MODIS and Vector-Borne Diseases

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Figure 1. Aedes albopictus (tiger mosquito) after blood meal. Image Credit: M. Neteler.

Abstract

Many regions in the world face an increasing risk for new or re-emerging vector-borne diseases. Subsequently, there is a strong need in addressing increasing challenges for human and veterinary public health across the globe. Dengue fever, borreliosis (Lyme disease), plague, West Nile fever, and tularaemia are examples for globally distributed vector-borne diseases with a high potential to affect people. Tick-borne rickettsial diseases (Ehrlichiosis, Anaplasmosis, Rocky Mountain spotted fever) are common in North America, whereas tick-borne encephalitis is widespread in Europe and Asia. Hantaviruses, transmitted by rodents, can cause different diseases in the Old and New World. Common to all these vector-borne diseases is an urgent need to gain better understanding of spatio-temporal patterns in disease transmission and diffusion. Disease vectors depend in most cases on climatic and environmental conditions which in turn can be observed using Earth Observation (EO) instruments. New methods including the use of high-resolution time series from satellites in spatial models enable researchers to predict species invasion and survival, and to assess potential health risks. Of high importance are the daily data obtained by MODIS (Moderate Resolution Imaging

Spectroradiometer), which is flown on board the satellites Terra and Aqua. More than a decade of high quality data sets and operational products are freely available. These can be leveraged to assess the spread of disease vectors in order to assist decision-makers and public health authorities to develop surveillance plans and vector control.

Introduction

The ongoing and increasing spread of vector-borne diseases on many continents calls for action. Vector-borne diseases are caused by bacteria and viruses transmitted mostly by arthropods including mosquitoes, ticks and fleas. Among them ranks malaria as the most deadly vector-borne disease which kills more than 1.2 million people annually, most of them African children under the age of five (WHO). The World Health Organization (WHO) classifies dengue, also spread by mosquitoes, as the world's fastest-growing vector borne disease. The list of the top 10 vector-borne diseases with greatest potential to affect people include mostly mosquito-borne and tick-borne diseases (Dengue fever, Ehrlichiosis, Anaplasmosis, Rocky Mountain spotted fever, Lyme disease, plague, West Nile fever, and others; CDC 2013; ECDC 2013).

There is a strong application use of remote sensing for epidemiology, as remote sensing measures susceptible to environmental conditions that may correspond to the spread of many disease vectors and subsequently diseases is driven by host-pathogen systems. Furthermore, since the infectivity of a host varies between a few days and its life-time, spatio-temporal patterns are relevant for disease transmission. In order to perform risk prediction of exposure to vector-borne diseases, biotic data (e.g., tick and host abundance) and abiotic data (environmental constraints) are commonly employed. Remote sensing data can be processed with Geographic Information Systems (GIS) to gather information about environmental conditions, niches, trends and patterns from time series. Remote sensing is of particular relevance in areas where meteorological stations and ground surveys are sparsely or irregularly distributed. In contrast to field observations, satellite data are intrinsically spatialized, hence continuous. The crucial role of remote sensing for providing detailed environmental analysis and understanding of disease patterns has long been recognized (Hay et al., 1996; Wood et al., 2000; Thomson and Connor, 2000; Rogers and Randolph, 2003; Tatem et al., 2004). In the past, the creation of ecological indicators from polar-orbiting EO satellite time series was limited (e.g., Herbreteau et al., 2005) especially due to the complex processing of data originating from Advanced Very High Resolution Radiometer (AVHRR) (the only long-term daily EO data source until 2000) and lack of the required computational resources. These problems have been overcome with the advent of MODIS and the nonlinear increase of both computational power and performance of processing software.

In times of "Open Data" and the availability of new satellite sensors, the gap between high-spatial resolution versus high-temporal resolution is becoming well-addressed. The freely accessible archive of global MODIS data is offering a cost-effective data source for creating eco-health indicators through remote sensing at medium spatial resolution. MODIS, a key instrument for obtaining time series of various environmental parameters, is a most important payload on the Terra and Aqua NASA satellites. Terra satellite overpasses at approximately 10:30 and 22:30 local solar time, while Aqua overpasses at approximately 01:30 and 13:30 local solar time (Wan et al., 2004). Due to this solar-synchronous time pattern, MODIS data are available four times a day. MODIS is a whisk-broom sensor with 36 channels ranging from visible to thermal-infrared (Justice et al., 2002). Data are delivered at 250-meter (Red, Near Infrared: bands 1-2), 500-meter (Mid Infrared: bands 3-7) and 1,000-meter resolution (Thermal Infrared: bands 8-36). NASA produces a series of operational products including Land Surface Temperature and Emissivity products, vegetation indices, snow and ice cover, and surface reflectance which can be used to derive additional environmental parameters such as water indices and drought indicators.

MODIS data are usually processed and published less than one week after acquisition on a NASA web site. Of great help for daily users is the pyModis software which is a free and open-source Python-based library to bulk-download MODIS data for selected time ranges. This application automatically mosaics tiles, converts Hierarchical Data Format (HDF) to common GIS formats, and reprojects from Sinusoidal to other projections.

METHODS: From satellite data to eco-health indicators

Indicators based on high temporal resolution data are crucial for the analysis and the understanding of disease patterns. Eco-health indicators can be generated at a global scale from optical and thermal remote sensing data (with the exception for highly cloud-dominated areas). Thorough pre- and post-processing, making use of the included detailed quality assessment can minimize artifacts.

Land Surface Temperature maps: LST

A set of MODIS products are available. The highest temporal resolution are four LST coverages per day at 1-kilometer or lower resolution; additionally, data sets aggregated over 8 and 16 days to minimize cloud effects are offered. The MODIS LST algorithm is aimed at reaching an accuracy better than 1 Kelvin for areas with known emissivities in the range from minus 10 degrees Celsius to 50 degrees Celsius (Wan et al., 2004). In many epidemiological applications, LST has been preferred over near-surface air temperature as surrogate variable for many years (Hay et al., 1996; Randolph, 2004). Importantly, LST should not be used as straight substitution for air temperature (Green and Hay, 2002).

A central problem of optical and thermal satellite data is cloud contamination. MODIS LST data reconstruction overcomes missing data caused by cloud contamination. Additionally, despite a series of filters applied by NASA to filter clouds in the LST product, some outliers still remain (undetected clouds which introduce very low temperatures in the LST maps and reprojection artifacts). Since it is ideal to work with complete maps when deriving climatic parameters from LST time series, a reconstruction of the missing pixel areas is needed.

Several authors have been working on further improvement of the LST product, particularly aiming at gap-filling to overcome data voids due to clouds. Such time series were produced by data reconstruction in the temporal domain using Fourier transform (Scharlemann et al., 2008) which processed MODIS LST at full global extent for the years 2001 to 2005 and extracted parameters for the annual, bi-annual, and tri-annual cycle with a resolution of 1,000 meters. However, inter-annual variations are getting lost in this approach since multi-annual data are aggregated.

Recent efforts address the huge amount of data (to date more than 17,000 MODIS maps have been collected for each MODIS map tile) requires the automation of data processing. Neteler (2010) and Metz et al. (submitted) reconstructed daily LST in the spatio-temporal domain, achieving a final resolution of 250 meters. They developed a self-contained LST reconstruction algorithm which does not depend on meteorological data since they are often unavailable and also of different nature in terms of data acquisition.

Time series of these MODIS products allow the derivation of many indicators that can be used to improve predictive epidemiological risk modeling (Rizzoli et al., 2007; Carpi et al., 2008). In terms of modeling related to vector-borne diseases, daily gap-filled LST can be aggregated to extract annual/monthly minima/maxima temperatures, late frost periods, hot summer temperatures, growing degree days, and autumnal temperature decrease. These high-resolution time series also enable researchers to identify anomalies, i.e., the creation of maps depicting temperatures higher than long(er)-term average (drought risk; longer period over minimal threshold for development/molting); the identification of colder-than-usual winters (winter survival of vectors) or warmer-than-usual winters (higher rodent reproduction); number of mild winter days (e.g., above 7 degrees Celsius, triggering activity of ticks); calculation of gradients of spring temperature rise (“spring warming”, ticks synchrony among different live stages) and autumn decrease (“autumnal cooling,” may trigger behavioral diapause in ticks); identification of special temperature conditions over several years (which may trigger tree masting which is of relevance for the reproduction of rodents); insect life cycle influence like the completion of molting before onset of winter (based on growing degree days); and the identification of extended spring and autumn seasons (more days with minimum temperatures not lower than 5-8 degree Celsius). Relevant is also the identification of urban heat islands from LST as important refugee for vectors seeking a safe place for overwintering.

Vegetation indices

Vegetation indices are generally measuring actively growing vegetation by responding to chlorophyll activity. Vegetation index values are usually higher for forests and lower for grasslands. Time series of vegetation indices permit to detect seasonal vegetation differences, spring/autumn detection and the length of growing season. Vegetation indices, in particular the Normalized Difference Vegetation Index (NDVI), can be used to describe habitat suitability for different species of mosquitoes (Brown et al., 2008; Kleinschmidt et al., 2000; Lourenço et al., 2011). These studies found a relation between patterns in spatio-temporal variability of NDVI and the occurrence of vector-borne diseases. An Enhanced Vegetation Index (EVI) has been proposed which shows more detail for tropical forests (Huete et al., 1997). Both vegetation indices NDVI and EVI are readily available as MODIS products at different spatial and temporal resolutions. As with other remote sensing products, gaps must be filled and outliers removed. A well-established method to reconstruct NDVI time series is the harmonic analysis of time series (Roerink et al., 2000).

Water indices

Normalized Difference Water Indices (NDWI) can be used as proxies for vegetation water content (Gao, 1996) or to delineate open water bodies (McFeeters, 1996; Xu, 2006), depending on the reflectance bands used to calculate the index. The variant related to vegetation water content can be combined with NDVI and other environmental parameters for vector distribution modeling (Eisen and Eisen, 2011). Spatio-temporal changes in water indices allow for the detection of droughts which can in turn lead to aggregations of disease vectors and consequent disease outbreaks (Epstein, 2001). Another water index, the Disease Water Stress Index (DWSI) has been shown to be related to disease vector distribution (Brown et al., 2008). These water indices can be calculated from the MODIS surface reflectance products. As for the MODIS NDVI products, gaps due to cloud cover can be removed with a harmonic analysis of time series (Roerink et al., 2000).

MODIS products in epidemiological modeling

MODIS data are increasingly used in vector-borne disease modeling. Kalluri et al. (2007) published a detailed review of surveillance of arthropod vector-borne infectious diseases using various EO systems. At present, the MODIS sensor provides an optimal match of temporal and spatial resolution. This section reviews a series of studies in which MODIS data have been used.

Tick-borne disease vectors

Remote sensing as input source to epidemiological remote sensing is relevant when diseases show different epidemiological and spatial patterns while being transmitted by the same vector. This has been demonstrated by Randolph (2001) for Lyme disease and tick-borne encephalitis. Through the aggregation of MODIS LST time series a higher-than-average rate of the autumnal temperature decrease (“autumnal cooling”) could be used as an index to a specific pattern of the population dynamics: Rapid autumnal cooling triggers overwintering of unfed larvae which then emerge synchronously with nymphs in the following spring (Carpi et al., 2008). Altobelli et al. (2008) combined different satellite products: Land Surface Temperature (LST), Land Surface Water Index (LSWI), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI) in a spatial model to predict the abundance of infected ticks (Ixodes ricinus) in North-eastern Italy. A different tick, Hyalomma marginatum, which is known to transmit the Crimean-Congo hemorrhagic fever virus, was assessed for distribution and spread in parts of Europe (Estrada-Peña et al., 2012).

Rodent-borne disease vectors

Hantaviruses transmitted by rodents can cause hantavirus pulmonary syndrome in the Americas and hemorrhagic fever with renal syndrome, called nephropathia epidemica (NE) in Asia and Europe. The transmission rate of these diseases from rodents to humans depends on rodent abundance and rodent behavior (Tersago et al., 2010). Rodent abundance in turn depends on food availability and overwintering survival rate. High food availability, in particular high tree seed production (tree masting) is related to unusually high summer and autumn temperatures (Tersago et al., 2008). There seems to be a direct link between climate and human cases of hantavirus infections.

Furthermore, the amount of snow cover providing shelter for rodents can influence the infection risk. Little or no snow cover forces rodents to search for warm places such as human dwellings which in turn increases the infection risk for humans. Unusually mild winters with more surviving rodents will also lead to higher rodent abundance. The Hantavirus outbreak in Yosemite National Park in 2012 might have been caused by a combination of climatic conditions favorable for rodents and new tourist accommodations also favorable for rodents. Temperature anomalies seem to be the main factor driving rodent abundance which can be detected with MODIS temperature time series.

Mosquito-borne disease vectors

In a series of studies, MODIS data have been employed to assess mosquito distribution and risk of encountering mosquito-borne diseases. As key predictor variables changes in land cover and land use were used together with vegetation indices, NDWI as well as LST maps.

In a study on the West Nile virus (WNV) incidence in the northern Great Plains of the United States, the authors used non-linear generalized additive models (GAMs) to evaluate the influence of deviations of cumulative LST and NDVI derived from MODIS, and actual evapotranspiration on WNV (Chuang and Wimberly, 2012). Seasonal changes in WNV transmission were driven by the timing of spring green up (from NDVI), by temperature variability (from LST) and by moisture availability (from actual evapotranspiration), in spring and summer.

Two studies focused on the spatial prediction of the presence of Aedes albopictus (tiger mosquito, vector of several emerging diseases): the authors assessed the winter survival of mosquito eggs and adult life cycle for Northern Italy and Switzerland (Roiz et al., 2011; Neteler et al., 2013). From gap-filled LST data, January temperature thresholds and growing degree day indicators were derived and applied to identify suitable habitats in complex terrain. The more recent study also evaluates the temperature thresholds for the species in Europe.

MODIS NDVI was used to model the density of Anopheles atroparvus in Portugal in order to determine the potential of malaria re-emergence in temperate regions (Lourenço et al., 2011). A Remote Vector Model (RVM) was developed based upon temperature and NDVI. The authors propose RVM as a tool for vector density estimation, contributing to the risk assessment of transmission of mosquito-borne diseases with potential of an early warning system.

Several more epidemiological studies using MODIS products are listed on PubMed.

Conclusions

The wealth of available EO data, especially in terms of the potential to identify patterns from time series, is an important asset for research and public administration. With more than a decade of daily MODIS sensor data, detailed environmental monitoring has become available to a large community without overly high financial obstacles. MODIS is expected to remain operational, further building up the time series data. Furthermore, successors to the MODIS sensors are in planning. These time series are reducing the gap between high-spatial resolution (with typically low-temporal resolution) and high-temporal resolution (originally with low-spatial resolution, although this is now significantly enhanced). High-temporal resolution data from MODIS are of great relevance to the modeling of disease-transmitting ectoparasites since they allow an assessment of vector and disease distribution and their potential spread. Traditional epidemiological surveillance systems are recording clinical infections, but seldom take into consideration spatial patterns. Remote sensing can contribute to surveillance systems by adding a spatial component which allows for a more fine-grained risk assessment. Early warning systems predicting future outbreaks in space and time can be implemented with the identification of critical thresholds for environmental parameters. Even though detailed EO time series data have been available for over a decade by now, their full potential for epidemiological surveillance and modeling has yet to be tapped.

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References

Altobelli, A., Boemo, B., Mignozzi, K., Bandi, M., Floris, R., Menardi, G., Cinco, M., 2008. Spatial Lyme borreliosis risk assessment in north-eastern Italy. Int. J. Med. Microbiol. 298, 125–128.

Brown, H., Diuk-Wasser, M., Andreadis, T., Fish, D., 2008. Remotely-Sensed Vegetation Indices Identify Mosquito Clusters of West Nile Virus Vectors in an Urban Landscape in the Northeastern United States. Vector-Borne Zoonotic Dis. 8, 197–206.

Carpi, G., Cagnacci, F., Neteler, M., Rizzoli, A., 2008. Tick infestation on roe deer in relation to geographic and remotely sensed climatic variables in a tick-borne encephalitis endemic area. Epidemiol. Infect. 1416–1424.

Chuang, T.-W., Wimberly, M.C., 2012. Remote Sensing of Climatic Anomalies and West Nile Virus Incidence in the Northern Great Plains of the United States. PLoS ONE 7, e46882.

Eisen, L., Eisen, R.J., 2011. Using Geographic Information Systems and Decision Support Systems for the Prediction, Prevention, and Control of Vector-Borne Diseases. Annu. Rev. Entomol. 56, 41–61.

Epstein, P.R., 2001. Climate change and emerging infectious diseases. Microbes Infect. 3, 747–754.

Estrada-Peña, A., Sánchez, N., Estrada-Sánchez, A., 2012. An assessment of the distribution and spread of the tick Hyalomma marginatum in the western Palearctic under different climate scenarios. Vector Borne Zoonotic Dis. Larchmt. N 12, 758–768.

Gao, B., 1996. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sens. Environ. 58, 257–266.

Green, R., Hay, S., 2002. The potential of Pathfinder AVHRR data for providing surrogate climatic variables across Africa and Europe for epidemiological applications. Remote Sens. Environ. 79, 166–175.

Hay, S.I., Tucker, C.J., Rogers, D.J., Packer, M.J., 1996. Remotely sensed surrogates of meteorological data for the study of the distribution and abundance of arthropod vectors of disease. Ann. Trop. Med. Parasitol. 90, 1–19.

Herbreteau, V., Salem, G., Souris, M., Hugot, J.P., Gonzalez, J.P., 2005. Sizing up human health through remote sensing: uses and misuses. Parassitologia 47, 63–79.

Huete, A.R., Liu, H.Q., Batchily, K., van Leeuwen, W., 1997. A comparison of vegetation indices over a global set of TM images for EOS-MODIS. Remote Sens. Environ. 59, 440–451.

Justice, C.O., Townshend, J.R.G., Vermote, E.F., Masuoka, E., Wolfe, R.E., Saleous, N., Roy, D.P., Morisette, J.T., 2002. An overview of MODIS Land data processing and product status. Remote Sens. Environ. 83, 3–15.

Kalluri, S., Gilruth, P., Rogers, D., Szczur, M., 2007. Surveillance of arthropod vector-borne infectious diseases using remote sensing techniques: a review. PLoS Pathog. 3, 1361–1371.

Kleinschmidt, I., Bagayoko, M., Clarke, G.P.Y., Craig, M., Sueur, D.L., 2000. A spatial statistical approach to malaria mapping. Int. J. Epidemiol. 29, 355–361.

Lourenço, P.M., Sousa, C.A., Seixas, J., Lopes, P., Novo, M.T., Almeida, A.P.G., 2011. Anopheles atroparvus density modeling using MODIS NDVI in a former malarious area in Portugal. J. Vector Ecol. 36, 279–291.

McFeeters, S.K., 1996. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. Int. J. Remote Sens. 17, 1425–1432.

Metz, M., Rocchini, D., Neteler, M., submitted. Surface temperatures at continental scale: tracking changes with remote sensing at unprecedented detail.

Neteler, M., 2010. Estimating daily Land Surface Temperatures in mountainous environments by reconstructed MODIS LST data. Remote Sens. 2, 333–351.

Neteler, M., Metz, M., Rocchini, D., Rizzoli, A., Flacio, E., Engeler, L., Guidi, V., Lüthy, P., Tonolla, M., 2013. Is Switzerland suitable for the invasion of Aedes albopictus? PLoS ONE 8, e82090.

Randolph, S.E., 2001. The shifting landscape of tick-borne zoonoses: Tick-borne encephalitis and Lyme borreliosis in Europe. Philos. Trans. R. Soc. B Biol. Sci. 356, 1054–1056.

Randolph, S.E., 2004. Tick ecology: processes and patterns behind the epidemiological risk posed by ixodid ticks as vectors. Parasitology 129 Suppl, S37–65.

Rizzoli, A., Neteler, M., Rosà, R., Versini, W., Cristofolini, A., Bregoli, M., Buckley, A., Gould, E., 2007. Early detection of tick-borne encephalitis virus spatial distribution and activity in the province of Trento, northern Italy. Geospatial Health 1, 169–176.

Roerink, G.J., Menenti, M., Verhoef, W., 2000. Reconstructing cloudfree NDVI composites using Fourier analysis of time series. Int. J. Remote Sens. 21, 1911–1917.

Rogers, D.J., Randolph, S.E., 2003. Studying the global distribution of infectious diseases using GIS and RS. Nat. Rev. Microbiol. 1, 231–237.

Roiz, D., Neteler, M., Castellani, C., Arnoldi, D., Rizzoli, A., 2011. Climatic factors driving invasion of the tiger mosquito (Aedes albopictus) into new areas of Trentino, Northern Italy. PLoS ONE 6, e14800.

Scharlemann, J.P., Benz, D., Hay, S.I., Purse, B.V., Tatem, A.J., Wint, G.R., Rogers, D.J., 2008. Global data for ecology and epidemiology: A novel algorithm for temporal Fourier processing MODIS data. PLoS ONE 3, e1408.

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. Geoinformation 6, 33–46.

Tersago, K., Verhagen, R., Servais, A., Heyman, P., Ducoffre, G., Leirs, H., 2008. Hantavirus disease (nephropathia epidemica) in Belgium: effects of tree seed production and climate. Epidemiol. Infect. 137, 250.

Tersago, K., Verhagen, R., Vapalahti, O., Heyman, P., Ducoffre, G., Leirs, H., 2010. Hantavirus outbreak in Western Europe: reservoir host infection dynamics related to human disease patterns. Epidemiol. Infect. 139, 381–390.

Thomson, M.C., Connor, S.J., 2000. Environmental information systems for the control of arthropod vectors of disease. Med. Vet. Entomol. 14, 227–244.

Wan, Z., Zhang, Y., Zhang, Q., Li, Z.L., 2004. Quality assessment and validation of the MODIS global land surface temperature. Int. J. Remote Sens. 261–274.

Wood, B.L., Beck, L.R., Lobitz, B.M., Bobo, M.R., 2000. Education, outreach and the future of remote sensing in human health, in: S.I. Hay, S.E.R. (Ed.), Advances in Parasitology. Academic Press, pp. 331–344.

Xu, H., 2006. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. Int. J. Remote Sens. 27, 3025–3033.