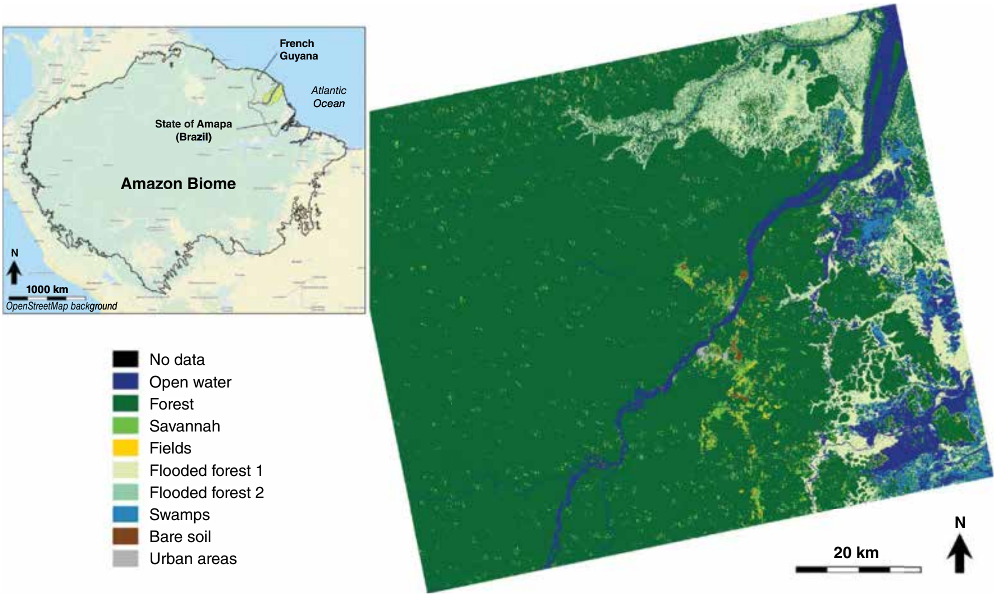

Fig. 2.1.1. Example of a land cover map based on the analysis of multi-sensor satellite imagery for classifying wetland areas in a densely forested area at the border between French Guiana and Brazil, South America. Cloud-penetrating Sentinel-1A C-band SAR data were combined with Sentinel-2 optical data (both at 10 m resolution) to produce a general land cover map. A combination of C-band and ALOS L-band SAR data was then analyzed to discriminate and map wetlands, especially flooded vegetation areas. (From: Catry *et al*., 2016, 2018b.)

efforts to transfer knowledge gained and to implement successful EO utilization in operational mosquito-borne disease programs. An example is the MALAREO project, which has developed and implemented EO-based capabilities for national malaria control programs in the southern portion of Africa. High-resolution land cover and wetland maps were produced and integrated in a geographic information system (GIS) to identify potential vector habitats and risk associated with different human activities (Franke *et al*., 2015). The spatial detail of the EO data has an intrinsic value for identifying and classifying habitat because ground-truthed information is rare and inconsistent. Furthermore, repeat coverage can be utilized to detect important changes with regard to habitat, land use, and land cover (Lucas *et al*., 2015). While weather and climate may be among the most intensively measured environmental variables, interpolation of data points is a common practice in mosquito-borne disease suitability mapping. In some circumstances, EO data were found to outperform interpolated weather station data, especially in regions with a low-density network of meteorological stations (Hay and Lennon, 1999).

Recent studies have shown that SAR and optical EO data are strongly complementary in the assessment of the relationships between environment components and mosquito-borne disease transmission (Machault *et al*., 2011; Li *et al*., 2016, 2017). EO by means of radar remote sensing has great potential to assist with the characterization of vegetated wetlands (Catry *et al*., 2018a; see also Fig. 2.1.2). In practical and technical terms, radar capabilities are based in part on a large variety of cloud-penetrating sensors that operate at different wavelengths, polarizations, and temporal and spatial resolutions useful for wetland analyses. Furthermore, data access is facilitated by open data policies, such as those governing the use of the European Copernicus Programme and Sentinel-1 data archives. These aspects are favorable for EO research and applications regarding the epidemiology of mosquito-borne diseases like malaria.

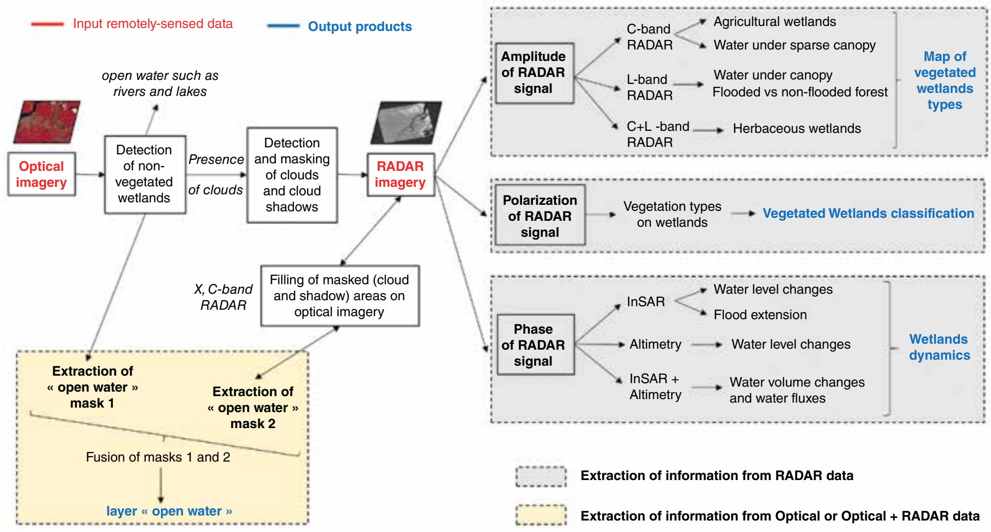

Fig. 2.1.2. Framework of combining optical and SAR remotely sensed data for characterizing and mapping wetlands and accumulations of water. (From: Catry *et al.*, 2018a.)

For instance, *Anopheles* mosquitoes depend, to some degree, on the presence of forested areas and strongly depend on the presence of water for their survival and propagation. However, deforested areas provide favorable conditions for malaria vector breeding and feeding, and forest and secondary forest provide resting sites for adult mosquitoes after feeding (Yasuoka and Levins, 2007; Vittor *et al.*, 2009; Hahn *et al.*, 2014; MacDonald and Mordecai, 2019).

Challenges and questions

The tasks of identifying and quantifying environmental determinants involved in the transmission of mosquito-borne diseases are the main challenges and opportunities for the use of EO data in public health. In addition, researchers need to gain a better understanding of how these determinants relate to socio-economic, socio-demographic, and human behavioral factors. Depending on scope and purpose, assessments of mosquito-borne disease risks require EO data at various levels of detail, ranging from very high to moderate spatial resolution, and at various temporal scales, involving seasonal to daily data acquisition. Many environmental variables can be derived from EO data streams, including temperature, humidity, wind and wind speed, as well as land use and land cover information. For detailed geospatial mosquito habitat assessment, several thematic data sources need to be collated. These can be used to gauge the impact of actual weather conditions, to map land use and land cover, and to relate the information to settlement locations, exposure, built-up area configurations, and behavioral patterns of the local population. On one hand, previous studies have noted insufficient EO data for the composition of coherent time series and the lack of accessible very-high-resolution data or SAR data (Herbreteau *et al.*, 2007; Machault *et al.*, 2011). The high cost for very high spatial resolution satellite data for producing adequate spatial coverage is a barrier for the R&D use of such data and its application in public health programs. On the other hand, researchers and practitioners are faced with mounting data assimilation and processing demands and a dearth of available processing capabilities.

There are several questions and critical issues that need to be answered and resolved, including:

- What EO data sets are most suitable, accessible, and practical for producing risk maps of mosquito-borne disease transmission, i.e. for identifying where mosquito-borne disease transmission can occur?

- What EO data sets are most suitable, accessible, and practical for determining seasonal or weekly changes in risk associated with changes in mosquito density and infection, i.e. for forecasting risk on a weekly to monthly basis associated with rates of mosquito reproduction and mortality and development rates of pathogens in mosquitoes?
- What are the main constraints in terms of obtaining, maintaining, and delivering EO-derived products and services to researchers, public health policy makers, and practitioners involved in mosquito-borne disease control programs?

Responses and options

Below are the comments and suggestions of the experts consulted about critical issues and EO data requirements in the study and analysis of mosquito-borne diseases:

- Objectives requiring timely geospatial information on mosquito habitats can be achieved with EO-based land cover and land use mapping, with a focus on urban and agricultural areas.
- Objectives based on information on mosquito abundance require timely EO-derived information on temperature, humidity, precipitation, and suitable environment, and require mosquito distribution maps at various spatial resolutions.
- In some instances, a combination of optical, thermal, and SAR data may be needed.
- The spatial and temporal resolution of EO data required to develop risk maps for public health needs to match weather and environmental determinants that drive, in part, the transmission of mosquito-borne diseases. There is a need to characterize and identify, at a local scale, areas of high spatial and temporal mosquito density; medium to high spatial resolution is required for identifying mosquito habitat areas.
- There is a need for multi-temporal EO data acquisitions, selection of complementary data sets, skillful application of image processing techniques, and allocation of sufficient financial resources to accomplish the above.

Modeling environment–human–vector interaction hazard using EO data and land cover maps in a local, cross-border setting between French Guiana and Brazil

The prevention and control of mosquito-borne diseases are challenging public health issues. Disease transmission is a multi-scale process, strongly controlled by weather and environmental factors. Remote sensing data analyses are suitable for characterizing spatial and temporal dynamics of such diseases. Yet, despite the growing number of EO data sources and various technical capacities currently available, the selection of suitable EO data for the production of hazard maps and exposure risk maps remains a challenging task. The crucial issue is the selection of adequate EO-derived geospatial time series that fit the temporal and spatial dynamics of the studied disease.

We present here as a case study the research of Li *et al*. (2016), in which the role of land cover classes involved in the life cycle of the malaria vector (*Anopheles darlingi*) in the Amazon region was investigated. SPOT 5 (Satellite pour l'Observation de la Terre 5), optical satellite imagery taken in 2012 at 10 m resolution was used to produce a land cover map from which landscape indicators were derived, including forest fragmentation and density of boundaries between forested and non-forested areas (Fig. 2.1.3).

The study relied on partial knowledge-based modeling of malaria transmission risk for a 500 km^2 area in the Amazon region between French Guiana and Brazil, using a landscape-based approach and review of pertinent literature. A landscape model was obtained by generating land use and land cover (LULC) maps of the area, followed by computing and combining landscape metrics to build a set of normalized landscape-based hazard indices. The quantitative landscape characterization involved defining a spatial window for the metrics computation. The dimension of this window corresponds to a zone where the landscape characteristics are

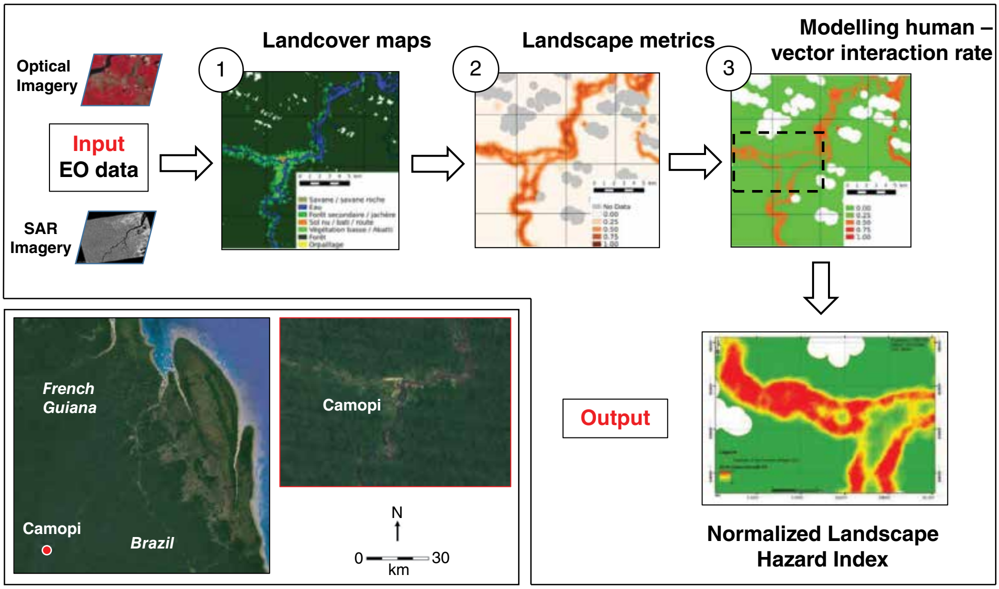

Fig. 2.1.3. Flow chart outlining vector-human interaction hazard mapping in the study of Malaria, with land cover classification derived from optical and SAR EO data for the Camopi area in the border region between French Guiana and Brazil in South America. (From: Li *et al*., 2016).

most likely to influence the chance of encounter between *Anopheles* mosquitoes and human beings. A Normalized Landscape-based Hazard Index (NLHI) was selected in conjunction with the knowledge-based model and connection with incidence of malaria caused by *Plasmodium falciparum* (Li *et al*., 2016).

Analysis results revealed that hazard-free areas (green color on index map in Fig. 2.1.3) around the village of Camopi consist of dense forest areas that are not affected by deforestation and areas where the anthropogenic pressure is high, for example at the confluence of two rivers. Conversely, high hazard areas (yellow and red colors) correspond to the areas where there is a high density of forest edge and where the percentage of forest is higher than in the zones with the highest anthropogenic pressure. Li *et al.* (2016) validated this approach with actual malaria incidence from the cross-border region between French Guiana and Brazil. This study confirms that EO data can be an efficient tool for identifying environmental features related to malaria transmission and that an NLHI of malaria transmission can be developed using satellite imagery.

However, the presence of clouds and cloud shadows in many tropical environments results in missing data on optical images. Likewise, many wetland areas that are obscured from view by vegetation canopies – and hence are not observable by optical remote sensing – can conceivably contain breeding sites for malaria vectors. Alternatively, SAR can be used or combined with optical imagery for extracting environmental information related to vector habitats, as SAR has proven itself capable of penetrating clouds and detecting water bodies reliably. Further research should consider the temporal aspects of deforestation by producing a time series of land cover maps and then studying the evolution of the NLHI associated with malaria in the Amazon region. Institutions in Brazil, such as the National Institute for Space Research (INPE), already produce such deforestation maps derived from satellite imagery under Project PRODES.[2] Li *et al.* (2017) demonstrated that the NLHI calculation can be scaled up from a local scale to a regional scale. The NLHI calculations for the Amazon region currently involve biomass map products[3] of Landsat-based deforestation time series over the Brazilian territory.

Expected outcomes and impacts

This study establishes a malaria hazard index that is driven by spatial knowledge and landscape information using EO data as an important input. The index can be produced on a regular basis in support of malaria prediction, surveillance, and control. The index is calculated using LULC maps as input in the geospatial model; the model output maps serve actors of disease surveillance and vector control (Fig. 2.1.3). These maps identify areas where interactions between malaria vectors and human populations are likely to occur, based on the spatial configuration of landscape features. In essence, the maps provide information on locations where people are more likely to be exposed to mosquitoes and infected by malaria pathogens. This is a key element to take into account when defining and optimizing vector control strategies for public health responses.

The example presented here shows an application of EO data to health issues at a local scale. This approach was subsequently applied at a regional scale (Li *et al.*, 2017) and is currently extended to include the entire Amazon region. Since this region covers more than 6.5 million km^2 and spans nine countries (Bolivia, Brazil, Colombia, Ecuador, France/French Guiana, Guyana, Peru, Suriname, and Venezuela), working at this scale requires the use of EO data in order to produce the required geospatial information and address public health issues. It is extremely difficult to deal with the health problems of different countries when data sources are heterogeneous in terms of content and quality. The example of the cross-border area between French Guiana and Brazil demonstrates that EO data analysis is an effective way to produce homogeneous and standardized information that overcomes this problem. Updates of these maps are possible using multi-temporal EO data – weekly, monthly, or seasonal EO-based updates can be provided depending on the satellite and sensor system selected. In fact, current SAR and optical imagery from the Sentinel Constellations and the European Space Agency's (ESA) Copernicus Programme provide weekly data free of charge at a spatial resolution that is adequate for such large-scale cross-border applications of EO for health issues.

The end users for such maps are actors in the public health domain representing local, regional, and national institutions. More specifically, the primary users of these maps are concerned with the elaboration of vector control strategies and activities in the field. EO data can potentially bridge part of the information gap that confronts health surveillance communities. Yet, going beyond the scope and content of the case studies presented here, the needs of public health actors in terms of various geospatial data and products are not always satisfied for two reasons. First, satellite sensors are not primarily designed for health applications, often rendering spatial, temporal, or spectral data properties inadequate for addressing public health issues. Second, the methodologies for the production of hazard and risk maps developed by researchers of the EO community may not always be suitable or adequate in a public health context due to the complexity of the methodologies, the cost of high-resolution data, and the lack of computing resources.

Technical considerations and perspectives for producing risk maps

The production of LULC maps and hazard maps like those shown in Fig. 2.1.1 and Fig. 2.1.2 requires optical and SAR images at various spatial and temporal resolutions. In this case, environmental variables are extracted from three different sources.

High-resolution EO products with high temporal resolution, including Sentinel-1 and ALOS SAR data and Sentinel-2 optical data, are the primary products needed for the generation of these maps. Data access is free and data acquisition can occur worldwide every 5–12 days. The high-resolution products can be complemented with very-high-resolution imagery, albeit less frequently. For instance, optical sensors of the French Pléiades satellite constellation can acquire images at 50 cm resolution. Although extremely useful for detailed studies of mosquito-borne diseases within urban environments, in an operational context, the cost and volume of such data could prove prohibitive. Commercially available SAR data are also very expensive. Lower resolution images from the advanced very high resolution radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS) or Visible/Infrared Imager Radiometer Suite (VIIRS) sensors are a suitable source for identifying microclimatic indicators related to variables like surface temperature, surface moisture, near-surface air temperature, and water stress; these data are acquired daily and can be accessed without charge.

Frequent updates and cloud presence require the use of a multi-temporal series of optical EO data and the combination of optical and SAR data. This necessitates considerable data storage resources for regular production of land cover and risk maps, and for their use in an operational context. The addition of sensors recently launched (such as the RADARSAT Constellation Mission), or future launches such as the Surface Water Ocean Topography (SWOT) satellite planned for 2022 and the BIOMASS for 2023, will increase the volume of EO data utilization and attendant data storage issues. Future developments in EO big data storage and sharing will also have to take these aspects into account and possibly rely on cloud computing for data storage, processing, and analysis. Following the model currently proposed by "Google Earth Engine," large volumes of data could be remotely processed and analyzed without downloading the data.

Using EO big data implies the development of adapted computing methods such as artificial intelligence and machine learning algorithms. Together with storage capacities, computing resources will have to be customized for such applications. Automated and generic methods are preferred as they would facilitate the production of EO-based products like land cover maps anywhere in the world. Likewise, the analysis of images and the production of the risk maps require image processing software and a GIS capability. Expertise in EO image analysis, geo-informatics, and mapping is essential for the development of risk maps. Availability of freeware and EO and GIS "toolboxes," open access to EO data, as well as training programs strongly encourage the use of EO products by non-specialists, including those in the public health sector. Note that the Copernicus RUS (Research and User Support) service portal, managed by the ESA, offers assistance to users. The portal promotes the uptake of Copernicus data and helps the scaling up of R&D activities with its data. They also offer free access to computing resources, storage, and freeware for processing data and developing technical solutions customized to users' needs, they provide a dedicated helpdesk for assistance, and they organize regular training sessions.[4]

Many new sensors are to be launched in the next few years, offering new possibilities in terms of spatial and temporal resolutions, and technical capabilities. Together with the currently orbiting high- and moderate-resolution sensors, the RADARSAT Constellation Mission and the SWOT and BIOMASS missions, among others, will provide new EO data sources to produce more accurate land cover maps, time series, and quality information for vector control and surveillance. While EO products and methodologies will initially have to be custom designed to better fit public health needs, proven methodologies need to be automated in the future and be robust and user-friendly enough to be implemented by non-specialists. To do so, the remote sensing, entomology, epidemiology, and public health communities have to interact more efficiently. They need to form a community of practice, integrating data from a wide variety of sources at various scales and qualities to help mitigate public health issues such as mosquito-borne diseases.

Risk mapping of entomological Rift Valley fever in Senegal at high spatio-temporal resolution using remote sensing

The emergence and re-emergence of infectious diseases with high epidemic potential, such as Rift Valley fever (RVF), have caused public health actors to adapt their management strategies concerning human and veterinary health. RVF is transmitted by mosquitoes and is naturally maintained by wildlife reservoir hosts. In outbreak situations, transmission cycles among wildlife spill over into livestock. Humans can acquire infections from mosquitoes but also from infected livestock. This adaptation requires the development of new means of risk prediction. In this context, the study of vector-borne infectious diseases requires the knowledge of factors conducive to the emergence and spread of those diseases.

The French space agency Centre national d'études spatiales (CNES) and its partners have applied the conceptual approach of tele-epidemiology to RVF (Fig. 2.1.4). Factors determining the occurrence and spread of pathogens can be environmental, climatic, demographic, socio-economic, and/or behavioral. Some can be identified by EO data analysis, which requires the development of effective methods to use remote sensing for risk factor characterization, mapping, and monitoring. This methodological approach has been successfully applied to RVF in the Ferlo region of Senegal, leading toward the development of a dynamic mapping procedure of Zones Potentially Occupied by Mosquitoes (ZPOMs) (Lacaux *et al.*, 2007). RVF is a viral disease that occurs largely in Africa, causing very serious economic losses in livestock.

The RVF project presented here depends on the cooperation of French and Senegalese institutions, including the Centre de Suivi Ecologique, the Dakar Pasteur Institute, the Direction of Veterinarian Services, Météo-France, and CNES (Lafaye *et al.*, 2013). The project has developed a new decision support tool utilizing SPOT-5 satellite imagery with the objective to improve animal health management and support local users in the public health sector. Funding support was provided by the French Ministry of Ecology.

In the Ferlo region of Senegal, the abundance of the main RVF vectors (*Aedes vexans* and *Culex poicilipes*) is directly linked to the occurrence and extent of surface water ponding, which is closely related to the spatio-temporal variability of rainfall events

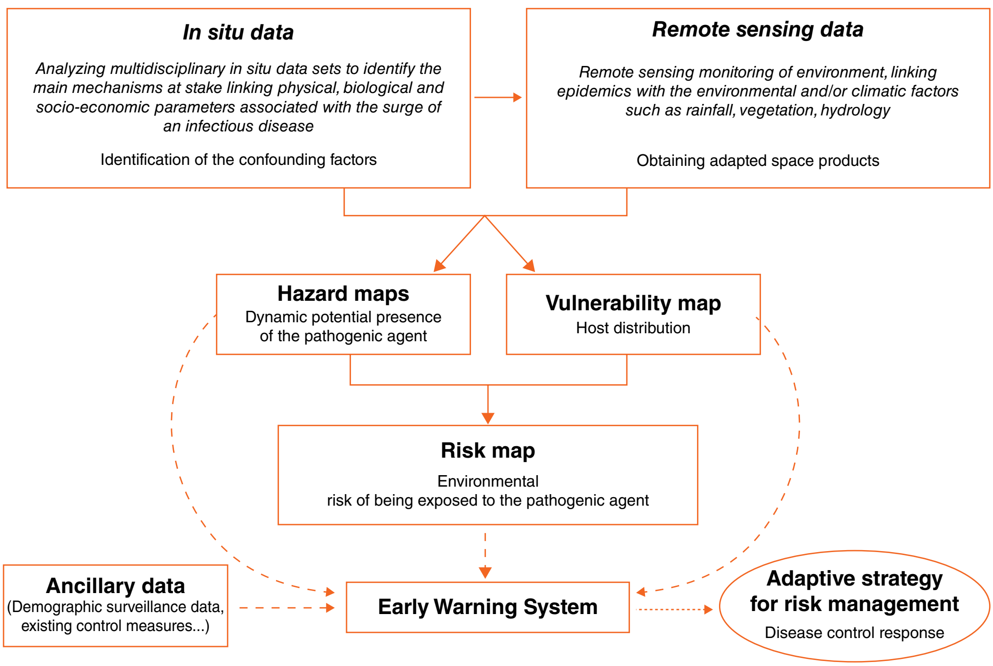

Fig. 2.1.4. The conceptual approach of tele-epidemiology for vector-borne diseases.

(Guilloteau *et al.*, 2014). Hence, rainfall distribution and its spatial heterogeneity is a key parameter for the emergence of the main RVF vectors. The goal of the project was to use GIS tools and EO data to detect ponds as potential breeding sites and evaluate the risk of exposure for cattle to vector bites. A risk model for the emergence of mosquitoes has been developed and validated using field entomological surveillance (Bicout *et al.*, 2003, 2015; Porphyre *et al.* 2005).

Three steps have been necessary to achieve the goal. As a first step, a procedure and index were established for detecting and mapping small and temporary ponds with high-resolution SPOT-5 imagery. Repeat satellite data acquisitions provided synoptic views concerning the dynamics of the approximately 1300 ponds as potential vector breeding sites in the Barkédji area. A Normalized Difference Pond Index (NDPI) was obtained by combining data of the green and short-wave infrared (SWIR) bands.

The second step involved modeling ZPOMs by linking rainfall variability, pond dynamics, and density of aggressive vectors. Spot-5 images and meteorological information from *in situ* data collection or data from five satellite-based rainfall products – Tropical Rainfall Measuring Mission (TRMM), Global Satellite Mapping of Precipitation (GSMaP), African rainfall estimate (RFE), Climate Prediction Center morphing method (CMORPH), and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) – were used to fit a model with hydrological and entomological components. The modeling results consisted of dynamic maps that were generated on a daily basis at a spatial resolution of 10 m to predict the entomological risk for RVF in the Ferlo region of Senegal (Fig. 2.1.5).

The third step consisted of overlaying vector hazard information in the form of the dynamic ZPOMs and host vulnerability information in the form of the location of beef feedlot cattle grazing area to evaluate the environmental risk of cattle exposure to vector bites. Integrating the dynamic model on mosquito proliferation and the position of actual livestock grazing areas into a GIS allowed the Directorate of Veterinary Services of Senegal to issue, on a trial basis, weekly risk zone forecasting bulletins valid for the subsequent 10 days.

Expected outcomes and impacts

The maps generated by this project indicate and outline the RVF risk areas associated with surface water ponding, mosquito breeding, and cattle grazing for a test area in Senegal. EO satellite data offered synoptic views and repeated measurements concerning the location and extent of more than 1300 ponds. The scope and frequency of this undertaking would not have been feasible by means of *in situ* data collection.

The end user of the RVF project products is the Directorate of Veterinary Services of Senegal, who can integrate this information into its adaptation strategy of animal health management. This strategy could include the following recommendations to effectively mitigate the exposure of cattle to RVF, and thus to minimize infection risk for humans:

- (Re-)locate livestock grazing areas away from risk zones, with warning signs in local languages posted near the ponds to inform breeders to keep their animals at least 500 m away from the ponds.
- Issue regular bulletins so the Pasteur Institute of Dakar can organize efficient larval and vector control actions.
- Issue regular bulletins so the Directorate of Veterinary Services of Senegal can organize and optimize vaccination campaigns in the riskiest zones.
- Establish a joint communication strategy by integrating information of the forecasted risk bulletins into the National Information System of Surveillance of Epidemics used by the Ministry of Livestock in Senegal and the Headquarters of the Directorate of Veterinary Services of Senegal and its local representatives in rural districts.
- Plan to broadcast RVF-related messages in local languages through local radio stations.

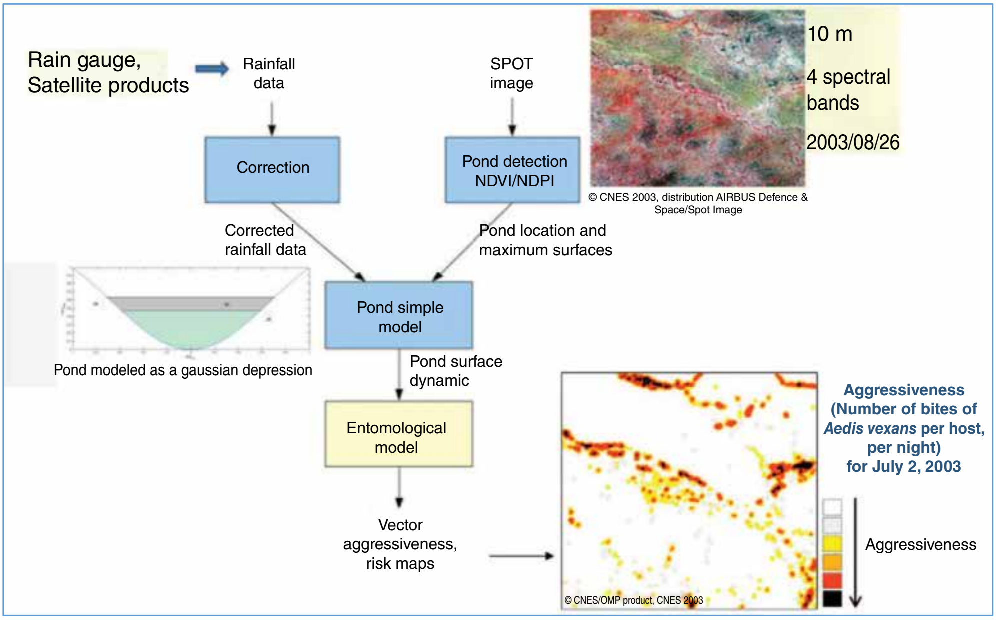

Fig. 2.1.5. Flow chart outlining the RVF entomological risk modeling approach.

Technical considerations and perspectives for producing risk maps

The RVF maps have been built based on a value chain proposition that clearly identifies satellite data sources and data provider, the service provider, and the end user (Table 2.1.1). EO data analysis and the production of the risk map require image processing GIS software packages. Expertise in EO image analysis, geo-informatics, and mapping is essential for the production of risk maps.

In the absence of SPOT-5, which ceased operation, the opportunity exists to access Sentinel-2 satellite data for mapping rain-fed ponds in the manner proposed by the RVF tool. The constellation of the Sentinel-2A and Sentinel-2B satellites could deliver images with adequate spectral, spatial, and temporal resolution required to produce the risk maps at the scale that meets the needs of the user. Future development should consider the implementation of this tool through an open-source software. The following table lists examples of EO-derived products that are potentially useful as geospatial reference or background formation for public health-related studies and applications. While these products have not been devised initially with public health applications in mind, they could provide important resources and insights for the understanding of mosquito-borne disease dynamics (Table 2.1.2).

Notes

[1] http://www.who.int/campaigns/world-health-day/2014/global-brief/en/, see also World Meteorological Organization (WMO) 2014.
[2] http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes (accessed 31 December 2021).
[3] http://mapbiomas.org (accessed 31 December 2021).
[4] https://rus-copernicus.eu/portal/ (accessed 31 December 2021).

Table 2.1.1. The value chain of the RVF project.

Satellites →	Data provider →	Service provider →	End user →	Benefit
		Centre de Suivi Ecologique de Dakar	Directorate of Veterinary services of Senegal	*Better management of animal health*
SPOT-5 ===➤	Optical image By Airbus Defense and Space	Small and temporary pond mapping at 10 m resolution	End user adapts and optimizes their strategy of animal health management	
TRMM ===➤ GPM-core GCOM-W-AMSR2 DSMP-SSMI NOAA-AQUA NOAA-AMSU METOP-AMSU GOES-8 GOES-10 Meteosat-6 Meteosat-7	Satellite rainfall estimates TMPA (TRMM Multi-satellite Precipitation Analysis) by NASA/JAXA GSMap (Global Satellite Mapping of Precipitation) products by JAXA-CREST RFE (African Rainfall Estimation) by NOAA-CPC PERSIANN (Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks) by the CHRS, University of California CMORPH product from the DMSP, NOAA, Aqua, and TRMM satellites by NOAA-CPC **Ground data** Entomological data by the Dakar Pasteur Institute	Dynamic high-resolution maps (10 m spatial resolution, daily temporal resolution) predicting the entomological risk for Rift Valley fever (presence of mosquitoes) Forecasting bulletins of risk zones for cattle exposed to mosquito bites		

AMSU, Advanced Microwave Sounding Unit; AQUA, Aqua Earth-observing satellite mission; CHRS, Center for Hydrometeorology and Remote Sensing (University of California); NOAA CMORPH, Climate Prediction Center morphing method; CPC, Climate Prediction Center; DMSP, NOAA Defense meteorological satellite program; GCOM-W-AMSR2, Global Change Observation Mission – Water "Shizuku" – Advanced Microwave Scanning Radiometer 2; GOES, Geostationary Satellite Server; GPM, global precipitation measurement mission; JAXA, Japan Aerospace Exploration Agency; Metop, meteorological operational satellite; NOAA, National Oceanic and Atmospheric Administration; SPOT 5, Satellite pour l'Observation de la Terre 5; SSMI, special sensor microwave imager; TRMM, tropical rainfall measuring mission.

Table 2.1.2. Examples of EO-derived products that are potentially useful as geospatial reference or background formation for public health-related studies and applications.

Product type	Application in public health
Global land cover maps (e.g., MERIS GlobCover, PALSAR forest vs. non-forest maps, SAR global wetland maps)	For coarse identification of environmental features and habitat suitability to vectors for targeted studies
Vegetation indices (NDVI or EVI from MODIS or AVHRR)	For showing the evolution of vegetation cover (deforestation) and its implications on the distribution of vectors
Soil moisture (SMOS)	For mapping potential breeding sites for some mosquito species

Continued

Table 2.1.2. Continued.

Product type	Application in public health
Continental water quality maps from MODIS	For assessing the suitability of water and wetlands to the development of mosquito larvae (potential breeding sites)
DEMs from SRTM or TandDEM-X	For assessing the role of topography on water circulation and breeding site distributions
Time series of EO products	For assessing the dynamics of the relationships between environmental features and disease transmission
Meteorological sensors	For assessing the role of climate variables on disease transmission
Climate models	For providing scenarios and predicting disease distributions worldwide

AVHRR, advanced very high-resolution radiometer; DEM, Digital Elevation Model; EO, Earth Observation; EVI, Enhanced Vegetation Index; MERIS GlobCover, Medium Resolution Imaging Spectrometer, Global land cover; MODIS, Moderate Resolution Imaging Spectroradiometer; NDVI, Normalized Difference Vegetation Index; PALSAR, Phased Array L-band Synthetic Aperture Radar; SAR, synthetic aperture radar; SMOS, Soil Moisture Ocean Salinity; SRTM, Shuttle Radar Topography Mission; TandDEM-X, TerraSAR-X add-on for Digital Elevation Measurement.

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