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Understanding an urbanizing planet: Strategic directions for remote sensing

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A B S T R A C T

Scientific contributions from remote sensing over the last fifty years have significantly advanced our understanding of urban areas. Key contributions of urban remote sensing include but are not limited to characterization of urban areas, urban land cover changes and thermal remote sensing of urban climates. Today, the proliferation of new sensors, long time series of the satellite record, joint analysis of Earth observation data with ancillary data sets, widespread availability of high-performance computing facilities, and slow but increasing use of remote sensing data and methods in non-remote sensing fields together offer new opportunities to generate scientific knowledge for an urbanizing planet. Simultaneously, the scale and pace of contemporary urbanization require new information about urban areas from both the science and policy communities. This paper examines remote sensing contributions to the scientific understanding of urban areas over the last 50 years until today. Based on this assessment and current needs by user communities, we identify four strategic directions for future urban remote sensing research: high temporal frequency analysis, characterization of urban heterogeneity, characterization of urban form and structure in two and three dimensions, and linking remote sensing with emerging urban data. Advances in these four areas are likely to generate significant new insights that will be useful to both science and policy.

1. Introduction

Urban areas are central to sustainability. They generate more than 75% of global GDP, contribute to about 75% of carbon emissions from global final energy use, and produce approximately 2 billion tons of waste per year (Hoornweg and Bhada-Tata, 2012; Seto et al., 2014). Every week, the global urban population increases by about 1 million. Every day urban areas expand by an area equivalent in size to 20,000 American football fields (Seto et al., 2011; United Nation, 2018). The resources required to build and operate the cities of tomorrow will be enormous, social and governance challenges aside. The world needs scientific knowledge that can help transition society into a more sustainable urban future.

The need for this knowledge has become apparent in the last few years to governments and decision-makers, at the local, national, and even international level. Indeed, several international agreements and frameworks have highlighted the need for more information about cities and urban areas. For example, in 2015, more than 150 world leaders adopted the 2030 United Nations Sustainable Development Agenda, including a stand-alone Sustainable Development Goal (SDG) to "make cities and human settlements inclusive, safe, resilient and sustainable". One year later, 170 countries agreed to the UN New Urban Agenda (NUA). A central part of the NUA is recognition of the importance of National Urban Policies (NUPs) as a key component of achieving national economic, social, and environmental goals. In response to these efforts, decision-makers are asking for more urban knowledge from scientists that can inform policies to help create a more sustainable urban future.

Concurrently, the evidence has been mounting on how urban systems significantly impact key components of the Earth system: the

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atmosphere, biosphere, geosphere, and pedosphere (Zhang et al., 2013a; Zhang et al., 2013b). Beyond the environment, urban areas and the socio-technological systems within them also have been shown to affect many human and social issues, including health and well-being, economic development, and social cohesion (Eckert and Kohler, 2014). As such, a number of science communities from global change to the health sciences are calling for more science-based knowledge about urban areas in order to better understand a changing planet.

It is against the backdrop of these recent developments that we assess how remote sensing can contribute to creating knowledge of our urbanizing planet that is needed by both science and policy communities. The primary goal of this paper is to assess the key types of Earth Observation (EO) based information that informs urban research, and at what spatial and temporal scales. We review the literature and provide a broad overview of the types of information that the remote sensing community has produced to date, and suggest directions for future urban remote sensing research that could generate significant insights useful for science and policy communities.

2. The science we need for an urbanizing planet

Who are the research and policy communities that want urban information and what type of information do they need? How frequently do they need this information and at what spatial scale? The United Nations, the Intergovernmental Panel on Climate Change (IPCC), Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), the UN Convention on Biodiversity (CBD), and the World Health Organization (WHO) are just some examples of the supra-national organizations that use urban information. The CBD recently initiated the second Cities and Biodiversity Outlook, an international assessment of the threats to biodiversity from urbanization. The IPCC recently convened its first Cities and Climate Change conference, the goal being to inspire new research on how cities can mitigate and adapt to climate change. The conference produced a Research and Action Agenda on Cities and Climate Science, which includes a call for more observational data at the urban scale (Prieur-Richard et al., 2018). The recent Global Urban Observation and Information Implementation Plan for 2020–2022 identifies a range of global scale and regional stakeholders for satellite-based urban information, including UN-Habitat, World Bank, and the EU Directorate for Regional Policy.

Although there is much need for information that will support these scientific and policy efforts, the majority of the scientific literature on urban areas tends to be single case studies, with significantly fewer studies that are comparative. A 2017 special issue of the *Proceedings of the National Academy of Sciences of the USA* highlighted the lack of comparative empirical work on urban sustainability: "…cross-comparative empirical work on sustainability crossing typologies of urban areas and across different geographic regions is sparse" (Seto et al., 2017). The special issue also highlighted the need for more solutions-oriented fundamental science that is both place-based and spans multiple geographic and administrative scales. In a similar vein, the urban science-policy Expert Panel for *Nature Sustainability* concluded that there is a need "to forge new knowledge that corresponds to complex urban challenges" and "to accelerate the uptake of urban science by practitioners" (Acuto et al., 2018).

In order for urban science to be used by practitioners, however, remote sensing scholars need to produce scientific findings that have practical utility. Currently, the majority of remote sensing studies are focused on methodological advancement, especially algorithm development. Fig. 1 illustrates the number of peer-reviewed articles since 1991 in the urban remote sensing domain in the two remote sensing journals with the highest current impact factors (*Remote Sensing of Environment* and *ISPRS Journal of Photogrammetry and Remote Sensing*), and a common non-remote sensing journal (*Applied Geography*). We searched the archive since 1991 according to the same keywords: 'urban' and 'city', among others. In addition, in Applied Geography, we added method-specific terms like "remote sensing", "Earth observation", etc. All papers were divided into two categories: 1) 'Methods', if the main focus of the paper was on data (pre-) processing algorithms, and 2) 'Applications', if the main focus of the paper was on geographical findings. In general, we found an uptake of urban remote sensing studies. However, only recent studies were focused on applications, and most were published in Applied Geography. It is worth noting that the general increase in urban scientific remote sensing studies since 1999 was likely triggered by the advent and proliferation of very high spatial resolution satellite sensors.

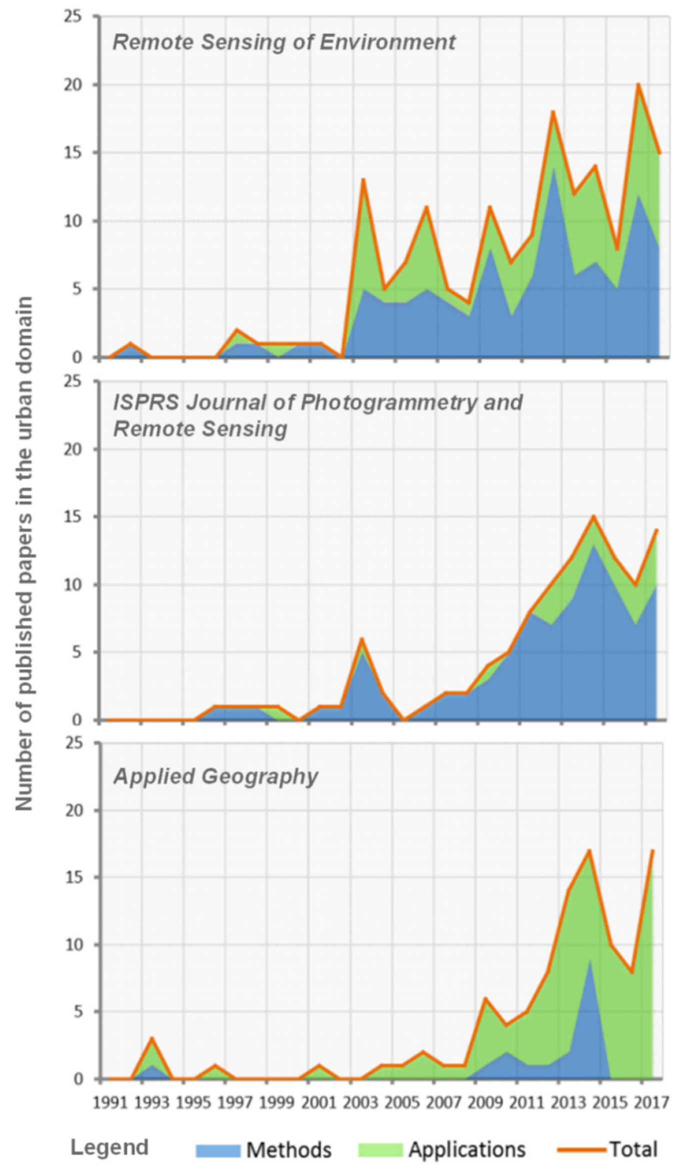

Fig. 1. Number of peer-reviewed articles since 1991 in the urban remote sensing domain for three selected journals.

There is a growing consensus among decision-makers that more data does not necessarily lead to better decision-making. The *Nature Sustainability* Expert Panel as well as the cities IPCC research agenda makes that clear. A lot of data being generated are not accessible either tangibly or conceptually to the decision-making or practitioner communities. Hence, it is not just a matter of providing more data points. There is a need to provide different types of information that can be used, interpreted or digested.

Science and policy communities are calling for more and new information about variation within urban areas and comparative analysis across urban areas. In order to understand the impact of policy, we need benchmark data across spatial and temporal scales. This requires information about change, changing conditions and changing outcomes that are comparable. Although a snapshot about conditions is more valuable than no information at all, it is clear that change information is essential to know if we are making progress towards sustainable urban systems and to evaluate whether policies are effective.

Moreover, urban remote sensing studies need to be focused on a higher diversity of regions and urban area sizes. The majority of urban remote sensing studies focus on either large cities or those located in China, the U.S., or Europe. As one example, although data from the UN Urbanization Projections show that most of the future urbanization will occur in medium-sized cities of half a million to two million, 54% of urban change detection algorithms developed since 1981 have been developed for cities of greater than five million (Reba and Seto, in review). Nearly 40% of all urban change detection algorithms were developed for China, despite the country having 19% of the world's urban population (Reba and Seto, in review). To better inform science and policy, urban remote sensing research must be more representative, that is, focused on a higher diversity of regions and urban area sizes.

The science and policy communities are also calling for more harmonized data collection and data interpretation efforts. There is no consensus of what is urban, or at which scales comparisons are meaningful, and remote sensing science can fill this gap. New methodologies predominantly in the machine learning domain (e.g., deep learning) are incredibly powerful ways to identify patterns of physical urban structure, but in many cases, there is limited understanding of what the outcomes mean. An open question is whether machine learning should be embraced as central to remote sensing applications or used cautiously because of its black-box characteristics (Zhu et al., 2017).

Practitioners who are engaged in design, planning, and architecture in urban areas also have expressed a need for more, relevant, and spatially explicit scientific knowledge (Felson et al., 2013; McGrath, 2018; Steiner, 2014). Urban planners and designers often think, imagine, create and communicate ideas and strategies for cities through spatial visualizations (Marshall et al., 2019). The intrinsic spatiality of EO data and their classification products contain a visual language that can relate to the workflow of these practitioners and their concerns, such as sustainability in cities, neighborhood revitalization, and installation of green and blue infrastructure to promote health and manage stormwater.

In short, urban data needs to be measured across several dimensions: within urban heterogeneity and across time. Urban data needs to be consistent and harmonized for boundaries, comparable across cities and over time. Urban data also needs to be more relevant to inform solutions such as policy, planning and design solutions and user communities such as practitioners, policymakers, and the public and private sectors.

3. Historical developments of urban remote sensing

Urban remote sensing has been evolving consistently over the last fifty years. With the first urban land cover maps derived from color infrared film on hand-held camera from the Gemini and Apollo mission in 1965 (Thrower, 1970), urban remote sensing was mostly based on aerial photo interpretation in the early days. On July 23, 1972, the launch of Landsat-1 (originally named Earth Resources Technology Satellite 1), revolutionized urban remote sensing and transitioned it from airborne to satellite remote sensing. The series of Landsat satellites have been the “gold standard” for urban remote sensing with myriads of applications (Donnay et al., 2014; Forster, 1983; Lo and Welch, 1977), because of their moderate spatial resolution that is fine enough to capture various kinds of urban developments and their long-term continuity. Since 1982, the thermal band included on Landsats 4–8 started to provide consistent measurements of land surface temperature that are ideal for urban heat island studies (Voogt and Oke, 2003; Roy et al., 2014). In 1999, the launch of commercial high spatial resolution satellites (5–0.5 m), such as IKONOS and QuickBird has further stimulated urban remote sensing research (Bhaskaran et al., 2010; Myint et al., 2011). These commercial satellites can provide imagery at a similar spatial resolution to aerial photos, but they provide this data routinely and with synoptic coverage of Earth's surface. Global, wall-to-wall mapping of urban areas was not possible until the launch of the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor in 1999 (Friedl et al., 2002; Schneider et al., 2009).

Though a majority of urban remote sensing studies are based on daytime optical and thermal sensors, there are other sensors that also provide unique observations of urban characteristics, such as nighttime lights sensors, LiDAR, and RADAR. Nighttime light sensors can measure anthropogenic light at night, which corresponds with urban extents and certain human activities (Elvidge et al., 1997). The Defense Meteorological Satellite Program Operational LineScan System (DMSP-OLS) and VIIRS Day/Night Band are the two major sensors, and the latter provides daily observations with improved capabilities for detecting city lights at night, especially in small and less developed settlements (Román et al., 2018). Additionally, LiDAR system provides new measurements of the three-dimension features of urban infrastructure, but most of the studies are only based on airborne LiDAR system at the city scale (Yu et al., 2010), with very limited studies on space-borne LiDAR at the global scale (Gong et al., 2011). RADAR data has been used to map urban growth since the launch of the European Remote Sensing Satellite 1 (ERS 1) in 1991, but most of the studies are small scale applications. Nevertheless, with more RADAR satellites launched in the last decades (e.g., TerraSAR-X, TanDEM-X, and Sentinel-1), continental and global scale urban mapping is emerging (Esch et al., 2012; Lisini et al., 2018). Moreover, recent studies suggest RADAR and optical data are complementary with each other, and the combined use of the two can provide more accurate urban mapping results (Zhu et al., 2012). The detailed list of civilian satellites that have been discussed in this review for urban remote sensing is shown in Table 1.

4. Urban remote sensing contributions to environmental change and human dimensions research

In this section, we briefly summarize major contributions from remote sensing studies to knowledge about urban areas for *environmental change* and *human dimensions research*. Because methodological advances in urban remote sensing have been covered extensively in the literature elsewhere (Voogt and Oke, 2003; Weng, 2012, 2009; Wentz et al., 2014), we limit this discussion to contributions to non-algorithmic topical knowledge that provide measurable advances in the understanding of key urban processes.

Urban areas are multi-spatial coupled human-environment systems. By their very nature, urban systems link ecological, physical, and socioeconomic systems across spatial scales (Pickett et al., 2001). As such, efforts to separate them into various components or categories will always be limited, and absolute delineations of purely social or biophysical are not possible. Nevertheless, for this analysis, we distinguish between remote sensing contributions that focus more on issues of environmental change versus those that are more human in scope, recognizing that some topics, such as the built environment, span both categories. Furthermore, we analyze various applications of urban remote sensing in environmental change and human dimension research based on the relationship of spatial resolution versus spatial scale, and temporal frequency versus time scale, respectively (Fig. 2).

4.1. Contributions to environmental change research

Although there is a myriad of ecological processes to which urban areas contribute, we focus here only on environmental change, defined as change or disturbances of the environment, most often caused by

Table 1
A list of civilian satellites discussed in this review for urban remote sensing. From is launch date, to is end of (imaging) life, (Active means the satellite or at least one of the satellite series is still actively collecting data) Pan (Panchromatic), Optical (Optical multispectral sensor that is capable of recording in at least red and near-infrared), Thermal, Nighttime Light, LiDAR, and SAR provide highest resolution (in meters) for sensors carried by each mission. MSS: Multispectral Scanner System; DMSP: Defense Meteorological Satellite Program; OLS: Operational Linescan System; NOAA: National Oceanic and Atmospheric Administration; AVHRR: Advanced Very High Resolution Radiometer; TM: Thematic Mapper; European Remote Sensing (ERS); SPOT: Satellite Pour l'Observation de la Terre; SAR: Synthetic Aperture RADAR; ETM+: Enhanced Thematic Mapper Plus; MODIS: Moderate Resolution Imaging Spectroradiometer; ASTER: Advanced Spaceborne Thermal Emission and Reflection Radiometer; Envisat: Environmental Satellite; ASAR: Advanced Synthetic Aperture RADAR; MERIS: MEdium Resolution Imaging Spectrometer; ICESat: Ice, Cloud, and land Elevation Satellite; GLAS: Geoscience Laser Altimeter System; HJ: Huanjing; TanDEM-X: TerraSAR-X add-on for Digital Elevation Measurement; TanDEM-X (TerraSAR-X add-on for Digital Elevation Measurement); Suomi-NPP: Suomi National Polar-orbiting Partnership; VIIRS: Visible Infrared Imaging Radiometer Suite; OLI: Operational Land Imager; TIRS: Thermal Infrared Sensor; SLSTR: Sea and Land Surface Temperature Radiometer. HyspIRI: Hyperspectral Infrared Imager.

Satellite	Sensor	From	To	Pan	Optical	Thermal	Nighttime light	LiDAR	SAR
Landsat 1–3	MSS	1972	1983		79 × 57				
DMSP F1–F19	OLS	1976	Active				560		
NOAA 6–19	AVHRR	1979	2019		1100	1100			
Landsat 4–5	MSS/TM	1982	2013		30	120			
SPOT 1–4		1986	2013	10	20				
ERS 1–2	SAR	1991	2011						30
Landsat 7	ETM+	1999	Active	15	30	60			
IKONOS		1999	2015	1	3.3				
Terra	MODIS	1999	Active		250	1000			
Terra	ASTER	1999	Active		15	90			
QuickBird		2001	2014	0.6	2.4				
Envisat	ASAR	2002	2012						30
Envisat	MERIS	2002	2012		300				
Aqua	MODIS	2002	Active		250				
SPOT 5		2002	2015	2.5	10				
ICESat	GLAS	2003	2010					70	
WorldView 1		2007	Active	0.5					
TerraSAR X		2007	Active						1
HJ-1A		2008	Active		30				
HJ-1B		2008	Active		30	300			
WorldView 2		2009	Active	0.46	1.84				
TanDEM-X		2010	Active						1
Suomi-NPP	VIIRS	2011	Active		375	375	750		
ZiYuan3 01-02		2012	Active	2.1	30	100			
SPOT 6–7		2012	Active	1.5	8				
Landsat 8	OLI/TIRS	2013	Active	15	30	100			
Sentinel-1		2014	Active						5 × 20
Sentinel-2		2015	Active		10				
Sentinel-3	SLSTR	2016	Active		500	1000			
Luojia 1-01		2018	Active				130		
HyspIRI		Expected in 2022	3–5 years		60	60			

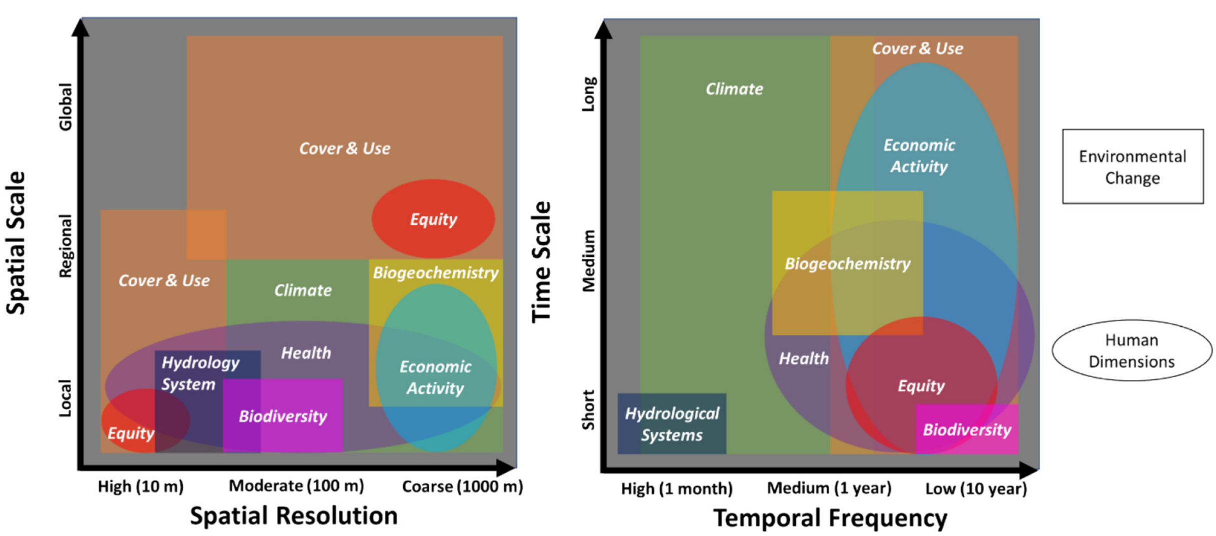

Fig. 2. Spatial resolution vs spatial scale and temporal frequency vs time scale for the remotely sensed imagery that have been applied in urban areas for environmental change and human dimension research. The sizes and locations of each rectangle or ellipse are approximate values estimated based on all the papers reviewed in this study.

human influences and natural ecological processes. Urban areas cause environmental change primarily through five mechanisms: 1) land use and cover, 2) biodiversity, 3) climate, 4) hydrological systems, and 5) biogeochemistry (Grimm et al., 2008). We briefly describe how urban remote sensing contributes to knowledge in these five domains.

4.1.1. Land use and cover

4.1.1.1. Defining and mapping urban areas. There are nearly 200 United Nations member states and almost every country has a different definition of urban. Urban areas are principally a type of human settlement, and about one hundred UN member states use country-specific minimum population thresholds to differentiate “urban” from other types of settlements. In addition to population thresholds, many UN member states define urban areas as human settlements which have a mix of built infrastructure (e.g. road, permanent dwellings, and municipal services such as electricity), and where a significant portion of the population engages in the non-agricultural economy. An examination of the definitions suggests that aggregating them into a single estimate is problematic for many reasons, including significant differences in scale and criteria. For example, urban is defined in Norway as localities with more than 200 inhabitants, while in Japan, it is defined as 60,000 inhabitants plus “urban facilities” and non-agricultural economic activities. In Nicaragua, localities need to have at least 2000 inhabitants as well as streets and electric lights in order to be deemed urban. Since there is no universal definition of urban, statistics on global urban population are developed by aggregating these vastly differing definitions, which is problematic.

Hence, one of the principal contributions of remote sensing to urban knowledge to date has been to characterize, measure, and map urban areas in a consistent fashion. Instead of relying on population size or density, urban areas are mapped based on the physical characteristics of land surface (e.g., the amount of impervious surface area or built-up area). From satellites, some of the earliest urban insights were the use of multispectral data to differentiate urban land cover from agriculture and forests (Haack, 1983; Quattrochi, 1985), to discriminate urban textures from surrounding rural areas using RADAR data (Henderson et al., 1980; Leonard Bryan, 1975), and to estimate urban population and densities (Kraus et al., 1974; Murai, 1974).

Today, with the routine collection of Earth observation data from a variety of satellites, more studies are focused on mapping urban areas at large scales (e.g., global urban area mapping), something that was unimaginable thirty years ago. Most of the global urban maps are derived from coarse spatial resolution images (300 m–10 km), such as MODIS (Schneider et al., 2009), Medium Resolution Imaging Spectrometer (MERIS) (Arino et al., 2008), and DMSP-OLS (Small et al., 2005; Zhou et al., 2015). Recently, a few global urban maps have been created with moderate to high resolution (10 m–50 m), including the Global Land Cover product (GlobeLand30) using Landsat and China Environmental Disaster Alleviation Satellite (HJ-1) (Chen et al., 2014), the Global Human Settlement Layer (GHSL) based on Landsat images (Pesaresi et al., 2016b), and the Global Urban Footprint (GUF) generated from RADAR satellite constellation of TerraSAR-X and TanDEM-X (Esch et al., 2012). Although estimates of global urban areas vary significantly, in part due to differences in the spatial resolution of the imagery and the varying accuracies across the globe (Klotz et al., 2016), these maps have been essential in building a scientific knowledge of the direct urban imprint on Earth.

While it is easier to map urban land cover as the physical evidence of the environment, it is more difficult to map urban land use – the human activities on land, particularly in modern cities where buildings often host multiple purposes and can be renovated and repurposed. The distinction of land cover and land use is important because land cover information relates to the natural environment of the urban system, while land use data relates to the human dimensions. Notably, some researchers argue for a joint human-natural structural characterization of urban (Rademacher et al., 2019). Texture, contexture, and proportional land cover data have been used in conjunction with spectral data to extract urban land use information (Gong and Howarth, 1990, 1989; Gong and Howarth, 1992a, 1992b).

4.1.1.2. Urban land cover and land use change. In addition to mapping a snapshot of urban areas at a single time point, the notion of using satellite data to identify urban change, such as from non-urban to urban land cover, has a long history (Howarth and Boasson, 1983; Maxwell and Riordan, 1980). Even before the launch of Landsat 1, geographers proposed urban change detection methods using aerial photography (Dueker and Horton, 1972). Thus, mapping urban areas and urban land cover change have been a fundamental contribution of remote sensing to urban knowledge.

The international research community has been instrumental in developing knowledge about urban areas. In particular, the inception of the NASA Land-Cover/Land-Use Change (LCLUC) program in 1996, the International Human Dimensions Programme (IHDP)/International Geosphere-Biosphere Programme (IGBP)'s Land Use/Cover Change international science project that existed from 1994 to 2005, and the IHDP Urbanization and Global Environmental Change Project that ran from 2005 to 2016, all helped to foster an international research community that examines land dynamics, including urban land change, and associated drivers and environmental and human impacts (Lambin et al., 2006; Seto et al., 2014, 2015). Urban land systems are now an integral part of the land system science research, a legacy that continues with the Future Earth Programme.

Remote sensing data have been used extensively to track urban expansion (Angel and Sheppard, 2005; Taubenböck et al., 2012; Wang et al., 2012; Zhou et al., 2018), to determine the drivers of urban land demand (Burchfield et al., 2006), and to forecast future urban growth (Seto et al., 2012). Since 1988, over 1080 peer-reviewed papers in English language journals covering over 800 locations have used remote sensing to detect, characterize and map urban land cover and land use change (Seto et al., 2011). Mapping urban land cover change continues to be a dominant component of urban remote sensing research and has been essential to understanding the drivers of urban development patterns. To date, satellite-based studies have shown that urban expansion is driven by population and economic growth, transportation infrastructure, governance and planning controls, and characteristics of the natural environment (Angel and Sheppard, 2005; Burchfield et al., 2006; Christensen and McCord, 2016; Seto et al., 2011).

4.1.2. Biodiversity

Urbanization impacts biodiversity directly through urban expansion, and indirectly through supply chains and consumption. Here we limit our discussion to direct urban impacts on biodiversity through land use. We discuss the insights from remote sensing of vegetation and green space within urban areas as well as urban expansion and habitat and biodiversity loss.

Though urbanization usually results in a reduction in biodiversity, urban vegetation, and green space can also play a vital role in supporting biodiversity by providing wildlife migration corridors or by acting as refuges for native biodiversity (Goddard et al., 2010). Advanced information on urban vegetation condition and green space distribution can assist planners in designing strategies for the optimization of urban ecosystem services and biodiversity conservation. Remote sensing is of great value in monitoring the condition of urban vegetation and mapping the spatial distribution of urban green space. Such studies are most often carried out at moderate scales, with a spatial resolution of 30 m (Small, 2001; Zhu et al., 2016). It has been demonstrated that finer resolutions are required to assess urban green space more comprehensively, since coarse imagery would miss small patches of vegetation (Qian et al., 2015). Habitat fragmentation is one of the most important concerns about urban expansion. Agricultural and pastoral lands, as well as production and native forests, remnant grasslands, and deserts, are threatened by urban land conversion. At the coarse scale, fragmentation in these productive, biodiverse, and native habits is readily detected by remote sensing (Skole and Tucker, 1993). Additionally, biodiversity as a concept has several dimensions. It addresses heterogeneity from the genetic to the landscape levels of organization. Most often in discussions of urban biodiversity, it is the species level that is of concern. Although the current satellite remote sensing systems are still too coarse to discriminate among species, they are increasingly feasible for mapping certain aspects of biodiversity, such as distinguishing species assemblages or diversity patterns (e.g., richness) (Alonzo et al., 2014; Bino et al., 2008; Goetz et al., 2007; Lawes and Wallace, 2008; Pu and Landry, 2012; Turner et al., 2003; Xiao et al., 2004).

4.1.3. Climate

Urbanization may profoundly affect climate locally, and even globally, by land cover conversion, increasing impervious surface, anthropogenic heat discharge, and greenhouse gases emissions (Chen et al., 2006; Wakode et al., 2018; Xiao et al., 2007; Zhou et al., 2012). These land surface processes that occur at the interface between the Earth's land and atmosphere are complex and influence the climate system at different scales (Gluch et al., 2006). One of the most important effects in climate induced by urbanization is the Urban Heat Island (UHI), referring to the temperature differences between urban and surrounding rural areas (Oke, 1982, 1973; Roth et al., 1989). Biogeophysical parameters of urban land surface cover and temperature from satellite observations are of great value for investigating urban surface energy budgets, and therefore improving the understanding of urbanization impacts on local and global climate.

With the advent of thermal remote sensing satellites, we are able to observe UHIs at large spatial scales and understand their primary causal factors (Voogt and Oke, 2003; Weng, 2009). Since the first UHI study by Rao (1972), a variety of remote sensing platforms and sensors have been used, of which Advanced Very High Resolution Radiometer (AVHRR) (Gallo and Owen, 1998; Kidder and Wu, 1987; Streutker, 2002), MODIS (Li et al., 2017; Meng et al., 2018; Schwarz et al., 2011), Landsat (Carnahan and Larson, 1990; Kim, 1992; Weng et al., 2004), and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) (Kato and Yamaguchi, 2007; Nichol et al., 2009; Tiangco et al., 2008) are the four most important sensors. Airborne data have also been widely explored in UHI studies (Ben-Dor and Saaroni, 1997; Jenerette et al., 2016). Although the coarse resolution data from AVHRR and MODIS are particularly useful for mapping urban temperature over large areas, they are not ideal for establishing meaningful relationships with ground measurement. Rather, moderate resolution data with spatial resolutions ranging from 60 to 120 m (e.g. Landsats 4–8), are more suitable to study UHI at regional scales. Studies that have used data at these scales have found that the Land Surface Temperature (LST) products derived from Landsat images can better reflect the spatial variation of LST, which is of great potential for study areas with high spatial heterogeneities. High spatial resolution imagery from airborne remote sensing systems have also been used to extract temperature from specific urban surfaces for analysis (Ben-Dor and Saaroni, 1997; Eliasson, 1992; Gaitani et al., 2017).

There is well-developed literature that uses large scale thermal remote sensing data to explore how urban biophysical factors relate to LST. These biophysical parameters extracted from satellite observations include land use and land cover type (Amiri et al., 2009; Li et al., 2009), vegetation indices (Gallo et al., 1995), subpixel vegetation abundance (Weng et al., 2004), subpixel impervious surface fraction (Imhoff et al., 2010; Yuan and Bauer, 2007), and landscape compositions and combinations (Li et al., 2011; Zhou et al., 2011). Studies have found that LST is usually negatively related to vegetation indices (e.g. NDVI), and positively correlated with urban land cover indices (e.g. impervious surface area). Instead of the traditional binary interplay between LST and a single spectral indicator, UHI is better modeled and explained as multiple interplays between LST and various land biophysical compositions with different thermal properties (Deng and Wu, 2013a). From a modeling perspective, LST is a product of the surface energy balance, and the physical basis of spatial variation in LST is the response to the factors that affect surface energy balance. These small spatial scales measurements can be made using ground or airborne thermal remote sensing. Therefore, the issue at the satellite scale is that much of the spatial variability of surface temperature is still at subpixel scale (mixed with issues related to emissivity and sensor viewing geometry). In addition to examining the direct association between LST and urban biophysical factors, surface UHI intensity, magnitude, and spatial extent have also been modeled as continuous functions (Rajasekar and Weng, 2009a, 2009b; Streutker, 2003, 2002).

New insights on urban climate are emerging in the remote sensing community, enabled by new data, new sensors, and new algorithms. *First*, remotely sensed big data (especially time series) has created the potential to depict and analyze UHI over time. Using these time series, the relationship between LST increases and urbanization can be determined (Fu and Weng, 2016). Also, because of the sensitivity of urban vegetation to urban climate change, long term time series satellite observations can be used to compare the annual vegetation phenological transition dates in urban areas to quantify the impacts of urbanization on urban climate (Zhang et al., 2004). Other new data, such as volunteer geographic data on weather websites, have been collectively used with remote sensing data for urban climate studies (Ho et al., 2014). *Second*, new sensors are emerging that can provide more spectral features or more frequent time series of urban climate variables. Two or more thermal bands are known to be able to provide more accurate estimation of land surface temperature and emissivity in urban areas (Wan, 1996). However, most of the current satellite sensors are either without any thermal band or only have a single thermal band. The Sentinel-3 Sea Land Surface Temperature Radiometer (SLSTR) that was launched in 2016 has three thermal bands for better estimates of land surface temperature (Donlon et al., 2012). The Hyperspectral Infrared Imager (HyspIRI) which will be launched in 2022 has eight thermal bands between 3 and 12 μm (Lee et al., 2015). Moreover, recent studies have explored the use of new geostationary satellites to create hourly land surface temperature at a similar spatial resolution to that of Landsat, which greatly improves our understanding of the spatio-temporal dynamics of urban thermal environments (Quan et al., 2018). *Finally*, new algorithms are being developed that improve on the low temporal frequency of existing moderate resolution thermal data by modeling of diurnal and annual time series that couples equations with remotely sensed data. For example, algorithms that are able to simulate daily or even hourly Landsat thermal images by using data fusion have been developed (Gao et al., 2006; Liu and Weng, 2012; Quan et al., 2018; Zhu et al., 2010).

4.1.4. Hydrological systems

Urban land cover and land use, especially urban form, have extensive impacts on hydrological processes such as surface runoff and infiltration in urban systems. The geometry of road networks, the height of buildings or infrastructure, and the configuration of pervious and impervious surfaces, have notable impacts on the flow vector and water depth during the surface runoff process in urban areas (Vojinovic et al., 2011; Yu and Coulthard, 2015), particularly during flooding events.

Recent innovations in this area include the use of SAR data to map flood dynamics and hydrologic characteristics such as channel and floodplain connectivity (Schumann et al., 2011). Satellite data can provide near real-time and cost-effective data for estimating stormwater runoff, urban floods, and other hydrological changes. SAR data can provide near real-time flood water levels that are closely correlated with data collected from gauges (Mason et al., 2012). The causes and propensity of urban-induced rainfall have also been explored, using remotely sensed imagery (Shepherd, 2005). These insights have important implications for post-disaster response, hazards management, and disaster risk reduction. Moreover, satellite-derived estimates of effective impervious surface area is an essential indicator for urban runoff and floods (Ebrahimian et al., 2016).

In addition to SAR, high resolution satellite data can provide finely resolved terrain information that is invaluable for modeling urban flood inundation. Although high resolution terrain data have been generated for rural and large floodplain areas for some time, urban areas present unique challenges due to the built-up infrastructure and small spatial dimensions of roads. Airborne LiDAR data have been used to estimate urban vertical structure with height accuracies in the range of 10–15 cm Root Mean Square Error (RMSE), which is sufficient for urban flood modeling (Schubert et al., 2008).

There is a strong correlation between urban development, urban subsidence and urban flooding (Abidin et al., 2011). As such, having information about subsidence can assist in the modeling of urban floods. InSAR data have also been used to quantify subsidence in urban areas (Crosetto et al., 2003; Raucoules et al., 2013).

4.1.5. Biogeochemistry

Although biogeochemistry is a key component of urban ecosystems (Kaye et al., 2006), assessments by remote sensing are largely absent. Most remote sensing assessments of biogeochemical parameters such as productivity and productivity potential, or concentrations of nutrients in the system of interest have not addressed urban systems. Rather they have been applied in large, contiguous areas of non-urban aquatic marine, or terrestrial habitats (Asner and Vitousek, 2005; Schimel, 1995). A few studies have tried to model the carbon cycle of urban systems based on light use efficiency model and coarse resolution remotely sensed data from AVHRR (Imhoff et al., 2004; Zhao et al., 2007) and MODIS (Milesi et al., 2003). Different urbanization impacts on the carbon cycle have been reported, where both Imhoff et al. (2004) and Milesi et al. (2003) suggested that urbanization had a large negative impact on net primary productivity, while Zhao et al. (2007) indicated that the region-wide increase in tree cover in urban areas actually increased regional gross primary production. A more integrated evaluation of the most prominent impacts of urbanization and finer spatial resolution of satellite images are needed for better understanding of urbanization impacts on the carbon cycle.

Considering that the carbon cycle is just one of the many processes in urban biogeochemistry and the relevant studies using remote sensing data are very limited, there is a great need for remote analysis of urban biogeochemistry. We think future research should use higher spatial resolution remotely sensed data and include fine and medium scales (e.g., Landsat and Sentinel-2 data) at which ecosystem process are measured in watersheds and in the various terrestrial habitat types found in and around cities.

4.2. Contributions to human dimensions research

Remote sensing is a powerful tool in a wide variety of human dimensions research. Due to its high spatial and temporal resolution and global availability, remote sensing data is a complement to demographic, social, economic, and health surveys that are sparse and difficult to obtain, and often limited in geographic coverage. Here we discuss the key insights of urban remote sensing data to human dimensions research, focusing on health, economic activity, and equity. We organize the discussion around the main topics where satellite data have been applied and the key remote sensing contributions to each area.

4.2.1. Health

Urbanization impacts health directly both through the natural environments that are altered and the urban environments that are built, and indirectly through the way urban environments shape human behaviors. Insights from remote sensing on monitoring these impacts are organized around three types of pathways: how urban environments affect the prevalence and spread of infectious diseases, how they influence environmental exposures that lead to non-communicable disease or mortality risks, and how they shape human behaviors and lifestyles.

4.2.1.1. Infectious diseases. Infectious diseases can be caused by various biological agents, such as bacteria, viruses, parasites or fungi, and can be spread between people either directly or indirectly. Though the agents that cause many infectious diseases are not unique to urban areas, urban environments can shape the breeding ground of disease-carrying vectors and can influence interactions between vectors and human hosts (Goodman et al., 2018; LaDeau et al., 2015), or human hosts with each other. Urban remote sensing of the study of infectious diseases has therefore revolved around three topics: (1) understanding the distribution of disease vectors; (2) mapping urban environments that increase disease risk; and (3) understanding disease transmission within urban areas.

While remote sensing has been used extensively to map the environmental attributes that influence the reproductive rates and distribution of a wide variety of disease vectors, studies with an urban-focus are almost entirely limited to research on mosquitos. Mosquitos are the primary vector of dengue, yellow fever, Zika, and malaria, and controlling them within urban areas is a policy priority for many developing cities. Recent research in Argentina (Albrieu-Llinás et al., 2018), the US (Hartfield et al., 2011; Liu and Weng, 2012), and parts of Africa (De Castro et al., 2004; Kabaria et al., 2016) have used high resolution imagery, and sometimes LIDAR, to monitor environmental variables for prediction of mosquito distribution and creation of probability maps. These types of studies have also shown how the same environmental conditions that cause urban heat islands can cause an increased incidence of mosquito-borne diseases. In Sao Paulo, for example, urban heat islands, mapped with land surface temperature data, were shown to have more dengue cases (Araujo et al., 2015). Risk distribution studies aim to provide urban decision makers with the information they need to try to control mosquito populations and mitigate outbreaks.

Other studies have focused on disease risk associated with the quality of urban built environments. It is estimated that about one out of three urban residents live in a slum or informal settlement, where the combination of high levels of poverty, dense housing, inadequate sanitation and waste collection, and poor drinking water supply contribute to high levels and rapid transmission of infectious disease. Understanding the urban mechanisms underlying infectious disease transmission is essential for early warning systems and control. Remote sensing has shown promise for slum mapping by differentiating between textures of formal and informal built environments (Kuffer et al., 2016; Wurm et al., 2017). These contributions can help identify communities for targeted interventions.

In addition to mapping the distribution of risk, urban remote sensing has been combined with demographic data to understand how human populations have interacted with disease vectors, and with each other to influence epidemic progression. One study tracked human seasonal population migrations in and out of urban areas in Niger using a time series of night-time light satellite images and found that these spatiotemporal changes in population density were associated with measles outbreaks (Bharti et al., 2011). Another study that mapped the temporal changes of malaria transmission risk in Dakar, Senegal found that urbanization decreased the risk of malaria transmission (Machault et al., 2010).

4.2.1.2. Environmental exposure and non-communicable diseases. Though less developed, there is a growing literature on the impact of environmental factors, measured with remote sensing data, on non-communicable diseases such as diabetes, obesity, heart health, cancers, and asthma, which are prevalent in urban environments. Though areas with high urbanization levels have been linked to a higher prevalence of chronic disease in recent decades (Li et al., 2012), the causal mechanisms are often less clear.

One mechanism, air pollution, is a common problem in many urbanizing areas that has been linked to several chronic diseases. Because of the absence of networks of ground-based indicators of particulates in some parts of the world (Engel-Cox et al., 2004; Schaap et al., 2009), the demonstrated relationship between aerosol optical depth (derived from MODIS) and standard particulate measures has proven a useful in epidemiological exposure assessment studies (Brauer et al., 2012; Jerrett et al., 2017; Kloog et al., 2011; Kumar et al., 2007; van Donkelaar et al., 2010; Wang and Christopher, 2003). However, because MODIS satellite observations only date back to 1999, satellite-based studies are limited in their characterizations of long-term changes in PM 2.5 (Butt et al., 2017).

Along with air pollution, the greenness of urban neighborhoods (measured in remote sensing as NDVI) has been linked to cardiovascular disease (Pereira et al., 2012). Urban light pollution, measured with night-time light satellites data has been shown to correlate with breast cancer (Kloog et al., 2010) and cardiovascular disease (Lane et al., 2017). Pollen released by vegetation in the urban and suburban area (measured in remote sensing as vegetation phenology) is the most important factor for respiratory allergies (Li et al., 2019a).

In addition, the health impacts of climate change are likely to be severe in urban areas because of the high concentration of people and infrastructure in one place. In the Carbon Disclosure Project's 2017 survey of leaders from 478 global cities, over half of respondents expected climate change to seriously compromise their public health infrastructure (Watts et al., 2018). Remote sensing is increasingly being used to understand the exposure of urban residents to hazards like extreme weather events, sea level rise, heat waves, flooding and landslides, associated with climate change. For instance, high resolution AVHRR and SPOT imagery were used to analyze the spatial variations in land surface temperature during the 2003 Paris heat wave that caused 4867 deaths (Dousset et al., 2011). Satellite-based emergency mapping, using SAR, VHR optical imagery, and thermal imagery was critical in major disaster events like the 2004 Indian Ocean Tsunami (Voigt et al., 2007), the Wenchuan Earthquake of 2008 (Tong et al., 2012), the Haiti earthquake in 2010 (Duda and Jones, 2011), and the Pakistan flood of 2010 (Gaurav et al., 2011). Recent disaster assessments have also included the use of night-time light sensors–tracking power outages from earthquakes, floods, and storms (Zhao et al., 2018), as well as long-term power restoration protocols after storms (Román et al., 2019).

4.2.1.3. Behaviors and lifestyles. There is additional epidemiological literature that has linked characteristics of urban environments with daily health habits, like physical activity (Sallis et al., 2016; Feng et al., 2010), dietary behaviors (Seto and Ramankutty, 2016), sleep (Carta et al., 2018), and access to health care (Sibley and Weiner, 2011; Caldwell et al., 2016). Measures of urban structure, such as street intersection density, land use mix, population, and housing unit density have all been positively associated with physical activity (Sallis et al., 2016; Feng et al., 2010; Saelens et al., 2003; Troped et al., 2010). However, few studies have used remote sensing data to measure these attributes of the urban built environment, more often relying on GIS or survey data.

4.2.2. Economic activity

Scholars have long been interested in the ability of remote sensing data to proxy economic activity. To this end, night-time light captured by the DMSP-OLS, has become commonly used proxies for local economic activity, since they reflect variation in population density (e.g. Sutton et al., 2001), energy use (e.g. Amaral et al., 2005), and infrastructure development (e.g. Imhoff et al., 1997). In cross-sectional studies, night-time light has been shown to correlate strongly with economic activity (Doll et al., 2000; Sutton and Costanza, 2002; Xin et al., 2017). As a thirty-year panel dataset, change in lights has also been used to approximate change in GDP growth, with a lights-GDP elasticity of 0.28–0.32 (Henderson et al., 2011).

Nightlights data have two main advantages for approximating economic activity and economic growth that are complementary to traditional measures. First, night-time light data is global in scope, whereas traditional economic data is difficult to assess for countries with low-quality statistical systems in place. Night-time lights have been used to estimate economic activity primarily in countries where data is sparse (Lee, 2018; Michalopoulos and Papaioannou, 2014). When included with traditional measures of GDP, nightlights improved the measurement of economic output in areas that had inferior statistical collection systems but added little information for areas with high-quality economic data available (Deville et al., 2014; Nordhaus and Chen, 2015). The second advantage is the fine spatial resolution of night-time light data, compared to conventional economic data, which is most often reported at the national level. Since sub-national data is typically unavailable, night-time light can be used to create a disaggregated map of economic activity (Ghosh et al., 2010), with lights as the means of proportionally allocating the national GDP. Downscaled proxies of national economic activity have been used in research about the determinants of variation in economic activity across cities (Florida et al., 2012), subnational administrative regions (Hodler and Raschky, 2014), and grid cells (Henderson et al., 2017). The launch of a new Day/Night Band on the Visible Infrared Imaging Radiometer Suite (VIIRS) with higher spatial, radiometric, and temporal resolution (Román et al., 2018; Román et al., 2019) presents a new opportunity to expand on previous efforts for using night-time light to understand economic activity.

Beyond night-time lights, the concentration of the built environment derived from passive or active sensors has been used to map and understand economic activity. At the continental scale city networks measured by settlement density are shown as a well-suited proxy for revealing economic disparities (Taubenböck et al., 2017a, 2017b). At the city scale, the specific characteristics of settlement structures, such as morphological slums, are also a proven proxy for the economic capabilities of a social group (Wurm and Taubenböck, 2018).

4.2.3. Equity

Though urban areas are sites of concentrated innovation and opportunity, they are also increasingly sites of concentrated poverty and inequality. Very high resolution optical satellite images have been used successfully to identify qualitative aspects of the built environment that identify informal housing (Kohli et al., 2012; Kuffer et al., 2016; Owen and Wong, 2013; Taubenböck and Kraff, 2014) and concentrated poverty. However, since morphologic forms of poverty vary significantly across the world (Taubenböck et al., 2018), detecting slums based on built-up characteristics in EO-data capture only one aspect of poverty. A combination of DMSP-OLS nighttime imagery with high-resolution Google Static Maps imagery were used to estimate household consumption and assets in five African countries—Nigeria, Tanzania, Uganda, Malawi, and Rwanda—all of which lack high resolution income data (Jean et al., 2016). In addition to mapping informal settlements, nightlights images have provided a new dataset for assessing energy poverty. Studies using DMSP have demonstrated the capability of night-time light to track rural electrification efforts in developing countries (Doll and Pachauri, 2010; Min et al., 2013; Min and Gaba, 2014). However, at present, these studies have only considered electricity access as a binary—whether there are lights or not. At higher resolution, Kuffer et al. (2018) have used night-time light data taken from ISS Astronauts to highlight the lower light emission in slum areas compared to formal settlement areas. In addition, electrification and infrastructure-poor development within urban areas have been identified by considering time series data from the VIIRS Day Night Band, land cover records, and population datasets together (Stokes and Seto,

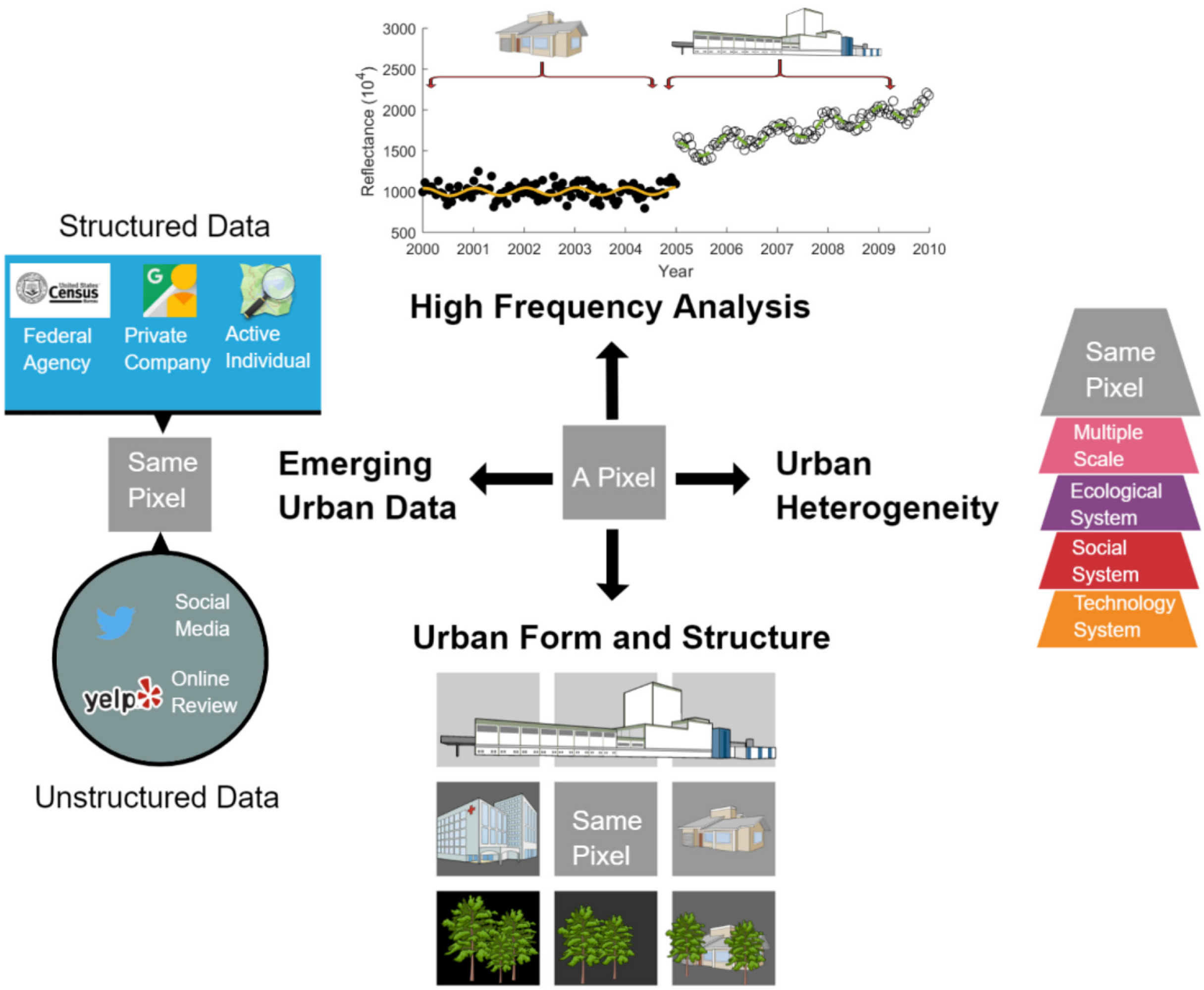

Fig. 3. Four major strategic directions for urban remote sensing research.

in revise). Capturing a more nuanced picture of the gradients of energy poverty and access could be a promising future direction of remote sensing research.

5. Strategic directions for urban remote sensing research

Improving the scientific understanding of urban areas in a rapidly changing and urbanizing world requires *four key advancements* (Fig. 3). *First*, the rapid rates of urban change require high frequency observations as well as a long temporal record. *Second*, urban environments vary significantly around the world as well as within particular cities, and there is a rich array of urban features and dynamics that might be better assessed by remote sensing. *Third*, the details of urban form and structure, the urban surface, and across the vertical dimension must be better and more widely known. *Finally*, linking remote sensing with emerging urban data that reflects the ecological, social, and economic processes of urban areas is urgently needed. We discuss these distinct, but related topics in this section.

5.1. High frequency analysis of urban environments

Unlike forests that can change frequently, urban environments are generally assumed to be a relatively stable land type (Mertes et al., 2015). Therefore, historically, urban areas were mapped at a time interval of 5 to 10 years apart (Seto et al., 2002; Xian and Homer, 2010; Yuan et al., 2005). However, in reality, urban environments are highly dynamic and can undergo many qualitative and subtle changes for which high frequency observations would generate significant new insights (Li et al., 2018). High temporal frequency analysis for urban remote sensing has become an emerging trend with the improvements in satellite technology (Schott et al., 2016), the open data policy (Zhu et al., 2019a), and application of methods from allied fields, such as geostatistics (Boucher et al., 2006), time series methods (Kaufmann and Seto, 2001; Zhu, 2017), among others. Nevertheless, the use of high frequency satellite data did not become the frontier of research until the Landsat data were provided free of charge after 2008 (Woodcock et al., 2008; Wulder et al., 2012; Wulder et al., 2019; Zhu, 2017; Zhu et al., 2019a), enabling new capabilities for mapping urban impervious surface area at annual time scales (Gao et al., 2012; Li et al., 2015; Sexton et al., 2013; Zhang and Weng, 2016). These newly developed approaches reveal the full continuum of change intensity of urban areas, including acceleration of urban growth and other nonlinearities in time, that the former approaches with low temporal frequency observations could not provide.

Mapping urban or urban impervious surface annually has improved knowledge about rates and patterns of urbanization. Nevertheless, considering the extremely dynamic character of urban environments, the capability of detecting urban change at sub-annual scale could illuminate different insights on urban development. This requires satellite observations with even higher temporal frequency (e.g., weekly or monthly), which will enable remote sensing applications for monitoring urban disturbance events that are usually transient in time, detecting subtle or gradual urban changes, and providing relevant near real-time information for urban response and management.

Unlike ecosystem disturbance, urban disturbance has been rarely studied. Grimm et al. (2017) defined urban disturbance as an event that disrupts any aspects of the structure of an urban system as specified in an explicit model, such as land cover and land use change, human activity, soil disturbance, and hazards/disasters (e.g., fire, heatwaves, flood, windstorms, and earthquakes). Most of these urban disturbances will only occur for a relatively short time, and this signal can be easily buried in annual time series. Though there are studies that use high temporal frequency time series for urban remote sensing, they either select the best observation per year or create an annual time series trajectory to map annual urban change, which would miss many urban disturbances or signals that occur seasonally. Moreover, most urban disturbances do not cause changes in urban area or impervious surface area, and are thus “invisible” to algorithms designed for mapping impervious surface area. For example, urban land surfaces can be highly dynamic, with frequent surface modifications caused by human activities, but with stable aggregate amounts of impervious surface area (Deng and Zhu, 2018). If we only focus on impervious surface area, all this disturbance information will be lost.

In addition, subtle and gradual qualitative changes, such as upgrading of the built environment, frequently occur in urban environments. Due to their small change magnitude, methods that select one image per year during the peak growing season are not able to capture these changes, since the magnitude of change can be smaller than the environmental and systematic noise in the imagery. Using high temporal frequency observations, remote sensing data can isolate “noise” in the time series, such as differences caused by urban vegetation phenology, solar angle change, inter-annual condition trends, and other predictable periodical and long-term changes (Zhu and Woodcock, 2014; Zhu et al., 2019b). With all those sources of “noise” excluded, subtle and gradual changes in urban environments can be identified more easily (Zhu et al., 2016). Moreover, with high temporal frequency observations, seasonal changes, which have caused dramatic changes in impervious surface area estimation and urban land cover classification (Deng et al., 2017; Zhu et al., 2012), can be estimated, modeled, and corrected (Deng and Zhu, 2018).

Near real-time monitoring of urban change is critical for raising quick awareness and reducing negative impacts in urban environments. At present, most urban change detection algorithms and products can provide accurate urban change maps, but usually, there is a substantial lag (a few years) between the time when the urban change occurred and the time when the change is detected. This delay in detection will greatly reduce the impact of change maps as they lose relevancy for response and management efforts. High temporal frequency observations are essential for near real-time response applications, such as mapping and evaluating urban fires, heatwaves, floods, windstorms, earthquakes, etc. For example, by combining Sentinel-2A/2B and Landsats 7–8, near real-time monitoring (3-day delay) of urban change at sub-30-meter resolution is possible.

Near real-time monitoring also requires change detection algorithms that are online. COntinuous monitoring of Land Disturbance (COLD: Zhu et al., 2019b), Continuous Change Detection and Classification (CCDC; Zhu and Woodcock, 2014), and Break detection For Additive Season and Trend (BFAST; Verbesselt et al., 2012) algorithms are three examples of methods. Note that COLD, CCDC, and BFAST are not specifically designed for monitoring urban change. COLD is designed for monitoring all land surface disturbances, CCDC is designed for monitoring all land cover types, and BFAST is designed for monitoring vegetation change. Similar methods that focus on monitoring urban change in near real-time are needed. The Continuous Subpixel Monitoring (CSM) algorithm is one of the few examples that integrate CCDC and subpixel mapping for continuous monitoring of urban impervious surface area (Deng and Zhu, 2018).

5.2. Urban heterogeneity

Urban environments vary significantly around the world as well as within particular cities or urban regions. Although urbanization is often presented as a uniform process, reflecting the northern hemisphere experience with industrial development, colonial metropolises, or post World War II suburbanization, there are many kinds and styles of urbanization underway today (Brenner, 2014; McGee, 2014; McHale et al., 2015; Taubenböck et al., 2018). Contemporary cities emerge or transform based on many rationales and drivers, including the familiar driver of industrialization, but also due to consumerism, the flight of refugees, dispossession in the countryside, shifts in government policy, and unfettered real estate speculation. Many cities, of course, combine several of these drivers. All of these drivers are themselves shaped by cultural, historical, climatic, regional environmental, geomorphic, economic, and governance contexts, among others. This variety of drivers creates the condition for a large heterogeneity of urban development patterns.

Despite this heterogeneity, the vast majority of urban remote sensing studies focus on a single “urban class”, particularly for studies based on coarse spatial resolution satellite data. In other words, the world is categorized as a binary — urban versus non-urban and the richness of urban form and heterogeneous ways in which it can change are not usually taken into account. Of course, the rampant patterns of urbanization in the world today do lend some value to such binary depictions, in which urban land conversion is illustrated by a garish red splotch overspreading the calm earth colors representing agricultural, village, pastoral, or wild lands. Such coarse scale changes have for a long time been of concern as pressing global changes (Berry, 1990; Vitousek, 1997).

However, such a coarse scale, aggregated approaches to quantifying urban change can be problematic. For example, “urban” in Lagos (Myers, 2011) is not equivalent to “urban” in Los Angeles (Dear and Dahmann, 2008). Furthermore, neighborhoods within Lagos and Los Angeles may be strikingly different in structure and form. Details relevant to the social, ecological, and economic aspects of urbanization, that is, the elements of sustainability, are hidden in such aggregated, generalized approaches to urban assessment. For example, shrinking cities in post-industrial situations (Haase, 2008), infill or replacement in older suburban zones (Wilson et al., 2013), and the dynamic creation and occupancy of vacant lands in even established city cores (Johnson et al., 2014; Li et al., 2018), are all invisible to the single class approach to urban mapping. There is a great opportunity to focus urban remote sensing on the within city scales that would better document and follow such patchiness and change. A further shortcoming of the coarse scale, binary approach to urban delineation, is that ecological structures, composition, and processes are essentially omitted by definition. If urban is defined as only built elements, then very likely only the largest green and blue spaces will be recognized, if any are recognized at all. Such conceptually coarse (as opposed to merely coarse in terms of pixel size) examinations will miss the small, interstitial green spaces, or the fact that many urban patches are to some extent hybrids of natural, engineered, and constructed components.

In contrast to the mixed pixel issue originated from per-pixel classification with coarse resolution remote sensing imagery, a variety of attempts have been made to alleviate the concerns of urban heterogeneity by characterizing inter-urban variation. These methods can be grouped into two categories. The first category is to develop new spectral indices specifically designed for depicting urban environments. Comparing to the binary urban/non-urban classification, these urban indices are usually easy to implement and convenient in practical applications (Deng and Wu, 2012; He et al., 2010; Zha et al., 2003; Zhang et al., 2013a; Zhang et al., 2013b). The second category is to improve information from the spatial domain. This can be achieved by mapping urban compositions at the subpixel level as a continuous field (Deng and Wu, 2013b; Powell et al., 2007; Roberts et al., 2012; Wetherley et al., 2017; Xian and Homer, 2010; Yang et al., 2003). Both approaches are designed to provide more heterogeneous information within each urban pixel by using continuous variables in the spectral or spatial domains, which is more beneficial and realistic for mapping the heterogeneous urban landscapes. In particular, by following Ridd's urban morphology model (Ridd, 1995) — the Vegetation-Impervious surface-Soil (VIS) model — multiple subpixel urban attributes can be simultaneously considered to characterize urban heterogeneity, which is already an improvement when compared with traditional binary classes from the per-pixel classification approach. Nevertheless, simply using three elements may be still far from enough to characterize the mixed nature of urban environment for applied practices.

Two recent classification frameworks have characterized inter-urban variation using more than three remotely-sensed based, or remotely-sensed derived elements. The first from urban climate/meteorology, the World Urban Databased and Portal Tool (WUDAPT) framework, uses multiple remotely-sensed variables to classify areas of the urban fabric according to how these areas shape Local Climate Zones (LCZs). Landscapes in this framework can be divided into 17 LCZs, in which 15 of them are defined by land cover and surface structure combinations, and 2 of them are defined by construction materials and anthropogenic heat emissions (Stewart et al., 2014; Stewart and Oke, 2012). A second example, the urban stands classification system, characterizes neighborhoods within urban areas based on their building layouts, street-network configuration, and job-housing balance. The stand classification concept has been used to characterize urban heterogeneity as it relates to the human and biophysical processes that occur (e.g. travel behavior) (Stokes and Seto, 2019). These novel representations of urban heterogeneity help to better describe the complexity of urban areas.

The points reviewed in this section suggest a rich array of urban features and dynamics that might be better assessed by remote sensing. Given the current and increasing sophistication of remote sensing, the field is poised to contribute to the understanding of urban systems at a wider range of scales, with sensitivity to a more inclusive range of urban drivers and resultant forms. If remote sensing can be more closely linked with other disciplines involved in understanding and predicting urban form and dynamics, it is easy to envision significant advances. Perhaps most obvious would be a processing system that takes into account the multiple scales of urban processes, the fact that cities are lived places as well as physical forms (Marcotullio and Solecki, 2013), and the fact that urban systems are — often cryptically — ecological as well as social and technological systems (Grimm et al., 2016).

5.3. Urban form and structure in two- and three-dimensions, emphasizing spatial patterns and connectivity

Many biophysical and socioeconomic processes are shaped by the vertical structure and form of urban areas (Grafius et al., 2018). Thus, in addition to heterogeneity, mapping urban form (e.g., built-up structures) is an essential dimension of future urban remote sensing research.

Urban form (or structure) plays a crucial role in how the urban biophysical environment functions and interacts with human activities. Urban form — the pattern and spatial configuration of land use, transportation, and urban designed elements (Hamin and Gurran, 2009; Seto and Dhakal, 2014) — is crucial for sustainable and smart urban development (Ramaswami et al., 2016). Urban form can be characterized by the physical urban extents, the layout of streets and buildings, as well as the internal configuration of settlements and greenspace (Seto and Dhakal, 2014). Moreover, the dynamics of urban form in the horizontal and vertical dimensions can shape many associated biophysical processes in the urban system (Grafius et al., 2018). It is worth noting that 3D urban models are not yet available for large areas due to data costs or data scarcity. However, recent efforts using digital surface models with lower resolutions (such as from stereo sensors like Cartosat or RADAR sensors such as TanDEM-X) than the commonly used VHR optical stereo sensors (such as WorldView) or airborne LIDAR data have proven their capability of significant reduction of data costs and overcoming data availability (Wurm et al., 2014; Geiß et al., 2017). This section provides insights on research opportunities for urban form in a variety of biophysical processes.

Urban form often emphasizes the variety of urban spatial arrangement in the form of two-dimensional maps. Even from this "flat" perspective, a rich typology emerges. Simple contrasts like spider webs, stars, corridors, infill, that describe the layout of urban land cover, are common, but urban form also includes finer patterns — the configuration of streets and blocks, plots or parcels, buildings, and greenspace (Oliveira, 2016). Urban form has been extensively studied in a variety of disciplines such as architecture, geography, history, and planning (Moudon, 1997; Conzen, 2001). When the third dimension is added, urban form appears as still more complex.

Urbanization does not just increase urban land cover but can also dramatically alter urban form (Dupras et al., 2016; Park et al., 2014). There has been a growing interest in capturing form, with an extensive body of work using landscape metrics regarding the size, density, shape, and distribution of urban patches to characterize and quantitatively describe urban form (Larondelle et al., 2014; Seto and Dhakal, 2014; She et al., 2017; Wang et al., 2017). For example, one study found that small urban patches will self-grow and/or merge with surrounding large urban clusters during the urbanization process (Li and Gong, 2016). As a consequence, the overall fragmentation of urban clusters increases simultaneously with urban expansion. Recent work in this area has used three simple dimension—human constructed, water, and soil-plant continuum—to develop a multi-dimensional conceptualization and mapping of urban form (Wentz et al., 2018).

The effect of urban form requires further investigation to advance our understanding of the urbanization impacts on all dimension of urban sustainability. For example, recent work has characterized the urban landscape with an explicit aim towards understanding how urban form relates to transport behavior and contributes to sustainability (Stokes and Seto, 2019). Another example is how urban form is related to biodiversity. Urban form influences the biodiversity in the urban ecosystem through changing its habitat environments and accessibility to surrounding ecosystems. In general, the influence of urban form on biodiversity can be depicted as the compositions of relevant elements such as residential area, pavements, road network, and green spaces (Nielsen and Jensen, 2015; Zhong et al., 2014). For example, the bird richness responds negatively to the fraction of impervious surface area (Silva et al., 2015). Compared to apartment buildings in a housing neighborhood, detached houses with interspersed trees among them have more insectivores (Andersson and Colding, 2014). Moreover, the connectivity of ecological corridors is crucial to maintaining the biodiversity and species abundance of urban ecosystem (Park et al., 2014; Silva et al., 2015).

Urban form assessed at the microscale could also inform future UHI studies. Urban form can intensify or mitigate UHI effects through changing relevant biophysical factors. The quantity and distribution of urban green spaces in the residential or commercial area can alter urban form through adjusting the spatial configuration of built-up areas, which will further affect the cooling effect offered by plants to mitigate UHI effects (Kong et al., 2014; Zhou et al., 2017). Urbanization encroaches upon natural areas with green spaces, generally leading to a more compact urban form, in turn, the UHI effect could be intensified. In addition to the biophysical environment, urban forms (e.g., sparse or dense residential areas) are also associated with human activities. Thus, building energy use and resulting anthropogenic heat discharge vary with different urban forms, resulting in different UHI effects (Güneralp et al., 2017; Rodríguez-Álvarez, 2016). Moreover, urban form induces changes in the surface energy balance and further affect the spatial pattern of UHI in the urban system (She et al., 2017; Tratalos et al., 2007). Change in urban form, which can foster natural ventilation in

Table 2
Comparisons between structured and unstructured data as a supplement data for urban remote sensing.

	Structured data	Unstructured data
Data source	Federal agencies, government departments, private sectors, individuals	Private sectors, individuals
Location/geographic information	Specific, and clear	Some are specific, while others are only implied in the text (or hashtag)
Data cleaning necessity	A few but limited	Considerable, and could be labor intensive
Data quality	Well organized	Unknown/poor
Data easiness to researchers	Easy access/downloadable	Usually by web scrapping
Supplement contents	Demographic and socioeconomic information, human activity	Human activity, human perception

building, has been proposed to improve the thermal environment with appropriate distribution of different height buildings (Middel et al., 2014).

The consideration of urban form, particularly its vertical dimension (i.e., building height and volume), will bring new insights in projecting future emissions under urbanization and climate change. Studies that compare the vertical dimension of urban areas to night lights or horizontal expansion show that cities with similar extent can vary significantly in terms of the building stock and vertical urban structure (Frolking et al., 2013). Greenhouse gases emissions, a primary source influencing future climate change, are associated with urban form (Hamin and Gurran, 2009). A compact urban form can reduce anthropogenic CO_2 emissions by enabling low-carbon transportation modes and travel behaviors (Rodríguez-Álvarez, 2016; Wang et al., 2017). With a spatially aggregated urban form having many high buildings, e.g., dense distributed residential and commercial areas (Zhong et al., 2014), per capita CO_2 emissions from transportation can be significantly reduced (Creutzig et al., 2016, 2015).

Understanding of the role of urban form in shaping the biogeochemical cycles of water, land, and atmosphere is also a significant gap. Nutrients such as atmospheric depositions, pet waste, and fertilizers, which have become a crucial threat to water quality in streams or rivers, are influenced by urban form during their transportation through the rainfall and surface runoff processes (Yang and Lusk, 2018). Soil sealing, defined as the covering of land by impervious surface areas, is a common phenomenon in suburban regions, due to expansive urban development and the prevalence of parking lots (Tombolini et al., 2016). Moreover, the geometry and distribution of buildings are closely related to the atmospheric environment (e.g., air quality), which is a rising concern to public health for people living in megacities. For example, fragmented cities are associated with higher pollution concentration (e.g., NO_x and PM 2.5) (Fan et al., 2018; Rodríguez-Álvarez, 2016; She et al., 2017).

5.4. Linking remote sensing with emerging urban data

Remote sensing has long been used to extract urban land cover and use information and to describe different aspects of urban environments, such as urban infrastructure, urban impervious surface, urban vegetation, urban tree canopy cover, and surface urban heat island. Despite the long history of success, the mere usage of remote sensing data in the literature may not be appropriate for future urban studies. The reason is twofold. *First*, only the physical environment information of urban can be retrieved from remotely sensed imagery, while other types of urban information cannot be directly obtained. Examples include land use (Huang et al., 2018c), sentiment and emotion in a city (Wang and Stewart, 2015), spatially explicit human activity and mobility (Frias-Martinez et al., 2012; Soliman et al., 2017). Such information is essential to understanding the interaction between human beings and their living environment, and analyzing how urban inhabitants view, sense, and change their living environment. *Second*, local knowledge is always required as an important input for per-pixel or sub-pixel image classification of urban environments. Such information, however, relies heavily on human inputs and the expertise of the researchers. In support of urban remote sensing for better understanding of urban environments, one of the solutions in the future is to take advantage of emerging urban information from a variety of data sources, especially those reported by humans as a new type of sensor which is called human sensors (Goodchild, 2007). More importantly, most, if not all, of these multi-source datasets are publicly available, and free of charge.

Two major types of open access urban data can be used to supplement remote sensing imagery – including structured and unstructured data. Structured data is preprocessed, well-organized, and generally, do not require substantial data cleaning. Structured data are usually collected and processed by federal agencies (e.g., U.S. Census and U.S. city open data), and more recently, private companies (e.g., Google street view, mobile phone data, subway smart card, and taxi GPS data), and active individuals (e.g., OpenStreet Map). Structured data usually contain a specific geographic location that can be directly and conveniently linked to remote sensing imagery. In contrast, unstructured datasets are more likely to be generated by numerous internet users and retrieved by researchers from the Internet. Such information is loosely distributed online without an appropriate organization. Examples include social media data (e.g., Twitter, and Flickr photos), and online text reviews (e.g., check-in data of FourSquare, and Yelp). A comparison of the characteristics of structured and unstructured data as a complementary dataset to remote sensing are described in Table 2.

Despite the complementary features between urban remote sensing imagery and open urban data, several data issues exist that make their integration challenging. *First*, open data and remote sensing data are collected at different scales. Social scientists, demographers, sociologists, urban planners, and policy makers prefer to employ predefined administrative boundaries, such as Census geographical unit, postal unit, school district, and congressional district boundaries. In addition, because open data is not collected evenly across space, using too fine a scale might lead to the data sparsity issue (i.e., few or no data in some areas), especially for social media data.

Comparatively, remote sensing scientists are used to employing uniform grids at a scale either inherently determined by the spatial resolution of remote sensing images or the image segment level. In most of the attempts to combine remote sensing and open data (most of which are point data), researchers still follow the tradition of remote sensing studies and select grid as the study scale, in which point-based open urban data are aggregated into each grid. These grids and scales, however, are not frequently used by domain experts. To make remote sensing research more useful and actionable, researchers can further spatially aggregate the per-pixel results in a scale or unit most commonly used in the relevant discipline. Another type of scale difference exists between Google street view and remote sensing imagery. The former data provide a 360-degree view of the streetscape of a city, while the latter only offers a vertical aerial view. For these cases, domain experts should play a major role on constructing a big picture of the application question, while remote sensing scientists may need to spatially aggregate the per-pixel results to a scale or unit most commonly used in the relevant discipline.

Second, open access urban data can be biased. For unstructured data, there is uncertainty around the data's representativeness, since the population of social media users is not reflective of the whole population. Additional sources of uncertainty include missing data from web crawling, repetitive posts from one single highly active user, under-representative samples (e.g., younger generations tend to dominate the contributing group). Prior to the collective usages of remote sensing imagery and open data for urban applications, considerable automated data collection, cleaning and matching, and compilation are necessary. To address this, remote sensing scientists may need to collaborate with urban data scientists who have expertise in addressing the challenges of unstructured data.

6. Concluding remarks and perspectives

Our assessment of the research literature and discussions between the policy and science communities leads us to conclude that urban remote sensing cannot continue to focus primarily on mapping urban cover and use. While continued assessments of urban land cover and land use will be necessary for a number of user communities, other types of analyses are needed. Strategic directions, including *high frequency analysis of urban environments*, *urban heterogeneity*, *urban form and structure in 2- and 3-dimensions*, and *improving the performance with other types of data* can expand the set of urban research question answerable with EO data.

Though this review focuses only on the major scientific advances in urban remote sensing, we cannot ignore the new technique and technology improvements that push urban remote sensing forward aggressively. For example, new machine-learning techniques, such as deep learning, are changing the game. Deep learning is characterized by neural networks (NNs), involving more than two layers (this is where the term “deep” originates). As a “black-box” solution, deep neural networks learn and explore exclusively from the data, without any domain-specific knowledge. The Convolutional Neural Networks (CNNs) approach has proven extremely effective for image analysis, due to its capability of considering the spatial patterns by interleaving convolutional and pooling layers. Though there are contrasting opinions in remote sensing community regarding the use of deep learning techniques, this technique has attracted much attention due to its superior performances (Zhang et al., 2016; Zhu et al., 2017). A recent study suggests that deep learning is particularly good at capturing the fine features of complex urban areas, and performs better than other traditional classification methods (Huang et al., 2018a; Huang et al., 2018b).

New remotely sensed big data streams are also revolutionizing urban remote sensing. Historically, the urban remote sensing community has relied on data from NASA assets. However, many new opportunities have emerged. The Sentinel mission from the European Earth monitoring program has started to launch a constellation of satellites since 2012 (Aschbacher and Milagro-Pérez, 2012). With a span of 13 spectral bands at a spatial resolution as high as 10 m, Sentinel-2 has great potential for urban remote sensing (Drusch et al., 2012). Studies have suggested that Sentinel-2 adds value to the mapping of built-up areas, over predecessor Landsat-based products (Lefebvre et al., 2016; Pesaresi et al., 2016a). China has also launched a few satellites that are unique for urban remote sensing. For example, high spatial resolution nigh-time light imagery (130-meter) are now available from Luojia-1 (Li et al., 2019b), and the multi-view imagery provided by ZiYuan-3 satellite can map urban in 3D at the global scale (Liu et al., 2019). At the same time, an almost unmanageable number of new commercial satellites, particularly smaller satellites, provide data with both high spatial resolution and high temporal frequencies. For example, a total of more than one hundred small satellites from Planetscope can monitor our planet at approximately 4 m every single day. These new datasets stimulate a variety of new urban remote sensing algorithms and applications. Over the past five years, the number of operational satellites has increased 40%, and nearly 1400 now orbit the Earth. The data collection capability of each new satellite iteration is also increasing at an astonishing rate. For example, Landsat 5 collects 40 GB of remotely sensed data per day, and Landsat 7, Landsat 8, and Sentinel-2 collect 260 GB, 750 GB, and 1.6 TB data per day respectively (Wulder et al., 2016). Those exponentially growing open and free satellite data create a new era for urban remote sensing, but also challenge the established urban remote sensing science and applications, as researchers are easily buried in this enormous volume of data. As this “data tsunami” arrives, the question becomes whether we are ready to derive meaningful new knowledge about cities and sustainable urbanization from it.

The rapid development of modern information technology, hosted computing platforms, such as cloud computing and grid computing, offer a promising solution (Esch et al., 2018). Google Earth Engine is one example of how big data and cloud computing can be seamlessly integrated, facilitating tens of thousands of researchers who may have limited remote sensing knowledge but need to process huge amount of remotely sensed data, requiring extensive computing resources (Gorelick et al., 2017).

Last but not least, remote sensing scientists need to collaborate more with other scholars and practitioners from other urban and allied fields. Urban scholars from other disciplines ask different types of questions from urban remote sensing. As a community, we need to think about not only *how* to derive the information (e.g., algorithms development), but *what* to do with it and *who* will use it. It is not sufficient to have one sentence at the end of a paper indicating “this will be useful” without a clear understanding of who will use it and how to use it. Urban remote sensing community should always keep science and policy in perspective to facilitate the transition towards a smart, sustainable, and healthy urban environment.

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