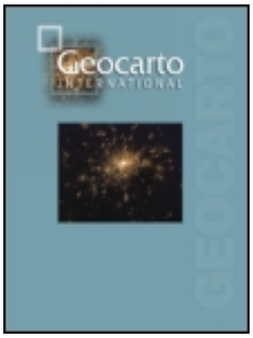

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# Use of earth observation data for applications in public health

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The Earth Observation (EO) data with their advantages in spectral, spatial and temporal resolutions have demonstrated their great value in providing information about many of the components that comprise environmental systems and ecosystems for decades that are crucial to the understating of public health issues. This literature review shows that in conjunction with *in situ* data collection, EO data have been used to observe, monitor, measure and model many environmental variables that are associated with disease vectors. Furthermore, satellite derived aerosol optical depth has been increasingly employed to estimate ground-level $PM_{2.5}$ concentrations, which have been found to associate with various health outcomes such as cardiovascular and respiratory diseases. It is suggested that Landsat-like imagery data may provide important data sources to analyse and understand contagious and infectious diseases at the local and regional scales, which are tied to urbanisation and associated impacts on the environment. There is also a great need of data products from coarse resolution imagery, such as those from moderate resolution imaging spectrometer, multiangle imaging spectroradiometer and geostationary operational environmental satellite, to model and characterise infectious diseases at the continental and global scales. The infectious diseases at greater geographical scales have become unprecedentedly significant as global climate change and the process of globalisation intensify. The relationship between infectious diseases and environmental characteristic have been explored by using statistical, geostatistical and physical models, with recent emphasis on the use of machine-learning techniques such as artificial neural networks. Lastly, we suggest that the planned HyspIRI mission is crucial for observing, measuring and modelling environmental variables impacting various diseases as it will improve both spectral resolution and revisit time, thus contributing to better prediction of occurrence of infectious diseases, target intervention and tracking of epidemic events.

**Keywords:** earth observation; satellite remote sensing; spatial resolution; spectral resolution; temporal resolution; infectious diseases; aerosol optical depth; $PM_{2.5}$; climate change; globalisation; urban; environmental characteristics; HyspIRI

## 1. Introduction

Public health has benefited from space-based technologies. Remote sensing data can be used to assist in taking into account multiple factors affecting human health, such as

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those contributing to environmental health hazards and contagious and infectious diseases. Remotely sensed data in combination with other data sources can provide spatial information on environmental conditions for understanding distributions of waterborne diseases, air quality, soil and vegetation as they influence community health and livestock. Remote sensing and geographic information system (GIS) technologies, in combination with biological, ecological and statistical methods, have been extensively applied in epidemiological studies globally.

Urban environmental problems have become unprecedentedly significant in the twenty-first century. This is not a simple consequence of ever increasing urban population and land, but also because urbanisation is one of the most profound examples of human modification of the Earth. Urbanisation may have an impact on local energy, water and carbon exchanges, and affect climate, habitat, biodiversity; and depending on the size of the area affected these impacts may be of local, regional, or global scale (Weng 2011). The Decadal Survey (National Research Council 2007) suggests that continued urbanisation and associated impacts on the environment and human health should be given a higher priority by using the next generation of earth observation (EO) data and technology. In addition, due to the nature of cities as the most complex human settlements, urban areas are more vulnerable than rural settlements to the impacts of global climate change (CCSP 2008). Most impact concerns, including those on public health, water and infrastructures, severe weather events, energy requirements, urban metabolism, sea level rise, economic competitiveness, opportunities and risks and social and political structures can be addressed by, or be better understood with, the EO technology (Weng et al. 2013). Finally, the globalisation promoted by trade and tourism has fundamentally altered the spreading pattern of infectious diseases and intensified their level of transmission. As the process of globalisation intensifies, new travel and trade patterns and different migration trends will be formed under certain socioeconomic and political networks. Transmission of the diseases will therefore be heavily impacted by social connectivity in the global system (Xu et al. 2013).

For applications to measuring, assessing, monitoring and modelling of human settlements, remotely sensed data can be used to detect and measure changes in urban growth patterns and provide data that can elucidate how urbanisation impacts the environment and human health. Remote sensing data with their advantages in spectral, spatial and temporal resolutions have demonstrated their power in providing information of physical characteristics of urban areas, including the size, shape and rate of change and have been widely used for mapping and monitoring of urban biophysical features (Haack et al. 1997; Jensen & Cowen 1999; Weng 2012). Some examples of use of remote sensing images in the urban areas include providing land cover/use data and biophysical attributes (Treitz et al. 1992; Haack et al. 2002; Weng et al. 2006; Weng & Hu 2008), extracting and updating transportation network (Harvey et al. 2004; Song & Civco 2004) and buildings (Lee et al. 2003; Miliaresis & Kokkas 2007), and detecting urban expansion (Yeh & Li 1997; Weng 2002).

This paper does not intend to provide a complete assessment of current use of EO data and techniques in public health, since it would be very challenging if not impossible. Instead, we offer a brief review of recent studies on the use of remotely sensed data and techniques to address three public and environmental health applications, that is, the impact modelling of spatial and social connectivity on infectious disease spread, the outbreak and dissemination of West Nile Virus (WNV), and using aerosol optical thickness to predict ground-level $PM_{2.5}$ concentrations. The authors have conducted various studies on these topics over the past decade, and thus think to be able to

provide some useful insights. At the end of the paper, we offer to speculate on the implication of future EO data for public health studies. In particular, a potential future satellite mission by NASA, that is, the HyspIRI mission, and its impact on public health research are discussed. We intend to provide some thought over why the mission is critical for observing, measuring and modelling environmental factors that are associated with vector – and animal borne diseases.

## 2. Modelling the impact of spatial and social connectivity on infectious disease spread

The emergence of new infectious disease and re-emergence of previously controlled infectious diseases have attracted a significant amount of attention from both scientists, professionals, politicians and the general public. Their relationship, however, is a complicated one that presents a difficult challenge to scientists from many disciplines covering biological, medical, social and environmental sciences that study pathogen, human environment and the impact of environmental change (Xu & Gong 2009).

Severe acute respiratory syndrome (SARS) rapidly spread over 30 countries and regions during a period of less than half a year from the beginning of 2003, leading to over 8000 infected people and over 700 deaths (http://www.cdc.gov/ncidod/sars/). The WNV, originating from Uganda, was found in New York in 1999 and had spread to over 44 states by 2002; in 2003 and 2004, the WNV had infected over 12,000 people, killing 350 (http://www.cdc.gov/ncidod/dvbid/westnile/). On average, interpandemic influenza took 5.2 weeks to spread across the lower US during 1972–2002 (Viboud et al. 2006). After battling schistosomiasis for many years along the Yangtze River Basin, many counties in China had the disease under control for some time. However, there have been recent resurgences in many counties. In 2004 alone, seven counties had resurgences of the disease (Liang et al. 2006). It has been 17 years since the first goose case of H5N1 avian influenza was discovered in Hong Kong in 1996 (Xu et al. 1999). As of 19 May 2013, H5N1 has caused 628 human cases of infection with 374 deaths in 15 different countries (WHO 2013). Due to the high lethality and virulence of H5N1, its epizootic presence, its increasingly large host reservoir, its significant ongoing mutations, and its transmissibility potential between humans, the H5N1 virus is the world's largest current pandemic threat. A new subtype of Influenza A virus, H1N1 of swine, human, and avian origin, emerged in the US and Mexico in April of 2009, quickly and extensively spread around the globe through human-to-human transmission. As of 1 August 2010, worldwide more than 214 countries and overseas territories or communities have reported laboratory confirmed cases, including over 18,449 deaths (WHO 2013). Latest statistics from China Animal Agriculture Association reported that Chinese poultry industry lost more than $16.3 billion in two weeks of H7N9 avian influenza outbreak (Reuters 2013). Billions of dollars are being spent researching various aspects of infectious diseases and preparing for potential pandemic. However, the transmission mechanisms of many infectious diseases in human society with a changing environment and connected society remain poorly understood.

Disease vector surveillance is often difficult and time-consuming. This is particularly true over large areas. Satellite remote sensing offers a unique opportunity for large-scale EO and monitoring of the environmental variables that are associated with disease vectors. Research has been carried out on the use of EO data in modelling of such infectious diseases as Tryponosomiasis (Rogers & Randolph 1991; Kitron et al. 1996; Rogers et al. 1997), rift valley fever (Linthicum et al. 1987, 1999), malaria (Beck

et al. 1997; Thomson et al. 1997; Hay 1998), Lyme disease (Dister et al. 1997; Kitron & Kazmierczak 1997) and Schistosomiasis (Malone et al. 1997; Seto et al. 2002; Zhou et al. 2002; Xu et al. 2004; Bergquist & Rinaldi 2010).

Spatial-temporal models have been used extensively in ecology, typically under the heading of metapopulation models. These models simulate populations that live within a network of connected environmental patches (Grenfell et al. 1995; Grenfell & Harwood 1997; Hanski 1999). Spatial-temporal models have been used to study a variety of diseases including malaria (Rodriguez & Torres-Sorando 2001), bubonic plague (Keeling & Gilligan 2000a, 2000b), rotavirus (Pitzer et al. 2009), measles (Grenfell et al. 2001), rabies (Smith et al. 2002), foot and mouth disease (Ferguson et al. 2001), and SARS epidemic (Hufnagel et al. 2004; Brockmann et al. 2006).

Spatial interaction and connectivity are important factors in the spread of infectious diseases. A spatial-temporal model considered neighbourhood relationships and hydrologic connectivity to assess the effect of inter-village parasitic transport on schistosomiasis transmission and control. Satellite remote-sensing data served as input to the model for predicting snail density and deriving a digital elevation model that was used to quantify hydrologic connectivity (Xu et al. 2006). These findings suggest that better understanding of inter-village connectedness can be exploited in the design of cost-effective control strategies. A study on the global spread of the avian influenza using phylogenetic relationships of virus isolates indicate that migratory bird movements, and trade in poultry and wild birds could determine the pathway for 52 individual introduction events into countries and predict future spread (Kilpatrick et al. 2006). Colizza et al. (2007) studied a metapopulation stochastic epidemic model on a global scale that considers airline travel flow data among urban areas. They compared the baseline cases with different containment strategies, including travel restrictions and the therapeutic use of antiviral drugs. Shoval and Isaacson (2007) introduces the method of sequence alignment as a tool for analysing the sequential aspects within the temporal and spatial dimensions of human activities. Balcan et al. (2009) studied the interplay between short-scale commuting flows and long-range airline traffic in shaping the spatiotemporal pattern of a global epidemic due to multi-scale mobility processes in the disease dynamics. Moreover, new interdisciplinary efforts using a combination of geospatial informatics and bioinformatics approaches have been made to improve understanding of global H5N1 transmission (Liang et al. 2010). The result that backyard poultry was significantly affected by neighbouring commercial poultry and close contact with wild birds was expected to improve our understanding of the transmission risks of infectious diseases and address the need to take preventive measures (Wang et al. 2013). Cauchemez et al. (2011) quantified how transmission of influenza was affected by social networks.

Undoubtedly, patterns of transmission of infectious diseases are related not only to the physical environment via human land-use activities but also to the social activity of human and their connectivity at various spatial and temporal scales (Wu et al. 2013; Xu et al. 2013). Quantification of the spatiotemporal transmission process of infectious diseases at the satisfactory level is important in making preventive and control policies.

## 3. Assessing and modelling environmental factors to the outbreak of WNV

WNV is a mosquitoborne disease first discovered in the West Nile District of Uganda in 1937. It has been found in Africa, the Middle East, Europe, Oceania, west and central Asia and North America. It is a seasonal epidemic in North America that normally

erupts in the summer and continues into the fall, presenting a threat to human and animal health. Its natural cycle is bird (reservoir) – mosquito (vector) – bird, human, or other mammals usually acting as incidental, dead-end hosts. The symptoms of severe disease include fever, head ache, neurological deficits, paralysis and coma, and about 10% of neurological cases are fatal. Environmental conditions, such as the presence of mosquito breeding habitats that are suitable for competent vector species, habitats suitable for competent avian hosts, and environmental temperatures play important roles in WNV dissemination in North America (Ruiz et al. 2004; Reisen et al. 2006; Liu et al. 2008). Mosquito Culex species appear to prefer some land-use and land-cover types (e.g. wetlands and some types of grasslands) than others (e.g. exposed dry soils). Mosquitoes in the canopy sites seem to possess more infections than those in the subterranean areas and on the ground (Anderson et al. 2006). Wetlands and storm water detention ponds, especially those under heavy shade, provide an ideal environment for mosquito breeding. Moreover, the spread of WNV has been found to significantly correlate with average summer temperatures in the USA (Reisen et al. 2006), and the seasonality of temperature may also affect the rate of WNV infection in birds (Pan et al. 2008). Anyhow, the spread of WNV is a complex environmental and public health issue because WNV propagates via the interactions between reservoir (avian), vector (mosquito) and hosts (human, other mammals and birds) populations; and these interactions are further influenced by risk factors underlying WNV incidences (Ghosh & Guha 2011). The four broad categories of risk factors have been identified, including: environmental (temperature, precipitation, vegetation, hydrologic features, parks), socioeconomic (occupation, income, housing age and condition), built-environment (catch basins, construction sites, ditches, scrap-tyre stockpiles, sewers), and existing mosquito abatement policies (Ghosh & Guha 2011).

Previous studies focused on building models to understand the relationships between WNV occurrence and potential risk factors assumed a priori that there is a linear relationship between those risk factors and WNV incidences (Brownstein et al. 2002; Bowman et al. 2005; Diuk-Wasser et al. 2006; Gibbs et al. 2006; Warner et al. 2006; David et al. 2007; Lian et al. 2007; Ruiz et al. 2004, 2007; Liu & Weng 2012). The mathematical methods employed include logistic regression analysis (Gibbs et al. 2006; Kunkel et al. 2006), principal component analysis (Mongoh et al. 2007; Liu & Weng 2009) and discriminate analysis (Wontroba 2003; Liu et al. 2008, 2011). However, statistical methods for WNV infection include several weaknesses, for example, they require prior knowledge about the statistical distributions in the data sources, and they are unable to deal with vague and noisy data (Benediktsson et al. 1990; Pan et al. 2008). The statistical models developed might be able to explain some of the natural and man-made risk factors that could trigger WNV amplification; however, it is difficult for linear models to derive both good prediction and explanation of the complexities of WNV transmission (Ghosh & Guha 2011). The use of non-linear, machine-learning techniques, such as, artificial neural networks has been demonstrated successfully to provide great potentials in interpreting the nonlinear interactions between infection of WNV virus and the environmental variables (Ghosh & Guha 2011; Pan et al. 2008).

Birds as virus hosts play important roles in the bird/mosquito/bird transmission/amplification cycle for WNV. WNV can be transmitted only when competent vector mosquito species bite infected birds (as host) and then bite birds or humans and other mammals. The natural cycle of WNV transmission indicates that infected birds must nest or rest close to or inside the habitats of those mosquito species that have the capability to transmit the virus to human or other mammals. Any statistical model failing to

account for this vector – host interaction between birds and mosquitoes would miss the significant contribution made by birds in the spread of WNV. Previous studies had also paid attention to assess the infection rate of infected dead birds and the locations that may provide favourable habitats for both appropriate bird species and mosquitoes in generating risk-area maps (Liu et al. 2011; Liu & Weng 2012).

Human related activities, such as travelling, have significant effects on WNV dissemination. The oviposition patterns of mosquito species were significantly different at urban and rural sites since oviposition activity of mosquitoes reached a peak in the evening and morning in urban areas but it did not have an obvious morning peak in rural areas (Savage et al. 2006). Scientists believed that flooding created by human activities such as logging rather than rainfall caused the increasing abundance of mosquitoes in many wet locations (Balenghien et al. 2006). Inner suburbs were found to have the highest incidence of WNV illness in Chicago and the characteristics of neighbourhoods were believed to be more important than the geographic locations where the illnesses were found in the same study area (Ruiz et al. 2007).

Remote sensing has been widely used in WNV studies, sometimes combined with other geospatial technologies, such as GIS and GPS. A common approach is to use remote sensing images to derive environmental variables associated with WNV disseminations, for example, land cover types and urban canopy (Anderson et al. 2006; Ruiz et al. 2007). These derived variables can be used to understand the physical landscape with WNV infections. More importantly, they can be input into various models for WNV analysis along with other variables, for example, climate and socio-economic conditions (Liu & Weng 2009; Liu et al. 2011). Continued improvements in remote sensors technology will contribute positively to WNV research. On one hand, high spatial resolution of satellite images allows more accurate risk assessment of WNV at the local scale. On the other hand, high temporal resolution makes it possible to investigate the relationship between WNV propagation and environmental variables at different time windows throughout a year. Advanced remote sensing techniques will be helpful too. Image fusion has recently been used to simulate images of both high spatial and temporal resolutions at desired time windows to identify WNV risk areas in Los Angeles, USA (Liu & Weng 2012).

## 4. Using aerosol optical thickness to predict ground-level $PM_{2.5}$ concentrations

$PM_{2.5}$ is the fine particles having aerodynamic diameter less than 2.5 μm. It consists primarily of combustion particles from motor vehicles and burning of coal, fuel oil, biomass, waste, gasoline and diesel and also contains some crustal particles such as finely pulverised road dust and soils. Carbonaceous aerosol is a dominant component of $PM_{2.5}$ and has significant impacts on the global radiation balance and on the global climate change via direct and indirect radiation forcing (Lonati et al. 2007). In general, $PM_{2.5}$ can be divided into organic carbon (OC) and elemental carbon (EC). EC is a product of incomplete combustion of carbon-based materials and is primary in nature, while OC can be directly released into the atmosphere or generated through secondary gas-to-particle conversion process. EC absorbs and scatters solar radiation. As a result, it is associated with global warming (Dan et al. 2004) and visibility reducing (Na et al. 2004). On the other hand, OC plays a key role in the formation of cloud condensation nuclei that result in a higher albedo of cloud and global climate change (Hitzenberger et al. 1999).

Previous studies have shown that long- and short-term exposures to $PM_{2.5}$ are associated with various health outcomes such as cardiovascular and respiratory diseases. For instance, Studies showed that elevated $PM_{2.5}$ exposure might increase the risk of triggering cardiovascular and respiratory diseases (Dominici et al. 2006), increased concentrations of $PM_{2.5}$ tend to raise the risk of myocardial infarction (MI) (Peters et al. 2001) and significantly reduced heart rate variability (HRV) is associated with elevated $PM_{2.5}$ concentrations (Gold et al. 2000). Furthermore, $PM_{2.5}$ exposure also has adverse health effects on children, causing respiratory problems and deficits in lung development (Dockery et al. 1989; Gauderman et al. 2004). A study implemented in six eastern US cities pointed out that a 10 $\mu g/m^3$ increase in two-day mean $PM_{2.5}$ was related to a 1.5% increase in total daily mortality, 3.3% increase in chronic obstructive pulmonary disease related mortality, and a 2.1% increase in ischemic heart disease related mortality (Schwartz et al. 1996). A similar study conducted in 27 US communities also showed that a 10 $\mu g/m^3$ increase in previous day's $PM_{2.5}$ led to 1.21% increase in all-cause mortality, a 1.78% increase in respiratory related mortality, and a 1.03% increase in stroke related mortality (Franklin et al. 2007). Due to the adverse effects on public health, US Environment Protection Agency (EPA) in 2006 has revised the National Ambient Air Quality Standard (NAAQS) to include a 24-h standard for $PM_{2.5}$ of 35 $\mu g/m^3$ and an annual standard of 15 $\mu g/m^3$ (EPA 2006). Thus, it is essential to obtain the long-term and spatially resolved distribution of $PM_{2.5}$ concentrations in order to evaluate the health effects of various levels of exposure, and accurate $PM_{2.5}$ exposure predictions are crucial not only to air quality assessment, but also to address public health concerns.

Many stationary ambient monitoring (SAM) sites have been set up to measure ground-level $PM_{2.5}$ concentrations that was used as surrogates for personal exposure of $PM_{2.5}$ by many epidemiological studies (Ito et al. 2001; Pope et al. 2002). However, the number of SAM sites is limited, and the distribution is unbalanced. As a result, using satellite derived aerosol optical depth (AOD) to estimate ground-level $PM_{2.5}$ concentrations has become more and more popular due to its comprehensive spatial coverage. AOD is a measure of the degree to which aerosols prevent light from penetrating the atmosphere. In addition, AOD retrieved at visible channel is most sensitive to particles with size from 0.1 to 2 μm (Kahn et al. 1998) and can be used to measure loadings of fine particles. To date, a number of AOD products retrieved from various satellite sensors such as the moderate resolution imaging spectrometer (MODIS) (Kumar et al. 2007; Zhang et al. 2009; Hu et al. 2013), the multiangle imaging spectroradiometer (MISR) (Liu, Koutrakis, & Kahn 2007; Liu, Koutrakis, Kahn, Turquety, et al. 2007), and the geostationary operational environmental satellite (GOES) aerosol/smoke product (GASP) (Paciorek et al. 2008; Liu et al. 2009). Paciorek et al. (2008) used GASP AOD to predict ground level $PM_{2.5}$ concentrations and compared the results to previous MODIS and MISR predictions. Although the correlations between GASP AOD and PM $_{2.5}$ on daily basis were lower than MODIS and MISR AOD, given the dense temporal coverage, GASP AOD had the potential to improve the exposure estimates for epidemiological studies. Liu, Franklin, et al. (2007) compared the ability of MODIS and MISR AOD in predicting ground level $PM_{2.5}$ concentrations, and the results indicated that although the overall results of MISR were slightly better than MODIS, they both contributed significantly to the predictions of $PM_{2.5}$ concentrations and had their own advantages in $PM_{2.5}$ exposure prediction. For example, MISR had higher predicting accuracy, while MODIS had better spatial coverage. In addition, Tian and Chen (2010) predicted the ground level $PM_{2.5}$ concentrations using MODIS

AOD incorporated with meteorological parameters and found that surface temperature and relative humidity were significant in improving the model predictability. Liu et al. (2005) found that planetary boundary layer height and relative humidity impact the relationship between $PM_{2.5}$ and AOD. Furthermore, Liu, Franklin, et al. (2007) pointed out that surface wind speed, surface temperature, and mixing height were all significant predictors of $PM_{2.5}$. Liu et al. (2009) further found that land use variables also were effective predictors of $PM_{2.5}$.

To establish the quantitative relationship between ground level $PM_{2.5}$ concentrations and AOD, many methods have been presented by previous research. For example, numerous studies used linear regression model to examine the association between $PM_{2.5}$ and AOD (Liu et al. 2005; van Donkelaar et al. 2006; Kumar et al. 2007; Wallace et al. 2007; Schafer et al. 2008; Schaap et al. 2009). Liu et al. (2009) conducted a two-stage generalised additive model (GAM) to predict $PM_{2.5}$ exposure from GASP AOD combined with meteorological fields and land use information in Massachusetts domain. Wallace et al. (2007) used a linear regression to examine the relationship between MODIS AOD and ground level $PM_{2.5}$ concentrations. All those models are considered to be global methods that are based on an assumption that the relationship between $PM_{2.5}$ and AOD does not vary over space. However, this is not necessarily the case for many studies. Engel-Cox et al. (2004) found that the correlations between $PM_{2.5}$ and AOD were better in eastern and mid-west part of the US and poorer in the western US. A similar phenomena was also reported by Hu (2009). Both studies might indicate that the correlations between $PM_{2.5}$ and AOD were spatially non-stationary and varied over space. As a result, Hu et al. (2013) developed a geographically weighted regression model by incorporating MODIS AOD as the primary predictor and meteorological and land-use variables as the secondary predictors to account for the spatial variability between the $PM_{2.5}$-AOD relationship. In addition, Lee et al. (2011) and Kloog et al. (2011) argued that the $PM_{2.5}$–AOD relationship varies day-to-day, and the temporal variability needs to be accounted for in order to improve performance of the AOD-based prediction models. As a result, both studies developed a linear mixed effects model to incorporate daily calibration of the $PM_{2.5}$–AOD relationship and obtained predictions with high accuracy.

## 5. Perspectives on future EO data for public health research

EO technology, in conjunction with *in situ* data collection, has been used to observe, monitor, measure, and model many of the components that comprise environmental systems and ecosystems cycles for decades that are key to the understating of public health issues. There are a number of satellite remote sensing systems capable of imaging the Earth surfaces to the details needed for global assessment of local and regional ecosystems. Most of the satellite systems are at the level of coarse-resolution (larger than 100 m in spatial resolution) and medium-resolution (10–100 m), but more and more satellite systems are now capable of high-resolution imaging (less than 10 m). This review has shown that Landsat-like imagery provide important data sources to assess and model infectious diseases such as WNV at the local and regional scales. AOD data products from coarse resolution imagery, such as those from MODIS, MISR and GOES, are effective for modelling and predicting ground-level $PM_{2.5}$ concentrations. The scientific and user community is exciting to learn the recent successful release of Landsat-8 data, and is exploring its various usages. Earlier, the National Research Council Decadal Survey indicated the need for such a satellite sensor to

extend the more than three decade-long mission. In addition, the Hyperspectral Infrared Imager (HyspIRI) is defined as a mission with Tier-2 priority to be launched in the next 8–10 years. Because of its hyperspectral visible and shortwave infrared bandwidths and its multispectral thermal infrared capabilities, HyspIRI will be well suited for deriving land cover and other biophysical attributes for environmental and public health studies (refer to the HyspIRI web site at http://hyspiri.jpl.nasa.gov/ for more information). The wide-swath hyperspectral sensor provides a global coverage in 19 days. Its TIR imager is expected to provide 7 bands between 7.5–12 μm and 1 band at 4 μm, all with 60 m resolution and 5-day revisit at the equator (1 day and 1 night imaging). These improved capabilities would allow for a more accurate estimation of LST and emissivity and for deriving unprecedented information on biophysical characteristics (e.g. vegetation state, soil moisture, and land cover composition) in a shorter revisit time, and even socioeconomic information such as population, quality of life indicators, and human settlements. These variables affect the outbreak and transmission of vector – and animalborne diseases, and such information cannot be obtained from current generation of satellites in orbit, such as MODIS, Landsat, or ASTER. Two major areas of application identified by the HyspIRI science team are urbanisation and human health through the combined use of VSWIR and TIR data. Until then, we may have to bear with Landsat and ASTER for medium resolution data and MODIS, MISR, GOES etc. for coarse resolution data. It is from this perspective that international collaborations on Earth resources satellites become very important (Weng 2009).

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