Remote Sensing Applications: Society and Environment 14 (2019) 108–118

Contents lists available at ScienceDirect

Remote Sensing Applications: Society and Environment

journal homepage: www.elsevier.com/locate/rsase

Review of remotely sensed data products for disease mapping and epidemiology

Sabelo Nick Dlamini[a,b,c,d,*], Anton Beloconi[b,c], Sizwe Mabaso[d], Penelope Vounatsou[b,c], Benido Impouma[a], Ibrahima Socé Fall[a]

[a] World Health Organization, Regional Office for Africa, Brazzaville, Congo
[b] Swiss Tropical and Public Health Institute, Basel, Switzerland
[c] University of Basel, Switzerland
[d] University of Eswatini, Matsapha, Eswatini

ARTICLE INFO

Keywords:
Vegetation indices
Satellite-derived products
Disease mapping
Remote sensing

ABSTRACT

High resolution remotely sensed (RS) data products remain of interest in disease mapping studies. However, previous usage of such satellite-derived products had been limited by high costs. There is also unprecedented space activity characterized by prolific satellite launches for various purposes, the chief of which being land cover observation. Therefore, there is need for information availability on the type of data products obtainable from the captured satellite images in order to facilitate access and utilization. Clearly, the remote sensing landscape is changing with the advent of Unmanned Aerial Vehicle/drones and spatially explicit images being captured at relatively low costs. We conducted a review to find out which RS data products were accessible for disease mapping and epidemiology. Our aim was to document RS data products for disease mapping and to propose other such products that could be incorporated in disease mapping and epidemiology studies. In view of the fact that RS data products are rapidly evolving, image data of higher spatial and temporal resolutions in near-real time are already available to aid disease mapping. We presented a catalogue of indices from ecological studies that could be used as variables in disease mapping and epidemiology. Remotely sensed data products related to climate, meteorology, land use/cover, cartography and urban mapping are explored as potential indices for disease mapping. There remains a substantial amount of work to be conducted on the evaluation and validation of some of the indices presented in this study. Conversely, synergies between remote sensing experts and epidemiologists could be useful in the uptake and testing of some of the proposed RS data products presented in this work.

1. Introduction

Remotely sensed (RS) data prolifically continue to be used in disease mapping and epidemiology (Machault et al., 2014; Garni et al., 2014; Ozdenerol, 2015). Remote sensing is the acquisition of information about an object or phenomenon without making physical contact with the object and it remains an operational tool for rapid observation, assessment and monitoring of the global environment. Products of remote sensing include various vegetation indices which are derived from satellite images and used to elucidate land use and land cover changes. Vegetation indices are mathematical combinations of different spectral bands that are designed to numerically separate or stretch the pixel value of different features in an image (Viña et al., 2011; Usage of Indices for Extraction, 2018). RS products had been used in epidemiological disease mapping studies such as in risk mapping of malaria (Noor et al., 2014; Karagiannis-Voules et al., 2015a), soil-transmitted helminths (Karagiannis-Voules et al., 2015b), schistosomiasis and prediction of high risk areas for leishmaniasis in Brazil. Previous works include incorporation of RS data in human health studies and spatial targeting of trachoma control in Southern Sudan (Clements et al., 2010) by developing a national risk map and mapping tsetse fly habitat suitability among others (Robinson et al., 1997). In addition identification of environmental risk factors for cholera using satellite derived remotely sensed data products had been undertaken by (Identifying Environmental Risk, 2018). Determination of population living in a city using remotely sensed data products was carried out in a study by (Karume et al., 2018) whereby a GeoEye satellite image at 50 m resolution was used and population of the city was obtained by

* Corresponding author at: World Health Organization, Regional Office for Africa, Brazzaville, Congo.
E-mail addresses: sabelodlamini2004@yahoo.com (S.N. Dlamini), impoumab@who.int (B. Impouma), socef@who.int (I.S. Fall).

https://doi.org/10.1016/j.rsase.2019.02.005
Received 28 October 2017; Received in revised form 29 January 2019; Accepted 14 February 2019
Available online 15 February 2019

taking the number of houses times an average number of habitants per house. Such type of population estimation could be useful in disease mapping especially in the identification and quantification of at risk populations.

One of the main advantages of using RS data products is its near-real time availability for rapid assessment of at risk areas and prediction of disease distribution especially in inaccessible areas that may also lack baseline data (Yang et al., 2005). The increase in the launch of higher resolution satellites and advances in processing techniques have enabled wider adoption of RS data (Kaptein et al., 2014). In economically-disadvantaged areas with poor ground measurement meteorological station networks, RS data maybe preferred and used as environmental proxies in disease risk mapping and prediction. As new sensors with better spatial and temporal resolutions become available, new opportunities are presented in the application of remote sensing products in disease mapping (Correia et al., 2004).

From the first generation of ecological studies that demonstrated the capability of RS products in disease mapping (Thomson et al., 1997; Beck et al., 1994; Correia et al., 2004; Hay MJP, 1997), there had been a sustained proliferation of such studies in disease mapping. The application of geostatistical techniques to identify spatial heterogeneities in disease distributions, patterns and trends as well as forecasting for epidemic preparedness planning had been demonstrated in studies by 21 and 22 inter alia. The theory behind incorporation of RS data in disease mapping was based on the established association between environmental conditions and some of the disease causing vectors (Tran et al., 2013; Hassan et al., 1998; Dlamini et al., 2015). For instance, some studies have demonstrated the association between radiation reflectance as measured by satellites and certain land cover types which have been used as environmental proxies for measurement of presence of a disease and its vectors (Garni et al., 2014).

However, there had been very little effort made to document and inventorize existing and potential RS data products that could be used in disease mapping. An overview of products relevant to disease mapping and epidemiology and that are derived from MODIS and ASTER sensors were provided by (Tatem et al., 2004). It had been mentioned by (Weiss et al., 2015) that past remote sensing products selection criteria had been biased and ad hoc rather than objective and quantitative. This had been partly due to lack of RS data listing and thus an inconvenience for epidemiologists as it is often hard for non-remote sensing experts to locate and identify data that will be useful for their analysis. An example of this is demonstrated by the high number of studies that used temperature and rainfall as covariates in malaria mapping in the study by (Weiss et al., 2015).

A compendium of civilian and commercial satellites that had been launched with the aim of gathering global land cover observations was prepared by (Belward and Skøien, 2015). However, the study documented satellite launches and not the type of RS data products that could be obtained from the land cover images captured by those satellites. Although a number of environmental indices/proxies had been derived from RS images by remote sensing experts (Dobbie and Dail, 2017), yet still little is known about potential environmental indices relevant to disease mapping studies that could be derived from current satellite-based products. Furthermore, present documentation of RS data products from space satellites is ad hoc, incomplete and characterized by duplication and redundancy between access websites. For example, MODIS products were found across access sources such as Sentinel Scientific Data Hub (Copernicus), USGS Earth Explorer, NASA Earth Data among others.

Although numerous studies on derivation and application of various vegetation indices exist, such indices had not yet been inventorized, especially for disease mapping and epidemiological studies. Table 1 presents some of the links with free access to RS data direct download from processing and supply agency websites.

Previously, a National Aeronautics and Space Administration (NASA) monthly bulletin called Spacewarn was launched in 1991 (http://nssdc.gsfc.nasa.gov/spacewarn/) to raise awareness about newly launched satellites and their missions to the general public. Unfortunately, this bulletin was discontinued with the last issue available until July 2011. Recently, there was an initiative headed by the European Commission (EC) in partnership with the European Space Agency (ESA) - Sentinel Scientific Data Hub - a remote sensing website project by Copernicus (http://www.copernicus.eu/) which had been establishment and it promised to be a pool of all RS information globally. The Copernicus Earth Data facility aims to serve both scientific and commercial customers with RS data sets covering forests, crops, water bodies and other environmental conditions of interest (Joppa et al., 2016).

As resolution of imagery data is of primary concern, distributions of sensors and RS products by spatial resolution (Remote sensing links, 2017) is shown in Fig. 1 where low resolution is above 100 m, medium resolution is between 10 and 100 m and high resolution is less than 10 m. Users of RS data products are often interested in the spatial resolution and the sampling frequency or temporal resolution at which the data is available as seen in studies using remote sensing products faithfully mentioning these characteristics (Weiss et al., 2015). Spatial resolution is the maximum separating or discriminating power of a sensor measurement usually referred to as pixel size (Spatial Resolution, 2017). Temporal resolution refers to the revisit period or length of time taken by a satellite to complete one orbit cycle (Théau, 2008). Equally interesting is the spectral resolution of the data which refers to the ability to resolve spectral features and bands into their separate components or to differentiate between two adjacent wavelengths (What is spectral resolution, 2018).

The list of sources of RS data found in (Remote sensing links, 2017) is limited to sensors and does not include compilation of products that could be derived from satellite images. To find out about products one has to follow each link to check if there are any end user RS data products available for download. Furthermore, most of the websites provide data in a way that is not easily understood by epidemiologists as often coding is used with little elaboration on type of products that could be derived and their potential application (https://earthdata.nasa.gov/user-resources/acronym-list). In 1978, (Carneggie, 1978) attempted to identify and define RS data products in terms of their characteristics and formats as these relates to the choice and selection of data products for any analysis. Many years after this study was first published, the characteristics and formats of RS data products as well as availability of handling software for interoperability still determine their usability by end users. These considerations are important to RS data end users as they could assist them efficiently access and utilize various RS products and justify their choice decisions (Schaeffer et al., 2013).

This review provided a list of new and dated environmental proxies/indices that have a potential to be incorporated in disease mapping and epidemiology. Although most of the indices had been used in ecological and air pollution studies, their uptake in disease mapping and epidemiology had been notoriously slow yet remote sensing applications remain useful in mapping infectious diseases (Tran et al., 2016). A comprehensive catalogue of satellite sensors and specifications of their data products and environmental proxies both those that are supplier processed and those that could be derived by the end-user are presented in this review.

2. Review, collation and inventorization of remotely sensed data products

The main sources of information used in this review were online remote sensing websites and hosting agencies. Firstly, we conducted an online web based search using the search terms “remote sensing data products” in Google search engine and had over 34 million hits in 0.66 s. The web links were then collated from internet websites in order to filter duplicated remote sensing data sources after realizing that

Table 1
Some global remotely sensed data sources available for direct download.

Full name	Acronym/alternate name	Website	Coverage
NASA's Socioeconomic Data and Applications Center	SEDAC	http://sedac.ciesin.columbia.edu/	Worldwide
NASA Earth Observations	NEO	https://neo.sci.gsfc.nasa.gov/	Worldwide
USGS Global Visualization Viewer	GloVis	https://glovis.usgs.gov/	Worldwide
NASA Earth Observation	NEO	https://neo.sci.gsfc.nasa.gov/	Worldwide
Copernicus Open Access Hub	Sentinels Scientific Data Hub	https://scihub.copernicus.eu/	Worldwide
USGS Earth Explorer	–	https://earthexplorer.usgs.gov/	Worldwide
NASA Earth Data	–	https://reverb.echo.nasa.gov/reverb	Worldwide
NOAA CLASS	NOAA	https://www.class.ngdc.noaa.gov/saa/products/	Worldwide
Earth Observation Link	EOLi	https://earth.esa.int/web/guest/eoli	Worldwide
National Institute for Space Research	INPE	http://www.dgi.inpe.br/CDSR/	South America and Africa
Bhuvan Indian Geo Platform of ISRO	–	http://bhuvan.nrsc.gov.in/data/download/index.php	India, Worldwide only for NDVI
JAXA's Global ALOS 3D World	–	http://www.eorc.jaxa.jp/ALOS/en/aw3d30/	Worldwide
Vito Vision	–	http://www.vito-eodata.be/PDF/portal/Application	Worldwide
Global Land Cover Facility	GLCF	http://glcf.umd.edu/data/	Worldwide
DigitalGlobe	–	http://www.digitalglobe.com/resources	Worldwide
Geo-Airbus		http://www.intelligence-airbusds.com/en/23-sample-imagery	Worldwide
UNAVCO	–	http://www.unavco.org/	Worldwide
IPPMUS Terra	–	https://www.terrapop.org/	Worldwide
Land, Atmosphere, Near-real time Capability for EOS	LANCE	https://earthdata.nasa.gov/earth-observation-data/near-real-time/rapid-response	Worldwide
Natural Earth	–	http://www.naturalearthdata.com/downloads/	Worldwide
OpenStreetMap	OSM	https://planet.openstreetmap.org/	Worldwide
OpenTopography	–	https://opentopography.org/	Worldwide
United Nations Environmental Data Explorer	UNEP	http://geodata.grid.unep.ch/	Worldwide
Terra Populus	TerraPop	https://www.terrapop.org/	Worldwide
WorldPop	–	http://www.worldpop.org.uk/data/get_data/	Worldwide

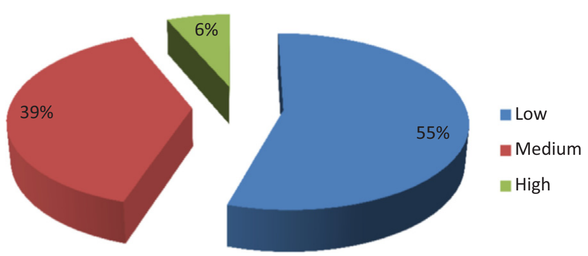

Fig. 1. Distribution of spatial resolutions of remote sensing sensors and products.

some hosting agencies were providing data from the same sensors. Both free and commercial access remote sensing products were collated according to the resolution of data variables and the sensors used to capture them as well as a brief description of the RS products that could be obtained. Two lists of satellites missions compiled by NASA (http://www.nasa.gov/missions/past/index.html#.VkCoYUYposI) and ESA (http://www.esa.int/ESA/Our_Missions) were used to find out which satellites were orbiting the earth and what data products could be obtained from those missions. The ESA missions comprised of 58 already launched and about 18 planned launches from year 2018 to 2028 while for the NASA missions we found about 200 missions alphabetically listed by the name given to that mission upon its launch.

Following and opening the link to each of the satellites and the responsible agencies led us to learn more about the RS data products, especially the spatial and temporal resolutions. While navigating through the different online links of remote sensing data products, we found various inexhaustive data download file transfer protocol (ftp) sites managed by both remote sensing agencies and private web bloggers who enthusiastically follow remote sensing issues (Belward and Skøien, 2015). For instance, such websites included NASA Goddard Space Flight Center found on https://www.nasa.gov/goddard, Copernicus Open Access Hub (previously known as Sentinels Scientific Data Hub) (https://scihub.copernicus.eu/), Observing Systems Capability Analysis and Review Tool (OSCAR), including NORAD Catalogue (http://satellitedebris.net/Database/), and Global Visualization Viewer (GLOVIS) inter alia.

There were some technical details that were used during products online search and profiling to identify the RS products. For example, some studies have indicated that high resolution to very high resolution RS data is the best for epidemiological mapping (Dlamini et al., 2015; Franke et al., 2015) especially in identification of spatiotemporal heterogeneities (Coly et al., 2015). For some epidemiological applications, however, the temporal resolution, (e.g. land cover and climate change), is more important than the spatial resolution. It is also important to know the level of data processing in order to understand the amount of preprocessing and data preparation required from the end-user.

3. Satellites and products selection criteria

The priority of satellite-derived products was on those with global or continental coverage scales and with data that had potential for application in disease mapping and epidemiology. We considered products with continuous or sustained acquisition programme as opposed to once-off project specific products, although some of them are presented as examples. We drew evidence from previously mentioned studies that used RS variables in their disease mapping efforts to support the environmental indices presented in this work. Each investigated RS product led to identification of the hosting agency from which the product could be obtained. This way we were able to find the websites where RS data could be downloaded by end-users. The list of products related to disease mapping was divided in the following three categories:

- Meteorological and Climate data
- Land use/Land cover
- Cartography and urban mapping

4. Processed vs. derived remotely sensed data products

The proposed RS products were further split into two groups comprising of processed and derived variables. In our case processed variables refer to the ones provided by the data supplying agency after all the necessary preprocessing steps had been conducted (Richardson and LeDrew, 2006). Those included RS data products that already approximated environmental proxies (Melesse et al., 2007) and that could be directly used in disease mapping studies. Derived variables were those that would still require the end-user to calculate them in order to establish a link between the environmental variable and its remotely sensed surrogate either using innovative or established mathematical and physical derivation algorithms (Lu et al., 2013). Thus, we reviewed ecological studies to find out environmental indices and proxies that could be used in disease mapping. The environmental proxies were organized according to the type of environmental variable measured and whether they were ready for use or had to be first derived from their surrogate indicators. The spatial and temporal resolutions of the products as well as their period of availability were presented.

5. Remotely sensed data products used in disease mapping and proposed new data products

From the review of ecological studies, we presented a library of environmental proxies that have a potential application as variables in disease mapping and epidemiology (Xue and Su, 2017). We found a number of both new and old environmental proxies and vegetation indices which were proposed by various ecologists and remote sensing experts. Most of the experts also provided the algorithm and equations for the index derivation to enable potential end-users to calculate the index themselves. The experts also presented the strengths and weaknesses of each index in terms of measuring a specific environmental condition in comparison to other known similar indices. A full reference list to each of the environmental proxies presented in this review is provided to aid end-users in learning more about each index listed in the catalogue. The presented environmental proxies and indices estimate environmental variables relevant to disease mapping and epidemiological studies. We also highlighted the indices which had already been used in epidemiology studies. Thus we created a catalogue of already utilized and potential RS data products that could be used with the aim to bring to the attention of end-users potential variables for consideration in disease mapping.

6. Remotely sensed data preprocessing steps

Remotely sensed data products varied according to the level of processing expected from the end-user. Some processing of the data were done by the supplier for most high demand products including Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST) and rainfall estimates (RFE). Typical data processing levels ranged from zero (unprocessed raw data) to four which were modeled outputs of data or variables derived from multiple measurements (147_XXXIII-part2.pdf Internet, 2017). Data preparation and processing included atmospheric noise cleaning, missing values imputation, alignment correction and rectification which maybe a constraint for non-remote sensing experts being unfamiliar with these issues (Kelcey and Lucieer, 2012). Remote sensing agencies such as NASA and ESA processed their data into different levels and provided accompanying documentation for each dataset accessed via their ftp sites, which is useful for end-users to a priori evaluate the usability of the data for their analysis. Most end-users prefer data that is processed up to level 3 comprising of variables mapped on uniform space-time grid with some completeness and level 4 (modeled outputs and results). The first and second processing levels are basic processing levels and are meant for end-users with advanced remote sensing data processing skills and are capable of using geometric procedures to correct the images themselves.

7. Remotely sensed image data sources

The Goddard Space Flight Center reported that there were about 2271 satellites currently in orbit (Garner, 2015) while the NORAD Catalogue website reports approximately 7142 satellites deployed into space including debris (http://www.satellitedebris.net/Database) since October 1957. The satellites included those deployed for Earth Observation and environmental monitoring as well as global security satellites launched for private use. Previously an online profile of RS data download websites was found in Exelis Visual Information Solutions which had been incorporated into Harris Geospatial Solutions and provides vendor information on RS products (http://harrisgeospatial.com/ProductsandTechnology/DataServices/SatelliteAerialImagery.aspx#vendors). Data access indicated that most RS data were available either for free or commercially to end-users. Remotely sensed data products show that those that were available for free have lower resolutions of about 250 m to 1.5 km compared to very high resolution products (from 5 m to 10 m) which were mostly available for sale. Examples of free products with lower resolutions included MODIS products such as NDVI, LST and Enhanced Vegetation Index (EVI) while very high resolution products included those captured by IKONOS, Orbview-3 and Quickbird satellites.

The most commonly used remotely sensed data products in epidemiological applications included proxies of temperature and precipitation i.e LST and (RFE). Vegetation indices such as NDVI and a host of land use/land cover (LULC) variables were also widely used. Some new indices like the Temperature Suitability Index (TSI) which converts observed land surface temperatures into predictions of ambient air temperature for malaria distribution in Africa had also been used (Weiss et al., 2014). Other indices were improvement from previous versions, for example a 90 m water resolution database had been recently developed by (Yamazaki et al., 2015a), while a 15 m water resolution database was developed by (Verpoorter et al., 2014). The new potential RS data products were therefore important for epidemiology as they provided more explicit spatial detail than previous coarser resolutions of same. This is important in disease mapping especially identification of spatial heterogeneities and understating the underlying courses of spatial variations of certain vector-borne diseases.

8. Processed RS data products for disease mapping

The literature on RS derived environmental indices showed a litany of available remotely sensed supplier processed variables that could be used for disease mapping. Most of them were found in ecological studies where an unlimited number of indices that could be derived from satellite images were presented. Numerous vegetation indices that could be used as an alternative to, for instance, NDVI were found. Some of those indices were an improvement of the NDVI which is based on the near infrared and visible spectral bands ((NIR-VIS)/(NIR + VIS)) and could potentially provide better estimates in disease mapping models. For example, the soil-adjusted vegetation index (SAVI) was developed in order to improve NDVI estimation by correcting the influence of soil brightness when vegetative cover is sparse by using the formula (1 + L) (NIR-RED)/(NIR + RED + L). The factor L adjusts for canopy background which eliminates the need for additional calibration for different soils, one of the limitations of the NDVI.

A majority of the indices (90%) were derived by remote sensing experts and have been extensively used in ecological studies, while many of them largely remained unknown to epidemiologist. The main variables that were already processed by the suppliers included temperature, rainfall, NDVI, and the EVI which were also extensively utilized in disease mapping studies (Weiss et al., 2015).

A comparison of the extensively used RS data products in epidemiology with other similar indices which had been proposed in

Table 2
Supplier processed remotely sensed data products.

Variable	Source/sensor	Temporal resolution	Spatial resolution	Period of data availability	Description & data cost/availability
1) **Meteorology and climate**					
Land Surface Temperature (LST) day and night	MOD11L2 MOD11(A1-A2) MOD11B1 MOD11 (C1-C3)	8 days	-250 m -500 m -1 km	1960–present	Measure of how hot or cold the "surface" of the earth is at a particular location. Data is free.
Rainfall Estimates (RFE)	FEWS NET FAO-RFE	-daily -10 days -monthly	8 km	2008–present	Measures the amount of accumulated rainfall from recent rain episode. Data is free.
2) **Landuse/landcover**					
Land Surface Water Index	MOD09A1	8 days	500 m	1981–2012	Measures the total amount of liquid water in vegetation and its soil background (Chandrasekar et al, 2010). Data is free.
Normalized Difference Vegetation Index (NDVI)	MOD13Q1 MYD13A2	16 days	250 M 500 M 1 KM	1999–present	Indicator used to assess whether the target being observed contains live green vegetation or not. Can be a proxy for water availability. Data is free.
Enhanced Vegetation Index (EVI)	MOD13Q1 MYD13A2	16 days	250 M 1 KM	1999–present	Designed to enhance vegetation sensitivity in high biomass regions and improved vegetation monitoring by correcting for atmospheric influences.
Global 3 arc-second Water Body Map (G3WBM)	Landsat Global Land Survey (GLS) 1975, GLS1990, GLS2000, GLS2005 and GLS2010	-	+90 m	2015	A high-resolution global water. body. map with information on the frequency of water body existence (Yamazaki et al., 2015).
Water Mask	MOD44W		250 m	2000	Measures surface water. Data is free.
Land/Water mask	-Global Land Cover Facility (GLCF) -MODIS	-	250 m		Measures surface water as improvement from 1 km MODIS mask data (Carroll et al., 2009). Data is free.
Global Land Cover Facility Inland water (GIW)	-Landsat TM/ETM +	-	30 m	2015	Provides an estimation of regional and global inland water area (Feng et al., 2015). Data is publicly available.
Global Lakes and Wetlands Database (GLWD)	Digital Chart of the World (DCW) of ESRI (1993)	-	1 km		Identifies global lakes and wetlands (Lehner and Döll, 2004). Available for free.
Soil moisture/Geology maps	- WindSat - Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI)	3 days (archived)	-60″ -1 km -50 km	2009	Used for agriculture, ecology, wildlife, and public health and is an important connection between the hydrological cycle and life involving animal, plant, and human (Lakshmi and Lakshmi, 2013). Data is free.
Landcover	-MOD44W -MCD12C1 -MCD12Q1 -MCD12Q2	Yearly	-500 m -1 km -1 km, 8 km -10 km	1999–present	Documents how much of a region is covered by forests, wetlands, impervious surfaces, agriculture, and other land and water types. Data is free but could cost 105 Euro/km^2 in some agencies.
Biodiversity/human impacts maps	-World Atlas Biodiversity -World Map of Human Impacts	-	-	2003–present	Used for understanding the environmental impacts of human populations. Data is free.
Lights at night images	-NOAA National centres for environmental information -OLS, SSM/I, SSM/T, SSM/T2, SSJ, SSIES, SSM	-	-500 m -48 km -174 km	 1992–2013	Indicates location and extentof human settlements. Cost about $ 43 per image (subject to scale & shipping costs).
Population	WorldPop, Terra Populus	- -	100 m -	2000–2020 1960–2011	Integrates GIS-linked database of census with official population estimate data. Data is free.
3) **Cartography and Urban Mapping**					
Altitude/Geomorphology	-NASA -NOAA -ASTER -SRTM30 PLUS -GTOPO30	-	-30 m -1 km -10 km	2011	Height above or below a fixed reference point as well as their topographic characteristics. Data is free.
Ecoregions/Biogeographic regions	-Terrestrial Ecoregions Olson et al. (2001)	-	-	2007–present	Geographical units with characteristic flora, fauna and ecosystems. Data is free
Forest/wildlife resources	-The world map of intact forest landscapes -World Wilderness Areas -UNEP GEO Data Portal	-	-	2005–present	Shows unbroken natural landscape of a forest ecosystem and its habitat, plant community components, in a current extant forest zone. Data is free.

-Details missing or not available
+Actual resolution coarser than the one stated

ecological studies would be important in order to find out how they could jointly be used in disease mapping. Variables that were processed by the supplier were grouped and are presented in Table 2 which shows data products that could be directly downloaded from remote sensing websites and handled in mapping and display interfaces such as Geographic Information System (GIS). We provided both temporal and spatial resolutions of the data as well as the period at which the data were captured. The list comprised of environmental indices that have applications to disease mapping and were therefore of epidemiological importance.

9. Derived remotely sensed data products for disease mapping

Table 3 presents a list of satellite image derived indices mainly from ecologists and remote sensing experts who also proposed the derivation algorithms and formula for calculating them. A description of what

Table 3
Derived remotely sensed data products.

Variable/index	Reference/source	Temporal resolution	Spatial resolution	Description
Temperature Suitability Index (TSI)"	Weiss et al. (2014)	8 days	1 km	Converts observed land surface temperatures into predictions of ambient air temperature. Derived variable (data unavailable)
Vegetation Change Tracker	Zhao et al. (2016); Vogelmann et al. (2011)	*	1 km	Automated forest change mapping algorithm based on the spectral and temporal properties of forest, disturbance and post-disturbance recovery processes (Li et al., 2009). Calculated (data unavailable)
Soil-Adjusted Vegetation Index (SAVI)	Huete (1988)	*	*	Developed as a modification of the NDVI to correct for the influence of soil brightness when vegetative cover is low. Calculated (data unavailable)
Modified Normalized Difference Vegetation Index (MNDV1)	Jurgens (1997)	*	*	Index used to determine frost damages in agriculture. Calculated(data unavailable)
Red Edge Normalized Difference Vegetation Index (NDVI705)	Gitelson and Merzlyak (1994)	*	*	Used in precision agriculture, forest monitoring, and vegetation stress detection. Calculated (data unavailable)
Atmospherically Adjusted Resistant Vegetation Index (ARVI)	Kaufman and Tanre (1992)	*	*	The index is an enhancement to the NDVI and uses blue reflectance to correct red reflectance for atmospheric scattering. It is most useful in regions of high atmospheric aerosol content, including tropical regions contaminated by soot from slash-and-burn agriculture. Calculated (data unavailable)
Green Near Infrared (G/NIR)	http://www.exelisvis.com/docs/BroadbandGreenness.html	*	*	Can be used for soil property analysis. Calculated (data unavailable)
Green Shortwave Infrared (G/SWIR)	http://www.exelisvis.com/docs/BroadbandGreenness.html	*	*	Used to study spectral properties of soils and green vegetation. Calculated(data unavailable)
Simple Ratio Index (SR)	http://www.exelisvis.com/docs/BroadbandGreenness.html	*	*	It is described as the ratio of light that is scattered in the NIR range to that which is absorbed in the red range. Calculated(data unavailable)
Sum Green Index (SG)	Gamon and Surfus (1999)	*	*	Used to detect changes in vegetation greenness and for detecting forest disturbance because it is highly sensitive to small changes in vegetation canopy opening. Calculated (data unavailable)
Modified Red Edge Simple Ration Index (mSR705)	Sims and Gamon (2002)	*	*	Used in precision agriculture, forest monitoring, and vegetation stress detection. Calculated (data unavailable)
Modified Red Edge Normalized Difference Vegetation Index (mNDVI705)	Datt (1999)	*	*	Used in precision agriculture, forest monitoring, and vegetation stress detection. Calculated (data unavailable)
Vogelmann Red Edge Index 1 (VOG1)	Vogelmann et al. (1993)	*	*	Used in vegetation phenology (growth) studies, precision agriculture, and vegetation productivity modeling. Calculated (data unavailable)
Red Edge Position Index (REP)	Curran et al. (1995)	*	*	Used in crop monitoring and yield prediction, ecosystem disturbance detection, photosynthesis modeling, and canopy stress caused by climate and other factors. Calculated (data unavailable)
Photochemical Reflectance Index (PRI)	http://www.exelisvis.com	*	*	Uses pigments that signify photosynthetic light use efficiency and are useful to quantify vegetation production and stress. Calculated (data unavailable)
Structure Insensitive Pigment Index (SIPI)	http://www.exelisvis.com	*	*	Used in areas with high variability in the canopy structure, or leaf area index. Calculated (data unavailable)
Red Green Ratio Index (RGR Ratio)	http://www.exelisvis.com	*	*	Used for making foliage development estimations, indicating leaf production and stress. Calculated (data unavailable)
Plant Senescence Reflectance Index (PSRI)	http://www.exelisvis.com	*	*	Indicates increased canopy stress (carotenoid pigment), the onset of canopy senescence, and plant fruit ripening. Applications include vegetation health monitoring, plant physiological stress detection and crop production, and yield analysis. Calculated (data unavailable)
Carotenoid Reflectance Index 1 (CRI1)	http://www.exelisvis.com	*	*	Measure of stressed vegetation as a consequence of harmful effects of too much light. Calculated (data unavailable)
Carotenoid Reflectance Index 2 (CRI2)	http://www.exelisvis.com	*	*	Modified measure of stressed vegetation as a consequence of harmful effects of too much light. Calculated (data unavailable)
Anthocyanin Reflectance Index 1 (ARI1)	Gitelson et al. (2001)	*	*	Measure of stressed vegetation and indicates changes in foliage via new growth or death. Calculated (data unavailable)
Anthocyanin Reflectance Index 2 (ARI2)	Gitelson et al. (2001)	*	*	Detects higher concentrations of anthocynanins in vegetation. Measures stressed vegetation and indicates canopy changes in foliage via new growth or death. Calculated (data unavailable)
Water Band Index (WBI)	Peñuelas et al. (1994)	*	*	Estimates leaf moisture and water content of vegetation. Calculated (data unavailable)
Moisture Stress Index (MSI)	Ceccato (2001)	*	*	Indicator of plant water content and water stress. Calculated (data unavailable)

(*continued on next page*)

Table 3 (*continued*)

Variable/index	Reference/source	Temporal resolution	Spatial resolution	Description
Normalized Difference Infrared Index (NDII)	Hardisky et al. (1983)	*	*	Used to detect plant water stress. Calculated (data unavailable)
Leaf Area Index (LAI)	Bréda (2003)	*	*	Characterizes plant canopies and predict photosynthetic primary production, evapotranspiration and is a reference tool for crop growth. Non remotely sensed but calculated
Normalized Dry Matter Index (NDMI)	Wang et al. (2013)	*	*	Estimates the dry matter content in green leaves. Calculated (data unavailable)
Normalized Difference Tillage Index (NDTI)	van Deventer et al. (1997)	*	*	Used for differentiation between crop residue and soils. Calculated (data unavailable)
Cellulose Absorption Index (CAI)	Nagler et al. (2003)	*	*	Relative depth of cellulose absorption by non-photosynthetic vegetation/biomass cover (Daughtry et al., 2005). Calculated (data unavailable)
Normalized Difference Lignin Index (NDLI)	Serrano et al. (2002)	*	*	Estimates Ligno-cellulose content or mass of senesced plant materials. Calculated (data unavailable)
Normalized Difference Nitrogen Index (NDNI)	Serrano et al. (2002)	*	*	For foliar nitrogen concentration estimation. Calculated (data unavailable)
Ligno-Cellulose Absorption Index (LCA)	Daughtry et al. (2005)	*	*	Used for live and senesced biomass (Numata et al., 2008). Calculated (data unavailable)
Shortwave Infrared Normalized Difference Residue Index (SINDRI)	Serbin et al. (2009)	*	*	Estimates the amount of crop residue cover over multiple locations. Calculated (data unavailable)
Dry Matter Content Index (DMCI)	Romero et al. (2012)	*	*	Used for estimation of plant canopy biomass (Wang et al., 2013). Calculated (data unavailable)
Reciprocal of Moisture Stress Index (RMSI)	Hunt and Rock (1989)	*	*	Measure of the effects of drought and catastrophic plant wetness (https://www.ncdc.noaa.gov/societal-impacts/cmsi/). Calculated (data unavailable)
Simple Ratio Water Index (SRWI)	Zarco-Tejada et al. (2003)	*	*	Calculated (data unavailable)
Plant Water Index/Plant Water Concentration (PWC)	Peñuelas et al. (1995)	*	*	Measures amount of water concentration in plants as a proxy for drought assessment. Calculated (data unavailable)
Modified Soil Adjusted Crop Residue Index (MSACRI)	Ren et al. (2012)	*	*	Estimating regional non-photosynthetic biomass. Calculated (data unavailable)
Soil Adjusted Corn Residue Index (SACRI)	Ren et al. (2012)	*	*	Estimating regional non-photosynthetic biomass. Calculated (data unavailable)
Difference Vegetation Index	Tucker et al. (1981), Jackson et al. (2004)	*	*	Distinguishes between soil and vegetation, but it does not account for the difference between reflectance and radiance caused by atmospheric effects or shadows (Broadband Greenness (Using ENVI), 2015). Calculated (data unavailable)
Normalized Difference Index (NDI)	Ren et al. (2012)	*	*	Estimating regional non-photosynthetic biomass. Calculated (data unavailable)
Normalized Difference Temperature Index (NDTI)	Peng et al. (2013)	*	*	Used for approximating moisture availability. Calculated (data unavailable)
Global Environmental Monitoring Index	Pinty and Verstraete (1992)	*	*	Used for global environmental monitoring from satellite imagery and attempts to correct for atmospheric effects. Calculated (data unavailable)
Green Atmospherically Resistant Index (GARI)	Gitelson et al. (1996)	*	*	This index is more sensitive to a wide range of chlorophyll concentrations and less sensitive to atmospheric effects than NDVI. Calculated (data unavailable)
Green Difference Vegetation Index (GDVI)	Sripada et al. (2006)	*	*	Used to predict nitrogen requirements for corn. Calculated (data unavailable)
Green Normalized Difference Vegetation Index (GDVI)	Gitelson and Merzlyak (1997)	*	*	This index is more sensitive to chlorophyll concentration than NDVI. Calculated (data unavailable)
Green Ratio Vegetation Index (GRVI)	Sripada et al. (2006)	*	*	Index minimizes the effects of background soil while emphasizing green vegetation and uses global coefficients that weigh the pixel values to generate new transformed bands. Calculated (data unavailable)
Infrared Percentage Vegetation Index (IPVI)	Crippen (1990)	*	*	This index is functionally the same as NDVI, but it is computationally faster. Calculated (data unavailable)
Modified Non-Linear Index (MNLI)	Yang et al. (2008)	*	*	This index is an enhancement to the Non-Linear Index (NLI) that incorporates the Soil Adjusted Vegetation Index (SAVI) to account for the soil background. Calculated (data unavailable)
Non-Linear Index (NLI)	Goel and Qin (1994)	*	*	This index assumes that the relationship between many vegetation indices and surface biophysical parameters is non-linear. Calculated (data unavailable)
Optimized Soil Adjusted Vegetation Index (OSAVI)	Rondeaux et al. (1996)	*	*	The index provides greater soil variation than SAVI for low vegetation cover, while demonstrating increased sensitivity to vegetation cover greater than 50% and is best used in areas with relatively sparse vegetation where soil is visible through the canopy. Calculated (data unavailable)
Renormalized Difference Vegetation Index (RDVI)	Roujean and Breon (1995)	*	*	Used to highlight healthy vegetation and is insensitive to the effects of soil and sun viewing geometry. Calculated (data unavailable)

(*continued on next page*)

Table 3 (*continued*)

Variable/index	Reference/source	Temporal resolution	Spatial resolution	Description
Transformed Difference Vegetation Index (TDVI)	Bannari et al. (2002)	*	*	Useful for monitoring vegetation cover in urban environments as it does not saturate like NDVI and SAVI. Calculated (data unavailable)
Visible Atmospherically Resistant Index (VARI)	Gitelson et al. (2002)	*	*	Used to estimate the fraction of vegetation in a scene with low sensitivity to atmospheric effects. Calculated (data unavailable)
WorldView Improved Vegetative Index (WV-VI)	Antonio and Wolf (2012)	*	*	This index uses WorldView-2 bands to compute NDVI. Calculated (data unavailable)
Topographic Wetness Index (TWI)"	(Cohen et al., 2013)	*	*	Measure representing the amount of water that should enter a given spatial unit divided by the rate at which the water should flow out of that unit (Sørensen et al., 2006). Calculated (data unavailable)
Urban Index	Kawamura et al. (1996)	*	*	Used as an indication for urban built up area intensity. Describes building density. Calculated. (data unavailable)
Normalized Difference Impervious Surface Index (NDISI)	Xu et al. (2013)	*	*	Used to investigate the impervious surfaces an area. Calculated (data unavailable)

*Details depend on the image that is used during index derivation.
"Indicates index already used in epidemiological studies.

each of the environmental indices estimated was presented to guide end-users' choices. In this list we did not include tassel cap indices as most of them are rather a transformation of the spectral bands already used in the original reflectance data. A number of vegetation indices had been calibrated to measure specific plant characteristics in relation to conditions such as moisture content and plant stress an important indicator of wetness and dryness especially for vector-borne diseases that depend on such conditions. The description provided can be used by epidemiologist to decide which index is more suitable for the disease being mapped. Therefore, it is entirely up to the end-user to decide which indices need to be combined or to be used jointly in their mapping work.

10. Drones and new remotely sensed data potential for disease mapping

Since the advent of drones for civilian and private use became accessible, some aspects of remote sensing capabilities are now available for scientific applications. Unmanned Aerial Vehicles (UAV) or simple drones are increasingly being used for a quick bird eye view in assessment of various humanitarian situations (Sandvik and Lohne, 2014). However drone data can be cumbersomely heavy to store and to process as it comprises of high resolution images at local scales. A single drone flight can collect over 70 terabytes of data and this indicates that a more sophisticated high processing and storage facility will be required to successfully manage drone data. Clearly drone data inevitably fall under the category of big data and will require storage optimization measures such as dumbing what is not necessary. Most companies that use drones already manage these massive amounts of data by simple taking and storing only what they need. A study by (Fornace et al., 2014) had already looked at the potential of drones in mapping infectious diseases. According to (Fornace et al., 2014) drones can provide spatially and temporally accurate data which is critical in understanding the linkages between disease transmission and environmental factors. In this case drones are not meant to replace conventional remote sensing methods but rather to augment existing ones by adding another dimension in the usability and localized applications of remotely sensed products for mapping.

An exploratory study by (Patra, 2017) used a hypothetical model fed with drone data to understand how germs could be mapped in the atmosphere and how microbial traffic like flu is transferred within the same species. In this study drones are considered because of their real-time capability and for their inherent high spatial and temporal resolutions at local scales which is useful for epidemiological applications. Their application in collecting real time data at relatively low cost had been explored and it is clear that drones could be useful for emergency mapping of disease outbreaks. Clearly, drones provide spatially and temporally explicit data (Using low-cost drones to map malaria, 2017) which is critical in identifying environmental determinants of infectious diseases especially because of their real time availability thus mapping changes as they occur. Current trends indicate that drones have come to stay as new uses are being discovered and more exploration of their full potential is ongoing.

11. Conclusions

This paper provided a review of some of the work that had been done to advance remote sensing technology and its applications in diseases mapping and epidemiology studies. From the review, it is clear that the RS landscape is constantly changing as new and improved satellites for global environmental monitoring purposes are continuously launched into space and new variable potential is presented. The recent applications of drones in complex heath and humanitarian situations has taken the remote sensing field to new heights and disease mapping experts are yet to unravel the full potential of this new technology. Resolutions for spatial details are constantly improving and so is the turnaround time from data collection to analysis and making of informed evidence-based decisions.

This work compiled remote sensing information relevant to disease mapping but we must allude to the fact that the RS area remains too complex for non-experts yet the new innovations promise to bring on board even laymen as the mapped images get more visible. There is need however, to go beyond the complex RS coding and abbreviations to more open RS data products that are accessible and easy to apply even for non-experts. Furthermore, remote sensing agencies websites showed that launches were escalating with each year, yet failed launches were not immediately known and consequently data availability from those missions remained a speculation. Online websites documenting spacecraft launches and data hosting agencies uniform resource locator (url) links were ad hoc and marked by duplication and redundancy and tended to present conflicting records as can be seen in the conflicting lists of satellites in orbit as recorded by the Goddard Space Flight Center (2271) and the NORAD Catalogue (7142) respectively.

Despite the good resolutions commercial data have remained under-utilized in disease mapping mainly because of the high purchase prices associated with it even though its development is driven by consumer demand and applications (Kaptein et al., 2014). For instance, high resolution data market represented 3% of the total data market in 2012 which signified a serious financial barrier. Conversely low resolution remote sensing products with resolutions ranging from 250 m to 1.5 km were available for free, for example in some NASA download sites such as Reverb Echo (https://reverb.echo.nasa.gov/reverb/). In addition, it is important for epidemiologists to pay attention to the processing levels of the remotely sensed data they use for analysis as this is the key to understanding the amount of data preparation efforts needed before the data is ready for use. For the processed data, time of availability from hosting websites and spatial resolutions varied across the globe and from region to region. As mentioned, some products had good resolutions but were limited only to national level like the Water resources which was available only for USA. In other cases descriptions of some of the data products were well provided while at the same time direct links to access those products were not provided. These were products like the Global Interannual Water Extent and Variation from the Special Sensor Microwave Imager; Global Inundation Extent from Multi-Satellites (GIEMS) and Shuttle Radar Topography Mission (SRTM) Water Body.

There were many environmental proxies that were proposed by ecologist which have however remained under-utilized partly because they had not yet been applied in disease studies and partly because they were time consuming to derive and interpret. For instance, a list of vegetation indices was found with some of the proxies advanced as an improvement to the commonly used NDVI such as the Atmospherically Adjusted Resistant Vegetation Index (ARVI) and the Soil-Adjusted Vegetation Index (SAVI). However the same indices remained under-utilized in disease mapping and epidemiology presumably because they were little known. Highly utilized proxies were those of NDVI, rainfall and temperature partly because they were readily available and partly because they had been extensively utilized in other studies. We presented a catalogue of potential and existing RS data products for end-users like epidemiologists to compare remote sensing products used in their analysis. Whereas some of these environmental proxies had been extensively explored in both ecological and remote sensing studies, their use in disease mapping had been limited to variables that are archived and ready for download from suppliers of remotely sensed data (Gómez et al., 2016).

New disease mapping potential was presented as high resolutions products were being developed as can be seen in the work of Yamazaki (2015) which showed an improved global water body map of up to 90 m spatial resolution and the GLObal WAter BOdies database project with 15 m spatial resolution. While epidemiological studies have shown that temperature and rainfall were important factors in the distribution of disease vectors (McMichael et al., 2018), none have assessed how modeling and mapping with such data could be affected by their resolutions. More research work aimed at addressing the above issues is important especially in the advent of drones and the explicit resolution scales presented to epidemiology and disease mapping studies. Some vegetation indices could not be found from purported access website links such as the humidity from MODIS Atmosphere and the Normalized Difference Water Index (NDWI) another MODIS product.

Documenting satellite launches into space and providing complete information on their mission and the anticipated data could be useful to the remote sensing end-user community in order to know what data is expected from those missions. A quick referral guide of remotely sensed data that had been coded or abbreviated on the hosting website could make searching for remote sensing products more efficient when end users could quickly find out what type of data variables are available or can be derived from the coded images listed. This review presented a catalogue of potential environmental proxies for disease mapping. The list may not be complete as new indices were being derived from new satellite images but it would help as a guide for available data products to those seeking to use such products in their analysis.

We also compiled a list of environmental proxies that had previously been derived by ecologists but have received very little attention from epidemiologists due to some of the reasons already mentioned above. We noted that documentation of space activities was ad hoc and uncoordinated with many sites duplicating and often providing conflicting statistics about space missions. This may make it hard for end-users to fully take advantage of the many data sources and products that space agencies could offer. There remains a substantial amount of work on evaluation and comparison of some of the environmental indices presented in this work against the conventionally and commonly used ones in disease mapping. Consequently, synergies between remote sensing experts and epidemiologists could be useful in the uptake and testing of some of the novice environmental indices presented in this work.

Acknowledgement

Not applicable.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and material

Public data and open access sources were used for this study.

Competing interests

The authors declare no competing interest.

Funding

No funding received for this study.

Author's contribution

SD conceived the research and drafted the manuscript. AB, SM, PV, IB and IF reviewed the manuscript and provided technical and analytical inputs. All authors read and approved the final manuscript

References

147_XXXIII-part2.pdf [Internet] [cited 2017Oct 20]. Available from: ⟨http://www.isprs.org/proceedings/XXXIII/congress/part2/147_XXXIII-part2.pdf⟩.
Antonio F. Wolf, 2012. Using WorldView-2 Vis-NIR multispectral imagery to support land mapping and feature extraction using normalized difference index ratios, in: Proc. SPIE. Presented at the Proc.SPIE.
Bannari, A., Asalhi, H., Teillet, P.M., 2002. Transformed difference vegetation index (TDVI) for vegetation cover mapping, in: IEEE International Geoscience and Remote Sensing Symposium. Presented at the IEEE International Geoscience and Remote Sensing Symposium, pp. 3053–3055 vol.5. https://doi.org/10.1109/IGARSS.2002.1026867.
Beck, L.R., Rodriguez, M.H., Dister, S.W., Rodriguez, A.D., Rejmankova, E., Ulloa, A., et al., 1994. Remote sensing as a landscape epidemiologic tool to identify villages at high risk for malaria transmission. Am. J. Trop. Med. Hyg. 51 (3), 271–280.
Belward, A.S., Skøien, J.O., 2015. Who launched what, when and why; trends in global land-cover observation capacity from civilian earth observation satellites. ISPRS J. Photogramm. Remote Sens. 103, 115–128.
Bréda, N.J.J., 2003. Ground-based measurements of leaf area index: a review of methods, instruments and current controversies. J. Exp. Bot. 54 (392), 2403–2417 (Nov 1).
Broadband Greenness (Using ENVI) | Exelis VIS Docs Center [Internet]. [cited 2015 Sep 28]. Available from: ⟨http://www.exelisvis.com/docs/BroadbandGreenness.html⟩.
Carneggie, D.M., 1978. Remote sensing data products: types and characteristics. Pecora IV Appl. Remote Sens. Data Wildl. Manag. 11.
Carroll, M.L., Townshend, J.R., DiMiceli, C.M., Noojipady, P., Sohlberg, R.A., 2009. A new global raster water mask at 250 m resolution. Int. J. Digit Earth 2 (4), 291–308 (Dec 1).
Ceccato, P., 2001. Estimation of Vegetation Water Content Using Remote Sensing for the Assessment of Fire Risk Occurrence and Burning Efficiency 169.
Chandrasekar, K., et al., 2010. Land surface water index (LSWI) response to rainfall and NDVI using the MODIS vegetation index product. Int. J. Remote Sens (LSWI_MODIS.pdf [Internet], [cited 2015 Nov 7], Available from: ⟨ftp://ftp.er-i.ucsb.edu/pub/org/swim/WTLDS/Encylopedia_Wetlands/papers/Chandrasekar_etal_2010_LSWI_MODIS.pdf⟩).
Clements, A.C.A., Kur, L.W., Gatpan, G., Ngondi, J.M., Emerson, P.M., Lado, M., et al., 2010. Targeting trachoma control through risk mapping: the example of Southern Sudan. PLoS Negl. Trop. Dis. 4 (8), e799 (Aug 17).
Cohen, J.M., Dlamini, S., Novotny, J.M., Kandula, D., Kunene, S., Tatem, A.J., 2013. Rapid case-based mapping of seasonal malaria transmission risk for strategic elimination planning in Swaziland. Malar. J. 12 (1), 61 (Feb 11).
Coly, S., Charras-Garrido, M., Abrial, D., Yao-Lafourcade, A.-F., 2015. Spatiotemporal disease mapping applied to infectious diseases. Procedia Environ. Sci. 26 (Suppl C), 32–37 (Jan 1).
Correia, V.R., de, M., Carvalho, M.S., Sabroza, P.C., Vasconcelos, C.H., 2004. Remote sensing as a tool to survey endemic diseases in Brazil. Cad. Saúde Pública. 20 (4), 891–904.
Correia, V.R. de M., Carvalho, M.S., Sabroza, P.C., Vasconcelos, C.H., 2004. Remote sensing as a tool to survey endemic diseases in Brazil. Cad. Saúde Pública. 20 (4), 891–904.
Crippen, R.E., 1990. Calculating the vegetation index faster. Remote Sens. Environ. 34 (1), 71–73 (Oct 1).
Curran, P.J., Windham, W.R., Gholz, H.L., 1995. Exploring the relationship between reflectance red edge and chlorophyll concentration in slash pine leaves. Tree Physiol. 15, 203–206. https://doi.org/10.1093/treephys/15.3.203.
Datt, B., 1999. Remote Sensing of Water Content in Eucalyptus Leaves. Aust. J. Bot. 47, 909–923. https://doi.org/10.1071/bt98042.
Daughtry, C.S.T., Hunt, E.R., Doraiswamy, P.C., McMurtrey, J.E., 2005. Remote Sensing the Spatial Distribution of Crop Residues. Agron. J. 97, 964–971. https://doi.org/10.2134/agronj2003.0291.
Dlamini, S.N., Franke, J., Vounatsou, P., 2015. Assessing the relationship between environmental factors and malaria vector breeding sites in Swaziland using multi-scale remotely sensed data. Geospat. Health 10 (1), 302.
Dobbie, M.J., Dail, D., 2014. Environmental indices. In: Wiley StatsRef: Statistics Reference Online. John Wiley & Sons, Ltd([Internet], [cited Oct 17 2017], Available from: ⟨http://onlinelibrary.wiley.com/doi/10.1002/9781118445112.stat07691/abstract⟩).
Feng, M., Sexton, J.O., Channan, S., Townshend, J.R., 2015. A global, high-resolution (30-m) inland water body dataset for 2000: first results of a topographic–spectral classification algorithm. Int. J. Digit Earth 0 (0), 1–21 (Mar 6).
Fornace, K.M., Drakeley, C.J., William, T., Espino, F., Cox, J., 2014a. Mapping infectious disease landscapes: unmanned aerial vehicles and epidemiology. Trends Parasitol. 30 (11), 514–519.
Franke, J., Gebreslasie, M., Bauwens, I., Deleu, J., Siegert, F., 2015. Earth observation in support of malaria control and epidemiology: MALAREO monitoring approaches. Geospat. Health 10 (1)([Internet], Jun 3, [cited 2015 Sep 2], Available from: ⟨http://www.geospatialhealth.net/index.php/gh/article/view/335⟩).
Gamon, J.A., Surfus, J.S., 1999. Assessing leaf pigment content and activity with a reflectometer. New Phytol.
Garner R., 2015. NASA's Goddard Space Flight Center [Internet]. NASA [cited 2015 Jun 15]. Available from: ⟨http://www.nasa.gov/centers/goddard/home/index.html⟩.
Garni, R., Tran, A., Guis, H., Baldet, T., Benallal, K., Boubidi, S., et al., 2014. Remote sensing, land cover changes, and vector-borne diseases: use of high spatial resolution satellite imagery to map the risk of occurrence of cutaneous leishmaniasis in Ghardaia, Algeria. Infect. Genet. Evol. 28, 725–734.
Gitelson, A., Merzlyak, M.N., 1994. Spectral Reflectance Changes Associated with Autumn Senescence of Aesculus hippocastanum L. and Acer platanoides L. Leaves. Spectral Features and Relation to Chlorophyll Estimation. J. Plant Physiol. 143, 286–292. https://doi.org/10.1016/S0176-1617(11)81633-0.
Gitelson, A.A., Kaufman, Y.J., Stark, R., Rundquist, D., 2002. Novel algorithms for remote estimation of vegetation fraction. Remote Sens. Environ. 80, 76–87. https://doi.org/10.1016/S0034-4257(01)00289-9.
Gitelson, A.A., Merzlyak, M.N., 1997. Remote estimation of chlorophyll content in higher plant leaves. Int. J. Remote Sens. 18, 2691–2697. https://doi.org/10.1080/014311697217558.
Gitelson, A.A., Merzlyak, M.N., Chivkunova, O.B., 2001. Optical properties and non-destructive estimation of anthocyanin content in plant leaves. Photochem. Photobiol. 74, 38–45.
Goel, N.S., Qin, W., 1994. Influences of canopy architecture on relationships between various vegetation indices and LAI and Fpar: A computer simulation. Remote Sens. Rev. 10, 309–347. https://doi.org/10.1080/02757259409532252.
Gómez, C., White, J.C., Wulder, M.A., 2016. Optical remotely sensed time series data for land cover classification: a review. ISPRS J. Photogramm. Remote Sens. 116 (Supplement C), 55–72 (Jun 1).
Hardisky, M.A., Michael Smart, R., Klemas, V., 1983. Growth response and spectral characteristics of a short Spartina alterniflora salt marsh irrigated with freshwater and sewage effluent. Remote Sens. Environ. 13, 57–67. https://doi.org/10.1016/0034-4257(83)90027-5.
Hassan, A.N., Beck, L.R., Dister, S., 1998. Prediction of villages at risk for filariasis transmission in the Nile Delta using remote sensing and geographic information system technologies. J. Egypt Soc. Parasitol. 28 (1), 75–87.
Hay MJP, S.I., 1997. The impact of remote sensing on the study and control of invertebrate intermediate hosts and vectors for disease. Int. J. Remote Sens. 18 (14), 2899–2930.
Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI). Remote Sens. Environ. 25, 295–309. https://doi.org/10.1016/0034-4257(88)90106-X.
Hunt, E.R., Rock, B.N., 1989. Detection of changes in leaf water content using Near- and Middle-Infrared reflectances. Remote Sens. Environ. 30, 43–54. https://doi.org/10.1016/0034-4257(89)90046-1.
Identifying Environmental Risk Factors of Cholera in a Coastal Area with Geospatial Technologies [Internet]. [cited 2018 Nov 26]. Available from: ⟨https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4306866/⟩.
Jackson, T.J., Chen, D., Cosh, M., Li, F., Anderson, M., Walthall, C., Doriaswamy, P., Hunt, E.R., 2004. Vegetation water content mapping using Landsat data derived normalized difference water index for corn and soybeans. Remote Sens. Environ., 2002 Soil Moisture Experiment (SMEX02) 92, 475–482. https://doi.org/10.1016/j.rse.2003.10.021.
Joppa, L.N., O'Connor, B., Visconti, P., Smith, C., Geldmann, J., Hoffmann, M., et al., 2016. Filling in biodiversity threat gaps. Science 352 (6284), 416–418 (Apr 22).
Jurgens, C., 1997. The modified normalized difference vegetation index (mNDVI) a new index to determine frost damages in agriculture based on Landsat TM data. Int. J. Remote Sens. 18, 3583–3594. https://doi.org/10.1080/014311697216810.
Kaptein, A., Janoth, J., Lang, O., Bernede, N., 2014. Trends in commercial radar remote sensing industry [industrial profiles]. IEEE Geosci. Remote Sens. Mag. 2 (1), 42–46.
Karagiannis-Voules, D.-A., Odermatt, P., Biedermann, P., Khieu, V., Schär, F., Muth, S., et al., 2015b. Geostatistical modelling of soil-transmitted helminth infection in Cambodia: do socioeconomic factors improve predictions? Acta Trop. 141 (Pt B), 204–212.
Karagiannis-Voules, D.-A., Biedermann, P., Ekpo, U.F., Garba, A., Langer, E., Mathieu, E., et al., 2015a. Spatial and temporal distribution of soil-transmitted helminth infection in sub-Saharan Africa: a systematic review and geostatistical meta-analysis. Lancet Infect. Dis. 15 (1), 74–84.
Karume, K., et al., Schmidt, C., Kundert, K., Bagula, M.E., Safina, B.F., Schomacker, R., 2017. Use of Remote Sensing for Population Number Determination. Open Access J Sci Technol 5 (3)([cited 2018 Nov 26], [Internet], Available from: ⟨https://www.agialpress.com/articles/use-of-remote-sensing-for-population-number-determination.pdf⟩).
Kaufman, Y.J., Tanre, D., 1992. Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. IEEE Trans. Geosci. Remote Sens. 30, 261–270. https://doi.org/10.1109/36.134076.
Kelcey, J., Lucieer, A., 2012 May. Sensor correction of a 6-band multispectral imaging sensor for UAV remote sensing. Remote Sens. 4 (5), 1462–1493.
Lakshmi, V., Lakshmi, V., 2013. remote sensing of soil moisture, remote sensing of soil moisture. Int. Sch. Res. Not. 2013 (2013), e424178 (Mar 7).
Lehner, B., Döll, P., 2004. Development and validation of a global database of lakes, reservoirs and wetlands. J. Hydrol. 296 (1–4), 1–22 (Aug 20).
Li, M., Huang, C., Zhu, Z., Shi, H., Lu, H., Peng, S., 2009. Assessing rates of forest change and fragmentation in Alabama, USA, using the vegetation change tracker model. For. Ecol. Manag. 257, 9. https://doi.org/10.1016/j.foreco.2008.12.023.
Lu, J., Tang, R., Tang, H., Li, Z.-L., 2013. Derivation of daily evaporative fraction based on temporal variations in surface temperature, air temperature, and net radiation. Remote Sens. 5 (10), 5369–5396 (Oct 22).
Machault, V., Yebakima, A., Etienne, M., Vignolles, C., Palany, P., Tourre, Y.M., et al., 2014. Mapping entomological dengue risk levels in martinique using high-resolution remote-sensing environmental data. Isprs Int. J. Geo-Inf. 3 (4), 1352–1371.
McMichael A.J., Haines J.A., Slooff R., Sari Kovats R., Health WHOO of G and IE, Change WTG on HIA of C. Climate change and human health : an assessment [Internet]. Geneva: Geneva : World Health Organization; 1996 [cited 2018 Dec 12]. Report No.: WHO/EHG/96.7. Available from: ⟨http://apps.who.int/iris/handle/10665/62989⟩.
Melesse, A.M., Weng, Q., S.Thenkabail, P., Senay, G.B., 2007. Remote sensing sensors and applications in environmental resources mapping and modelling. Sensors 7 (12), 3209–3241 (Dec 11).

Nagler, P.L., Inoue, Y., Glenn, E.P., Russ, A.L., Daughtry, C.S.T., 2003. Cellulose absorption index (CAI) to quantify mixed soil–plant litter scenes. Remote Sens. Environ. 87, 310–325. https://doi.org/10.1016/j.rse.2003.06.001.
Noor, A.M., Kinyoki, D.K., Mundia, C.W., Kabaria, C.W., Mutua, J.W., Alegana, V.A., et al., 2014. The changing risk of plasmodium falciparum malaria infection in Africa: 2000–10: a spatial and temporal analysis of transmission intensity. Lancet 383 (9930), 1739–1747 (May 17).
Numata, I., Roberts, D.A., Chadwick, O.A., Schimel, J.P., Galvão, L.S., Soares, J.V., 2008. Evaluation of hyperspectral data for pasture estimate in the Brazilian Amazon using field and imaging spectrometers. Remote Sens. Environ. 112, 1569–1583. https://doi.org/10.1016/j.rse.2007.08.014. Remote Sensing Data Assimilation Special Issue.
Olson, D.M., Dinerstein, E., Wikramanayake, E.D., Burgess, N.D., Powell, G.V.N., Underwood, E.C., D'amico, J.A., Itoua, I., Strand, H.E., Morrison, J.C., Loucks, C.J., Allnutt, T.F., Ricketts, T.H., Kura, Y., Lamoreux, J.F., Wettengel, W.W., Hedao, P., Kassem, K.R., 2001. Terrestrial Ecoregions of the World: A New Map of Life on Earth A new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. BioScience 51, 933–938 https://doi.org/10.1641/0006-3568(2001)051[0933:TEOTWA]2.0.CO;2.
Ozdenerol, E., 2015. GIS and remote sensing use in the exploration of Lyme disease epidemiology. Int. J. Environ. Res. Public Health 12 (12), 15182–15203 (Dec 1).
Patra C., 2017. Geospatial monitoring of infectious diseases by unmanned aerial vehicles, 6.
Peng, J., Liu, Y., Loew, A., 2013. Uncertainties in estimating normalized difference temperature index from TOA radiances. IEEE Trans. Geosci. Remote Sens. 51 (5), 2487–2497.
Peñuelas, J., Gamon, J.A., Fredeen, A.L., Merino, J., Field, C.B., 1994. Reflectance indices associated with physiological changes in nitrogen- and water-limited sunflower leaves. Remote Sens. Environ. 48, 135–146. https://doi.org/10.1016/0034-4257(94)90136-8.
Pinty, B., Verstraete, M.M., 1992. GEMI: a non-linear index to monitor global vegetation from satellites. Vegetatio 101, 15–20. https://doi.org/10.1007/BF00031911.
Remote sensing links [Internet]. [cited 2017 Sep 27]. Available from: 〈http://www.ncl.ac.uk/tcmweb/msc_tcm/rs.htm〉.
Ren, H., Zhou, G., Zhang, F., Zhang, X., 2012. Evaluating cellulose absorption index (CAI) for non-photosynthetic biomass estimation in the desert steppe of Inner Mongolia. Chin. Sci. Bull. 57, 1716–1722. https://doi.org/10.1007/s11434-012-5016-3.
Richardson, L.L., LeDrew, E.F., 2006. Remote Sensing of Aquatic Coastal Ecosystem Processes: Science and Management Applications. Springer Science & Business Media (350 p).
Robinson, T., Rogers, D., Williams, B., 1997. Mapping tsetse habitat suitability in the common fly belt of Southern Africa using multivariate analysis of climate and remotely sensed vegetation data. Med. Vet. Entomol. 11 (3), 235–245 (Jul 1).
Romero, A., Aguado, I., Yebra, M., 2012. Estimation of dry matter content in leaves using normalized indexes and PROSPECT model inversion. Int. J. Remote Sens. 33, 396–414. https://doi.org/10.1080/01431161.2010.532819.
Rondeaux, G., Steven, M., Baret, F., 1996. Optimization of soil-adjusted vegetation indices. Remote Sens. Environ. 55, 95–107. https://doi.org/10.1016/0034-4257(95)00186-7.
Roujean, J.-L., Breon, F.-M., 1995. Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. Remote Sens. Environ. 51, 375–384. https://doi.org/10.1016/0034-4257(94)00114-3.
Sandvik, K.B., Lohne, K., 2014. The rise of the humanitarian drone: giving content to an emerging concept. Millennium 43 (1), 145–164 (Sep 1).
Schaeffer, B.A., Schaeffer, K.G., Keith, D., Lunetta, R.S., Conmy, R., Gould, R.W., 2013. Barriers to adopting satellite remote sensing for water quality management. Int. J. Remote Sens. 34 (21), 7534–7544 (Nov 10).
Serbin, G., Hunt, E.R., Daughtry, C.S.T., McCarty, G.W., Doraiswamy, P.C., 2009. An improved ASTER index for remote sensing of crop residue. Remote Sens. 1, 971–991. https://doi.org/10.3390/rs1040971.
Serrano, L., Peñuelas, J., Ustin, S.L., 2002. Remote sensing of nitrogen and lignin in Mediterranean vegetation from AVIRIS data: Decomposing biochemical from structural signals. Remote Sens. Environ. 81, 355–364. https://doi.org/10.1016/S0034-4257(02)00011-1.
Sims, D., Gamon, J.A., 2002. Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages. Remote Sens. Environ. 81, 337–354. https://doi.org/10.1016/S0034-4257(02)00010-X.. References - Scientific Research Publishing [WWW Document], n.d. URL https://www.scirp.org/(S(i43dyn45teexjx455qlt3d2q))/reference/ReferencesPapers.aspx?ReferenceID=797192 (accessed 2.19.19).
Sørensen, R., Zinko, U., Seibert, J., 2006. On the calculation of the topographic wetness index: evaluation of different methods based on field observations. Hydrol. Earth Syst. Sci. Discuss. 10, 101–112.
Spatial Resolution [Internet]. [cited 2017Oct 17]. Available from: 〈http://www.dspguide.com/ch25/1.htm〉.
Sripada, R.P., Heiniger, R.W., White, J.G., Meijer, A.D., 2006. Aerial color infrared photography for determining early in-season nitrogen requirements in corn. Agron. J. 98, 968–977. https://doi.org/10.2134/agronj2005.0200.
Tatem, A.J., Goetz, S.J., Hay, S.I., 2004. Terra and aqua: new data for epidemiology and public health. Int. J. Appl. Earth Obs. Geoinf. ITC J. 6 (1), 33–46.
Théau, J., 2008. Temporal resolution. In: Encyclopedia of GIS. Springer, US, pp. 1150–1151([Internet], Available from: 〈http://link.springer.com/referenceworkentry/10.1007/978-0-387-35973-1_1376〉).
Thomson, M.C., Connor, S.J., Milligan, P., Flasse, S.P., 1997. Mapping Malaria Risk in Africa: What Can Satellite Data Contribute? Parasitol Today Pers Ed 13. pp. 313–318.
Tran, A., Ippoliti, C., Balenghien, T., Conte, A., Gely, M., Calistri, P., et al., 2013. A geographical information system-based multicriteria evaluation to map areas at risk for Rift Valley fever vector-borne transmission in Italy. Transbound. Emerg. Dis. 60 (Suppl 2), 14–23.
Tran, A., Kassié, D., Herbreteau, V., 2016. Applications of Remote Sensing to the Epidemiology of Infectious Diseases: Some Examples. Elsevier(Available from: 〈http://hal.univ-reunion.fr/hal-01486537〉, [Internet]).
Tucker, C.J., Holben, B.N., Elgin, J.H., McMurtrey, J.E., 1981. Remote sensing of total dry-matter accumulation in winter wheat. Remote Sens. Environ. 11, 171–189. https://doi.org/10.1016/0034-4257(81)90018-3.
Usage of indices for extraction of built-up areas and vegetation features from landsat TM image: a case of Dar Es Salaam and Kisarawe Peri-Urban areas, Tanzania | Francis Mwakapuja - Academia.edu [Internet]. [cited 2018 Nov 26]. Available from: 〈http://www.academia.edu/9341512/Usage_of_Indices_for_Extraction_of_Built-up_Areas_and_Vegetation_Features_from_Landsat_TM_Image_A_Case_of_Dar_Es_Salaam_and_Kisarawe_Peri-Urban_Areas_Tanzania〉.
Using low-cost drones to map malaria vector habitats [Internet]. [cited 2017 Oct 13]. Available from: 〈https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5237572/〉.
van Deventer, A.P., Ward, A.D., Gowda, P.H., Lyon, J.G., 1997. Using Thematic Mapper Data to Identify Contrasting Soil Plains and Tillage Practices 7.
Verpoorter, C., Kutser, T., Seekell, D.A., Tranvik, L.J., 2014. A global inventory of lakes based on high-resolution satellite imagery. Geophys. Res. Lett. 41 (18) (Sep 28, 2014GL060641).
Viña, A., Gitelson, A.A., Nguy-Robertson, A.L., Peng, Y., 2011. Comparison of different vegetation indices for the remote assessment of green leaf area index of crops. Remote Sens. Environ. 115 (12), 3468–3478.
Vogelmann, J.E., Kost, J.R., Tolk, B., Howard, S., Short, K., Chen, Xuexia, Huang, Chengquan, Pabst, K., Rollins, M.G., 2011. Monitoring Landscape Change for LANDFIRE Using Multi-Temporal Satellite Imagery and Ancillary Data. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 4, 252–264. https://doi.org/10.1109/JSTARS.2010.2044478.
Vogelmann, J.E., Rock, B.N., Moss, D.M., 1993. Red edge spectral measurements from sugar maple leaves. Int. J. Remote Sens. 14, 1563–1575. https://doi.org/10.1080/01431169308953986.
Wang, L., Hunt, E.R., Qu, J.J., Hao, X., Daughtry, C.S.T., 2013. Remote sensing of fuel moisture content from ratios of narrow-band vegetation water and dry-matter indices. Remote Sens. Environ. 129, 103–110. https://doi.org/10.1016/j.rse.2012.10.027.
Weiss, D.J., Bhatt, S., Mappin, B., Boeckel, T.P.V., Smith, D.L., Hay, S.I., et al., 2014. Air temperature suitability for Plasmodium falciparum malaria transmission in Africa 2000–2012: a high-resolution spatiotemporal prediction. Malar. J. 13 (1), 171 (May 3).
Weiss, D.J., Mappin, B., Dalrymple, U., Bhatt, S., Cameron, E., Hay, S.I., et al., 2015. Re-examining environmental correlates of plasmodium falciparum malaria endemicity: a data-intensive variable selection approach. Malar. J. 14 (1), 68 (Feb 7).
What is spectral resolution and when is it needed? - HORIBA [Internet]. [cited 2018 Nov 26]. Available from: 〈http://www.horiba.com/us/en/scientific/products/raman-spectroscopy/raman-academy/raman-faqs/what-is-spectral-resolution-and-when-is-it-needed/〉.
Xu, H., Lin, D., Tang, F., 2013. The impact of impervious surface development on land surface temperature in a subtropical city: Xiamen, China: The Impact of Impervious Surface Development on Land Surface Temperature. Int. J. Climatol. 33, 1873–1883. https://doi.org/10.1002/joc.3554.
Xue, J., Su, B., 2017. Significant remote sensing vegetation indices: a review of developments and applications. J. Sens([Internet], cited 2017 Oct 20), (Available from: 〈https://www.hindawi.com/journals/js/2017/1353691/citations/〉).
Yamazaki, D., Trigg, M.A., Ikeshima, D., 2015a. Development of a global ~90 m water body map using multi-temporal Landsat images (Dec 15). Remote Sens. Environ. 171, 337–351. https://doi.org/10.1016/j.rse.2015.10.014.
Yamazaki, D., Trigg, M.A., Ikeshima, D., 2015. Development of a global ~90 m water body map using multi-temporal Landsat images. Remote Sens. Environ([Internet], [cited 2015 Nov 19], Available from: http://www.sciencedirect.com/science/article/pii/S0034425715301656).
Yang, G.-J., Vounatsou, P., Xiao-Nong, Z., Utzinger, J., Tanner, M., 2005. A review of geographic information system and remote sensing with applications to the epidemiology and control of schistosomiasis in China. Acta Trop. 96 (2), 117–129 (Nov 1).
Zarco-Tejada, P.J., Rueda, C.A., Ustin, S.L., 2003. Water content estimation in vegetation with MODIS reflectance data and model inversion methods. Remote Sens. Environ. 85, 109–124. https://doi.org/10.1016/S0034-4257(02)00197-9.
Zhao, Y., Feng, D., Yu, L., Wang, X., Chen, Y., Bai, Y., Hernández, H.J., Galleguillos, M., Estades, C., Biging, G.S., Radke, J.D., Gong, P., 2016. Detailed dynamic land cover mapping of Chile: Accuracy improvement by integrating multi-temporal data. Remote Sens. Environ. 183, 170–185. https://doi.org/10.1016/j.rse.2016.05.016.