CHAPTER 11

Leveraging Earth observation data for surveillance of vector-borne diseases in changing environments

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Abstract

Vector-borne disease transmission is driven by environmental factors determining the distribution and spread of pathogens, vectors and human and animal populations. Earth observation (EO) data, such as satellite and drone imagery, can be used to characterise these factors and identify high risk geographical areas and populations. While the use of EO data to understand vector-borne disease epidemiology has a long history, the rapid expansion of satellite and aerial data, analysis methods and computing power offer new opportunities to integrate EO data into disease surveillance. We review sources and characteristics of EO data and analysis methods, identify commonly used EO-derived metrics for a range of diseases and present case studies on specific applications of EO data for disease surveillance. We additionally describe key considerations for disease control programmes considering the use of EO data, highlighting the applicability of different data types and analysis methods for different ecological contexts and use-cases.

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Keywords

Earth observation – geographical information systems – remote sensing – spatial epidemiology – surveillance

1 Background

Vector-borne diseases (VBDs), such as malaria and dengue, are well-established as highly sensitive to environmental conditions. Local land use practices and meteorological factors directly determine the spatial and temporal distributions of mosquito larval aquatic habitats (Fornace *et al.* 2021, Patz *et al.* 2004, Thomson *et al.* 2006, Vittor *et al.* 2009). Wider climatic changes and disruptions to existing ecosystems can alter the abundance and behaviour of mosquito species and lead to expansion of these vectors into new locations (Caminade *et al.* 2019, Iwamura *et al.* 2020, Jones *et al.* 2008, Metcalf *et al.* 2017). These ecological changes interact with socioeconomic systems in complex and context-specific ways to impact VBD transmission risks (Baeza *et al.* 2017, de Castro *et al.* 2006, Keiser *et al.* 2005).

With unprecedented levels of global environmental change, it is increasingly critical to monitor changing VBD dynamics. Increasing quality and availability of Earth observation (EO) data provides new opportunities to characterise the impacts of environmental change on VBD transmission and develop targeted surveillance methods. EO refers to the collection of physical and biological data on planetary surfaces obtained using remote sensing methods, typically sensors based on satellites or aircraft. These data can be used to monitor factors such as land cover, vegetation levels, water body distribution and extents of human settlements (Finer *et al.* 2018, Lloyd *et al.* 2017, Pekel *et al.* 2016, Wardrop *et al.* 2018, Wimberly *et al.* 2021). Since the launch of the satellite Landsat-1 in 1972, the quantity and quality of satellite-based EO data has grown exponentially (Finer *et al.* 2018). Simultaneously, aerial technologies, such as low-cost drones, are increasingly accessible and are now widely used to collect EO data at user-defined locations (Koh and Wich 2012). This expansion of EO data has been accompanied by technological developments in computing and imagery analysis methods enabling processing and interpretation of these data sources.

The potential utility of EO data for VBD epidemiological studies has been widely recognised since the 1970s (Cline 1970). Motivated by increasing mosquito resistance to insecticides and bans on the widespread use of chemicals such as DDT and outdoor disease transmission, early uses of EO data focused on characterising aquatic mosquito larval habitats to better target control measures. In 1971, the National Aeronautics and Space Administration (NASA) conducted targeted aerial surveys in New Orleans, demonstrating the capacity of multispectral imaging using the visible to near-infrared region of the electromagnetic spectrum to identify mosquito breeding sites (NASA 1973). These techniques were later deployed operationally within other areas of the United States to target the breeding sites of mosquito vectors during an outbreak of St. Louis encephalitis virus (Wagner *et al.* 1979). Subsequent studies illustrated how different types of aerial and space-borne EO data could be used to locate aquatic habitats of mosquito larvae and characterise wider types of land cover associated with abundance of adult mosquitoes and malaria transmission (Bergquist *et al.* 2021, Hay 2000, Hay *et al.* 1998).

Since these early uses of EO data to characterise vector habitats at local scales, there has been a rapid increase in the use of spatial and environmental data for VBD studies. Initiatives such as the Malaria Atlas Project use geo-referenced data and covariates (e.g. precipitation, temperature, vegetation) derived from planetary-level EO data to develop high resolution maps of global vector and VBD distributions (e.g. (Bhatt *et al.* 2013, Sinka *et al.* 2016, Weiss *et al.* 2019)). EO data is also increasingly incorporated into VBD early warning systems, with metrics derived from EO data used to inform predictions of disease outbreaks and trigger VBD control measures (e.g. (Lowe *et al.* 2013, Thomson *et al.* 2006)). These data are also used to plan and inform surveillance activities, such as mapping health facility catchment areas, defining survey populations or identifying high priority areas for vector monitoring (e.g. (Fornace *et al.* 2018, Franke *et al.* 2015, Noor *et al.* 2009, Stresman *et al.* 2014)). At much finer scales, very high resolution EO data has been used to monitor changes in land cover, mosquito breeding sites and human and wildlife disease reservoir distribution to understand the mechanisms driving infectious disease emergence (e.g. (Carrasco-Escobar *et al.* 2019, Fornace *et al.* 2014, Minakawa *et al.* 2005)).

However, despite these advances, only a relatively small proportion of available EO data is actively used for VBD surveillance. There remain significant barriers to integrating EO data into health surveillance systems in many high VBD burden countries; these challenges often include limited access to equipment, computing infrastructure or specialised technical remote sensing expertise within disease control departments. Additionally, with the wide range of types of EO data and analysis methods now available, it can be challenging to identify the best data for specific use cases. Within this chapter, we review available EO data sources, characteristics and analysis methods. We then examine existing applications of EO data to study VBD epidemiology, present examples of how EO data can be leveraged to improve VBD surveillance in changing environments and discuss considerations for the use of EO data, highlighting the need for knowledge of local vector ecology to inform EO data selection and applications.

2 Sources and characteristics of Earth observation data

EO involves the use of sensors to collect data used to measure characteristics of planetary surfaces from reflected or emitted radiation from a distance. Although EO can be conducted using aerial and ground-based platforms, spaceborne satellites

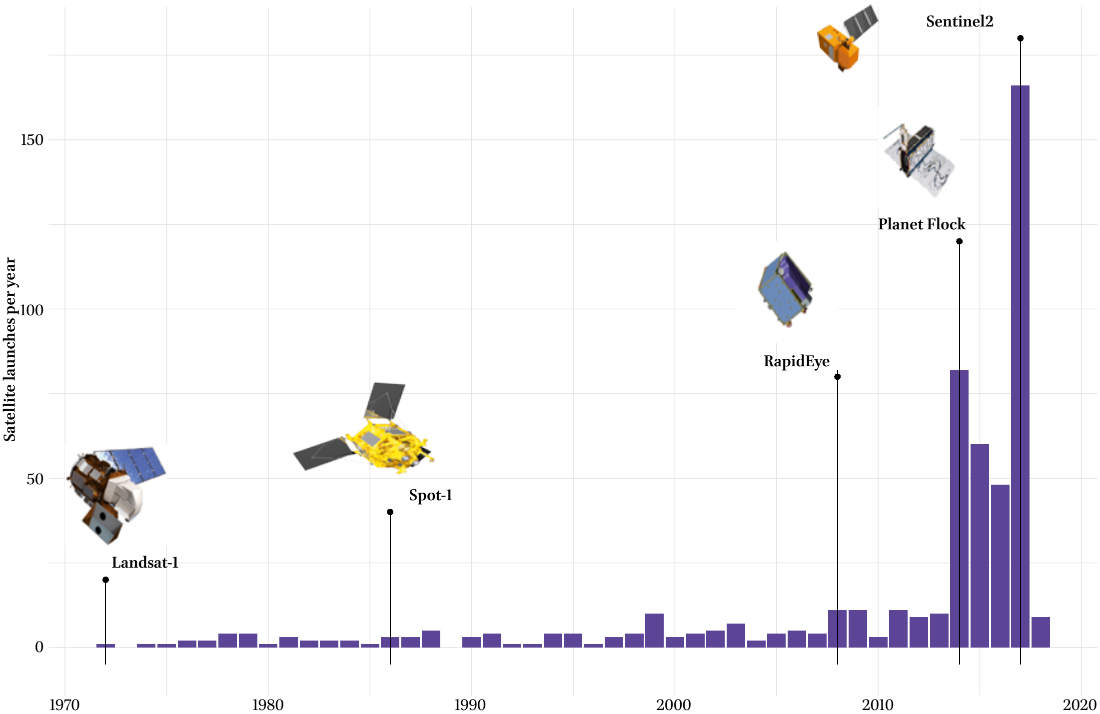

FIGURE 1 Earth Observation satellites launched by year (data obtained from Union of Concerned Scientists 2021)

are by far the largest source of EO data. Since the first launch of the EO satellite Sputnik 1 by the former Soviet Union in 1957, over a thousand EO satellites have been launched (Figure 1), (Tatem *et al.* 2008, Union of Concerned Scientists 2021). These data are available through a range of public and private sources, such as the European Space Agency, NASA and commercial companies such as Maxar Technologies (https://www.maxar.com/) and Planet (https://www.planet.com/). Costs for these data range from freely available to thousands of dollars for specifically tasking commercial satellites to cover target areas. While most free EO data is available through government or intergovernmental agencies, corporate partnerships and outreach programmes have vastly increased access to high resolution EO data. For example, a partnership between Planet and Norway's International Climate and Forests Initiative provides free access to high resolution satellite data for tropical areas for non-profit uses (https://www.planet.com/nicfi/). These data can be further supplemented by local EO data collection using aerial platforms such as drones and other aircraft (e.g. (Carrasco-Escobar *et al.* 2019, Fornace *et al.* 2014, Hardy *et al.* 2017, Wagner *et al.* 1979)).

The characteristics of the EO data collected are determined by the specific type of sensor used for data collection. Passive sensors measure light reflected by the sun while active sensors have their own source of electromagnetic energy and measure the backscatter reflected from this source. While passive sensors include instruments such as cameras, active systems use technologies such as radar and lidar. These systems are characterised by radiometric resolution based on the sensitivity of sensors to measure these differences in reflected or emitted energy. The region of the electromagnetic spectrum covered and the number of bands or channels used to sample this region of the spectrum determines the spectral resolution of a system. This spectral resolution represents the degree of precision to which reflected energy from the Earth's surface is being sampled. For example, low spectral resolution systems (e.g. many cameras carried by low-cost drones) sample the visible part of the spectrum in three bands: blue, green and red. In contrast, more sophisticated systems sample the spectrum from the visible to the near infrared and shortwave infrared over a number of bands (e.g. Landsat TM system with six bands, MODIS with 32 bands) which enables spectral detection of more complex features, such as different habitat types or calculation of vegetation indices (Wimberly *et al.* 2021).

All EO data is additionally characterised by temporal resolution, the frequency at which data are collected, and spatial resolution, the pixel size of data collected. With satellite-based EO data, the temporal resolution is determined by the satellite orbit or specific tasking requests determining the frequency at which a satellite passes over a specific location and collects data. Temporal resolution may be additionally determined by the availability of usable data; critically, for optical satellite-based systems, cloud cover is a major limitation for obtaining usable data over areas within the tropics (Burke *et al.* 2021). These limitations have led to a rapid expansion of other types of platforms used to collect EO data underneath the clouds, such as drones (also known as unmanned aerial vehicles or UAVs). These technologies allow targeted collection of EO data at user defined time intervals. Drones additionally allow collection of data with a much higher spatial resolution than most satellites (e.g. <10 cm/pixel for standard drone data vs >10 m/pixel for most freely available satellite data). These resolutions, as well as the cost and feasibility of using different platforms, impact the suitability of different types of EO data for VBD applications (Figure 2). Due to the difficulties in obtaining cloud-free satellite imagery, increasingly, studies look towards the use of radar imagery resulting from active satellite-based systems operate within the microwave part of the spectrum that is not inhibited by cloud cover. Radar imagery can provide valuable information for vector disease applications, such as wetland mapping, land cover mapping and forest cover. Some sources of radar imagery are free and are routinely collected (e.g. Sentinel-1 with a 12-day return period for the tropics) adding to its value within operational monitoring programs. But, like optical satellite imagery, its spatial resolution is currently limited to 10 m which may be inadequate for many vector disease applications.

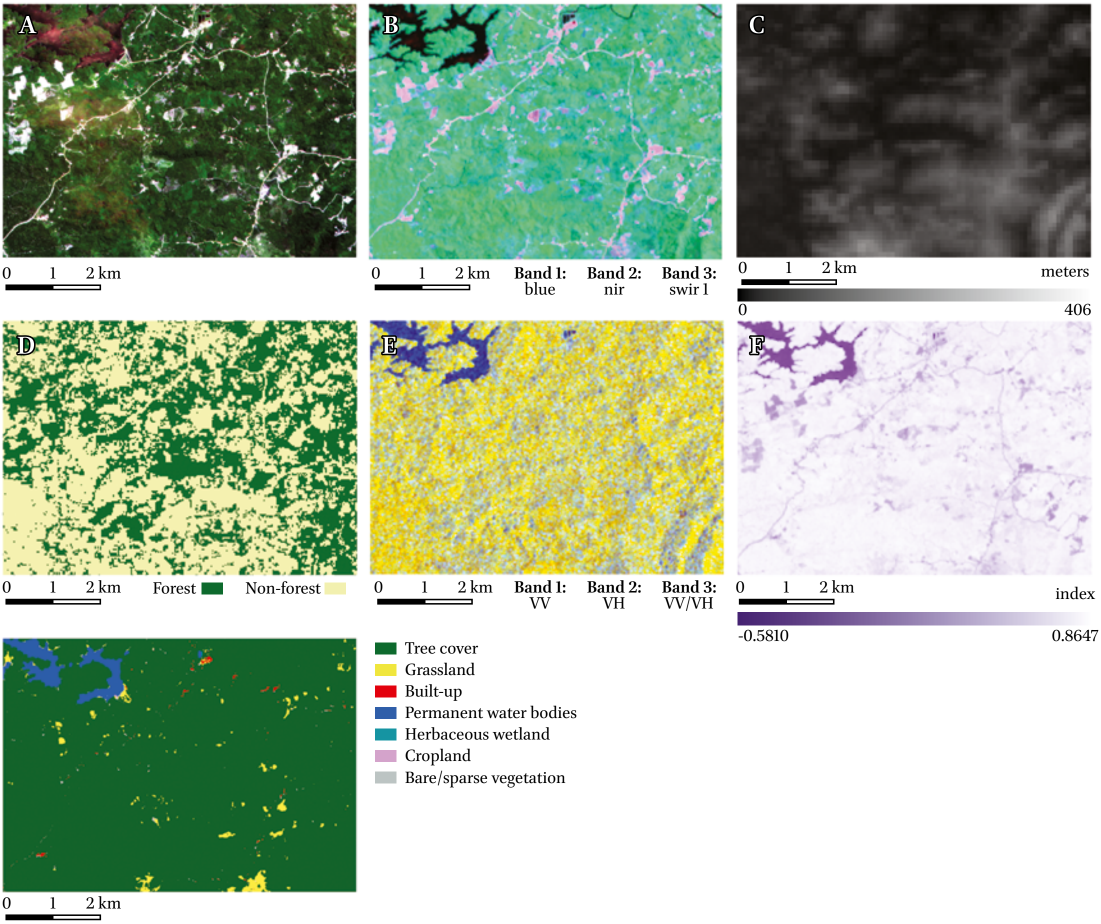

FIGURE 2 Example of sources, spatial resolutions and spectral capacity of Earth Observation data in April 2021 in Sabah, Malaysia (A) PlanetScope Tropical Visual Archive; (B) Landsat 8 (Band 1 = Blue, Band 2 = near infrared (NIR), Band 3 = short wave infrared (SWIR); (C) Elevation (SRTM 1 arc-second); (D) Classified forest cover (0, 1) (Hansen *et al.* 2013); (E) Sentinal-1 radar image (Band 1 = VV, Band 2 = VH, Band 3 = VV/VH composite); (F) Normalised Difference Vegetation Index (NVDI), derived from Landsat 8; (G) Land cover thematic map (WorldCover)

3 Analysing Earth observation data

After acquiring EO data, these data are typically analysed to identify features of interest. For example, these may include specific land classes associated with vector habitats, types of water bodies where vectors breed or locations of houses comprising the target population at risk. EO-derived metrics are often used as covariates in models to identify risk factors or predict risks of vector occurrence or disease risks (Weiss *et al.* 2015). On more operational levels, EO data may inform planning of

VBD surveillance and control measures through identification of high-risk areas or target populations.

The intended end use of the data, the feature(s) of interest and available resources determine the analysis approach used for EO data. Prior to analysis, a number of pre-processing steps are typically conducted to improve the data quality before analysis. This can include radiometric calibration to transform the radiance measured by the sensor to reflectance, the proportion of solar radiation reflected back to the sensor, to adjust for atmospheric effects. Additional pre-processing steps may include masking clouds or unreliable values (i.e. due to a fault in the sensor) and excluding these from further analysis. Orthorectification methods may also be used to adjust for distortions from the terrain and satellite or platform motion.

After pre-processing steps have been completed, the EO data can be analysed using a range of different methods. One of the most frequently used methods is the calculation of spectral indices as a ratio between two or more bands in optical data. Commonly used indices include the normalised vegetation index (NDVI), enhanced vegetation index (EVI) and soil adjusted vegetation index (SAVI), measures of greenness used to assess vegetation (Weiss *et al.* 2015, Wimberly *et al.* 2021). Different band combinations may also be used to create natural colour and false colour composites to visualise EO imagery and aid manual identification of key features of interest.

EO data are also frequently classified into thematic maps to identify key features of interest, such as water bodies or land cover types. These classification approaches can use a wide range of methods spanning simple visual identification to advanced machine learning and artificial intelligence methods. Visualising and manually digitising EO data remains one of the simplest, and often the most accurate and quickest, methods of identifying features in complex images. This requires informed users to detect and label features or classes of interest. Although this can be labour-intensive, increasingly citizen science approaches have been used to engage volunteers in labelling large numbers of images using online platforms such as Zooniverse (Simpson *et al.* 2014). Additionally, digitally assisted technological approaches, such as region growing, allow users to identify features and rapidly label similar surrounding pixels more efficiently (Hardy *et al.* 2022a).

Alternatively, model-based methods can be used to automatically identify features in EO data. These model-based methods can be split into two categories: supervised learning, in which labelled data are used to fit a model of predetermined features of interest, and unsupervised learning, which analyses unlabelled datasets to group features into different categories (Mather and Koch 2010). Supervised learning approaches require labelled training data of the specific classes to be identified; these can include ground-truthed data (such as from field surveys of vector breeding sites) or labelled examples of features of interest. While unsupervised approaches do not require training data, results may be more challenging to interpret and require an operator to match an unsupervised class to an information class of interest.

Traditionally, pixel-based classification is one of the most commonly utilised methods of image classification. This method assigns individual pixels into different class types, typically on the basis of spectral information available for individual pixels. In contrast, object-oriented classification methods classify groups of similar pixels using both pixel-level values and the spatial relationships of pixels to each other (Liu and Fan 2010). Images are typically segmented into groups of similar pixels which are subsequently assigned to specific objects or classes. More recently, deep learning approaches, such as convolutional neural networks (CNN), have revolutionised image analysis. These methods allow efficient analysis of image textures, patterns and spectral characteristics by using artificial intelligence approaches to identify features in complex environments (Cheng *et al.* 2020). Although computationally intensive, more efficient deep-learning architecture and cloud-based computing are increasingly accessible and applied for ecological analysis of EO data, e.g. (Bravo *et al.* 2021, Gray *et al.* 2019, Kattenborn *et al.* 2019). While these approaches can capture complex patterns in the data to improve classification output, these typically require very large training datasets.

4 Existing use of Earth observation-derived data for vector-borne disease surveillance: a scoping review

These different data sources and analysis methods can be used to generate a wide range of environmental covariates to integrate into VBD epidemiological studies. To evaluate the most commonly used EO-derived metrics and data sources, a brief scoping review was conducted using Medline (through PubMed) and Scopus since 2012. We sought studies which used satellite data to describe, analyse or forecast human vector-borne diseases. We restricted the search strategy on the last 10 years but did not restrict the studies to population ages or countries.

Based on identification of relevant VBD, the following search strategy was used: ('Chikungunya' OR 'Lyme Disease' OR 'Plague' OR 'Relapsing Fever' OR 'Rocky Mountain Spotted Fever' OR 'Tularemia' OR 'Typhus' OR 'West Nile Virus' OR 'Zika' OR 'trypanosomiasis' OR 'schistosomiasis' OR 'leishmaniasis' OR 'dengue' OR 'malaria' OR 'vector-borne disease' OR 'mosquito-borne disease' OR 'WNV' OR 'chikungunya' OR 'filariasis' OR 'yellow fever' OR 'Japanese encephalitis' OR 'onchocerciasis' OR 'tungiasis' OR 'crimean-congo haemorrhagic fever' OR 'lyme disease' OR 'spotted fever' OR 'Q fever' OR 'chagas') AND ('Earth observation' OR 'Remote sensing' OR 'Satellite data'). We used EndNote20 and Rayyan to remove duplicates from the search results. Data on the disease focus, EO data source and metrics used were extracted by four reviewers; discrepancies were solved by consensus. A qualitative synthesis was conducted whereby the characteristics of the variables which were used by the satellites.

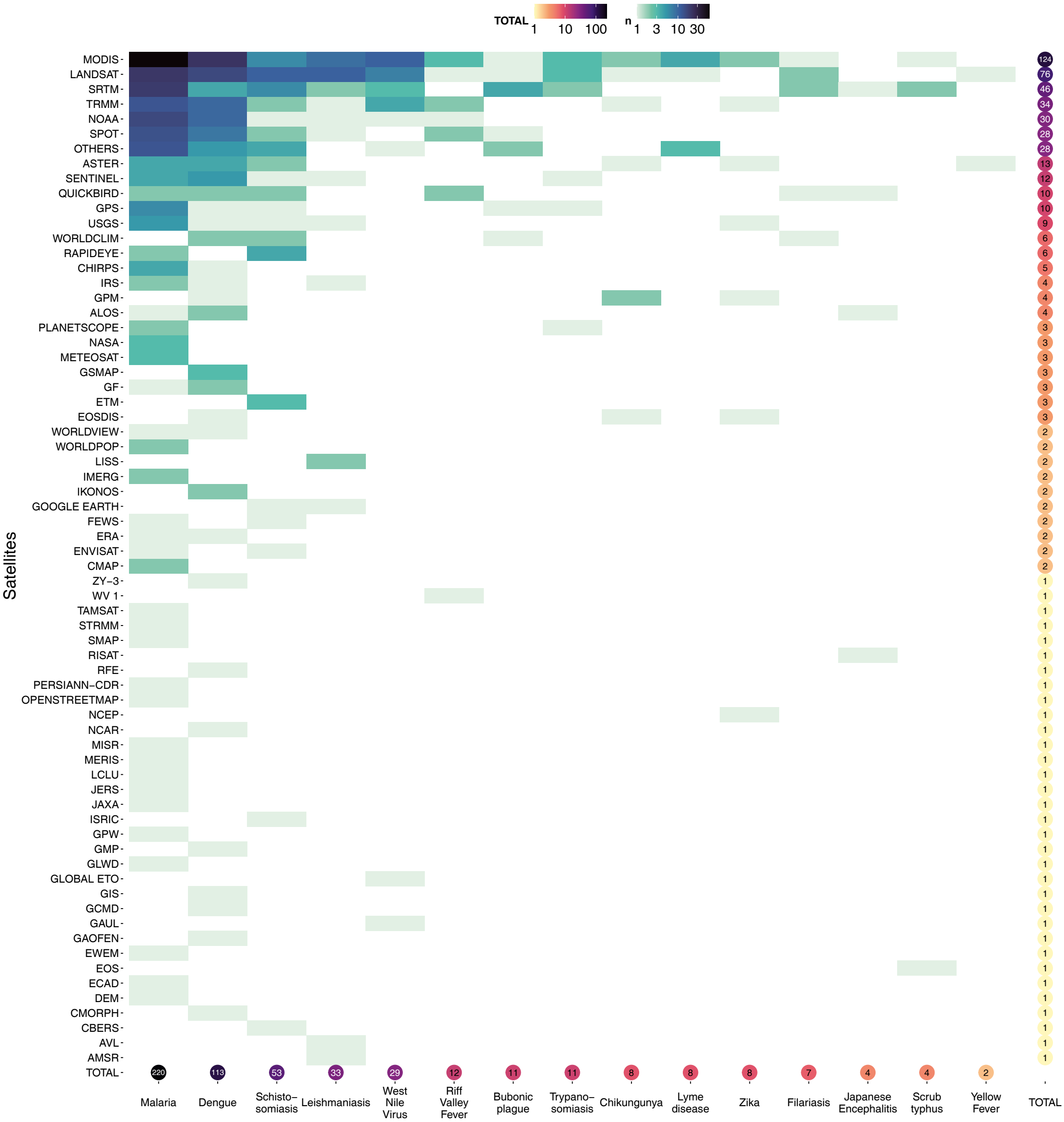

FIGURE 3 Use of sources of Earth observation data by VBD (results from scoping review)

Within this review, there was an initial total of 963 studies identified; out of these, 714 studies were excluded due to duplicates, out of scope or not specifying the vector-borne disease they were studying. From the 249 studies which were included, we extracted the name of the EO source data, type of data used, and the vector-borne disease which were studied. Figure 3 summarizes the number of EO data sources used for each vector-borne disease's studies. The most popular EO data

TABLE 1 Earth observation-derived variables used per vector-borne disease

Variables used	Malaria	Dengue	Schistosomiasis	Leishmaniasis	West Nile Virus	Chikungunya
Normalized difference vegetation index	61	28	23	17	10	6
Precipitation	54	35	7	7	9	6
Land surface temperature	53	26	13	7	9	4
Land cover	32	28	6	8	4	
Altitude	42	7	11	4	4	1
Temperature	22	21	5	4	4	3
Soil-related information	21	4	7	5	2	2
Water-related information	19	6	13	3	2	
Total	304	155	85	55	44	22

sources are the Moderate-Resolution Imaging Spectroradiometer (MODIS) and the Landsat satellite, possibly due to the open data repositories and long-term existence, respectively. In terms of mosquito-borne diseases, the use of these EO data sources is predominantly reported for malaria, dengue, leishmaniasis, and West Nile virus. However, a substantial number of studies using MODIS, Landsat, and the Shuttle Radar Topography Mission (SRTM) sources assessed infectious diseases transmitted by other arthropod and non-arthropod vectors such as freshwater snails (schistosomiasis), fleas (bubonic plague), triatomine bugs, and flies (trypanosomiasis).

The distribution and epidemiology of all vectors transmitting these diseases depend on their interactions with the environment, with varying characteristics important for the ecology of different vectors. Table 1 describes the most common EO-derived variables used for each vector-borne disease. Normalized Difference Vegetation Index (NDVI), precipitation and land surface temperature are the most common types of data used to study the distribution of these diseases, especially for mosquito-borne diseases. In contrast, other variables are more frequently used for non-mosquito-borne diseases; for example, hydrological variables are most frequently reported for studies on schistosomiasis due to the habitats of the snail vector. It is important to take into consideration that the use of a specific type of data will depend on the type of vector, reservoirs, transmission mechanism, and the distribution of each disease.

Rift Valley Fever	Zika	Bubonic plague	Lyme disease	Trypano-somiasis	Filariasis	Yellow Fever	Scrub typhus	Japanese Encephalitis	Total
5	4	2	2	3		1	1		163
3	6	2	1	1	1	1	0	0	133
	3		1	2					118
2			2	1	3	1	1		88
3	1	2	0	0	1	1	1	0	78
1	4	2	2	1	1	1			71
6	2	2	1			1		1	54
				1					44
20	20	10	9	9	6	6	3	1	749

5 Applications of Earth observation-derived data for VBD surveillance and control

These studies use EO-derived data for a wide range of applications, from understanding the basic epidemiology and distributions of the vectors to designing early warning systems and surveillance approaches. EO data can be used to describe habitats of vectors or hosts, identify larval breeding sites or target control measures. Within this section, we describe case studies of specific applications of EO data and integration into VBD surveillance and control measures.

5.1 *Spatial distribution of vector species*

One of the primary uses of EO-derived data in VBD epidemiology is the development of maps of distribution of vector species. This spatial distribution of particular vector species has often been used as a proxy for risk of disease exposure (Kraemer *et al.* 2019, Messina *et al.* 2019, Ryan *et al.* 2019), contributing to strategic planning and informed management decisions. Ecological niche models (ENMs, also known as Species Distribution Models), which determine environmental conditions that meet a species' ecological requirements and predict the relative suitability of habitat have been employed in spatial epidemiology to determine environmental conditions associated with disease occurrence (Peterson 2014,

FIGURE 4 Example drone imagery in VBD surveillance, detecting (A) goats in Kenya; (B) human settlements in Zanzibar; (C) vector breeding sites in Peru; (D) landscape modification in Malaysia

Phillips *et al.* 2006). These models can be also used to predict the range of vectors, usually merging ground-based observations (e.g. from surveillance records) and potential environmental predictors. For example, in Ecuador, the distribution of *Ae. aegypti* was projected to the year 2050 under a variety of models of climate change, predicting shifts in the mosquito range and reinforcing surveillance on human populations that may be at risk of exposure to diseases vectored by *Aedes* (Lippi *et al.* 2019). Species distribution models have been also used to optimise a tsetse fly eradication campaign in Senegal, allowing more efficient control operations for the deployment of insecticide-treated targets and release of sterile males in the fight against human and animal trypanosomiasis (Dicko *et al.* 2014). Pareyn *et al.* (2021) identified that suitable habitats for *Phlebotomus pedifer*, vector of cutaneous leishmaniasis in Ethiopia, are more extensive than thought and that the main environmental drivers of their distribution were mean annual temperature, precipitation seasonality and Enhanced Vegetation Index, among others (Pareyn *et al.* 2020). In seven predominant *Culex* mosquito species in the Americas, temperature, humidity, urban/built-up land class, and cultivated and managed vegetation were important environmental drivers structuring the spatial distribution of these species (Gorris *et al.* 2021).

On finer spatial scales, monitoring changes in landscape can be used to identify changes to vector habitats and design targeted entomological surveillance. A study in Sabah, Malaysia and Palawan in the Philippines demonstrated the use of UAVs to map environmental risk factors for transmission of the zoonotic malaria *Plasmodium knowlesi* (Fornace *et al.* 2014). Due to the difficulty obtained cloud-free satellite data, a UAV was used to provide data with higher spatial and temporal resolution. Consolidated and adaptive mapping of an area over a set time period (December 2013 to May 2014) also allows for repeat sampling of areas seen to be undergoing rapid land use change, which generates datasets of land cover that are accurate for the desired timeframes. This ability to adapt and map study areas in real-time and produce maps with high temporal and spatial granularity is an essential tool for understanding the dynamic interactions between environmental factors, vector ecology and local transmission patterns (Figure 4). Resulting maps can then be used to systematically characterise land use types over the study area and create accurate spatial sampling frames for entomological surveys in areas undergoing rapid deforestation (Byrne *et al.* 2021a).

5.2 *Surveillance of invasive mosquito species*

The use of EO might be particularly useful to identify pathways for vector introduction from abroad and to support strong surveillance systems and effective interventions (Caminade *et al.* 2012). *Anopheles stephensi*, an endemic malaria vector in Asia, has been detected in Africa, particularly in the Horn of Africa – Djibouti (Faulde *et al.* 2014), Ethiopia (Carter *et al.* 2018), Somalia (World Health Organisation 2019) – and now spread to several regions in the continent (Ahmed *et al.* 2021), raising concerns about the impact on malaria transmission. This mosquito species thrives in clean water containers, abundant in urban landscapes. Because most malaria vector control strategies in Africa target rural environments, the prospect of this malaria vector in urban areas is of great concern for the malaria control and elimination programs (World Health Organisation 2019). Due to the confirmed vector competence in *An. stephensi* Ethiopian and Djibutian populations (Seyfarth *et al.* 2019), its association to malaria outbreaks and increased reported cases in Djibuti (Faulde *et al.* 2014), extended mosquito presence in the dry season (Seyfarth *et al.* 2019) and reduced susceptibility to multiple insecticides classes (Yared *et al.* 2020), WHO considers the spread of *An. stephensi* a major potential threat to malaria control and elimination in Africa and Southern Asia (World Health Organisation 2019). As a result, several measures have been recommended to tackle its invasion and spread. One of the core interventions is to conduct active surveillance for *An. stephensi* aquatic stages in urban and peri-urban areas – in addition to routine surveillance in rural environments. EO data could be extremely advantageous for mapping and monitoring typical breeding sites – water storage containers outside the home, rainwater collections, roof tops, wells or large human-made cisterns – to identify high risk urban areas in which *An. stephensi* will have the best conditions to establish.

The potential for *An. stephensi* invasion across sub-Saharan Africa has been predicted combining occurrence data from 1985–2016 with satellite imagery data sets (Sinka *et al.* 2020). The habitat suitability modelling study, which includes several environmental variables extracted from MODIS (annual mean temperature, Index and Tasselled Cap Wetness, Enhanced Vegetation and land cover classification) ((Deblauwe *et al.* 2016), CHIRPS (seasonal precipitation)), GMIA (Irrigation – Global Map of irrigated areas FAO, United Nations, and International Geosphere and Biosphere Programme (GBP) (human population density and Crop mosaic), projected that the invasion of this mosquito into African urban environments could place an additional 126 million people at malaria risk (Sinka *et al.* 2020). EO data is essential to design effective surveillance systems to monitor areas suitable for *An. stephensi*.

5.3 *Detection of surface-water bodies for effective mosquito larvae control*

For vectors with an aquatic life stage, systematic identification of dynamic hydrological systems can be valuable in identifying breeding sites and inform larval source management. While both satellite and aerial-based EO can be used to identify breeding sites, an increasing number of studies are using drones due to the high spatial resolution, ability to detect breeding sites within a specified time frame and ownership of these systems by disease control organisations.

In Unguja, Zanzibar Archipelago, a Spatial Intelligence System (SIS) was designed to identify all surface water bodies within malaria transmission hotspots over a wide area, defined using satellite radar and optical EO imagery (Hardy *et al.* 2017). In this study, off-the-shelf DJI Phantom 4 drones, fitted with a standard 4k RGB (Red-Green-Blue) camera, were used to collect detailed imagery of potential breeding sites at a high spatial resolution (0.1 m/pixel). Temporal resolution was determined by the hydrological conditions of the study area with new drone surveys being commissions where rainfall events led to a significant change in surface water extent. Surface water were very varied, including large inundated rice paddies, natural swamps with aquatic vegetation, and small (<2 m in diameter) ponding of water in tyre ruts and paths where soil infiltration rates are low. This complex array of water bodies was mapped using manual digitising assisted using a freely available region growing tool (Hardy *et al.* 2022a). Subsequent information on water body location and extent was uploaded to a smartphone app (Zzapp Malaria: https://www.zzappmalaria.com/) which was used by field operatives to locate and systematically treat potential *Anopheles sp.* breeding sites.

In Cote d'Ivoire, a technical workflow was established to integrate satellite data and drone surveys with mosquito larval sampling to identify large, semi-permanent water bodies that provide potential breeding sites for malaria vector *Anopheles funestus* (*Byrne et al. 2021b*). Using Sentinel-2 high-resolution multispectral satellite imagery, the study area was stratified into four environmental strata according to spectral profiles and derived vegetation indices from satellite data and sampled proportionally to identify semi-permanent water bodies across variable rural landscapes. Red-Green-Blue (RGB) mapping of areas surrounding surface water bodies was conducted using an off-the-shelf DJI Phantom 4 drone. To achieve the required spatial resolution for fine-scale mapping, drones were flown at 150 m altitude, generating a high resolution of 0.04 m/pixel. With the aim to develop a systematic approach and inform deep-learning approaches to EO data classification, this illustrates drone surveys conducted in a spatially representative sampling frame developed in conjunction with freely available satellite datasets.

In Maynas Province, Peru, the use of drone-based imagery has also been demonstrated in identification of *Nyssorhynchus darlingi* aquatic breeding sites in malaria hotspots (Carrasco-Escobar *et al.* 2019). Here, local vector ecology, the hydrological context and research aims determine a different set of requirements. To identify the most productive water bodies in a riverine environment, the study prioritised high-resolution images over a small study area (~1 km) and multispectral imagery. Conventional RGB imagery was captured using a DJI Phantom 4 Pro quadcopter with a DJI 4K RGB flown at an altitude of 100 m to give a spatial resolution of 0.1 m/pixel. In addition, multispectral imagery was collected using a 3DR Solo quadcopter, fitted with a Parrot Sequoia sensor composed of single-band cameras (Green, Red, Red Edge and Near Infrared – NIR). The 3DR Solo was flown at an altitude of 50 m, which gives a ground sampling distance of 0.02 m/pixel. This demonstrates the flexibility and richness of data available with tailored use of UAV technology and specific sensors. The study design itself provided proof-of-concept for using high-resolution imagery from UAV to differentiate the spectral profiles of productive water bodies where *Ny. darlingi* is likely to breed in Amazonian Peru, an innovation which could be applied to integrating larval source management in malaria elimination strategies.

5.4 *Early warning systems and automated mosquito surveillance using Earth observation*

EO data is also widely used to develop predictive models enabling deployment of targeted control measures. In the last decade, the emergence and re-emergence of VBD reinforced the need for an effective early warning, surveillance and control of vectors and preparedness (Weaver 2013). Due to arthropod vectors being especially sensitive to changes in climate, forecasting systems driven by EO data have been useful for predicting disease risk and to guide epidemiological surveillance and decision-making process (Thomson *et al.* 2006, Thomson *et al.* 2008). The publication of guidelines of Malaria Early Warning Systems for Africa by the WHO, offered a valuable framework for integrated approach response strategies and epidemic preparedness (DaSilva *et al.* 2004, Thomson and Connor 2001, World Health Organisation 2001). Social, environmental and epidemiological factors are involved in malaria epidemics prediction and together with weather monitoring and seasonal climate forecasts, can be incorporated in malaria early warning systems (Thomson *et al.* 2006, World Health Organisation 2001). Dengue ecology and its strong relationship with climate variation is another example of how risk prediction studies and modelling approaches could help in the forecast of outbreaks (Colón-González *et al.* 2018, Colon-Gonzalez *et al.* 2021, Lauer *et al.* 2018, Lowe *et al.* 2016, Petrova *et al.* 2019) (see Finch *et al.* Chapter 12 for detailed environmental EO predictors and EWS in VBD).

Other innovative approaches for VBD surveillance using EO, automated sensors and algorithms/machine learning are still underway. For instance, VECTRACK (https://vectrack.avia-gis.com/) is an Earth Observation service for preventive control of insect disease vectors. This project seeks to generate an automated surveillance system combining an Earth Observation (EO) Sentinel service and satellite data with a network of ground optoelectronic sensors and traps to enable fully remote and automated counting and classification of the target mosquitoes (McEntaggart *et al.* 2020). This combined data will then feed into spatial models, and along with data on meteorological and environmental conditions, this can be used to generate large-scale risk maps. The use of this approach might help to significantly reduce costs and time of monitoring and surveillance and allows for more rapid intervention; however, this has yet to be fully evaluated.

5.5 *Use of Earth observation data to map animal reservoirs and human populations at risk*

The use of EO data in ecological or conservation studies is already well established; for example, in aerial surveys of large wild mammals over sparse areas (Koh and Wich 2012). However, in the study of vector-borne diseases with sylvatic life cycles in wildlife reservoirs, ecology intersects with public health and EO data of human and animal hosts can also provide critical information on transmission cycles and potential distribution of disease.

Yellow Fever (YF) is a zoonotic disease endemic in neotropical forests, transmitted by *Haemagogus* spp. mosquito vectors and with reservoirs of Yellow Fever Virus (YFV) circulating in non-human primate hosts. In Brazil, satellite-derived EO data has been used to estimate the distribution of the primate host species *Alouatta caraya* and *A. guariba clamitans*, which is then built into ecological niche models using maximum entropy modelling (Maxent) to identify geographic areas at risk of sylvatic outbreaks and human populations at risk (de Almeida *et al.* 2019). Explanatory variables include topography derived from the SRTM (Jarvis *et al.* 2022) and climatic variables derived from WorldClim (e.g. rainfall, temperature, solar radiation, water vapor pressure, wind speed), which uses meteorological station data validated by MODIS-derived satellite data (Fick and Hijmans 2017) at 1 km resolution. Here, use of satellite EO data to predict the distribution of reservoir species provides a valuable tool in building spatial risk models to inform public health interventions.

EO data has also be used to provide detailed estimations of human populations for VBD surveillance and management (Tatem *et al.* 2012). Sub-national metrics for population density are vital to mitigate VBD, with population denominator data required to define infection rates, allocate resources and measure the impact of interventions. However, accurate population data can be lacking in resource-poor settings. In addition, non-uniform distributions of people within administrative boundaries can lead to miscalculations. Recent computational approaches have been used to map population density as a continuous surface, using available survey/census data and drawing on high-resolution satellite-derived remote sensing variables (e.g. topography, elevation, mean reflectance in specific bands, vegetation indices) to create a gridded population distribution (Qiu *et al.* 2022). Advances in high-quality and high-resolution (<10 m) satellite imagery has further improved global estimates, allowing human-built structures to be identified, counted and incorporated into models to generate spatially disaggregated estimates of human population distribution at resolutions of 90 m (Lloyd *et al.* 2017, Wardrop *et al.* 2018). In geographic areas that are at risk of VBD transmission but lack the infrastructure for updated or fine-scale demographic information, WorldPop population distribution surfaces can be vital in ensuring accurate risk mapping and targeted interventions.

At more localised spatial scales, UAVs can be used to map animal reservoirs of VBDs. Rift Valley Fever (RVF) is a viral zoonotic disease of wild ungulates in sub-Saharan Africa, that can be transmitted to humans through infective fluids or through bites from mosquito vectors. In Kenya, the commercially available senseFly eBee drone was used to identify the density and distribution of livestock and wildlife hosts of RVF (https://www.zooniverse.org/projects/rfv-drones/rift-valley-fever-drones). The UAV was fitted with the senseFly S.O.D.A sensor, a drone-specific photogrammetry camera that can capture sharp images and 3D digital surface models. From this, orthomosaic images were produced with a resolution of 0.03 m/pixel. This study required high resolution imagery across large study areas, with a view to identifying goats, camels and cattle and managing the disease reservoir. Imagery of this kind can be used to train machine learning algorithms to track and identify key mammal species in sparse landscapes that are integral to disease transmission cycles.

In Kinabatangan, Malaysia, a study aimed to identify and count the roosting sites of non-human primates (Jumail *et al.* 2021). Non-human primates are a reservoir for *Plasmodium knowlesi*, the aetiological agent of zoonotic malaria across Southeast Asia and most notably in East Malaysia. Unlike the broad swathes of savannah imaged in the previous example, this study looked at fine-scale 1 km transects of riverine forest. To obtain the required data, teams used a custom built hexacopter drone fitted with a FLiR Thermal Camera. Thermal images could then be used for visual identification of monkeys and counting of roosts across the transects. This is an example of the adaptability and user customisation possible with UAV technology, with equipment and sensors selected and modified to meet the requirements of both the ecological context and research aims.

6 Considerations for use of Earth observation data for VBD surveillance

Although these examples highlight how EO data can contribute to VBD surveillance, EO data remains underutilised in many VBD-endemic countries. While many sources of EO data are now freely available, one of the primary barriers to uptake remains technical expertise on remote sensing within disease control departments. This can be further challenged by the wide array of data sources and analysis platforms currently available. Decisions on EO data sources and analysis methods should be guided by local knowledge of vector ecology and the control strategies to be deployed. Factors to be considered include the following.

6.1 *Area of interest*

The geographical location and extent of the target area of interest will have determine the applicability of different data types. For example, fine-scale mapping may use targeted drone surveys while more extensive risk-mapping at larger spatial scales requires satellite-based EO data. Additionally, specific countries or regions may have targeted satellite or aerial EO data collection, such as through satellites run through national mapping services. The location also determines the feasibility of using different data sources; optical satellite data coverage may be limited in tropical forested areas with high cloud cover and drones may not be feasible in cities or areas with military activities.

6.2 *Mapping objectives*

The choice of EO data and analysis methods are also highly dependent on the objective of the mapping exercise and the corresponding features to be detected. For many risk mapping exercises, this may consist of a list of potential environmental covariates associated with a particular vector or VBD distribution. In other cases, the objective may be to detect specific vector breeding sites to deploy larval source control measures or to locate houses to plan a survey. In all cases, the specific features to be detected, and the characteristics of these features, should be identified. This may also consider specific types of EO data frequently used to detect these features, e.g. LIDAR data to measure canopy structure or optical data including NIR to calculate NDVI as a measure of greenness.

6.3 *Spatial and temporal resolution*

The spatial and temporal resolutions of these features should inform the selection of EO data with corresponding resolutions. For example, *An. funestus* typically breeds in large, semi-permanent water bodies which can be detected by coarser satellite-based EO data collected at irregular intervals. Other studies aiming to map the distribution of short-lived temporary water bodies, such as the breeding sites for *An. arabiensis*, or movements of disease hosts would be required to identify EO data with higher temporal resolutions to capture these dynamic features. Similar factors should be considered when mapping changing environments such as actively deforested areas. This should identify the temporal and spatial resolutions needed to capture these changes. Conversely, much coarser data may be required for large-scale mapping to capture broad environmental trends. Studies should consider the minimum resolutions of EO data required and trade-offs between computational requirements and higher resolution data.

6.4 *Cost and logistics*

Despite many sources of EO data being freely available, all mapping exercises require resources, such as personnel time, expertise, computing infrastructure or equipment purchase. These costs may increase when specialised equipment or data is required. For example, this may include the purchase of drones and sensors or tasking commercial satellites to cover specific areas. For studies requiring field activities, such as drone mapping or collection of ground-truthing data, these will require resources to support field staff, local transport and other consumables. Additionally, these studies typically require advanced permissions to collect samples, personnel data or to conduct drone mapping. This will often require permissions from Civil Aviation Authorities or other mapping agencies as well as local community acceptance and consent (Hardy *et al.* 2022b).

6.5 *Availability of training data*

One of the main determinants of analysis methods to be used is the availability of training data used to fit supervised models (such as machine learning and Artificial Intelligence approaches). The types and characteristics of training data needed are highly dependent on the target features to be identified. For example, algorithms designed to detect breeding sites of specific vector species are largely dependent on data from ground-based entomological surveys. Studies aiming to identify wider habitat types (e.g. forests or large water bodies) may be able to generate training data remotely by labeling high resolution imagery using GIS or specialised software tools. For specific applications, additional labelled training datasets may be available through online repositories (e.g. labelled agricultural data through Radiant Earth, https://www.radiant.earth/). The amount of training data required is dependent on the complexity of the feature to be identified as well as the type of algorithm used and may be a limiting factor in choosing specific algorithm types. However, there are example studies where training data has been generated automatically for machine learning models applied to satellite EO data providing an end-to-end automated mapping system, although such approaches have not yet been applied to drone-EO data (Hardy *et al.* 2019).

6.6 *Technical expertise and computing infrastructure*

Decisions on the types of EO data and analysis methods should also consider the availability of technical expertise needed to process EO data and develop algorithms. This should also assess how the data will be used, the time frames required and the primary end user. For example, if local health departments need to use information from drone surveys immediately after flights are conducted, the most feasible approaches may be manually digitising images in field settings offline. In other cases where mapping is repeatedly conducted over wide areas, it may be more feasible and cost-effective to develop deep-learning algorithms to automatically identify target features. Specific governments agencies or research programmes may additionally have access to dedicated servers or infrastructure to support repeated data analysis. In contrast, other smaller research projects or disease control agencies may need to rely on local infrastructure or cloud-based computing. The level of technical expertise available should be considered when planning any mapping activities and may impact the feasibility of different approaches.

7 Conclusions

Most VBD are governed by geographical components and decisions made in terms of controlling these diseases are often made a large (regional or national) scales. As such, EO has, and will continue to play a vital role in tackling VBDs. The rapid expansion of EO data and analysis methods offers new opportunities for VBD surveillance, from tracking habitats of invasive vector species to developing early warning systems or planning vector control activities. Rapidly changing environmental conditions increase the need for these methods and data sources to characterise changing VBD epidemiology. Within this chapter, we have given an overview of EO data sources and analysis methods as well as example applications. We have additionally outlined key considerations for the integration of EO data into VBD surveillance and priorities for determining the feasibility of different data sources and analysis strategies. While these technologies have the potential to transform VBD surveillance, EO data applications need to be designed to be appropriate for specific contexts and ecological settings.

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