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Remote Sensing and Human Health: New Sensors and New Opportunities

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Introduction

Remote sensing data enable scientists to study the earth's biotic and abiotic components. These components and their changes have been mapped from space at several temporal and spatial scales since 1972. A small number of investigators in the health community have explored remotely sensed environmental factors that might be associated with disease-vector habitats and human transmission risk. However, most human health studies using remote sensing data have focused on data from Landsat's Multispectral Scanner (MSS) and Thematic Mapper (TM), the National Oceanic and Atmospheric Administration (NOAA)'s Advanced Very High Resolution Radiometer (AVHRR), and France's Système Pour l'Observation de la Terre (SPOT). In many of these studies (Table 1), remotely sensed data were used to derive three variables: vegetation cover, landscape structure, and water bodies.

Table 1. Research using remote sensing data to map disease vectors[a]

Disease	Vector	Location	Sensor	Ref.
Dracunculiasis	***Cyclops*** spp.	Benin	TM	1
	Cyclops spp.	Nigeria	TM	2
Eastern equine encephalomyelitis	***Culiseta melanura***	Florida, USA	TM	3
Filariasis	***Culex pipiens***	Egypt	AVHRR	4
	Cx. pipiens	Egypt	TM	5,6
Leishmaniasis	***Phlebotomus papatasi***	SW Asia	AVHRR	7
Lyme disease	***Ixodes scapularis***	New York, USA	TM	8,9
	I. scapularis	Wisconsin, USA	TM	10
Malaria	***Anopheles albimanus***	Mexico	TM	11
	An. albimanus	Belize	SPOT	12
	An. albimanus	Belize	SPOT	13
	An. albimanus	Mexico	TM	14
	An. spp.	Gambia	AVHRR, Metosat	15,16
	An. albimanus	Mexico	TM	17,18
Rift Valley fever	***Aedes*** & ***Cx.*** spp.	Kenya	AVHRR	19,20
	Cx. spp.	Kenya	TM, SAR	21
	Cx. spp.	Senegal	SPOT, AVHRR	22
Schistosomiasis	***Biomphalaria*** spp.	Egypt	AVHRR	23
Trypanosomiasis	***Glossina*** spp.	Kenya, Uganda	AVHRR	24
	Glossina spp.	Kenya	TM	25
	Glossina spp.	West Africa	AVHRR	26
	Glossina spp.	Africa	AVHRR	27
	Glossina spp.	Southern Africa	AVHRR	28

[a]See Appendix A for explanation of sensor acronyms

Click image for larger view of table 1

International space agencies are planning an estimated 80 earth-observing missions in the next 15 years (29). During these missions >200 instruments will measure additional environmental features such as ocean color and other currently detectable variables, but at much higher spatial and spectral resolutions. The commercial sector is also planning to launch several systems in the next 5 years that could provide complementary data (30). These new capabilities will improve spectral, spatial, and temporal resolution, allowing exploration of risk factors previously beyond the capabilities of remote sensing. In addition, advances in pathogen, vector, and reservoir and host ecology have allowed assessment of a

greater range of environmental factors that promote disease transmission, vector production, and the emergence and maintenance of disease foci, as well as risk for human-vector contact. Advances in computer processing and in geographic information system and global positioning system technologies facilitate integration of remotely sensed environmental parameters with health data so that models for disease surveillance and

In 1998, the National Aeronautics and Space Administration's (NASA) Center for Health Applications of Aerospace Related Technologies (CHAART) evaluated current and planned satellite sensor systems as a first step in enabling human health scientists to determine data relevant for the epidemiologic, entomologic, and ecologic aspects of their research, as well as developing remote sensing-based models of transmission risk. This article discusses the results of the evaluation and presents two examples of how remotely sensed data have been used in health-related studies. The first example, a terrestrial application, illustrates how a single Landsat TM image was used to characterize the spatial patterns of key components of the Lyme disease transmission cycle in New York. The second example, which focuses on the coastal environment, shows how remote sensing data from different satellite systems can be combined to characterize and map environmental variables in the Bay of Bengal that are associated with the temporal patterns of cholera cases in Bangladesh. These examples demonstrate how remote sensing data acquired at various scales and spectral resolutions can be used to study infectious

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CHAART was established at Ames Research Center by NASA's Life Sciences Division, within the Office of Life & Microgravity Sciences & Applications, to make remote sensing, geographic information systems, global positioning systems, and computer modeling available to investigators in the human health community.

Lyme Disease in the Northeastern United States

During the past 10 years, NASA's Ames Research Center has been collaborating with the New York Medical College and the Yale School of Medicine to develop remote sensing-based models for mapping Lyme disease transmission risk in the northeastern United States (31,32). The first study compared Landsat TM data with canine seroprevalence rate (CSR) data summarized at the municipality level (31). The canine data were used as a measure of human exposure risk, the assumption being that dogs were more likely to acquire tick bites on or near their owner's property. The second study used TM data to map relative tick abundance on residential properties by using TM-derived indices of vegetation greenness and wetness (32). Figure 1 shows a subset of the TM data used in both studies, as well as some of the products (e.g., maps) derived from the data. Each product

illustrated Lyme disease transmission variables, such as vector and reservoir habitats, as well as human risk for disease. Figure 1a shows raw Landsat-5 TM data, which are recorded in six spectral bands (excluding a seventh thermal band) at a spatial resolution of 30 m. These data were processed to derive the products shown in Figures 1b-d.

The image in Figure 1b was used to explore the relationship between forest patch size and deer distribution. Because white-tailed deer serve as a major host of the adult tick as well as its primary mode of transportation, deer distribution was a potentially important factor in a Lyme disease risk model.

Figure 1c shows 12 classes used in two separate analyses of risk at two different scales (31). These classes include water, evergreen trees/vegetation, sparse deciduous trees, dense deciduous trees, clearings, golf courses (managed grass), urban/commercial, miscellaneous urban, residential-lawn, residential-sparse vegetation, residential-medium vegetation, and residential high-vegetation. In the first scale, the amount of remotely sensed deciduous forest was positively correlated (r-0.82) with canine exposure to ***Borrelia burgdorferi***, as indicated by CSR data summarized by municipality. In the second analysis, a linear regression of the residentialhigh vegetation pixels (i.e., wood-edge) and CSR data resulted in a correlation coefficient of 0.84- indicating that human-host contact risk (e.g., deer leaving the forest to feed on residential ornamental vegetation) might be a good measure of human-vector contact risk.

The image in Figure 1d was derived from the Landsat TM data by a Tasseled Cap Transformation (33). Tasseled Cap greenness and wetness were positively correlated with tick abundance on residential properties in this study area (32).

Cholera in Bangladesh

The second example of the use of remotely sensed data to provide information for health research and applications concerns cholera in Bangladesh. In this study, described by Lobitz et al. (34), remotely sensed datasets, downloaded from the Internet at no cost, were used to search for temporal patterns in the Bay of Bengal associated with cholera outbreaks in Bangladesh.

Figure 2a shows a color-infrared image of the Ganges River, where it empties into the Bay of Bengal. These data, which were acquired by NOAA's AVHRR sensor, have a spatial resolution of 1.1 km. The sediment load, transported to the Bay of Bengal by the Ganges and Brahmaputra rivers, includes nutrients that could support plankton blooms. Plankton is an important marine reservoir of Vibrio cholerae, which attaches primarily to zooplankton, which, in turn, is associated with phytoplankton (35).

In Figure 2b, the AVHRR data shown in Figure 2A were processed to show sea surface temperature (SST) (36). Because these data are for large-area studies, they

have been processed at a spatial resolution of 18 km. Figure 2c represents sea surface height (SSH) anomaly data derived from the TOPEX/Poseidon satellite (37). These data have a spatial resolution of 1 degree. Increases in SST and SSH have preceded cholera outbreaks in Bangladesh (34).

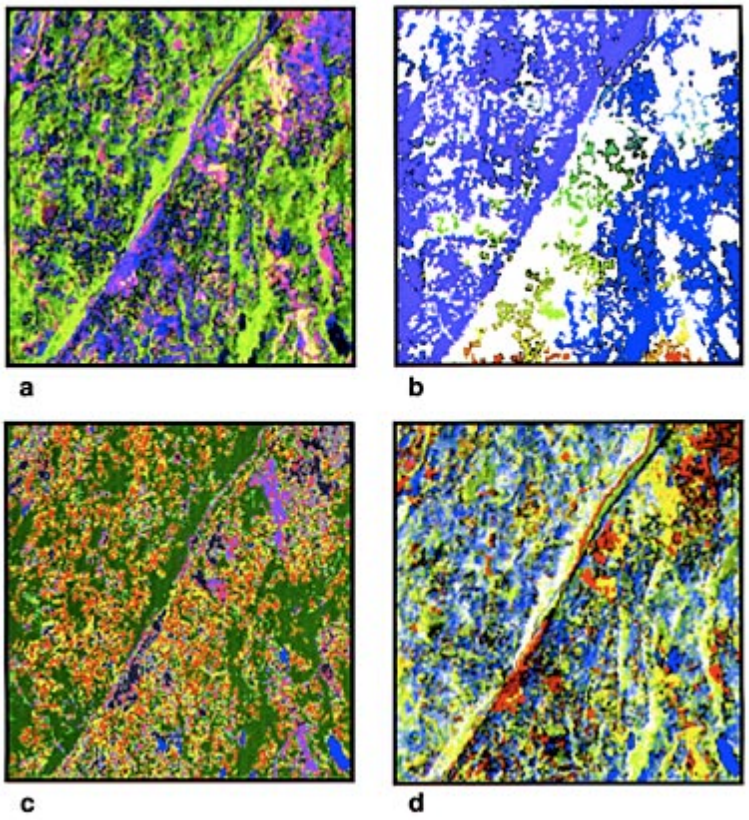

Figure 1: Landsat Thematic Mapper (TM) satellite data for a 6x6-km area in Westchester County, New York. Shown are the raw data (a), as well as products (e.g., maps) derived from the data (b-d) that might be used for modeling Lyme disease transmission risk. a) Raw Landsat TM image composed of bands 5, 4, and 3 (mid-infrared, near-infrared, and red bands). Vegetation is shown in shades of green, with bare soil and urban areas shown in shades of pink and purple. The spatial resolution of these data is 30x30 m. b) Map showing contiguous forest patches, derived from a Landsat TM classification. Colors represent discrete patches, with white indicating the absence of contiguous forest. c) A 12-class land cover map derived from the Landsat TM data. d) Composite image of three spectral indices derived from the Landsat TM data, showing the contributions of scene brightness in red, greenness in green, and wetness in blue.

In the next 15 years, new sensors will provide valuable data for studies of infectious diseases similar to the ones described here. For Lyme disease, new sensors could provide similar information about ecotones, human settlement patterns, or forests. These sensors include ARIES-1, scheduled for launch by Australia; CCD and IR/MSS sensors onboard CBERS, launched by China and Brazil in late 1999; Ikonos, a commercial satellite with 4-m spatial resolution; LISS III, onboard the orbiting Indian IRS-1C and -1D satellites; and ASTER, onboard the recently launched Terra satellite. Information from these sensors could also be used to address other vector-borne diseases, such as malaria, schistosomiasis, trypanosomiasis, and hantavirus, whose patterns are likewise influenced by environmental variables.

SeaWiFS, the Sea-Viewing Wide Field-of- View Sensor, with its increased spectral resolution of 1.1 km, is already providing imagery critical to understanding the temporal and spatial pattern of cholera risk (35). This sensor was specifically designed to gather information about ocean color (38) (Figure 2d).

Sensor Evaluation Project

CHAART evaluated data from current and planned satellite instruments for mapping, surveillance, prediction, and control of human disease transmission activities, including vector ecology, reservoir and host ecology, and human settlement patterns. From hundreds of potential sensors, 54 were identified that were current (or would be launched within the next 5 years), operational (not reserved for the scientific community), and digital (not photographic).

Beginning in 1985, NASA has held a series of workshops to elicit input from the health community on the use of remote sensing in the areas of entomology, ecology, epidemiology, vector control, and infectious diseases. In addition, NASA has participated in sessions on remote sensing and health at professional meetings sponsored by national and international health organizations. On the basis of this experience as well as a review of the scientific literature (Table 1), there does not appear to be consensus in the health community regarding requirements for a remote sensing system. Some investigators use remotely sensed data to resolve questions regarding the relationship between an aspect of disease transmission and an environmental variable. Other researchers already have a model of disease transmission and have specific spatial, temporal, or spectral requirements for the remotely sensed variables.

The information gathered during the CHAART sensor evaluation process is available at http://geo.arc.nasa.gov/sge/health/sensor/sensor.html.

No single spatial, temporal, or spectral resolution is universally appropriate for understanding the transmission risk for any disease, given the variety of vectors, reservoirs, hosts, geographic locations, and environmental variables associated with that disease. Therefore, in evaluating the existing sensors, CHAART used an approach that allowed individual investigators to identify satellite data appropriate for their own needs. This approach defined 16 groups of physical factors that could be used for both research and applications. Each factor is essentially an environmental variable that might have a direct or indirect bearing on the survival of pathogens, vectors, reservoirs, and hosts. These factors may also affect many types of non-vectorborne diseases, such as waterborne diseases. The factors are vegetation or crop type, vegetation green-up, ecotones, deforestation, forest patches, flooded forests, general flooding, permanent water, wetlands, soil moisture, canals, human settlements, urban features, ocean color, SST, and SSH. Precipitation, humidity, and surface temperature were not included because deriving these measurements from raw data requires highly specialized processing and calibration, routinely performed by qualified groups who often make the information available on Internet websites.

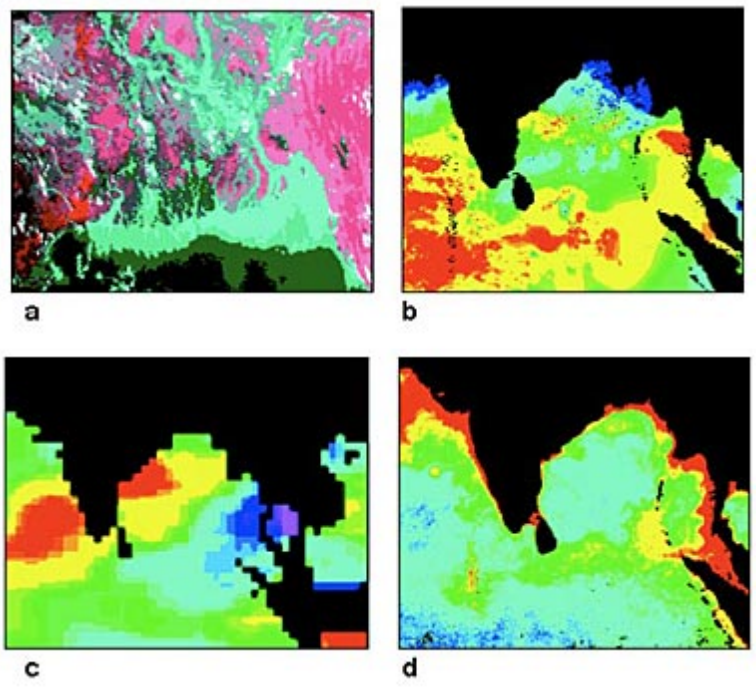

Figure 2: Datasets used to model the temporal patterns of cholera outbreaks in Bangladesh. a) Advanced Very High Resolution Radiometer (AVHRR) satellite image showing the mouth of the Ganges River and the Bay of Bengal. Vegetation is shown in shades of red and water in shades of blue. The spatial resolution of these data is 1.1 km. b) Sea surface temperature data, derived from AVHRR thermal bands. Temperatures range from low (purple) to high (red). c) Sea surface height data, derived from TOPEX/Poseidon satellite data. The spatial resolution

of these data is 1 degree. d) Image derived from the Sea-Viewing Wide Field-of-View Sensor (SeaWiFS) showing chlorophyll concentration, ranging from low (blue) to high (red). These satellite data have a nominal spatial resolution of 1.1 km.

The sensor evaluation project generated a series of tables that associated each of the 16 factors with the 54 sensors according to spatial, temporal, and spectral characteristics. For example, factors requiring frequent monitoring, such as vegetation green-up, are linked with sensors with shorter repeat overpasses. Similarly, factors requiring very high spatial resolution, such as mapping urban features, are linked with sensors having a spatial resolution of 10 m or less, regardless of their temporal or spectral resolutions.

Perhaps the broadest use of Landsat and SPOT data has been to identify and map vegetation or crop types. This factor is important because the distribution of vegetation types integrates the combined impact of rainfall, temperature, humidity, topographic effects, soil, water availability, and human activities. Nearly all vector-borne diseases are linked to the vegetated environment during some aspect of their transmission cycle; in many cases, this vegetation can be sensed remotely from space. The spatial and temporal distribution of vector or reservoir and host species may relate to the occurrence and distribution of specific vegetation or crop types, not simply to whether an area has forests or grasslands. For example, food and cover preferences of the white-tailed deer, the host for adult ticks that transmit Lyme disease in the northeastern United States, might well encourage deer to live near certain types of forest. Crop-type information may also be important for studying the effects of pesticides (e.g., vector resistance; illnesses caused by exposure to toxins). The sensor evaluation procedure has identified many potentially useful sensors for mapping vegetation and crop type beyond the Landsat and SPOT systems (Table 2). A ground resolution threshold of 30 m was used as the upper limit for exploring the relationship between vegetation (or crop) type and disease vectors, reservoirs, and hosts; above 30 m, vegetation and crop type are more difficult to ascertain. Many of the sensors could also be used for mapping the boundary between vegetation types, or ecotones, which provide habitat for insects and animals critical to the maintenance and transmission of vectorborne diseases. These edges may be areas for increased risk for vector-human contact, as indicated by the relationship between Lyme disease transmission and suburban encroachment into forested areas in the northeastern United States. The movement of humans into forested edges where potential vectors are established could also be important for predicting malaria or yellow fever transmission.

Table 2. Current and proposed sensor systems for identifying and mapping vegetation and crop type[a]

Temporal resolution (d)	Spatial resolution[b] (m) 1-5	6-10	11-30
Daily	(QuickBird)[c]		
2-7	(Orbview-3,4) (QuickBird)	(Almaz-1b MSU-E2) (ALOS AVNIR-2) (Orbview-4) (SPOT-5a,b 3xHRG)	(ALOS AVNIR-2) (ARIES-1) SPOT-4 2xHRVIR
8-14	Ikonos	Priroda/Mir MOMS-2P	Priroda/Mir MOMS-2P
15-30			Terra ASTER IRS-1C,D LISS III Landsat TM Landsat-7 ETM+ SPOT-2 2xHRV
>30		(ALOS AVNIR-2)	(ALOS AVNIR-2)

[a]This matrix is the output from an interactive search with the search engine located at http://geo.arc.nasa.gov/sge/health/sensor/senchar.html.
[b]See Appendix A for explanations of sensor acronyms.
[c]Sensors in parentheses have not yet been launched.

Click image for larger view table 2

The list of 16 factors used in the CHAART evaluation includes some that have not yet been quantified because available sensors do not provide adequate spatial, spectral, or temporal resolutions. Two of these factors are briefly described below to illustrate how remotely sensed data might be used to explore their potential links to human health. More links between the factors and various diseases are listed in Table 3.

Table 3. Potential links between remotely sensed factors and disease

Factor	Disease	Mapping opportunity
Vegetation/crop type	Chagas disease	Palm forest, dry & degraded woodland habitat for triatomines
	Hantavirus	Preferred food sources for host/reservoirs
	Leishmaniasis	Thick forests as vector/reservoir habitat in Americas
	Lyme disease	Preferred food sources and habitat for host/reservoirs
	Malaria	Breeding/resting/feeding habitats; crop pesticides → vector resistance
	Plague	Prairie dog and other reservoir habitat
	Schistosomiasis	Agricultural association with snails, use of human fertilizer
	Trypanosomiasis	***Glossina*** habitat (forests, around villages, depending on species)
	Yellow fever	Reservoir (monkey) habitat
Vegetation green-up	Hantavirus	Timing of food sources for rodent reservoirs
	Lyme disease	Habitat formation and movement of reservoirs, hosts, vectors
	Malaria	Timing of habitat creation
	Plague	Locating prairie dog towns
	Rift Valley fever	Rainfall
	Trypanosomiasis	***Glossina*** survival
Ecotones	Leishmaniasis	Habitats in and around cities that support reservoir (e.g., foxes)
	Lyme disease	Ecotonal habitat for deer, other hosts/reservoirs; human/vector contact risk.
Deforestation	Chagas disease	New settlements in endemic-disease areas
	Malaria	Habitat creation (for vectors requiring sunlit pools)
		Habitat destruction (for vectors requiring shaded pools)
	Yellow fever	Migration of infected workers into forests where vectors exist
		Migration of disease reservoirs (monkeys) in search of new habitat
Forest patches	Lyme disease	Habitat requirements of deer and other hosts, reservoirs
	Yellow fever	Reservoir (monkey) habitat, migration routes
Flooded forests	Malaria	Mosquito habitat
Flooding	Malaria	Mosquito habitat
	Rift Valley fever	Flooding of dambos, breeding habitat for mosquito vector
	Schistosomiasis	Habitat creation for snails
	St. Louis encephalitis	Habitat creation for mosquitoes
Permanent water	Filariasis	Breeding habitat for ***Mansonia*** mosquitoes
	Malaria	Breeding habitat for mosquitoes
	Onchocerciasis	***Simulium*** larval habitat
	Schistosomiasis	Snail habitat
Wetlands	Cholera	***Vibrio cholerae*** associated with inland water
	Encephalitis	Mosquito habitat
	Malaria	Mosquito habitat
	Schistosomiasis	Snail habitat
Soil moisture	Helminthiases	Worm habitat
	Lyme disease	Tick habitat
	Malaria	Vector breeding habitat
	Schistosomiasis	Snail habitat
Canals	Malaria	Dry season mosquito-breeding habitat; ponding; leaking water
	Onchocerciasis	***Simulium*** larval habitat
	Schistosomiasis	Snail habitat
Human settlements	Diseases	Source of infected humans; populations at risk for transmission in general
Urban features	Chagas disease	Dwellings that provide habitat for triatomines
	Dengue fever	Urban mosquito habitats
	Filariasis	Urban mosquito habitats
	Leishmaniasis	Housing quality
Ocean color (Red tides)	Cholera	Phytoplankton blooms; nutrients, sediments
Sea surface temp.	Cholera	Plankton blooms (cold water upwelling in marine environment)
Sea surface height	Cholera	Inland movement of ***Vibrio***-contaminated tidal water

Click image for larger view table 3

Urban Features

The detection of urban features requires higher spatial resolution systems than needed for detecting the presence of human settlements. Some disease vectors are associated with specific urban features such as housing type, which can only be

detected by sensors with very high spatial resolution. In the future, new sensors may be able to provide information on the urban environment (Table 4).

Table 4. Current and proposed sensor systems for identifying and mapping urban features[a]

Temporal resolution (d)	Spatial resolution[b] (m) 1-5	6-10
Daily	(QuickBird)[c]	
2-7	(ALOS AVNIR-2) (Orbview-3,4) (QuickBird) (SPOT-5a,b 3xHRVIR)	(Almaz-1b MSU-E2) (ALOS AVNIR-2) (ARIES-1) IRS-1C,D PAN (Orbview-4) SPOT-4 2xHRVIR (SPOT-5a,b 3xHRVIR)
8-15	Ikonos	IRS-1C,D PAN Priroda/Mir MOMS-2P
15-30		IRS-1C,D PAN SPOT-2 2xHRV
>30	(ALOS AVNIR-2)	(ALOS AVNIR-2)

[a]This matrix is the output from an interactive search with the search engine located at http://geo.arc.nasa.gov/sge/health/sensor/senchar.html
[b]See Appendix A for explanations of sensor acronyms.
[c]Sensors in parentheses have not yet been launched.

Soil Moisture

Wet soils indicate a suitable habitat for species of snails, mosquito larvae, ticks, and worms. Several types of sensors can detect soil moisture, including synthetic aperture radars (SARs), shortwave-infrared, and thermal-infrared sensors (Table 5). SARs are particularly important for sensing ground conditions in areas of cloud cover or vegetation canopy cover, two factors commonly found in the tropics.

Table 5. Current and proposed sensor systems for identifying and mapping soil moisture[a]

Temporal resolution (d)	Spatial Resolution[b] (m) 11-30	101-500	501-1,000	1,001-4,000
Daily				NOAA AVHRR
2-7	(Almaz-1b SAR-70)[c] (ARIES-1) (ENVISAT-1 ASAR) Radarsat SPOT-4 2xHRVIR		(ADEOS II GLI) (Almaz-1b MSU-SK) (Almaz-1b SROSM) (ENVISAT-1 AATSR) Terra MODIS (EOS PM-1 MODIS) Resurs-01 N2,3 MSU-SK	
8-14	(LightSAR) Priroda/Mir MOMS-2P		Priroda/Mir MSU-SK	
15-30	Terra ASTER ERS-1,2 AMI-SAR Landsat TM Landsat-7 ETM+	Landsat TM TIR		
>30	ERS-1,2 AMI-SAR			

[a]This matrix is the output from an interactive search with the search engine located at http://geo.arc.nasa.gov/sge/health/sensor/senchar.html.
[b]See Appendix A for explanations of sensor acronyms.
[c]Sensors in parentheses have not yet been launched.

Click image for larger view table 5

Conclusions

The extent to which remotely sensed data are used for studying the spatial and temporal patterns of disease depends on a number of obstacles and opportunities. Many of the obstacles-including cost, inadequate spatial, spectral, or temporal resolutions, and long turnaround times for products-have restricted the use of remote sensing within the user community as a whole. Many of these barriers will be addressed by new sensor systems in the next 5 years. The recently launched Landsat-7 ETM+ sensor, for example, is now providing 30- m multispectral data, a 15-m panchromatic band, and an improved 60-m thermal infrared band, all at a cost that is an order of magnitude

With the higher spatial and spectral resolutions, more frequent coverage, lower price, and increased availability offered by the range of new sensors, human health investigators should be able to extract many more environmental variables than previously realized. These improvements will provide new opportunities to extend the uses of remote sensing technology beyond a few vector-borne diseases to studies of water- and soil-borne diseases (for example, cholera and schistosomiasis [waterborne] and the helminthiases) and the mapping of human settlements at risk. The next generation of earthobserving remote sensing systems will also allow investigators in the human health community to characterize an increasing range of variables key to understanding the spatial and temporal patterns of disease transmission risk. These improved capabilities, when combined with the increased computing power and spatial modeling capabilities of geographic information systems, should extend remote sensing into operational

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