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Earth Observation: Investigating Noncommunicable Diseases from Space

Peng Jia,[1,2] Alfred Stein,[1] Peter James,[3]
Ross C. Brownson,[4] Tong Wu,[5] Qian Xiao,[6]
Limin Wang,[7] Clive E. Sabel,[8,9] and Youfa Wang[10]

[1]Department of Earth Observation Science, Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, 7514 AE Enschede, The Netherlands; email: jiapengff@hotmail.com

[2]International Initiative on Spatial Lifecourse Epidemiology (ISLE), 7500 AE Enschede, The Netherlands

[3]Department of Population Medicine, Harvard Medical School and Harvard Pilgrim Health Care Institute, Boston, Massachusetts 02215, USA

[4]Prevention Research Center in St. Louis, Brown School; Department of Surgery and Alvin J. Siteman Cancer Center, Washington University School of Medicine, Washington University in St. Louis, St. Louis, Missouri 63130, USA

[5]School of Life Sciences, Arizona State University, Tempe, Arizona 85287-4701, USA

[6]Department of Health and Human Physiology, University of Iowa, Iowa City, Iowa 52242-1111, USA

[7]National Center for Chronic and Non-Communicable Disease Control and Prevention, Chinese Center for Disease Control and Prevention, Beijing 102206, China

[8]Department of Environmental Science, Aarhus University, DK-4000 Roskilde, Denmark

[9]Danish Big Data Centre for Environment and Health (BERTHA), DK-4000 Roskilde, Denmark

[10]Global Health Institute; and Department of Epidemiology and Biostatistics, School of Public Health, Xi'an Jiaotong University Health Science Center, Xi'an, Shaanxi 710049, China

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Abstract

The United Nations has called on all nations to take immediate actions to fight noncommunicable diseases (NCDs), which have become an increasingly significant burden to public health systems around the world. NCDs tend to be more common in developed countries but are also becoming of growing concern in low- and middle-income countries. Earth observation (EO) technologies have been used in many infectious disease studies but have been less commonly employed in NCD studies. This review discusses the roles that EO data and technologies can play in NCD research, including (*a*) integrating natural and built environment factors into NCD research, (*b*) explaining individual–environment interactions, (*c*) scaling up local studies and interventions, (*d*) providing repeated measurements for longitudinal studies including cohorts, and (*e*) advancing methodologies in NCD research. Such extensions hold great potential for overcoming the challenges of inaccurate and infrequent measurements of environmental exposure at the level of both the individual and the population, which is of great importance to NCD research, practice, and policy.

INTRODUCTION

Noncommunicable diseases (NCDs), also known as chronic diseases, are generally noninfectious diseases or medical conditions that last for long periods of time and progress slowly (103). According to the United Nations and the World Health Organization, NCDs will become the leading cause of death worldwide by 2030 (24, 102), as historically important infectious diseases such as cholera, malaria, and tuberculosis are brought under control. NCDs have increasingly become major sources of economic burden to health care systems already under pressure around the world (34, 36, 80). Moreover, NCDs tend to be more common in developed countries but also are of growing concern in low- and middle-income countries (LMICs), where nearly three-quarters of global NCD deaths occurred over the past decade (approximately 28.5 million in 2012 and 39.5 million in 2015) (103, 104). In addition to experiencing a loss of quality of life due to NCDs, NCD patients tend to be more susceptible to infectious diseases than are their healthy counterparts, due to a weakened immune system, and some infectious diseases (e.g., HIV) now have a long (chronic) duration owing to improved treatment (90). The considerable public health, socioeconomic, and ecological impacts of NCDs are expected to continue and even increase, given our current limited capacity to understand the multifactorial etiology of many complex NCDs, especially those of later life, which probably result from a combination of genetic and environmental exposures over the course of a lifetime (41).

In recent years, emerging research has demonstrated that environmental factors, including air pollution, temperature, green space, the built environment, and noise, may be important risk factors for NCDs (9, 20, 22, 33). These spatial factors may provide meaningful targets for interventions to reduce NCD risk. Geographic information systems (GIS) can provide environmental data products over large areas/populations, identify novel risk factors, and suggest potential areas for targeted interventions (3, 60, 61). Many creative and pioneering studies have already been conducted using an integration of statistical and GIS techniques to understand the patterns and mechanisms of NCDs, such as the visualization of NCD prevalence and risk factors (14, 108) as well as examinations of associations between NCDs and their risk factors (16, 17). However, many studies that measured multiple dimensions of environmental exposures over a long time period and identified their association with NCDs have been carried out at local scales (1, 8, 13, 15, 20, 22, 28). Efforts to tackle NCDs through GIS approaches need to be scaled and sped up to keep pace with the increasing global burden of NCDs (6, 7, 78, 87, 88, 93).

Geographic information systems (GIS): systems designed to capture, store, manipulate, analyze, manage, and present spatial or geographic data

One method to improve GIS approaches to studying NCDs is by increasing the utilization of earth observation (EO) technologies, which gather information about the earth's physical, chemical, and biological systems mainly via remote sensing (RS), supplemented by other earth-surveying techniques (35). In contrast with onsite observation, RS generally acquires information by spaceborne or airborne sensors, without making physical contact with the object or phenomenon. RS data are stored in a raster format, which consists of a matrix of pixels (or cells) organized into rows and columns (or a grid). Each pixel contains a value representing information, such as temperature, at that location. EO technologies have enabled all-around environmental monitoring of Earth, and RS data have been extensively applied in a wide range of fields, such as ecology, agriculture, oceanography, geology, and archaeology (5, 65–67, 72, 98, 110). However, compared with many large-scale and successful EO applications in infectious disease studies (44, 47, 52, 101), many opportunities remain for NCD research and interventions offered by EO technologies for researchers, decision makers, and other stakeholders (68). To date, a growing body of research has used RS data to examine environmental factors and NCD risk. For instance, studies have demonstrated associations between natural vegetation and mortality, cardiovascular disease, mental health, and birth outcomes; air pollution and cardiovascular disease, respiratory disease, cancer, and the mortality risks from these diseases; light at night and cancer; and temperature and cardiovascular and respiratory diseases (18, 25, 53–55, 57). That said, EO technologies hold still greater potential for NCD research and practice, especially as more techniques and data become available.

Pixel: the fundamental unit of data collection; represented in a remotely sensed image as a cell in an array of data values

Exposome: the measure of all the exposures of an individual in a lifetime and how those exposures relate to health

To better use and position EO technologies for future NCD research and interventions, EO scientists need to collaborate with epidemiologists and other researchers and practitioners in the related biomedical fields to understand how the environmental factors measured by EO technologies may affect NCD risks, to identify new research areas, and to develop more informative methods. However, such interdisciplinary collaboration requires researchers to reach outside their fields of expertise, which can be challenging. To address this challenge, this review aims to identify current limitations in NCD research where EO technologies might improve the field and to make EO-related recommendations for future NCD research. In addition, a complete list of satellite sensors that have been used or that show significant potential for applications in NCD research is provided as an important reference for NCD researchers. This review will help accelerate the integration of EO technologies and NCD research as well as the development of interventions and guidelines for NCD management and prevention.

RESEARCH GAPS AND CHALLENGES

The limited use of EO technologies accounts for a bottleneck in NCD research, which has likely prevented us from fully characterizing an individual's exposome, defined as the totality of an individual's environmental exposures over the total life course (105). Although an individual's time activity patterns over long time periods can now be captured by global positioning systems (GPS), GIS-based environmental data that temporally match individual movement patterns for better estimating individual exposures may not always be available. For the same reason, most studies using GIS data have been carried out either at a large scale, but with limited accuracy (coarse spatial resolution) and/or frequency (specific snapshots in time for the whole study period) of measurements, or at a local scale, with still limited frequency in most cases. This is especially true for built environment features relative to natural environment ones, due mainly to incomplete GIS-based environmental data archives (61). It is difficult to build integrated measures of exposure at the individual level, especially measurements of exposure to the built environment over long time periods; variability in individual movement patterns makes this process even more challenging (24, 50, 51).

From the perspective of the public health sector, financial investment and resources targeted at NCD prevention and control are limited relative to the high and sometimes prohibitive economic costs, especially in developing countries (77). Furthermore, not all strategies for managing NCDs will function equally or even toward the same positive direction in every setting. Tailoring these strategies to local conditions to achieve maximum health impacts for minimal investment is one of the most significant challenges encountered by public health agencies (45). Addressing this challenge necessitates a deeper understanding of heterogeneity in the mechanisms that link NCDs with population and environment at various places. Unfortunately, evidence for tailoring intervention strategies appropriately has been limited so far owing to difficult, expensive, and hence infrequent and localized data acquisition. If current NCD research and application cannot be expanded and intensified, relevant technological advances (e.g., exposome measurements, GIS) will not be able to keep pace with the global progression of NCDs.

Revisit time: the time elapsed between observations of the same point on earth by a satellite; depends on the satellite's orbit, target location, and swath of the sensor

RESEARCH OPPORTUNITIES

EO technologies, with simultaneous data acquisition capacity over a large scale and a short revisit time (i.e., the time elapsed between observations of the same location by a satellite) for the majority of Earth's landmasses, have been revolutionizing NCD research. For example, data from high-resolution sensors operating aboard the series of *Landsat* satellites, launched in 1972, have been vastly applied to broad environmental monitoring (43). When *Landsat* made its images free of charge in 2008, more than 1 million images were downloaded in that first year, compared with the previous peak of only about 25,000 images sold (106). Such high usage may continue, driven by the growing availability of high-resolution RS data—e.g., Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data, which, with a spatial resolution of 15 m, have been available to the public at no cost since April 1, 2016. Five major research opportunities brought by EO technologies are described below in detail. A list of satellite sensors showing significant potential for applications in NCD research by offering a range of useful environmental measurements is presented as an important reference for public health researchers and agencies to choose satellites and sensors in their own studies and surveillance efforts (**Table 1**).

Integrating Natural and Built Environment Factors into NCD Research

Research is growing on the natural and built environments in relation to NCD outcomes, especially behavior- or lifestyle-related NCDs (75, 82). The natural environment has been associated with a broad array of NCDs, such as the relationships between temperature and stroke (18), altitude and hypertension (79), and sunlight and skin cancer (73). Poor air and water quality, perhaps not acute in the short term, may cause physical discomfort if people are chronically exposed to them (e.g., gastrointestinal illness and seasonal allergic rhinitis) and eventually may lead to cardiovascular and respiratory diseases (27, 42, 99). To improve the predictability of NCD risk factors and facilitate the development of NCD prevention and control, it is necessary to deepen our knowledge of the underlying NCD risk factors, where the natural environment may play an important, although sometimes indirect, role. For example, frequent rainfall may reduce people's outdoor activity levels, even if individuals live in a highly walkable neighborhood (26). Thus, climate may shape long-term dietary and activity behaviors in a given population, and weather can influence energy balance dynamics during a short period (e.g., daily or weekly); these can all contribute to NCDs.

EO technologies enable all-around surveillance of the natural environment by monitoring factors such as land cover, water bodies, volume of evaporation, proportion of pollutants in the air, and concentrations of atmospheric particulate matter (PM) and carbon dioxide (CO_2) (5, 35, 67, 72, 98). Therefore, RS data provide capabilities for describing the natural environment, which complement built environment factors commonly used in NCD research. Furthermore, on the basis of these data, many RS indicators and products for the natural environment have been developed for easy use, such as normalized difference vegetation index (NDVI), daily climate variables (e.g., total precipitation, mean dew point temperature), and some bioclimatic variables (e.g., mean

Table 1 Technical specifications of satellite sensors that have been used or show significant potential for applications in noncommunicable disease (NCD) research

Satellite	Sensor	Band (number/order of bands)[a]	Spatial resolution (m)	Temporal resolution (day)	Launch year	Year (to be) taken out of service
Airbus Defense and Space (AIRBUS), France						
SPOT-6/7	NAOMI	V(3), N(1)	6	1–4	2012	2024
		P	1.5			
Centre national d'études spatiales (CNES), France						
SPOT-1/2/3	HRV	V(2), N(1)	20	1–4	1986	2009
		P	10			
SPOT-4	HRVIR	V(2), N(1), S(1)	20	1–4	1998	2013
		P	10			
	VGT	V(2), N(1), S(1)	1,165			
SPOT-5	HRG	V(2), N(1)	10	1–4	2002	2015
		S(1)	20			
		P	5			
	HRS	P	10			
	VGT-2	Same as VGT onboard SPOT-4				
Pléiades-1A/1B	HiRI	V(3), N(1)	2.8	26	2011	2017
		P	0.7			
China Meteorological Administration National Satellite Meteorological Center (CMA-NSMC)						
Fengyun-1A/1B/1C/1D	MVISR	V(4), N(2), S(1), M(1), T(2)	1,100	12	1988	2012
Fengyun-2A	S-VISSR	VN(1)	1,250	0.5–1	1997	2006
		M(1), T(1)	5,000			
Fengyun-2C/2D/2E/2F/2G/2H	S-VISSR	VN(1)	1,250	0.5–1	2004	2021
		M(2), T(2)	5,000			
Fengyun-3A/3B/3C	IRAS	VN(5), S(1), M(10), T(10)	17,000	6	2008	2018
	MERSI-1	V(3), N(1), T(1)	250			
		V(7), N(6), S(2)	1,000			
	VIRR	V(4), N(2), S(1), M(1), T(2)	1,100			
Fengyun-3D	HIRAS	M/T(1,370)	16,000	6	2017	2022
	MERSI-2	V(3), N(1), T(2)	250			
		V(7), N(6), S(2), M(3), T(1)	1,000			
	GAS	V(1), S(3)	10,000			
Fengyun-4A	GIIRS	V/M/T(1,650)	16,000	0.03–0.05	2016	2021
	AGRI	V(1)	500–1,000			
		V(1), N(1)	1,000			
		N(1), S(1), M(1)	2,000			
		S(1)	2,000–4,000			
		M(3), T(4)	4,000			

(*Continued*)

Table 1 (*Continued*)

Satellite	Sensor	Band (number/order of bands)[a]	Spatial resolution (m)	Temporal resolution (day)	Launch year	Year (to be) taken out of service
China National Space Administration (CNSA)						
Gaofen-1	PMS	V(3), N(1)	8	4	2013	2018
		P	2			
	WFV	V(3), N(1)	16			
Gaofen-2/8/9	PMS-2	V(3), N(1)	4	5	2014	2023
		P	1			
Gaofen-4	GF-4 imager	M(1)	400	0.01	2015	2023
		P	50			
Orbital Imaging Corporation, USA (turned into GeoEye in 2006 and merged into DigitalGlobe in 2013)						
OrbView-1	OTD	N(1)	10,000	2	1995	2000
OrbView-2	SeaWiFS	V(6), N(2)	11,000	1	1997	2010
OrbView-3	OHRIS	V(3), N(1)	4	3	2003	2007
		P	1			
DigitalGlobe, USA						
GeoEye-1	GIS	V(3), N(1)	1.64	3	2008	2017
		P	0.41			
WorldView-1	WV60	P	0.5	1.7	2007	2017
WorldView-2	WV110	V(6), N(2)	1.85	1–3.7	2009	2017
	WV60	P	0.46			
WorldView-3	WV110	V(6), N(2)	1.24	1–4.5	2014	2021
		S(8)	3.7			
		P	0.31			
	CAVIS	V(Band 1–4), N(Band 5–7), S(Band 8–12)	30			
WorldView-4	SpaceView-110	V(3), N(1)	1.24	1–4.5	2016	2023
		P	0.31			
IKONOS	OSA	V(3), N(1)	3.2	3	1999	2017
		P	0.82			
QuickBird	BGIS-2000	V(3), N(1)	2.44	1–3.5	2001	2015
		P	0.61			
European Space Agency (ESA), France						
Sentinel-2A	MSI	V(1), N(1), S(1)	60	10	2015	2022
		V(3), N(1)	10			
		V(3), N(1), S(2)	20			
Sentinel-2B	MSI	Same as MSI onboard Sentinel-2A		5	2017	2024
Meteosat-1/2/3	MVIRI	V(1)	2,500	0.02	1977	1991
		T(2)	5,000			

(*Continued*)

Table 1 (*Continued*)

Satellite	Sensor	Band (number/order of bands)[a]	Spatial resolution (m)	Temporal resolution (day)	Launch year	Year (to be) taken out of service
EUMETSAT, Germany						
Meteosat-4/5/3(ADC)/3(XADC)/6/7/5(IODC)/7(IODC)/6(IODC)	MVIRI	V(1)	2,500	0.02	1989	2017
		T(2)	5,000			
Meteosat-8/9/10/11/8(IODC)	SEVIRI	V(1), N(1), S(1), M(1), T(7)	3,000	0.01	2002	2022
		P	1,000			
	GERB	V(1)	42,000			
Brazilian Institute of Space Research (INPE)						
CBERS-1/2	HRCC	V(3), N(1), P	20	26	1999	2007
	IRMSS	S(2), P	80			
		T(1)	160			
	WFI	V(1), N(1)	260			
CBERS-2B	HRCC	Same as HRCC onboard CBERS-1		26	2007	2010
	HRPC	P	2.7			
	WFI	Same as WFI onboard CBERS-1				
CBERS-4	MUXCAM	V(3), N(1)	20	26	2014	2017
	PANMUX	V(2), N(1)	10			
		P	5			
	WFI-2	V(3), N(1)	73			
	IRMSS-2	VN(1), S(2)	40			
		T(1)	80			
Korea Aerospace Research Institute (KARI)						
KOMPSAT-1	EOC	P	6.6	28	1999	2008
	OSMI	V(7), N(1)	1,000			
KOMPSAT-2	MSC	V(3), N(1)	4	28	2006	2017
		P	1			
KOMPSAT-3	AEISS	V(3), N(1)	2.8	28	2012	2017
		P	0.7			
KOMPSAT-3A	AEISS-A	V(3), N(1)	2	28	2015	2019
		P	0.5			
	IIP	M(1)	5.5			
National Aeronautics and Space Administration (NASA), USA						
Landsat-1/2/3	MSS	V(3), N(1)	79	16	1972	1983
Landsat-4/5	TM	V(3), N(1), S(2)	30	16	1982	2013
		T(1)	120			
	MSS	Same as MSS onboard Landsat-1				

(*Continued*)

Table 1 (*Continued*)

Satellite	Sensor	Band (number/order of bands)[a]	Spatial resolution (m)	Temporal resolution (day)	Launch year	Year (to be) taken out of service
Landsat-7	ETM+	V(3), N(1), S(2)	30	16	1999	2017
		T(1)	60			
		P	15			
Landsat-8	OLI	V(4), N(1), S(3)	30	16	2013	2018
		P	15			
	TIRS	T(2)	100			
Terra	MODIS	V(Band 1), N(Band 2)	250	1–2	1999	2017
		V(Band 3–4), N(Band 5), S(Band 6–7)	500			
		V(Band 8–15), N(Band 16–19), S(Band 26), M(Band 20–25), T(Band 27–36)	1,000			
	MISR	V(3), N(1)	275	7–9		
	ASTER	V(Band 1–2), N(Band 3)	15	5–16		
		S(Band 4–9)	30			
		T(Band 10–14)	90			
Aqua	AIRS	V(Band 1–3), N(Band 4), M(Band 5), T(Band 6–7)	13,500	0.5	2002	2017
	MODIS	Same as MODIS onboard Terra		1–2		
EO-1	ALI	V(Band 2–5), N(Band 6–7), S(Band 8–10)	30	16	2000	2017
		P	10			
	Hyperion	V/N/S(242)	30			
	LAC	N(256)	250			
National Oceanic and Atmospheric Administration (NOAA)						
TIROS-N/ NOAA-6/8/10	AVHRR	V(1), N(1), S(1), T(1)	1,100	1	1978	2001
NOAA-7/9/ 11–19	AVHRR/2	V(1), N(1), S(1), T(2)	1,100	1	1981	2017
NOAA-15	AVHRR/3	V(1)	500	1	1998	2017
		N(2), S(1), T(2)	1,000			
GOES-1/2/3	VISSR	V(1)	900	1	1975	1993
		T(1)	6,900			
GOES-4/5/6/7	VAS	V(1)	900	0.5–1	1980	1996
		M(3), T(2)	13,800			
		T(8)	6,900			
GOES-8/9/10/ 11/12/9(GMS backup)/13/ 10(S-America)/ 14/15/ 12(S-America)	Imager	V(Band 1)	1,000	0.02	1994	2020
		M(Band 2), T(Band 4–5)	4,000			
		T(Band 3)	8,000			
	Sounder	V(Band 19), M(Band 13–18), T(Band 1–12)	8,000			

(*Continued*)

Table 1 (*Continued*)

Satellite	Sensor	Band (number/order of bands)[a]	Spatial resolution (m)	Temporal resolution (day)	Launch year	Year (to be) taken out of service
GOES-16 [R]	ABI	V(Band 2)	500	0.01	2016	2027
		V(Band 1), N(Band 3), S(Band 5)	1,000			
		S(Band 4 and 6), M(Band 7), T(Band 8–16)	2,000			
Planet Labs, USA						
RapidEye	REIS	V(4), N(1)	5	5.5	2008	2017

[a]M, mid-wavelength infrared (MWIR); N, near-infrared (NIR); P, panchromatic (PAN); S, short-wavelength infrared (SWIR); T, thermal infrared (TIR); V, visible (VIS); VN, visible and near-infrared (VNIR).

temperature/precipitation of warmest/coldest quarter) (37, 48, 63, 64, 71, 86, 89). These indicators are available at a spatial resolution of 0.25–1 km, mainly produced using data from TM and ETM+ on Landsat, Advanced Very High Resolution Radiometer (AVHRR) onboard NOAA (National Oceanic and Atmospheric Administration) satellites, and Moderate Resolution Imaging Spectroradiometer (MODIS) onboard NASA (National Aeronautics and Space Administration) satellites. End users may further implement image processing and spatial analyses to customize specific products on the basis of the existing variables (63).

Explaining Individual–Environment Interactions

Information from RS data can provide better explanations for human behaviors and decision making (96). Human behavior depends not only on what is in their surroundings, but also on what they perceive and how they make decisions (23). Built environment data and GIS analysis tools provide only the destinations that people tend to reach, and calculate the pathway with the shortest distance or travel time if speed limit information is available; location-aware technologies (e.g., GPS) can further obtain actual routes of individuals (109). Additional information from EO technologies may help explain why they choose any particular route to reach a given destination, which could alter the interaction with and exposure to the environment. For example, people may abandon the shortest path and instead be predisposed to taking another path through more vegetated areas if there is not much impedance. This action could, in turn, expose them to better air quality. Using satellite data on greenness indices (e.g., NDVI) and air pollutants may explain individuals' behavior and measure the exposure to air pollution along travel routes (19). Also, using frequent road network data extracted from high-resolution RS data (e.g., one scene of imagery per month) may detect changes in road infrastructure and explain potentially correlated variation in the accessibility of certain food outlets (obtained from GIS data) and subsequently in local dietary patterns and NCD risk.

In urban settings, using EO technologies to better understand the relationship between urban form and NCDs is only just coming to the fore. For example, urban form and structure impacts air pollutant generation and dispersion, which impacts respiratory and cardiac illnesses. But consider for a moment less obvious health issues such as mental health and well-being and how these could be impacted by our urban environments (29, 40). The reasons for or determinants of those less obvious health issues are concerned with not only the density or proximity of green and blue spaces, which can be factors and have been measured by EO, but also issues such as the density of residential areas, street layout, height of buildings, and segregation of different groups in society, such as that related to varying socioeconomic statuses, ethnicities, and even age. EO can extract information about urban structure and changes over a temporal scale from months to decades. EO methods and algorithms have great utility to investigate changing urban structure within cities, across continents, and particularly in areas of the world that are less accessible by ground survey methods. Allied with health and GIS data collected through official government registries and through citizen-science volunteered initiatives (38, 58), we can test hypotheses between a range of NCD health outcomes and urban structure.

Big data: data sets that are so voluminous and complex that traditional data-processing application software is inadequate to deal with them

Hyperspectral, i.e., capable of capturing data in hundreds of contiguous narrow wavebands (11), and very high spatial-resolution (VHR) satellite imagery can also provide a wealth of data and useful methods for extraction of features/conditions favorable to NCDs, as well as support explanation and prediction of individuals' behaviors and decision making. For example, hyperspectral images from the *Hyperion* sensor onboard NASA's *Earth Observing-1* (EO-1) satellite, with 220 wavebands at a relatively coarse spatial resolution (30 m), are extensively used for the extraction of urban features (46). The data with the highest publicly available spatial resolution to date that are useful for identifying urban features are obtained from commercial satellites, such as WorldView-3/4 (0.31 m), GeoEye-1 (0.41 m), and QuickBird (0.61 m). These satellites are capable of collecting imagery from around the globe on a daily basis and have narrowed the gap between satellite images and aerial photos. Furthermore, the increasing accessibility of these data with declining costs—e.g., free public access to ASTER data since April 1, 2016—could herald a new era of high-resolution RS data and provide a range of useful environmental measurements for NCD studies at the lowest costs to date.

Scaling Up Local Studies and Interventions

The use of EO technologies offers possibilities for scaling up NCD research and management efforts from local scales, as earth-observing satellites can provide an unprecedented view of the land surface and global environment (37). Many current studies aiming to measure multiple dimensions of individuals' environmental exposure have been restricted to a local scale, owing mainly to limited high-quality data (4, 74). To scale up individual-level measurements of exposure to both natural and built environments, researchers require an economically feasible way to procure large volumes of environmental data to overcome current data bottlenecks. For instance, some factors such as air pollution, altitude, and light at night had been previously measured at a high cost using traditional approaches (e.g., ground-level monitoring stations and ground surveying) (25, 54). EO technologies feature a simultaneous data acquisition capacity at a large scale, over a short time period, and in a manageable and affordable manner, which makes it possible to realize unparalleled massive measurements while concomitantly reducing measurement errors. For example, covering 99% of Earth's landmasses at a high spatial resolution from 15 to 90 m, ASTER data can provide a range of useful environmental measurements in NCD contexts, such as land cover, vegetation, and land surface temperature, which are available for any spot on Earth every 16 days. Furthermore, when a study exploring the local determinants of NCDs is scaled up to a large area, some effects may be proven untrue (30). Some risk factors may cause NCDs only by working with other factors under specific circumstances. In addition, EO technologies can capture a wide variety of environmental factors at a large scale, which may allow us to generate and test novel hypotheses as well as to map environmental profiles for finding similar areas to scale up interventions and for tailoring efforts to different areas.

Furthermore, with advanced machine learning and other data science approaches, analyses of such big data can be done faster, more accurately, and more creatively than ever before. For example, the Google Earth Engine (GEE) is an online environmental data monitoring platform that incorporates data from the NASA Landsat program and uses Google's cloud computing resources to access and process these satellite data over its online system. GEE is designed to extend access to petabyte-scale analysis-ready archives of RS data to researchers outside the RS field, to liberate researchers from the difficulties and inefficiencies of working in a parallel processing environment, and to help researchers easily disseminate their results to field-workers and policy makers (39).

Providing Repeated Measurements for Longitudinal Studies Including Cohorts

EO technologies can provide temporally abundant data in a cost-effective way to match individual location and behavioral data, allowing us to measure individual environmental exposure over long time spans more accurately than by using only limited GIS data products. This approach is suitable for many longitudinal NCD studies that require repeated individual-level measurements of environmental exposure regularly over long time periods (54). Also, historical archives of RS data may be used to determine past environmental exposures, which can be linked with past cohort studies and, in particular, hold great potential for designing more retrospective cohort studies (94). For example, data from the NOAA's AVHRR sensor going back to the 1980s are available and can be used for producing the twice-daily NDVI, which is a measure of the amount of green vegetation for a given area of the land surface (9). The Landsat data can also date back to the 1980s with a spatial resolution of 30 m. This ability to "go back in time" could reconstruct a more complete spectrum of environmental exposure for participants and may provide new explanations for the outcomes of interest. Therefore, the high temporal resolution of EO technologies significantly facilitates progress in life course measurements of human environmental exposure.

Moreover, RS satellite systems, especially those VHR systems, are usually designed to be programmable. Large-scale health surveys are often planned in advance. When neither the existing RS data nor the current plans of data collection can meet the demand for measuring the exposure of participants in planned studies, communication between spatial and health sectors at an early stage will promote a better fit between data provision and needs for NCD research. In addition, even though some types of built environment variables are available on a large scale, such as street connectivity (available nationwide for the United States), these data sets are infrequently updated and hence temporally insufficient to measure changes accurately in individual exposure to built environments (100). The up-to-date maintenance of such large-scale data sets using RS technologies would provide significant benefits, especially considering the free, full, and open data policies of many data sets (e.g., Landsat, Sentinel-2, and ASTER).

Advancing Methodologies in NCD Research

The incorporation of EO technologies into NCD research could trigger the application of some advanced spatial analysis and modeling approaches from infectious disease to NCD studies. One example is ecological niche modeling (ENM), a spatial approach that associates the occurrence location of infectious diseases (i.e., presence of infected cases) with a set of environmental variables, which would allow for the prediction of infection risk at an unknown location, on the basis of environmental similarities to the location where infection occurred (63, 83). The ENM outputs the prediction of geographic ranges for disease agents. In NCD contexts, location of NCD cases or high prevalence or risk of NCDs, based on existing evidence, could be considered as presence data to be linked with spatial data sets of sociodemographics, lifestyles/behaviors, and natural and built environments (91).

The potential usage of ENM in NCD contexts highlights another problem with data format often observed in existing studies: Most of the current GIS-based built environment indicators are measured and stored in a vector format (i.e., lines or polygons). This format is not compatible with ENM inputs of environmental data and therefore needs to be converted into the raster format. As each raster pixel is assigned a value that denotes relevant environmental characteristics over that area, rasterized built environment data may provide more flexibility compared with the vector data format in terms of spatial resolution (e.g., easy to change the spatial resolution of environment data) to better describe the heterogeneity of the environment, especially in some crowded metropolitan areas (e.g., Beijing, New York, and Tokyo).

In addition, the raster format technically allows for more accurate representation of exposure to built environments, which used to be treated as a constant for all residents with access to the same features or who live in the same geographic/administrative unit. Now, although most researchers have moved beyond administrative units to assign exposure when individual addresses are available [e.g., using straight-line or network-based buffer zones as the boundary to count how many food outlets of each type exist within that unit (61)], each outlet is dichotomously considered to be either influential or not influential to an individual. The effect of each food outlet on all who have it within their buffer zones is considered constant. This assumption is unlikely to be true in reality. Increasing the distance to a given destination normally decreases the likelihood of visiting that destination, which is known as the distance decay effect (69, 70). For each type of built environment feature, a raster data layer can be created, incorporated with road network data, and assigned the values that represent levels of real-world exposure to the corresponding features at that location (i.e., within that raster pixel), with distance decay effects taken into consideration. Therefore, the raster data format provides a supportive platform to refine vector-based measurements of individual environmental exposure in a meaningful way, which is extremely important for NCD studies but is difficult to estimate in a vector format.

Another quickly developing technology, unmanned aerial vehicles (UAVs) or drones, has been successfully applied in public health areas, such as in delivering test samples from remote rural clinics to national laboratories, monitoring human population movements, and providing spatially and temporally accurate data for understanding the linkages between infectious disease transmission and environmental factors (31). Monitoring equipment has been fitted to UAVs to collect information on airborne radioactive particles, levels of environmental toxins and pollutants, land cover and use, and other types of environmental data of public health relevance (21, 31, 85). Because attainable RS imagery may lack coverage of certain areas for financial and/or technical reasons (e.g., cloud cover), it is possible to employ UAVs to complement RS data under some circumstances, where environmental measurements during certain times and at certain locations are vital to estimating human exposure in prospective cohort studies.

FUTURE APPLICATIONS IN NCD RESEARCH, PRACTICE, AND POLICY

Although applications of GIS in NCD research have made great strides in the past two decades, EO technologies have not been fully applied. Much remains to be discovered in NCD contexts in terms of the complex interrelationships between humans and the environment. Such knowledge is essential to designing novel and effective interventions and mitigation measures for NCDs; however, development of this knowledge has been restricted, owing to the limited capacity of data acquisition in traditional NCD fields. Lack of frequently available environmental data also prevents us from measuring the synergistic (e.g., additive or multiplicative) effects of various environmental factors on NCD outcomes. Furthermore, NCD prevention and control could be even more difficult compared with those for infectious diseases, as there are many stakeholders (e.g., businesses) and grassroots demands (of which some could be detrimental to public health) behind the causative factors. This review identifies the advantages of EO technologies and summarizes their applications at each stage of NCD research and practice (**Figure 1**).

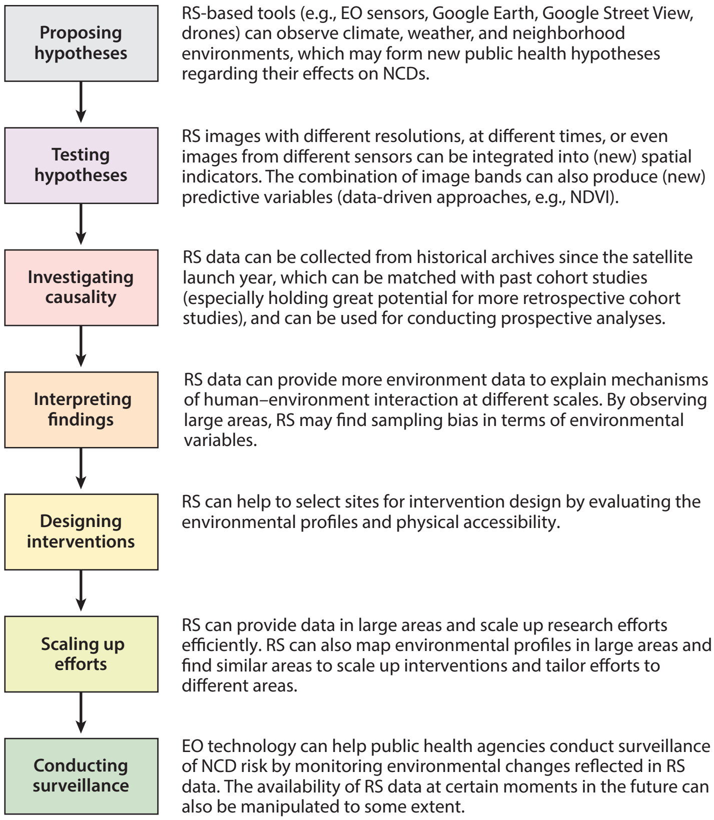

Figure 1

Applications of EO technologies at each stage of NCD research and practice. Abbreviations: EO, earth observation; NCD, noncommunicable disease; NDVI, normalized difference vegetation index; RS, remote sensing.

EO technologies provide equal access to environmental information regardless of place, time, and socioeconomic status, and thus they are especially vital in LMICs where, owing to a lack of resources, regular ground-level surveying and monitoring are difficult to undertake or maintain at a large scale. One example application of EO technologies is that much RS data has been used to map environmental and socioeconomic similarities between existing Health and Demographic Surveillance System (HDSS) sites and the rest of the LMICs (not covered by HDSS sites) in order to extrapolate data and findings from HDSS sites to a larger area and population where HDSS sites cannot be founded for various reasons (67).

Health and Demographic Surveillance System (HDSS) site: a research center undertaking intensive demographic and health surveys within a clearly circumscribed geographical area, belonging to the International Network for the Demographic Evaluation of Populations and their Health (INDEPTH)

Researchers from various fields have utilized RS data to ascertain the past, understand the present, and predict the future. Earth-observing satellite data are becoming increasingly available and accessible. Launched in 2013, *Landsat*-8 can collect more than 700 images per day, which is a 14-fold increase over the acquisition capability of the 1980s (106). Also, the development of new platforms and sensors is proceeding at a rapid pace, such as China's Tiangong-2 Space Laboratory, which was launched in September 2016. Therefore, EO technologies can play a pivotal role in overcoming the current data bottlenecks in NCD research, moving this multidisciplinary research area onto a big data stage. These data will provide new insights and explanations for NCD mechanisms and create solid evidence for NCD prevention and control. For example, human migration and dietary patterns, both being disease risk factors, may be driven by climate change and agricultural growth, which can be monitored by EO technologies (10, 32, 81).

There is usually a trade-off among spectral, spatial, and temporal resolution owing to technical constraints. Although this trade-off may limit the utilization of EO data in health research, we can increasingly overcome these challenges through progress on satellite and sensor technologies. For instance, China's TianGong-1 sensor, launched on September 29, 2011, has maintained hyperspectral capabilities and further advanced the spatial resolution to 10–20 m, allowing for more accurate extraction of urban information. Each scene image with a high spatial resolution can usually cover a small area with a long revisit period, but the Sentinel-2 sensor, designed as a two-satellite constellation (Sentinel-2A and -2B) with a 10-m spatial resolution and an initial global imaging cycle of every ten days by Sentinel-2A alone, has now achieved a temporal resolution of five days since February 17, 2018 (after Sentinel-2B became operational in orbit). That said, with such a high spatial resolution, multiple images and subsequently high costs are needed to cover a large area. This cost can rapidly increase if researchers order more than one snapshot in time. Despite this knowledge, the general trend of such costs has been downward and some, as mentioned above, have even become free of charge (e.g., ASTER data).

The choice of satellite images for NCD research should depend on answering specific research questions. The research question can inform necessary compromises in terms of spectral, spatial, and temporal resolution. For instance, if no specific spatial resolution is required, researchers may choose images with medium spectral, spatial, and temporal resolutions (**Table 1**). In such a case, special attention should be paid to the spectral resolution as it determines whether and to what extent the variable(s) of interest could be identified and distinguished from other similar types of variables under a major category (e.g., different species of vegetation). A clear emphasis on one (or two) specific resolution(s) will lead to low resolution in other aspects. The sacrifice of a spatial or temporal resolution could be compensated by spatial modeling approaches. The spatial resolution of the variable of interest can be enhanced by modeling approaches on the basis of finer ancillary data (spatial or ground truthing), also referred to as dasymetric mapping approaches (62). In this way, original information at a coarse spatial resolution can be disaggregated onto finer-scale grids for optimal estimation. The temporal frequency of the variable of interest can also be increased by data fusion approaches, which incorporate high-temporal-frequency and high-spatial-resolution satellite observations to generate synthetic observations with both high spatial and high temporal resolutions (49).

The importance of other ancillary spatial data and techniques, such as ground-truth data, GPS, and GIS, cannot be ignored. Ground-truth data are important for validating EO data, especially natural environment factors, and for ensuring that EO data can supply accurate estimates for environmental factors. Such sources include Surface PARTiculate mAtter Network (SPARTAN) (95), Aerosol Robotic Network (AERONET) (51), and the Chinese Environmental Monitoring Network (76) for monitoring the ground-level concentration of air pollutants. Although VHR satellite data could be used for field validation of many built environment features, in light of the cost of VHR data and the cloud cover issues in some regions, ground-truth data are still needed, especially when the features of interest have complex spatial structures (e.g., slums) or operate on a smaller scale than the spatial resolution of affordable medium- or high-resolution EO data. GPS techniques (e.g., GPS devices, location-aware smartphone data) have been used to collect geographic coordinates over a certain time interval, which can be used to infer individuals' locations, movements, modes of transportation, and activities (2, 56). In combination with EO data sets, GPS data can better approximate individual exposures and move us closer to characterizing the exposome (81, 97). GIS techniques provide not only spatial data, but also a powerful platform to support data integration from multiple sources; thus, EO data could be used as crucial and accurate input in exposure models through integration with ground-truth, GPS, and GIS data.

We foresee a promising future for using EO technologies in NCD research and practice. For example, the recently launched Healthy Cities in China (107) and Preventive Medicine Initiative (92) will bring high-level criteria and demand for quantification of the environment in order to measure long-term environmental exposure at both the individual and population levels. Additional higher-spatial-resolution, more-frequent-coverage (i.e., shorter revisit time or repeat overpasses), and even freely available earth-observing satellite data are under way and planned for the near future. For example, the planned Multi-Angle Imager for Aerosols (MAIA) will conduct radiometric and polarimetric measurements for characterizing the sizes, compositions, and quantities of PM in the air; Sentinel-2C/D are planned for 2022–2023 to further improve the quality of Sentinel-2A/B data. These advances will offer public health researchers countless opportunities to extend the usage of EO technologies to understand NCD risk. Both natural and built environments will be quantified to an unprecedented degree of frequency and accuracy, enabling the advancement of research for managing, alleviating, and ultimately preventing NCDs through the integrated management of NCD ecology and epidemiology. Team science is the key to realizing this potential by building multidisciplinary research teams to work with EO technologies, including public health researchers, geographers, climatologists, architects, city planners, and policy makers. Some pioneering transdisciplinary collaborative endeavors, such as those by the US Environmental Protection Agency (EPA) EnviroAtlas (84), the Canadian Urban Environmental Health Research Consortium (CANUE) (12), and the International Initiative on Spatial Lifecourse Epidemiology (ISLE) (59), have been made to facilitate the availability of EO data in a partly processed format to cohorts and health researchers; they can thus be easily linked to the extensive health cohort and administrative health data. Greater efforts are needed in the future to train a new generation of researchers and public health practitioners with interdisciplinary/transdisciplinary training backgrounds and experiences to carry out this type of innovative work.

Team science: a collaborative effort to address a scientific challenge, which leverages the strengths and expertise of professionals trained in different fields

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