Remote Sensing Applications for Malaria Research: Emerging Agenda of Medical Geography*

Park, Sunyurp**

원격탐사 자료를 이용한 말라리아 연구: 보건지리학적 과제와 전망*

박 선 엽**

Abstract : Malaria infection is sensitively influenced by regional meteorological conditions along with global climate change. Remote sensing techniques have become an important tool for extraction of climatic and environmental factors, including rainfall, temperature, surface water, soil moisture, and land use, which are directly linked to the habitat qualities of malaria mosquitoes. Improvement of sensor fidelity with higher spatial and spectral resolution, new multinational sensor development, and decreased data cost have nurtured diverse remote sensing applications in malaria research. In 1984, eradication of endemic malaria was declared in Korea, but reemergence of malaria was reported in mid-1990s. Considering constant changes in malaria cases since 2000, the epidemiological management of the disease needs careful monitoring. Geographically, northmost counties neighboring North Korea have been ranked high in the number of malaria cases. High infection rates in these areas drew special attention and led to a hypothesis that malaria dispersion in these border counties might be caused by north-origin, malaria-bearing adult mosquitoes. Habitat conditions of malaria mosquitoes are important parameters for prediction of the vector abundance. However, it should be realized that malaria infection and transmission is a complex mechanism, where non-environmental factors, including human behavior, demographic structure, landscape structure, and spatial relationships between human residence and the vector habitats, are also significant considerations in the framework of medical geography.
Key Words : malaria, remote sensing, vector, habitat condition, medical geography

요약 : 지구온난화로 대표되는 전반적인 기후변화 속에서도 지역적인 기상조건에 따라 말라리아 감염 사례의 증감이 비교적 민감하게 영향 받는 것으로 사료된다. 말라리아를 매개하는 모기의 서식환경에 직접적인 영향을 주는 기후환경적인 인자, 즉 강수, 기온, 지표수 분포, 토양수분, 토지이용에 대한 광범위한 관측과 추정에 원격탐사 자료의 적용이 매우 중요한 수단이 되었다. 다국적 원격탐사 센서의 개발이 이어지고 있고, 공간 및 분광해상도 면에서 기술적인 진화를 보이고 있으며, 자료 획득에 필요한 비용도 크게 줄어드는 등 말라리아를 비롯한 모기매개 감염병 연구에 원격탐사 기법의 적용이 크게 각광받을 전망이다. 우리나라의 경우, 1980년대에 퇴치되었던 것으로 보고된 말라리아는 1990년대 중반부터 크게 증가하여 2000년 이후 증감을 거듭하고 있어 보건관리의 주요 대상으로 떠올랐다. 감염자수로 볼 때, 휴전선 인근 지역에서 큰 비중을 차지하고 있기 때문에 말라리아 보균 모기의 북방 유입설 등 지리적인 특성에 주목할 필요가 있다. 말라리아 매개모기의 환경적인 서식조건은 모기 개체수 규모를 추정하는 데에 중요한 역할을 하지만, 말라리아 감염과 전파는 환경조건 외에도 인간의 활동, 인구구성, 경관의 구조, 거주지와 매개모기 서식처간의 공간적 관계 등 매우 복합적인 보건지리학적 메카니즘의 산물이라는 점을 이해해야 한다.
주요어 : 말라리아, 원격탐사, 매개모기, 서식조건, 보건지리학

1. Introduction

Malaria, an infectious disease transmitted to humans by infected anopheline mosquitoes, is a deadly health problem killing about one million people each year. Particularly, malaria is a very difficult disease among the poorest and responsible for more than one-third of deaths of children under five (WHO, 2010). Although malaria infection depends on land use change, disease-control efforts, and sociodemographic factors, the spatial distribution and transmission dynamics of malaria is highly climate-sensitive. Difficulties of public health issues reside in the fact that the

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** 부산대학교 사범대학 지리교육과(Department of Geography Education, Pusan National University)(spark@pusan.ac.kr)

impact of climate change on disease occurrence and dispersal is fairly complex and involves uncertainties (Wilcox and Colwell, 2005). Moreover, the density of weather stations that is much coarser than that of disease cases makes it very difficult to determine geographical relationships between climate factors and the disease. Therefore, environmental conditions, such as climate seasonality, temperature, precipitation, humidity, and surface moisture conditions must be carefully considered when the spatial epidemiology or transmission cycle of malaria is under investigation (Machault *et al.*, 2011).

Remote sensing imagery can be crucial part of input data to improve spatial models of disease control and to better understand geographical phenomena related to potential occurrence and epidemiology of the disease (Brownstein *et al.*, 2003; Clennon *et al.*, 2004). Since various digital maps and remotely sensed data are regularly acquired and disseminated over large area in a timely manner, the use of the data are beneficial for spatiotemporal understanding of the characteristics of mosquito-borne diseases, such as malaria (Smith *et al.*, 1993; Snow *et al.*, 1993; Hay *et al.*, 1998a). As more study results confirm the seasonal and geographical nature of mosquito-borne diseases, including El-Nino and drought episodes, the roles of remote sensing techniques in public heath studies are being emphasized (Glass *et al.*, 1995; Kitron, 1998; Melnick, 2002; Bunnell *et al.*, 2003; Napier, 2003; Kolivars, 2006).

Meteorological data can be combined with contiguous geospatial data to generate environmental variables involved in disease outbreaks overcoming limitations of discrete point data. Advances in remote sensing techniques for estimation of air temperature and precipitation and interpolation methods of ground observations contribute to development of spatial epidemiology (Hay and Lennon, 1999). Hay *et al.* (2010) is conducting a global mapping of malaria cases, and recently suggested that remote sensing imagery should be used in geographical studies of vector-borne diseases to improve maturity and accuracy of research projects.

Remote sensing technologies have been available for diverse environmental studies for about 40 years now, but it is only recent years that they have been adopted by malaria control and management people. Today, tremendous amount of remotely sensed data are provided by a wide range of sensors, and proven technologies and algorithm development related to malaria distribution and dispersion are useful for operational malaria warning systems and decision makers. Infectious diseases are geographically limited, and this spatial tendency is associated with environmental and biological conditions that support the pathogen, its vectors, and reservoirs (Ostfeld *et al.*, 2005). Therefore, if malaria occurrence, habitat conditions, and the linkage between them are determined, malaria threats can be predicted and avoided for millions of people. The purpose of this article is to review the recent use of remotely sensed data as emerging agenda in malaria research and provide key issues and opportunities of remote sensing technologies in the field of geography.

2. Geography of Malaria

Malaria infection is typically caused by the bites of female anopheles mosquitoes that carry malaria parasites, such as *Plasmodium falciparum*, the most common and serious species. Therefore, malaria transmission depends directly on mosquito development cycles. Surface water collections are required for mosquito breeding, but other conditions, including temperature, turbidity, salinity, and sunlight, should be favorable to harbor Anopheles mosquito larvae. Coexistence of anophelene vectors and malaria parasites mosquitoes is primarily influenced by rainfall and temperature conditions, and it is known that the optimum range of adult mosquito emergence is between 18℃ and 26℃ with the minimum-to-maximum range from 18℃ to 34℃ (Bayoh and Lindsay, 2003). Land use and land cover (LULC) is related to the natural environment and to the human impact on the landscape. The LULC is an important component in the study of malaria because it is directly related to the malaria burden through its impact on breeding sites and the adult mosquito survival rate and dispersal (Machault *et al.*, 2011). Their flight range is shorter in highly-populated urban areas compared to rural areas, where they fly as far as several kilometers (Charlwood and Alecrim, 1989; Trape *et al.*, 1992; Manga *et al.*, 1993; Robert *et al.*, 1993).

As of the year of 2000, WHO estimates that 300 to 500 million people are infected each year and the annual deaths reach up to 2.5 million (WHO, 2003). About 85% of the deaths occurs in Africa, and most cases are concentrated on sub-Saharan regions. The reason why so many malaria deaths occur in tropical Africa comes from the nature of the vector. The prevailing species of Anopheles mosquitoes in tropical Africa is known as Anopheles gambiae, and it carries the deadliest parasite, *Plasmodium falciparum*. The species has co-evolved with humans, and unlike other species, it mainly bites humans rather than animals. If the species bites were not selective for humans, malaria infection and transmission would not have been very efficient in tropical Africa (De Blij, 2009). Dunavan (2005) reported that the likelihood of malaria transmission in tropical Africa would be eight to nine times higher than that in India, where mosquito species feed both on humans and animals.

For the past decades, the geographic areas of high risk of malaria has decreased significantly with efforts of vector control and protection (Figure 1). Unfortunately, scientists in recent years report that a resurgence of malaria is causing a great concern, and it is attributed to

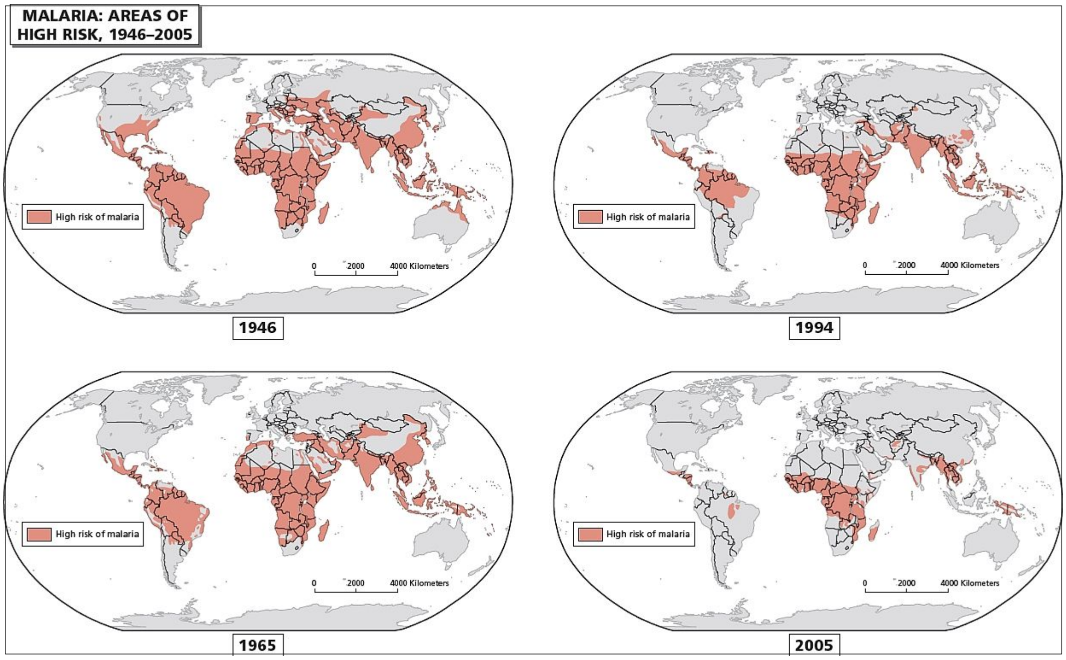

Fig 1. High-risk areas of malaria (1946~2005). From De Blij (2009) and Gallup and Sachs (2001).

global warming. A rise in temperature of only 2℃ in the next 50 years is expected to expand the geographic area that Anopheles mosquitoes can flourish from 42% to 60% (Hidore *et al.*, 2010).

Malaria spreads into highlands of Africa due to increases of temperature, population growth, and deforestation. A warming trend in the East African coincides well with the resurgence of malaria (Hay *et al.*, 2002). A major epidemics in the East African highlands in the mid and late 1990s motivated researchers to investigated the influence of global warming on malaria outbreaks (Chaves and Koenraadt, 2010; Chaves *et al.*, 2012; Githeko and Ndegwa, 2001; Abeku *et al.*, 2003; Bouma, 2003; Wort *et al.*, 2004; Mabaso *et al.*, 2007; Thomson *et al.*, 2005; Shanks *et al.*, 2002). In fact, there is a wide spectrum of views on the relationships between malaria trends and climate change (Alonso *et al.*, 2011; Reiter, 2008). While there is no robust proof explaining the role of climate change on malaria transmission, there seems to be a heterogenous pattern of malaria trends across the landscape. Chaves *et al.* (2012) reported that malaria cases decreased in the late 1980s at low altitudes (<1,600m), but they increased at higher altitudes (>1,600m) in late 1990s. The increasing malaria in East Africa had a correlation with broad-scale climatic phenomena, such as the Indian Ocean Dipole (IOD) Mode and ENSO, but it is also indirectly associated with population pressure in the region (Lindblade *et al.*, 2000). Population growth tends to move local people to valley bottoms where they are more likely exposed to vectors and malaria transmission (Munyekenye *et al.*, 2005).

3. Remote Sensing and Epidemiology

1) Remote Sensing Needs

The use of spatially and temporally continuous, geographically referenced environmental data is required in malaria mapping. Remotely sensed data are the only practical option for the requirement, especially for global mapping. Remote sensing, which refers to the collection of data by instruments measuring physical and biological characteristics of objects without direct contact, provides useful indirect information, and the use of remotely sensed data has become a crucial component of a modeling process that determines the ecological niche and potential habitat of disease-transmitting agents. This is because the geospatial data are processed to produce climatic, ecological, and anthropogenic information related to malaria transmission, such as elevation, land surface temperature, humidity, vegetation covers, and land use (Hay *et al.*, 1996; Hay *et al.*, 1998; Beck *et al.*, 2000; Machault *et al.*, 2011; Park, 2011). Considering that these environmental variables have a direct impact on the ecology of life cycles of vectors, spatiotemporal interactions between climatic factors and vector-borne diseases will be an important research agenda in spatial epidemiology (Green and Hay, 2002; Hay *et al.*, 2002: Rogers *et al.*, 2002; Eisele *et al.*, 2003; Scharlesmann *et al.*, 2008).

By no means is remote sensing perfect for epidemiological research. Systematic sensor degradations, cloud covers, and atmospheric interference are common problems of remotely sensed data. The number of spectral bands, pixel size, and the revisit time of a sensor are also restricted to a certain capacity. Despite the inherent limitations of remote sensing technologies, earth-orbiting satellite data have been increasingly used for epidemiological applications. Satellite data are consistently collected at the global scale, and often more contemporary and of higher spatial resolution than interpoated climatologies (Green and Hay, 2002; Hay *et al.*, 2006; Scharlesmann *et al.*, 2008). In addition, researchers' interests expand to active remote sensors, which can produce imagery under adverse atmospheric conditions, to overcome weakness of passive remote sensing systems. For instance, microwave –based techniques are advantageous over optical or thermal wavelength applications for soil moisture estimation due to their ability to penetrate materials, including clouds and surface vegetation cover (Goetz *et al.*, 2000). Although majority of this type of work has been focused on passive microwave detection, active remote sensing, such as radar measurements, has also been used for surface wetness extraction (Wang *et al.*, 1997; Owe *et al.*, 1999; Kaya *et al.*, 2004).

Geospatial data and remote sensing imagery have become more important then ever to estimate the optimal habitat ranges of malaria–transmitting vectors and their potential changes. This is because these data play a pivotal role in improving mapping accuracy of elevation, land surface temperature, land use, and vegetation cover, which indirectly reflect air temperature and humidity (Hay *et al.*, 1996; Hay *et al.*, 1998b; Park, 2011).

2) Advances in Remote Sensing

Early studies in public health used remote sensing data from Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM), the National Oceanic and Atmospheric Administration (NOAA)'s Advanced Very High Resolution Radiometer (AVHRR), and French Système Pour l'Observation de la Terre (SPOT) to derive vegetation cover, landscape structure, and water bodies. New remote sensing capabilities with higher spatial, temporal, and spectral resolution have allowed researchers to assess further environmental factors that promote disease transmission, vector production, and the emergence of disease foci, and rick for human–vector contact as understanding of pathogen, vector, reservoir, and host ecology evolved (Beck *et al.*, 2000).

Chambers *et al.* (2007) categorized rapidly advancing remote sensing methods into four themes. First, very high spatial (hyperspatial) and spectral (hyperspectral) resolution data have been available in new sensors. In remote sensing communities, the term 'hyper' has become widespread, referring to a condition where new sensors provide much greater detail than previously available technology does in terms of spatial, spectral, and temporal resolution. With these hyperspatial and hyperspectral capabilities, ecological and environmental measurements are now available from remotely sensed imagery. Two recent high–resolution satellite systems, RapidEye and WorldView–2, are of particular interest to many researchers. RapidEye is a constellation of five multispectral satellite sensors that was launched in August 2008 primarily for agricultural applications (Tapsall *et al.*, 2010). It collects 5–band imagery everyday with five–meter spatial resolution (at nadir). Balancing between high spatial and temporal resolutions, this system gives a unique opportunity for spatial epidemiology communities. WorldView–2 is another state–of–the–art commercial satellite sensor that provides sub–meter (46cm) panchromatic and 1.85 meter multispectral resolution (Digital Globe, 2011). Unique capability of the sensor is its very high spatial resolution with eight spectral bands ranging from blue to the near infrared wavelengths. Compared to analyses based on the typical four multispectral bands that are available in similar satellite sensors, such as GeoEye–1. IKONOS, or QuickBird–2, the blue (400–450 nm), yellow (585–625nm), red–edge (705–745 nm), and near–infrared 2 (860–1,040nm) bands may beneficially increase the LULC classification accuracy by up to 30% (Novack *et al.*, 2011).

Second, limitation of pixel–based discrete land cover classification is overcome by hyperspatial data analyses, which allow us to perform sub–pixel fractional image classification. This is important because the sub–pixel analyses make it possible to more directly link ecological meaningful remote-measurements to field data. For instance, fractional abundances of green vegetation, bare soil, and non-photosynthetic vegetation can be represented for a given pixel as opposed to a single nominal classification class of green vegetation, bare soil, or non-photosynthetic vegetation. Third, hypertemporal observations of the land surface significantly improve the chances of cloud-free remote sensing coverage. This is extremely beneficial for research opportunities on the temporal domain of cloud-prone regions. Finally, integration of field data, remote sensing techniques, and simulation modeling becomes available, and comprehensive approaches on ecosystem processes are now possible.

Temporal dimension of remote sensing data is particularly important in public health research because environmental conditions are not constant and explicit seasonality has to be measured over broad areas. Time series of earth-orbiting satellite data is increasingly used to extract ecologically important parameters (Hay *et al*., 2006; Scharlemann *et al*., 2008). Temporal Fourier analysis (TFA) is a mathematical technique for a variety of time-series data and frequently used to simplify time series of remote sensing data. TFA, also known as spectral analysis, or harmonic analysis, has been applied to temporal domain of remote sensing data to extract major periodic fluctuation signals, or wave forms from a periodic phenomenon, such as the phenological development of vegetation (Olsson and Eklundh, 1994; Rogers *et al*., 1996; Roerink *et al*., 2000; Jakubauskas *et al*., 2001; Moody and Johnson, 2001; Julien *et al*., 2006; Park, 2009a; Park, 2010). The mathematical technique decomposes a time series into its constituent parts and transforms a complex time series to a sum of many sinusoidal functions, or harmonic terms. Most of these studies have shown that satellite-derived measures of vegetation amount or growth, such as Normalized Difference Vegetation Index (NDVI), are adequately summarized and represented by TFA.

Improved spatial, spectral, and temporal resolutions of recent earth-observing satellite systems have given remote sensing communities a new horizon for epidemiology and public health research. The Terra and Aqua satellites of National Aeronautics and Space Administration (NASA), for example, have particular advantages over its predecessor, Advanced Very High Resolution Radiometer (AVHRR), providing researchers with higher spatial, spectral, and radiometric resolutions (Teillet *et al*., 1997). New remote sensing technologies allow researchers to define more accurately human population distribution, urbanization, water body distribution and land uses, which have major effects on malaria transmission, prevalence and morbidity estimates (Tatem *et al*., 2004).

Terra and Aqua are the first two satellites of NASA's Earth Observing System (EOS), which consists of a series of multi-instrument spacecraft. The main objective of EOS is to distinguish short-term anomalies, natural interannual to interdecadal oscillations, and human-induced changes, observing land surface, biosphere, solid Earth, atmosphere, and oceans (NASA Goddard Space Flight Center, 2004). To be able to accomplish the objective, EOS data are being collected over a broad spectral range with high and moderate spatial resolutions. The primary mission of Terra is to perform high accuracy measurements of parameters that describe the state of the Earth and its atmosphere, while Aqua's mission has a particular emphasis on water on or near the Earth's surface as liquid, vapour, or solid form (Kaufman *et al*., 1998; Parkinson *et al*., 2003). Terra and Aqua sensors are a sun-synchronous polar orbiter with the equatorial crossing times of 10:30AM and 1:30PM, respectively to reduce cloud contamination.

One advantage of these satellites is to extend satellite measurements of their predecessors, such as Advanced Very High Resolution Radiometer (AVHRR) and the Coastal Zone Color Scanner (CZCS) (Tatem *et al.*, 2004).

3) Remotely-Measured Land Surface Variables

(1) Land surface temperature (LST)

Life cycles of the vector and the survivorship of juvenile and adult stages are temperature-dependant. Different species require varying optimum ranges of temperature, and the geographic limits of the species differ with elevation (Ceccato *et al.*, 2005). For example, the minimum temperatures are required for Plasmodium falciparum, which is the dominant malaria parasite in Africa, compared to Plasmodium vivax (Bruce-Chwatt, 1991). In highlands, where vector survivorship is not always successful, increased appearance rates are significantly correlated with above-average minimum temperatures (Bouma *et al.*, 1994). Remotely-sensed thermal infrared data are a useful indicator for moisture conditions because land surface temperature is strongly coupled with the net radiation flux received by the surface and the surface moisture condition. Thermal energy converted from incoming solar radiation depends on the surface's properties, such as land cover, soil moisture content and soil types (Park *et al.*, 2005).

Various thermal sensors are being used for surface temperature estimation, including NOAA-AVHRR, MODIS, ASTER, and METEOSAT. More detailed description about these sensors are available from Hay (2000). Omumbo *et al.* (2002) tries improve historical maps of malaria transmission intensity using several remote sensing datasets, including land surface temperature (LST), vegetation index, and rainfall estimates, and concluded that LST turned out to be the most determinant predictor of transmission intensity in East Africa. For instance, "malaria-free" areas were typically found at high altitude and characterized by much lower year-round temperature compared to moderate or intense transmission areas. They reported that malaria-free areas were predicted with an accuracy of 96%, whereas moderate and intense transmission areas were predicted with an accuracy of 72% and 87%, respectively.

Since remotely-sensed LST measures earth's surface temperature, it is not the ambient temperature. In addition, the amount of radiance emitted from the surface is effected by the properties and composition of the land surface. Particularly, spectral emissivity, the ratio of surface emission to that of a perfect emitted at the same temperature, varies across the landscape, and its impact on the actual radiometric temperature can be substantial (Goetz *et al.*, 2000). In many occasions, however, LST can be used to retrieve air temperature on vegetated surface with relatively constant emissivity. Contextual combination of vegetation indices and estimates of near-surface temperature has been widely adopted for air temperature estimation. Inference of air temperature is possible based on an assumption that the radiometric temperature of a vegetated surface is in equilibrium with ambient air temperature (Goward *et al.*, 1994; Goetz *et al.*, 2000). Data acquisition time should be considered as an important factor for temperature retrieval. If a sensor takes a mid-afternoon overpass time, such as AVHRR, estimates of air temperature typically approximate the daily maximum. Recent experiments in two different volcanic islands, Hawaii Island, Hawaii, USA and Jeju Island, Korea, clearly showed that land surface conditions had a substantial effect on the retrieval of air temperature (Park, 2009b; Park, 2011).

Daytime LST data of Hawaii Island had only a weak correlation with air temperature. Intense radiation received on the barren surface is converted to sensible heat fluxes on Hawaii Island, and it raises surface temperature, which significantly deviates from air temperature. It is believed that a significant amount of lava fields with various ages and complex assemblage of diverse land cover types are responsible for the large variations of LST and a poor correlation between daytime LST and air temperature. As a result, only nighttime LST had a significant relationship with air temperature on Hawaii Island. For Jeju Island, daytime and nighttime LST data had the highest correlation with daily maximum and minimum air temperature, respectively (Figure 2). This high correlation is attributed to the relatively uniform emissivity of gentle slopes mostly covered with grasslands (Kawashima *et al.*, 2000, Chung and Yun, 2004, Park *et al.*, 2005).

(2) Vegetation indices (VIs)

Habitat conditions of malaria mosquitoes are commonly estimated from indirect measures of green vegetation cover. There are a long tradition of using vegetation indices, which show a strong correlation with vegetation vitality, to extract their relationship with vector abundance. This effort makes sense because malaria cases are significant associated with the amount, conditions, and density of vegetation cover (Hay *et al.*, 1998b). This association comes from the co-variation of vegetation cover with a range of biophysical factors, including temperature, energy flux, and habitat diversity. Remotely-measured land surface conditions are suited to mapping the density of photosynthetically active material and its variations (Goetz *et al.*, 2000).

It is widely accepted that understanding of vegetation dynamics is possible using vegetation indices, which are expressed as ratio between reflectance measures of difference channels of

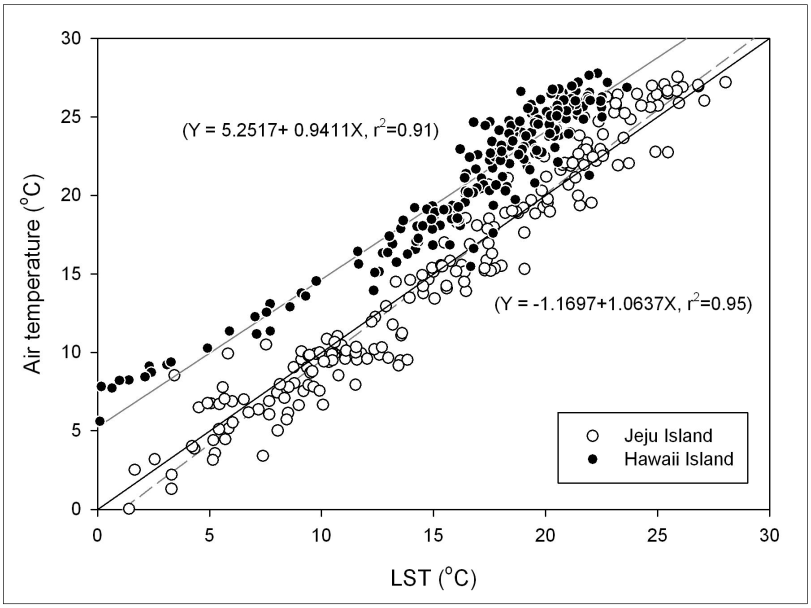

Fig 2. Correlations between LST and air temperature. Only nighttime LST had a significant relationship with air temperature on Hawaii Island. On Jeju Island, however, both daytime and nighttime LST had a strong direct relationship with air temperature (Park, 2011).

electromagnetic spectrum energy. The Normalized Difference Vegetation Index (NDVI), which is the normalized ratio between red and near-infrared bands, has been intensively used in remote sensing communities:

$$NDVI = (\rho_{nir} - \rho_{red}) / (\rho_{nir} + \rho_{red})$$

where ρ_{nir} and ρ_{red} are surface reflectance of near-infrared and red wavelengths.

Hay *et al.* (1998a) observed that the number of monthly childhood malaria admissions in three hospitals in Kenya was correlated with the previous month's NDVI. More studies showed that the duration of malaria transmission seasons in Kenya and Uganda could be predicted by determining the number of months in which a certain range of NDVI threshold values were exceeded (Hay *et al.*, 1998b; Hay, 2000).

In addition to NDVI, two new vegetation indices are formulated from MODIS. They are the Enhanced Vegetation Index (EVI) and the Land Surface Water Index (LSWI). The algorithm of EVI was developed to improve its sensitivity to densely vegetated areas (Huete *et al.*, 2002). This index alleviates atmospheric effects incorporating the blue band (ρ_{blue}) into its calculation, and has been applied to vegetation monitoring in the tropics, where seasonal burning of forests is common:

$$EVI = 2.5 \times (\rho_{nir} - \rho_{red})/(\rho_{nir} + (6 \times \rho_{red} - 7.5 \times \rho_{blue}) + 1)$$

Tucker (1980) first suggested that the short-wavelength infrared range (1.55-1.75μm) of the electromagnetic spectrum was useful for satellite monitoring of plant canopy water status. Xiao *et al.* (2004) used a near-infrared (0.86μm) and a short-wavelength infrared (1.64μm) bands of MODIS data and termed the new index the Land Surface Water Index (LSWI) (Chandrasekar *et al.*, 2010; Cheng *et al.*, 2008):

$$LSWI = (\rho_{nir} - \rho_{swir}) / (\rho_{nir} + \rho_{swir})$$

The usage of these vegetation indices are widespread, but seasonal patterns of vegetation dynamics represented by the three vegetation indices (NDVI, EVI, and LSWI) need to be carefully evaluated because they often do not correspond to each other (Xiao *et al.*, 2005).

(3) Wetness

Rainfall, surface water, and soil moisture are important wetness measures in malaria studies. In general, a positive relationship between malaria infection and precipitation has been known for decades. However, excessive rainfall can diminish malaria transmission by flushing out small breeding sites or decreasing temperature (Fox, 1957). The Famine Early Warning Systems Network (FEWS NET) is one of the principal activities for routine monitoring of climatic, agricultural, and socioeconomic conditions for decades. The goal of FEWS NET is to create timely and sustainable information system that supports food security in sub-Saharan Africa (http://www.fews.net). The impact of drought on food security is evaluated based on satellite rainfall estimates provided by the NASA Tropical Rainfall Measuring Mission (TRMM, http://trmm.gsfc.nasa.gov/) multisatellite precipitation analysis, and it assists the planning and disaster response phase of the early warning system (Huffman *et al.*, 2007; Funk and Verdin, 2009). TRMM satellite data provide near-real-time rainfall estimates based on passive microwave and active radar sensors (Han *et al.*, 2010). However, it should be noted that data accuracy varies with climate, location, topography, time period, cloud type, and data resolution (Barros *et al.*, 2000; Scheel *et al.*, 2011).

Knowledge on small water bodies, wetlands, and vegetative water content is useful to identify the source of malaria vectors. Particularly, the shortwave infrared (SWIR) energy is a useful indicator of wetness on the surface because it is absorbed by water. Recent studies have shown that SWIR-based vegetation indices are sensitive to vegetation water content (Ceccato *et al*., 2001; Chen *et al*., 2005) Park and Miura (2011) compared three MODIS-based vegetation indices, NDVI, EVI, and LSWI, for their sensitivity to leaf water content. The result showed that LSWI outperformed the NDVI and EVI, responding more sensitively to foliage water content in tropical environment (Figure 3).

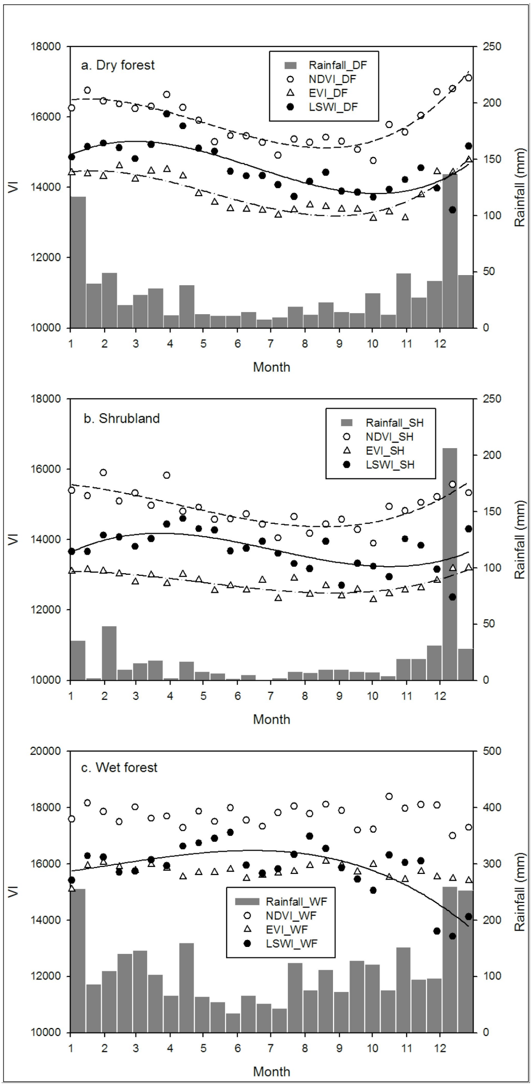

Fig 3. Biweekly records of NDVI, EVI, and LSWI in three ecoregions, dry forests (a), shrublands (b), and wet forests (c). For dry forests and shrublands, VIs represent winter-high and summer-low patterns, but a seasonal greenness pattern of wet forests (c) is represented only by LSWI (Park and Miura, 2011). Acronyms, DF, SH, and WF refer to dry forests, shrublands, and wet forests.

Soil moisture is another important factor for malaria monitoring because wet soils are preferred for mosquito habitats. Among other remote sensors, synthetic aperture radars (SARs) are particularly promising for soil moisture and flooded area detection (Kandus *et al*., 2001). The use of radar systems is advantageous because earth surface monitoring is possible at night or during cloudy situations. ALOS, ENVISAT, RADARSAT, and ERS are viable satellite remote sensing systems for radar applications (Table 1).

(4) Land use and urbanization

Human-induced landscape change often worsen existing mosquito-borne problems because it expands mosquito habitats, creates new habitats, or modifies habitats in such a way that mosquito populations can explode (Norris, 2004). Malaria infection and transmission mechanism is a dynamic process, where landscape structure and arrangement of diverse land uses are playing an important role. A spatial analysis by Wood *et al.* (1991) indicated that high larval-producing fields were a mixture of orchards, cattle pastures, and native vegetation. By contrast, significantly fewer mosquitoes were found in an area where rice was only land use. Therefore, it is clear that spatial relationships between the vector's mobility and habitat preference need to be understood for the disease control.

The landscape ecology approach has been

successful in studies of malaria transmission, which is associated with irrigation, landuse change, and urban-rural interactions (Eisele *et al.*, 2003). High-resolution remote sensing data are more commonly used in malaria studies because ecological characteristics of irrigated fields and their surroundings are often derived from satellite-based, accurate maps. In northern Thailand, Overgaard *et al.* (2003) studied the effect of landscape structure on anopheles mosquito density an diversity. It has shown that anopheline species density was positively correlated with water-related landscape metrics, whereas it was negatively correlated with landscape diversity. In other words, forest fragmentation due to human activities increased landscape heterogeneity and it reduced anopheline species density. It is also found that landscape elements surrounding rural villages within the flight distance of malaria mosquitoes is an important factor to predict the abundance of adult mosquitoes. Beck *et al.* (1994) showed that the proportion of two landscape elements, unmanaged pasture and transitional swamp could predict villages with high density of adult malaria mosquitoes (*anopheles albimanus*).

As more satellite imagery becomes available in high spatial resolution, sometimes even at no cost, spatial analyses of remotely sensed data are expected to contribute far more than ever to malaria vector research. However, it is worth discussing limitations of very high spatial resolution (VHR) data when it comes to conventional pixel-based LULC classification. One important issue associated with VHR image classification is within-class spectral variation of ground features, which causes misclassification of confusing pixels (Townshend *et al.*, 2000; Liu *et al.*, 2008). An alternative approach, such as object-based image analysis (OBIA), has been recently adopted in LULC classification communities (Kim *et al.*, 2010; Kelly, *et al.*, 2011). Rather than pixel-by-pixel classification, OBIA classifies image object primitives, or regions, which are extracted in a previous image segmentation step using not only spectral information but also additional features, including shape, texture, and context (Benz *et al.*, 2004). This newer approach is likely to increase LULC classification accuracy, and it develops spatial topologies between objects for better understanding of human-disease-health systems (Kelly *et al.*, 2011).

4. Challenges and Opportunities

As a major mosquito-borne disease, malaria has been a constant concern in Korea. In fact, it was reported by Korea Center for Disease Control and Prevention (KCDC) that malaria has been the leading mosquito-borne infectious disease since 2000. An unusual meteorological event, such as persistent torrential rainfall, was thought to be a reason for seasonal decreases in vector population, but the environmental effect on vector abundance is yet to be determined. It is notable that the very first case of West Nile Virus (WNV), a mosquito-borne infectious disease, was recently reported in Korea. Although the report confirmed that the case had been infected overseas, its alert level should be raised because WNV-carrying mosquitoes are present in the country (KCDC, 2012). With the increasing number of travelers and climate change, occurrence of mosquito-borne infectious diseases is expected to grow.

Malaria was a nationally prevalent infectious disease in Chosun Dynasty, but it dramatically decreased with the advent of modern medical science. In 1984, endemic malaria was eradicated, but malaria cases started to reemerge early 1990s in the Demilitarized Zone (DMZ). While majority of malaria cases was found in military camps until 2000, the number of civilian cases has constantly increased near the Military Demarcation

Line afterwards. Geographically, northmost counties neighboring North Korea are the leading ones in numbers. It is believed that high infection rates in these border counties come from the dispersion of north-origin, malaria-bearing adult mosquitoes.

Resurgence of malaria after effective control becomes a threatening public health problem in

Table 1. Satellite sensors available for malaria studies (Ceccato *et al.*, 2005). PAN = panchromatic, VNIR = visible/near infrared, SWIR = shortwave infrared, TIR = thermal infrared, SAR = synthetic aperture radar, LST = land surface temperature.

mission	sensor	resolution(m)	swath(km)	launch	applications
Orbview-3	Orbview-3	PAN 1 VNIR 4	8	2003	urban, sub-urban areas
Ikonos	Ikonos	PAN 1 VNIR 4	11	1999	urban, sub-urban areas
Quickbird-2	Quickbird	PAN 0.61 VNIR 2.44	22	2001	urban, sub-urban areas
ALOS	AVNIR-2 PALSAR	PAN 3 AVNIR 10-15 L-band 10	35-70	2004	landuse and land cover, vegetation, and water bodies
SPOT5	HRG	PAN 5 VNIR 10 SWIR 20	60	2004	landuse and land cover, vegetation, and water bodies
Landsat7	ETM+	PAN 15 VNIR 30 SWIR 30 TIR 30	185	1999	landuse and land cover, vegetation, and water bodies
CBERS	CCD/ IR-MSS	PAN 20/80 VNIR 20 SWIR 20/80 TIR 80	120	1999	LST
Terra	ASTER MODIS	VNIR 15 SWIR 20 TIR 90 VNIR 250-1000 SWIR 500-1000 TIR 1000	60 2300	1999	vegetation, water bodies, and LST
ENVISAT	AATSR ASAR	VNIR 1000 SWIR 1000 TIR 1000 C-band 30	512 100	2002	forest weather, water bodies
Meteosat	SEVIRI	VNIR 1400 TIR 4800	hemisphere	2002	rainfall, LST
Radarsat-2	SAR	C-band 3-100	10-500	2007	forest, water bodies
NOAA-M	AVHRR	VNIR 1100 SWIR 11000 TIR 1100	3000	2002	vegetation, water bodies, and LST
ERS-2	AMI-SAR	C-band 30	100	1995	vegetation, water bodies, and weather

many parts of the world (Patz *et al*., 2008; Manh *et al*., 2011; Stern *et al*., 2011; Zhou *et al*., 2012). Although habitat conditions and disease control are important factors of undulating morbidity, they are only part of components that explain the reason for malaria occurrence and transmission. The effect of socioeconomic conditions and human behavior on the risk of dengue transmission, another mosquito-borne disease, on the U.S.-Mexico border is well illustrated. Even for communities sharing the same climatic regime, climatic factors may not explain the difference in mosquito-borne disease transmission (Reiter, 2003). An ongoing study showed that the amount of favorable breeding sites and surface conditions had only weak correlation with malaria morbidity (personal communication). Rather, spatial relationships between human residence and vector pools and arrangement of adequate habitats patches play an important role in explaining the distribution of malaria incidence (Zhou *et al*., 2012).

Urbanization pattern and demographic structure of human dwellings have a substantial impact on public health. For example, African urban dwellers are about ten times less likely to receive a malaria-infected bites and have better access to health care facilities than those in rural areas (Robert *et al*., 2003). Urban land use classification has been developed with a wide range of satellite sensors. In addition to traditional pixel-based classifiers, object-oriented classification, neural networks and support vector machines are commonly used. For cases where pixel size is too coarse for accuract urban land use mapping, subpixel classification approach based on spectral mixture analysis is also adopted.

Investigation on relationships between broad-scale atmospheric phenomena, such as El Nino Southern Oscillation (ENSO), and malaria incidence can be better assisted with remotely sensed sea surface temperature (Hales *et al*., 1999; Thomson *et al*., 2005). As global temperature increases, malaria occurrence and resurgence are reported at higher altitude (Hay *et al*., 2002). Weather stations are often coarsely distributed, and meteorological observations are strategically difficult in mountainous areas. Currently, meteorological variables are commonly derived from remote sensing techniques, and they are effectively compromised for the lack of ground measurements (Hay and Lennon, 1999; Park, 2011).

5. Conclusions

Advances in malaria epidemiology have been made with remote sensing technologies, which provided researchers with valuable surrogate information for land surface conditions. Rainfall, surface water, temperature, vegetation development, and land use change are crucial factors in malaria ecology and transmission, and they have been effectively estimated by various remote sensors. It is believed that malaria transmission is significantly associated with vegetation cover. An edge effect between forests and residential areas may play an important role in raising the probability of mosquito bites and potential contact of human population with the vector (Beck *et al*., 2000). Remote sensing-based high-resolution measurements of environmental variables are urgently needed in medical geography to deal with mosquito-borne infectious diseases.

Environmental malaria indicators, including land use and land cover, surface temperature, sea surface temperature, surface water content, and vegetation growth, are readily available from a suite of remote sensors. In some cases, remote sensing data can be acquired at nominal cost, or even at no cost. It is obvious that detection of optimal habitats for mosquito larvae is not enough for medical geographers to manage malaria problems. Deeper understanding of interactions between the environment and human behavior as well as vector ecology is required in malaria research.

Major malaria research has not started yet in medical geography in Korea probably because the disease is not recognized as a national threat and medical geography communities have not been formally organized. However, it should be realized that 1) malaria and other mosquito-borne infectious diseases are no doubt a climate-related issue, 2) malaria transmission is heavily associated with human factors and activities, and 3) malaria dispersion is characterized by a spatial pattern. Advances in sensor fidelity with higher spatial and spectral resolution, newly developed multinational sensors, and decreased data cost have become strong attraction for medical geography research in the field.

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• **Correspondence** : Sunyurp Park, Department of Geography Education, Pusan National University, Busan 609-735, Korea, E-mail: spark@pusan.ac.kr, Telephone: +82-51-510-2655, Fax: +82-51-510-2655.

교신 : 박선엽, 609-735, 부산광역시 금정구 부산대학로 63번길 2, 부산대학교 사범대학 지리교육과, 이메일: spark@pusan.ac.kr, 전화: 051-510-2655, 팩스: 051-510-2655.

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