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Advances in remote sensing applications for urban sustainability

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Abstract It is essential to monitor urban evolution at spatial and temporal scales to improve our understanding of the changes in cities and their impact on natural resources and environmental systems. Various aspects of remote sensing are routinely used to detect and map features and changes on land and sea surfaces, and in the atmosphere that affect urban sustainability. We provide a critical and comprehensive review of the characteristics of remote sensing systems, and in particular the trade-offs between various system parameters, as well as their use in two key research areas: (a) issues resulting from the expansion of urban environments, and (b) sustainable urban development. The analysis identifies three key trends in the existing literature: (a) the integration of heterogeneous remote sensing data, primarily for investigating or modelling urban environments as a complex system, (b) the development of new algorithms for effective extraction of urban features, and (c) the improvement in the accuracy of traditional spectral-based classification algorithms for addressing the spectral heterogeneity within urban areas. Growing interests in renewable energy have also resulted in the increased use of remote sensing—for planning, operation, and maintenance of energy infrastructures, in particular the ones with spatial variability, such as solar, wind, and geothermal energy. The proliferation of sustainability thinking in all facets of urban development and management also acts as a catalyst for the increased use of, and advances in, remote sensing for urban applications.

Introduction

Cities are engines of economic prosperity and social development that arise from the concentration of people and economic activities but often manifests in unsustainable urban environments [57]. Economic opportunities in cities act as a catalyst for rapid urbanisation across the globe. Urbanisation rates are uneven and are much faster in developing countries [7]. By 2030, the annual average rate of urban growth is expected to be 0.04 % in Europe, 1.5 % in the USA, 2.2 % in East Asia and the Pacific, 2.7 % in South Asia, 2.3 % in the Middle East and North Africa, and 3.6 % in Sub-Saharan Africa [80]. Increased urban migration has contributed to the unplanned or poorly planned and implemented growth and expansion of cities. The latter is a critical factor for urban stakeholders as unplanned urban growth can have a long-term negative impact on urban sustainability on a range of scales—local, regional, national, and potentially inter-governmental [75]. Impacts include *detrimental economic consequences* such as the reduction in the productivity of key economic sectors [18]; *environmental degradation* such as poor air quality, and increased urban temperatures and surface run-off

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[53, 85, 87]; and *negative societal impacts* such as increased morbidity and mortality, negative impacts on quality of life, and the fragmentation of neighbourhoods and related communities [29].

The effective management of the risks arising from the reformation of urban landscapes and related environmental systems requires evidence-based approaches for mitigating and adapting to the undesirable changes. Gathering evidence of urban change is typically a time and resource intensive process that needs the application of appropriate technologies to identify arising risks. Recent advances in satellite remote sensing offer opportunities to cost-effectively monitor urban change and its impact on the complex urban socio-technical systems and enable stakeholders to make informed decisions to reduce negative impacts on the environment. Remotely sensed data are an important and powerful source of information on urban morphology and changes over time [64]. In contrast, conventional observation techniques are often logistically constrained in that they require a great deal of effort, cost, and time to obtain information over a large spatial expanse in a consistent manner [52]. The lower cost and availability of data have facilitated the way researchers accomplish research objectives, and have fostered public engagement with remote sensing science.

There is a growing body of literature on the application of urban remote sensing—from the investigation on land-cover and land-use changes to the monitoring of microclimatic parameters and the assessment of renewable energy potential. Increased vulnerabilities from the impacts of climate change and disaster risks, and urban growth resulting from rapid urbanisation have influenced recent developments on integrated risk modelling that combine remote sense analysis with social and economic data for urban sustainability assessment [57]. Collaboration between expert stakeholders is essential to realise the full potential offered by remote sensing for urban sustainability [64]. Yet, there is a lack of understanding among urban professionals of the technical characteristics of remotely sensed data and their suitability for analysis, limitations, and potential for application. We aim to address the gaps in understanding by critically reviewing the technical characteristics of available remote sense sources and their applications for urban sustainability. The findings will act as a comprehensive resource on the state-of-the-art, and provide directions for future research.

Following the introduction, the paper is divided into three sections. First, existing remote sensing systems and available satellite data resources are reviewed and categorised to provide the context for subsequent discussions. The information will also act as an indispensable resource for urban professionals in identifying appropriate remote sensing data for specific applications. Second, a state-of-the-art review is presented on the applications of remote sensing in urban sustainability. Third, the limitations of the reviewed applications are highlighted with a discussion on future directions for research and development.

## Remote sensing systems and satellite data resources

Three distinct stages of the development of remote sensing (RS) instruments are illustrated in Fig. 1. The first generation RS instruments were of low spatial resolution, 1 km–100 m, increasing to 30–10 m in the second generation. The third generation instruments are more capable in observing the Earth's surface with a very high spatial resolution, 5–0.5 m and less, enabling the acquisition of further spatial details—resulting in more accurate feature recognition. To enable the reader to gain a high-level overview of RS characteristics, we categorised the satellites based on their orbit; sensor mode and instrument; resolution; and wavelength of electromagnetic radiation (EMR), as shown in Fig. 2.

Orbit

RS satellites roam in the two kinds of orbits: *sun-synchronous* and *geostationary*. Most RS platforms, such as Landsat, SPOT and IKONOS, operate in a near-polar (i.e. sun-synchronous) orbit at low altitudes and pass over each area before noon, at 10:30 am local time [62], allowing the acquisition of clearer images of the Earth's surface over a particular area on a series of days in similar illumination conditions; i.e. when the sun position is optimal, between 9.30 and 11.30 am local time [13]. In contrast, geostationary satellites are ideal for some communication and meteorological applications because of their very high altitudes allowing continuous coverage of a large area of the Earth's surface, with the trade-off being low spatial resolution.

Sensor mode and instrument

Spatial resolution is based on pixel size and is said to be low when it is greater than 100 m, medium when between 10 and 100 m, and high when it is less than 10 m [66]. Depending on the on-board sensor's spatial resolution, RS systems can be classified into two groups: low and medium, and high and very high. Existing low–medium, and high–very high RS systems and their potential applications are given in Tables 1 and 2, respectively. Most of the data are available at a low cost, and often free to download on the Internet. A summary of selected websites for downloading satellite imagery, radar, LiDAR, hyperspectral, aerial orthoimagery and digital spectral library data are presented in Table 3.
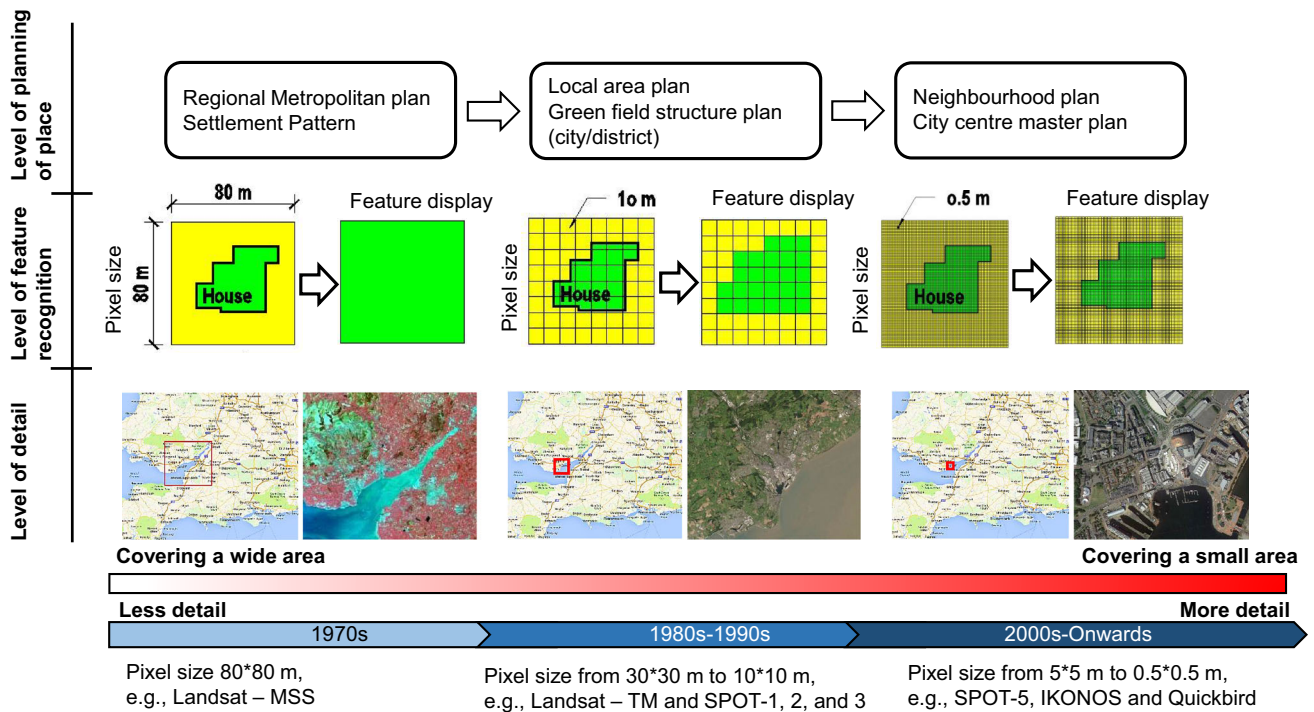
Fig. 1 A comparison of satellite generations in terms of detail, feature recognition and planning requirements. The *red square* represents the spatial resolution of the adjacent RS image. An image with a pixel size of 80 m (Landsat-MSS) cannot recognise an object, such as a house but its features can be effectively recognised with a pixel size of 0.6 m (QuickBird)
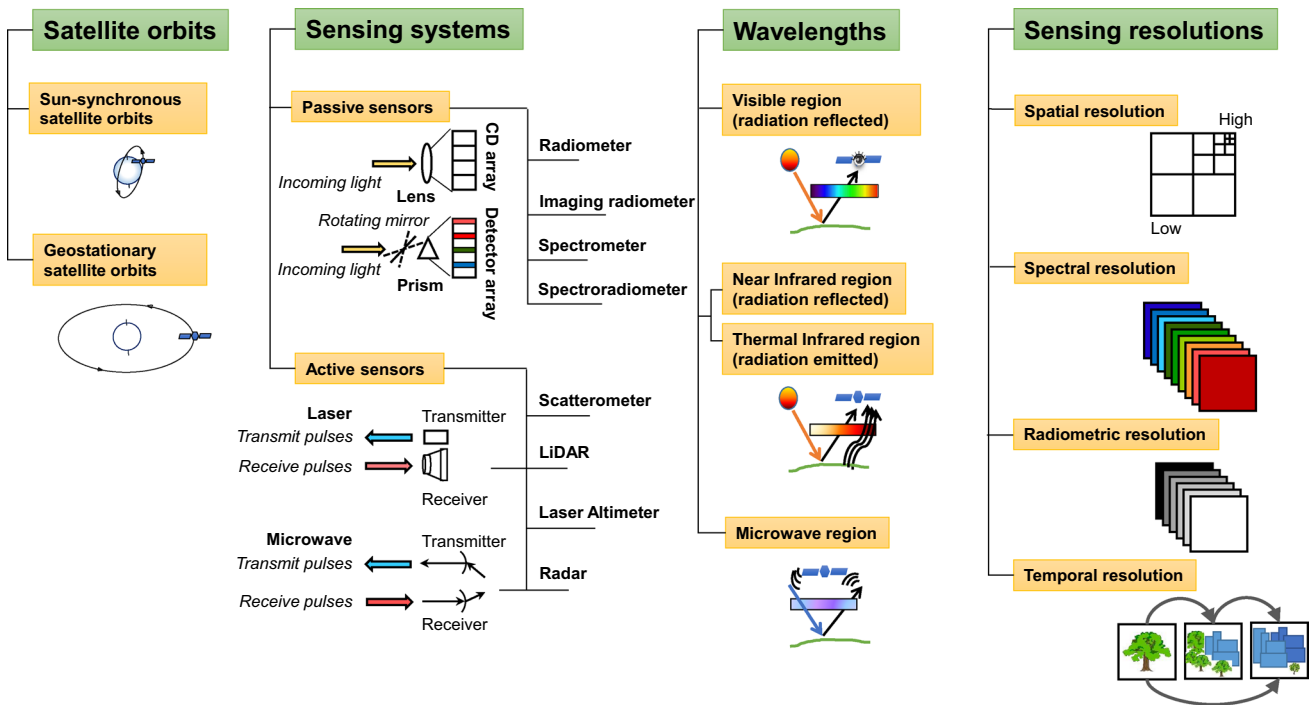
Fig. 2 Classification of remote sensing sensors based on their characteristics

Table 1 Characteristics of low and medium spatial resolution remote sensing systems and their applications

Launch year	Satellite sensor		Spectral range[a] (nm)	Bands[b]	Pixel size[c] (m)	Coverage[d] (km)	Revisit time[e] (days)	Dynamic range[f] (bit)	Mapping scale	Stereo-view	Applications
1972	Landsat-1, 2, 3	MSS	500–1100	4 (MS) 5 (Landsat-3 only)	80	185	18	6	1:2500–1:100,000		Land-use planning; vegetation inventories; crop growth and health assessments; discriminating different types and amounts of vegetation; and cartography
1984	Landsat-5	TM	450—2350	6 (MS)	30	185	16	8	1:2500–1:100,000		Surface temperature; discriminating vegetation type; water penetration; plant and soil moisture measurements; and identification of hydrothermal alteration in certain rock types
1997	SeaStar	SeaWiFS	402–885	8 (MS)	1100	2800	Daily	10	1:100,000–1:500,000		The concentration of microscopic marine plants; phytoplankton based on the colour of the ocean
1998	NOAA-15	AVHRR/3	580–12,500	6 (MS)	1090	2940	Daily	10	1:100,000–1:500,000		Surface mapping (daytime); land–water boundaries; snow and ice detection; cloud mapping (daytime and night); sea surface temperature
1999	Terra and Aqua	MODIS	620–14,385	2 (MS)	250	2330	Daily	12	1:100,000–1:500,000		Land, cloud, aerosols boundaries and properties; ocean colour, phytoplankton, biogeochemistry; atmospheric temperature; cirrus clouds and water vapour; ozone; surface and cloud temperature; cloud top altitude
1999	Terra	MISR	425–886	4 (MS)	275	360	9	14	1:100,000–1:500,000		Land use; ocean colour; air pollution; volcanic eruptions; desertification; deforestation; and soil erosion
1999	Landsat-7	ETM+	450–2350	6 (MS)	30	185	16	8	1:2500–1:100,000		Agriculture; forestry; land use; water resources and natural resource exploration; human population census and monitoring the growth of global urbanisation; deletion of coastal wetlands; and generating DEM
1999	Terra	ASTER	520–860	3 (MS)	15	60	16	8	1:2500–1:40,000		Land surface climatology; vegetation and ecosystem dynamics; volcano monitoring; hydrology; geology and soils; land surface and land cover change
2002	SPOT-5	2 HRGs	500–890	3 (MS)	10	60	26	8	1:10,000–1:25,000		Urban and rural planning; land use and Infrastructure planning; telecommunications; oil and gas exploration and mining; environmental assessment, natural disaster management; marine studies; agriculture; and 3D terrain modelling

Table 1 continued

Launch year	Satellite sensor	Spectral range[a] (nm)	Bands[b]	Pixel size[c] (m)	Coverage[d] (km)	Revisit time[e] (days)	Dynamic range[f] (bit)	Mapping scale	Stereo-view	Applications
2013	Landsat-8	OLI and TIRS	435–1551	8 (MS)	30	185	16	12	1:80,000–1:100,000	Mineral exploration; vegetation analysis; large regional coverage; extensive archive for change detection; availability of imagery over cloud affected areas (detecting cirrus clouds); and coastal zone

[a] Spectral resolution

[b] *MS* multi-spectral bands

[c] Spatial resolution

[d] Swath-width

[e] Temporal resolution

[f] Radiometric resolution

Resolution

The trade-off between spatial and temporal resolution need to be reconciled for the selection of satellite images for a particular application, as illustrated in Fig. 3. For instance, a high temporal resolution is essential for emergency situations, such as landfall due to hurricanes, because emergency situations change rapidly and require frequent observations on the day. In contrast, urban infrastructure planning applications require spatial understanding over a longer period, for which annual observations are often sufficient. However, both use cases sometimes require high spatial resolution images to observe their processes comprehensively. On the other hand, high temporal resolution is required for applications such as weather that changes rapidly. Operational weather forecast, therefore, requires satellite observations with high temporal resolution often at the cost of spatial resolution. Each RS application, thus, has its own unique resolution requirements which need to be appreciated.

Remote sensing of urban environments

Cities are unique because of the existence of dense artificial structures. The increasing urbanisation rate will eventually lead to the expedited consumption of non-renewable land resources such as water (on- and under-ground) and food [49], and energy resources such as oil, coal and gas—with environmental, social and economic impact on developing and developed countries alike [3]. Thus, the growth of urban areas can result in substantial land-cover and land-use changes—an ideal sustainability use case for the use of remote sensing. The next sections are devoted to review of remote sensing applications within urban environments, focussing on urban growth, sprawl and change; environmental impacts of urban growth; and sustainable energy applications.

Urban growth, sprawl and change

Urban growth refers to the transformation of the landscape from undeveloped to developed land [7]. More specifically, the growth away from central urban areas into homogeneous, low-density and typically car-dependent communities is often referred to as urban/suburban *sprawl*. In developing countries, urban sprawl can be unplanned and uncontrolled [9]. Consequently, urban growth leads to the loss of farmland, gives rise to economic and social issues, and increases water and energy consumption, and associated greenhouse gas emissions [25]. From stakeholders' point of view, the expansion of cities is a crucial change in

Table 2 Characteristics of high and very-high spatial resolution remote sensing systems and their applications

Launch year	Satellite sensor	Spectral range[a] (nm)	Bands[b]	Pixel size[c] (m)	Coverage[d] (km)	Revisit time[e] (days)	Dynamic range[6] (bit)	Mapping scale	Stereo-view	Applications
1999	IKONOS	445–853	4 (MS)	4	11.3	2.3–3.4	11	1:2500	Yes	Civil engineering works; land use and infrastructure planning; telecommunication; tourism; mapping and surveying; mining and exploration; oil and gas; environmental assessment; agriculture; and DEM generation
2001	QuickBird	450–900	4 (MS)	0.61	16.5	1–3.5	11	1:2000	No	Environment studies; oil and gas exploration; engineering and construction; land use and planning; agricultural and forest climates; telecommunication; and tourism
2007	WorldView-1	400–900	1 (PAN)	0.5	17.6	1.7	11	1:1500	Yes	Infrastructure planning; oil and gas exploration; mapping and surveying; telecommunications; and DEM generation
2008	GeoEye-1	450–920	4 (MS)	1.65	15.2	2.1–8.3	11	1:1500	Yes	Land use and infrastructure planning; environmental assessment; civil engineering works; natural resources; oil and gas; mining and exploration; tourism; agriculture; 3D urban terrain model; and DEM generation
2008	RapidEye	440–850	5 (MS)	5	77	5.5	12	1:5000	No	Industries; agriculture; forestry; oil and gas exploration; power and engineering and construction; cartography and mining
2009	WorldView-2	400–1040	8 (MS)	2	16.4	1.1	11	1:1500	Yes	Analysis of vegetation; coastal environments; agriculture; geology; tourism; civil engineering works; land use and infrastructure planning; and natural resources
2011	Pleiades-1A	430–940	4 (MS)	2	20	Daily	12	1:2000	Yes	Land planning and management; urban density assessment; detection and identification of small features; agriculture; homeland security; forestry; maritime and littoral surveillance; civil engineering monitoring; 3D geometry creation for the applications of flight simulators; high precision mapping; and renewable energy
2012	SPOT 6	450–890	4 (MS)	6	60	Daily	12	1:5000	Yes	Defence; engineering; coastal surveillance; agriculture; deforestation; environmental monitoring; and oil, gas and mining industries
2014	WorldView-3	400–1040	8 (MS)	1.24	3.1	<1	11 (PAN) and (MS)	1:500–1:2500	Yes	Defence and military applications; feature extraction and change detection; natural disaster and flooding; man-made materials and structures; oil and gas exploration; geology, mining, soil and vegetation; land classification; bathymetry and coastal

[a] Spectral resolution

[b] MS multi-spectral bands, PAN panchromatic

[c] Spatial resolution

[d] Swath-width

[e] Temporal resolution

[f] Radiometric resolution

Table 3 Remote sensing and geospatial data resources and providers

Provider	Source and type[a]			Comment
	Non-commercial		Commercial	
	RS	G	RS + G	
USGS Global Visualisation Viewer (GloVis)—http://glovis.usgs.gov/	✔			Various satellite and land characteristics datasets including the free Landsat archive
USGS Earth Explorer—http://earthexplorer.usgs.gov/	✔			Aerial photography, DEM, and various satellite datasets including the free Landsat archive
Global Land-cover Facility (GLCF)—http://glcf.umd.edu/data/	✔			Various satellite and DEM datasets including the free Landsat archive
USGS LP DAAC Global Data Explorer—http://gdex.cr.usgs.gov	✔	✔		ASTER Global DEM V2, SRTM, GTOPO30 and Blue Marble data
USGS Earth Resources Observation and Science (EROS) Centre—https://eros.usgs.gov/find-data	✔	✔		A collection of data sources
Sentinel Data Hub—https://senthub.esa.int	✔			Data from the ESA GMES/Copernicus Sentinel satellites
NASA EOSDIS Reverb|ECHO—http://reverb.echo.nasa.gov/	✔	✔		A wide variety of satellite and DEM datasets including ASTER Global DEM (G-DEM)
ESA Landsat 8 Web Portal—https://landsat8portal.eo.esa.int	✔			Landsat 8 datasets hosted by the European Space Agency (ESA)
Canadian Geospatial Data Infrastructure (CGDI) GeoGratis—http://geogratis.gc.ca/	✔	✔		Various RS, DEM and thematic data
Canadian Geospatial Data Infrastructure (CGDI) GeoConnections Discovery Portal—http://geodiscover.cgdi.ca/	✔	✔		Various RS, aerial photography and topographic data
Canadian Council on Geomatics (CCOG) GeoBase—http://www.geobase.ca/	✔	✔		DEM, SPOT, Landsat and RADARSAT-1
Brazil National Institute for Space Research—http://www.dgi.inpe.br/CDSR/	✔			CBERS-2 and CBERS-2B
CGIAR-CSI GeoPortal SRTM—http://srtm.csi.cgiar.org/SELECTION/inputCoord.asp	✔			90 m DEM data
ERSDAC—http://www.jspacesystems.or.jp/ersdac/GDEM/E/index.html	✔			ASTER Global DEM (G-DEM) with 30 m DEM data
USGS Global Multiresolution Terrain Elevation Data 2010 (GMTED2010)—http://topotools.cr.usgs.gov/	✔			Global DEM
USGS National Map Viewer—http://viewer.nationalmap.gov/	✔	✔		Orthoimagery, elevation, land-cover, US Topo, scanned historic topographic maps
USDA NRCS Geospatial Data Gateway—http://datagateway.nrcs.usda.gov/	✔	✔		Aerial orthoimagery and other geospatial data
Oregon State University HICO—http://hico.coas.oregonstate.edu/	✔	✔		Hyperspectral imager
USGS EROS Hazards Data Distribution System (HDDS)—http://hddsexplorer.usgs.gov/	✔			Hazards related imagery
USGS Land-cover Institute (LCI)—http://landcover.usgs.gov/landcoverdata.php		✔		Wide variety of land-cover datasets
Esri ArcGIS Online—http://www.esri.com/software/arcgis/arcgisonline/features	✔	✔		A wide variety of raster and vector geospatial datasets
Esri ArcGIS Online Image Services—http://www.arcgis.com/home/gallery.html	✔	✔		Providing multispectral, temporal, and event imagery, Basemaps
GIS Data Depot—http://data.geocomm.com/	✔	✔		A wide variety of raster and vector geospatial datasets
Dundee Satellite Receiving Station—http://www.sat.dundee.ac.uk/	✔			Images from NOAA, SeaStar, Terra and Aqua polar orbiting satellites
Landmap—http://www.landmap.ac.uk/	✔	✔		Providing a combination of remotely sensed imagery and a high quality spatial data

Table 3 continued

| Provider	Source and type[a]			Comment
	Non-commercial		Commercial	
	RS	G	RS + G	
ASTER Spectral Library—http://speclib.jpl.nasa.gov/				Digital spectral libraries
ASU Thermal Emission Spectroscopy Laboratory Spectral Library—http://tes.asu.edu/spectral/library/				
USGS View_SPECPR—Software for Plotting Spectra—http://pubs.usgs.gov/of/2008/1183/				
Reflectance Experiment Laboratory (RELAB) at Brown University—http://www.planetary.brown.edu/				
AVIRIS (Jet Propulsion Laboratory, Pasadena, CA)—http://aviris.jpl.nasa.gov/	✔			Hyperspectral data
Airbus Defence and Space—http://www.astrium-geo.com/			✔	A wide variety of remote sensing data products including SOPT-7 and providing sample imagery
Alaska Satellite Facility—https://www.asf.alaska.edu/			✔	
Apollo Mapping—https://apollomapping.com/			✔	
DigitalGlobe—http://www.digitalglobe.com/			✔	
LAND INFO Worldwide Mapping—http://www.landinfo.com/			✔	
MapMart—http://www.mapmart.com			✔	
Satellite Imaging Corporation—http://www.satimagingcorp.com/			✔	
Spatial Energy—http://www.spatialenergy.com/			✔	
Penobscot Corporation—http://www.penobscotcorp.com/			✔	
MDA Geospatial Services—http://gs.mdacorporation.com/			✔	RS, RADARSAT-1 and RADARSAT-2
Infoterra—http://terrasar-x-archive.infoterra.de/			✔	TerraSAR-X Archive
ImageSat International—http://www.imagesatintl.com/			✔	EROS A data
i-cubed—http://www.i3.com/			✔	Various geospatial data
German Aerospace Centre—http://www.dlr.de/hr/en/			✔	E-SAR data
eMap International—http://www.emap-int.com/			✔	Various geospatial data
Aero-Graphics—http://www.aero-graphics.com/			✔	Aerial orthoimagery, hyperspectral, LiDAR & Radar
Aerial Services—http://www.aerialservicesinc.com/			✔	

[a] *RS* remote sensing, *G* geospatial

terms of landscape transformation processes and urban sustainability. Continuous spatial and temporal monitoring is required to evaluate and understand such changes. The capabilities of RS satellites make them a robust and reliable source of data for monitoring the expansion of cities at different spatiotemporal scales [7, 19].

In a recent study, Cockx et al. [12] reported that land-cover and land-use information from remote sensing data is a key component in the calibration of many urban growth models. Van de Voorde et al. [81] noted that there is a strong relationship between the change of form in land-cover and the functional change in land-use through the analysis of satellite imageries. Classification-based approaches are routinely used to detect the expansion of cities by investigating land-cover and land-use changes [14, 20, 50, 73, 88, 92, 93, 97], and the analysis of urban sprawl [8, 26, 30, 32, 47, 96]. A comparison of environmental considerations and critical requirements between optical and non-optical sensors for urban change detection and monitoring the expansion of cities is provided in Fig. 4.

Medium-resolution satellite Landsat imagery has been widely used for urban change detection. Yang and Liu [95] derived urban impervious surfaces to characterise urban spatial growth. Ji et al. [35] characterised the long-term trends and patterns of urban sprawl using multi-stage Landsat Multi-Spectral Scanner (MSS), Thematic Mapper (TM) and Extended Thematic Mapper (ETM+) images based on landscape metrics. Similarly, Du et al. [16] used a time-series of multi-temporal Landsat TM images to derive the overall trend of changes through normalised difference vegetation index (NDVI) based classification. Taubenböck
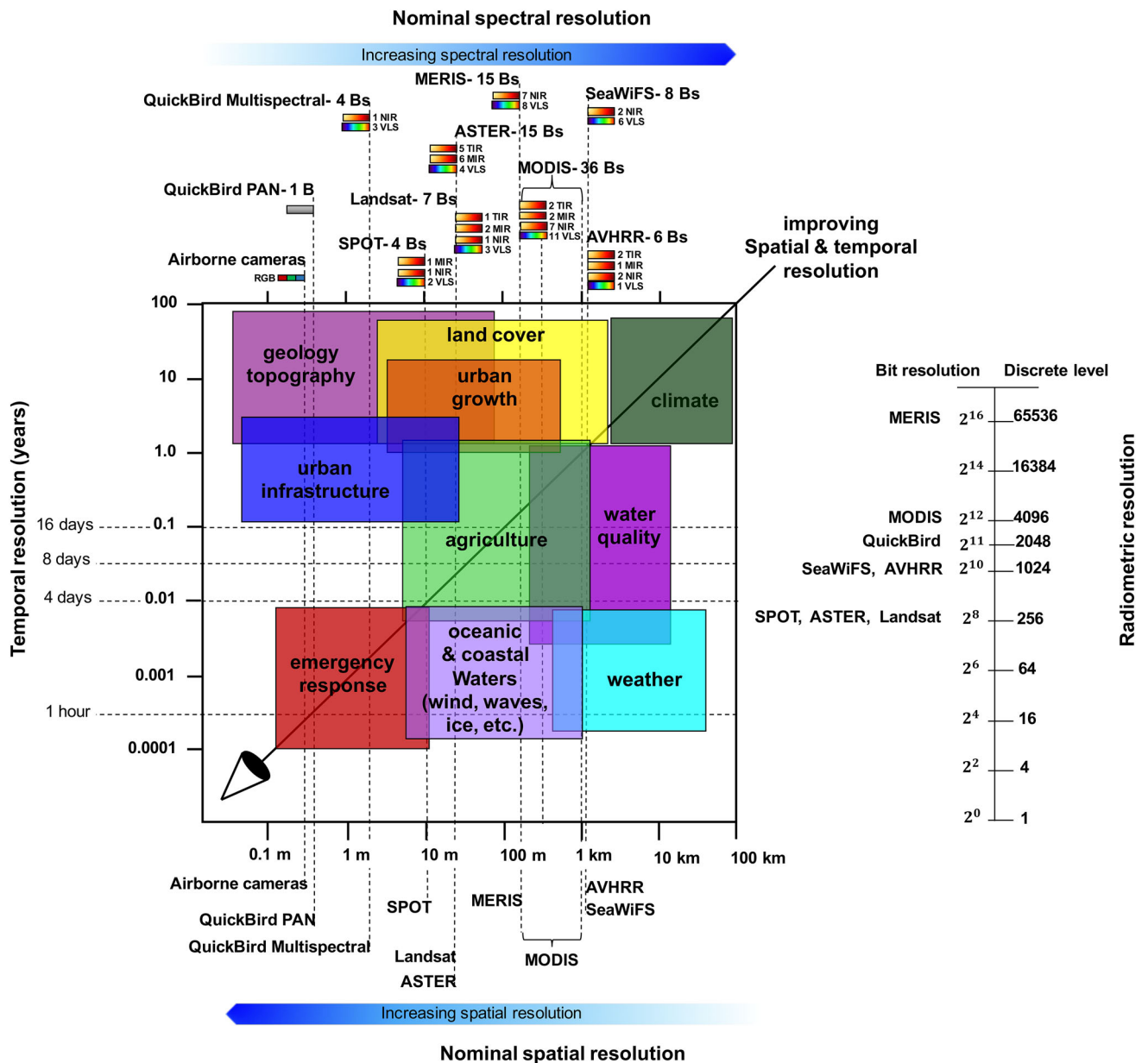
Fig. 3 An overview of spectral, spatial, temporal and radiometric resolution of different optical satellite systems. Spatial and temporal resolution requirements vary widely for monitoring terrestrial, oceanic, and atmospheric features and processes. Each application of remote sensing sensors has its own unique resolution requirements and, thus, there are trade-offs between spatial resolution and coverage, spectral bands and signal-to-noise ratios. Notes and symbols: Bs—the number of spectral bands, which include visible light spectrum (VLS), near-infrared (NIR), mid-infrared (MIR), and thermal infrared (TIR) portion of the electromagnetic spectrum; RGB—a colour digital image; and PAN—a panchromatic image Adapted from Jensen [34] and Purkis and Klemas [66]

et al. [78] detected temporal and spatial urban sprawl while Abd El-Kawy et al. [1] demonstrated that human activities were responsible for land degradation processes. Pham et al. [65] and Schneider [69] had shown that RS time-series data can be effectively used to determine long-term trends of urban changes. However, the mapping of some inner city areas for the observation of urban growth or detection of subtle changes is challenging at this level of spatial resolution.

Satellite images at medium spatial resolution (10–100 m) cover a large area, often making the urban landscape appear homogeneous, as different attributes of land within one pixel are combined into one. Researchers have, therefore, attempted to fuse multi-source (RS, socio-economic, vector) data with medium-resolution images to improve the overall resolution, increase model accuracy, and make change detection more perceptible. Jia et al. [36] proposed a method to improve land-cover classification by
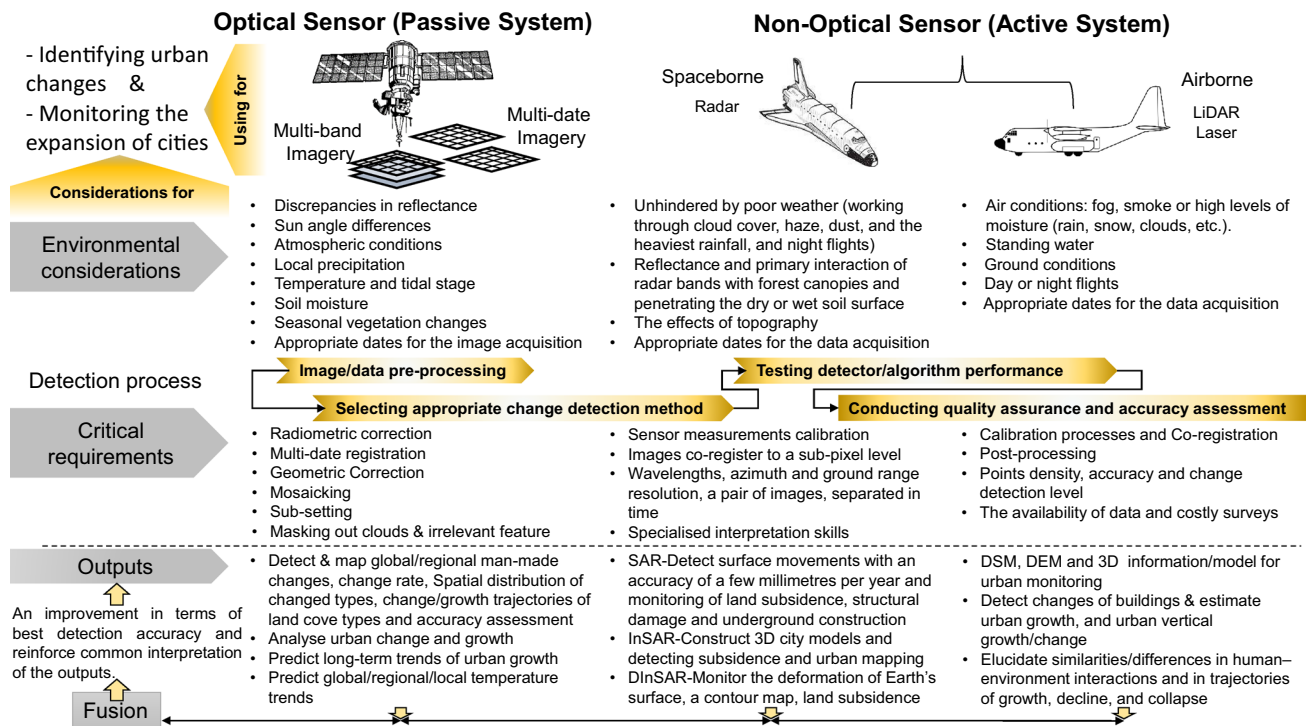
Fig. 4 A comparison of environmental considerations and critical requirements between optical and non-optical sensors for urban change detection and monitoring of the expansion of cities

fusing Landsat 8 Operational Land Imager (OLI) NDVI at 30 m with MODIS NDVI at 250 m, resulting in a 4 % improvement in the overall classification accuracy, compared to a single temporal Landsat data. On the other hand, Singh et al. [73] showed that the fusion of LiDAR and Landsat data can lead to increased accuracy in distinguishing heterogeneous land-cover over large urban regions. In another study, land-use change was inferred from Landsat ETM+ images integrated with aerial photos and population census data to reveal urban growth and sprawl by Martinuzzi et al. [51]. Change detection of urban land-use from low- and medium-resolution imagery without any improvement by applying other high-resolution RS data or integration with supplementary data, such as census data, is error-prone. The inaccuracy is attributed to mixed pixels that present a spectral mixture from the diverse built-up materials, eventually leading to greater uncertainties in land-cover/land-use classification.

The issue of mixed pixels can be resolved by obtaining more detailed information on urban morphology using high spatial resolution sensors. IKONOS pan-sharpened and SPOT images were combined with different vector maps by Noor and Rosni [61] to analyse the geospatial indicators based on spatial factors. Nassar et al. [59] identified the spatial evolution, urban expansion and growth patterns based on a hybrid classification method and landscape metrics using different datasets to derive suburban classes

(e.g. residential, commercial and industrial). Further, Kuffer and Barrosb [45] proposed an approach to monitor unplanned settlements in residential areas by identifying the morphology (size, density, and layout pattern) of urban areas. The mapping of urban land-cover and land-use from high spatial resolution images often faces the issue of spectral variability within one-class and the shadows of buildings and trees that reduce class separability and classification accuracy. Nevertheless, NASA [58] reports that the progression in the RS-based urban area mapping is contributing to the creation of more accurate and detailed maps of cities, enabling an unprecedented understanding of the dynamics of urban growth and sprawl.

Environmental impacts of urban growth

At a time when informal settlements are emerging as a result of population growth, the likelihood of increasing the occupation of spaces inside and outside cities will be higher, as is the risk of inappropriate urbanisation. The occupation of land as an uncoordinated form is motivated by several factors, namely: limited income of urban dwellers; increased housing demand; the lack of sustainable long-term urban planning; and the insufficiency of legal buildable land. These factors have led to the improper development of cities/urban areas, even in areas considered

at high risk from natural disasters such as landslide and flooding. The negative effects of the expansion of cities and urban growth are more motivational as a research agenda than the positive ones. One such application is the assessment of the quality of life and socio-economic conditions in urban slums, as for every three city dwellers worldwide one lives in a slum [63]. Many authors applied RS techniques to identify slum locations and classify slums from other land-use types [42–44, 67, 77, 83]. Graesser et al. [23] distinguished the boundaries between formal and informal settlements using an image classification approach. Weeks et al. [89] identified the location of slums and quantified their area using a vegetation-impervious-soil (VIS) model, image texturing, and census data to deduce land-use effects and to produce a slum index map. According to Hagenlocher et al. [24], a clear link between increasing new temporary settlements of population and decreasing natural resources in the vicinity of these settlements was revealed using a time-series of VHR optical satellite imagery.

Other research includes the identification of slum core and its impacts on the environment by Kit et al. [43], and slum area change patterns by Kit and Lüdeke [42]. Despite the progress made in slum detection, there is a need to develop methods that consider the interrelationships between the spatial distribution of slums and socio-economic variables. Moreover, the spatial patterns of slums

with the texture of a land-cover type must also be investigated within the urban environment in a consistent manner to improve the understanding of the interrelated land surfaces. In particular, exploiting textural differences between urban land-uses can be beneficial for improving urban mapping with regards to spectral heterogeneity within urban landscapes, as illustrated in Fig. 5, which shows the degree of spatial autocorrelation in the slums (informal) compared to the residential areas (formal). Urban differentiation in terms of similarity and dissimilarity of pixel values within a moving window was assessed using Moran's I in Eq. (1).
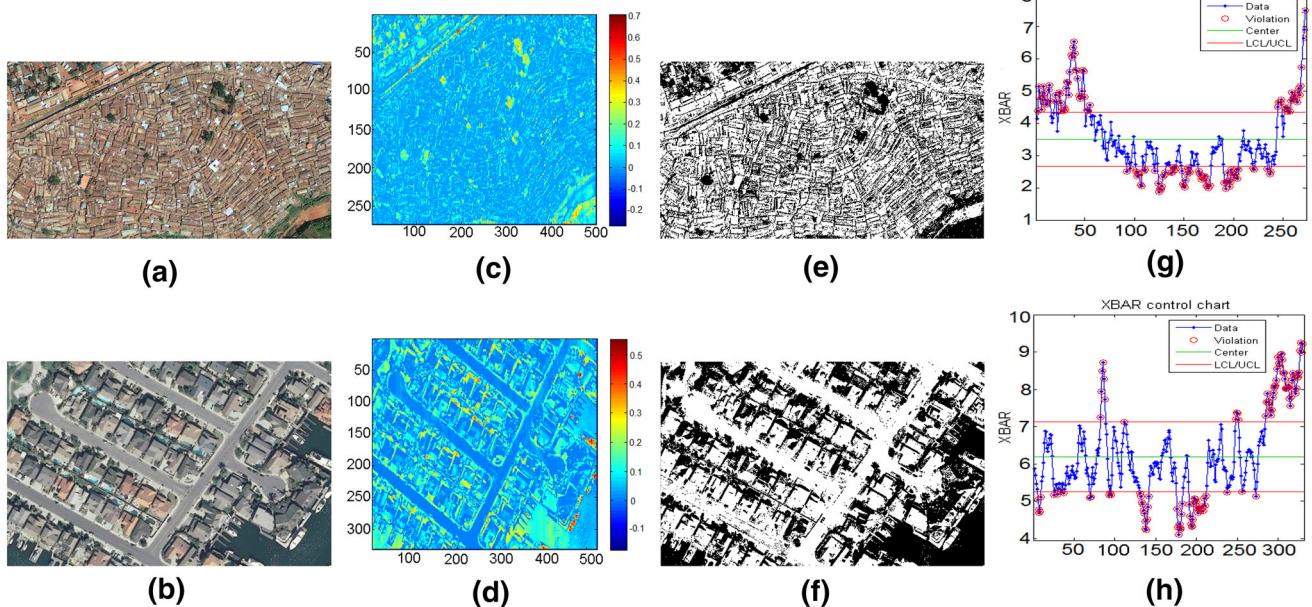
$$I = \frac{n}{s_o} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{1}$$

where z_i is the deviation of an attribute for feature i from its mean $(x_i - \overline{X})$, $w_{i,j}$ is spatial weight between features i and j, n is equal to the number of features, and s_o is the aggregate of all the spatial weights in Eq. (2).

$$S_o = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \tag{2}$$

The z_i-score for the statistic is computed as:

$$z_i = \frac{I - E[I]}{\sqrt{V[I]}} \tag{3}$$

Fig. 5 Moran's *I* for high-resolution satellite images using a 3 × 3 pixel moving window. **a** A QuickBird scene of informal residential area (slums). **b** A GeoEye-1 scene of formal residential area. **c** and **d** Moran's *I* measuring spatial autocorrelation based on both feature locations and feature values simultaneously. **e** and **f** The difference in the texture in the binary form. **g** and **h** The XBAR control chart of **c** and **d** to analyse the greatest similarity between the pixel values in each subgroup and the greatest difference between the pixel values in different subgroups

Fig. 6 Increasing temperature due to increased city size and the number of city dwellers Modified after Bhatta [7]
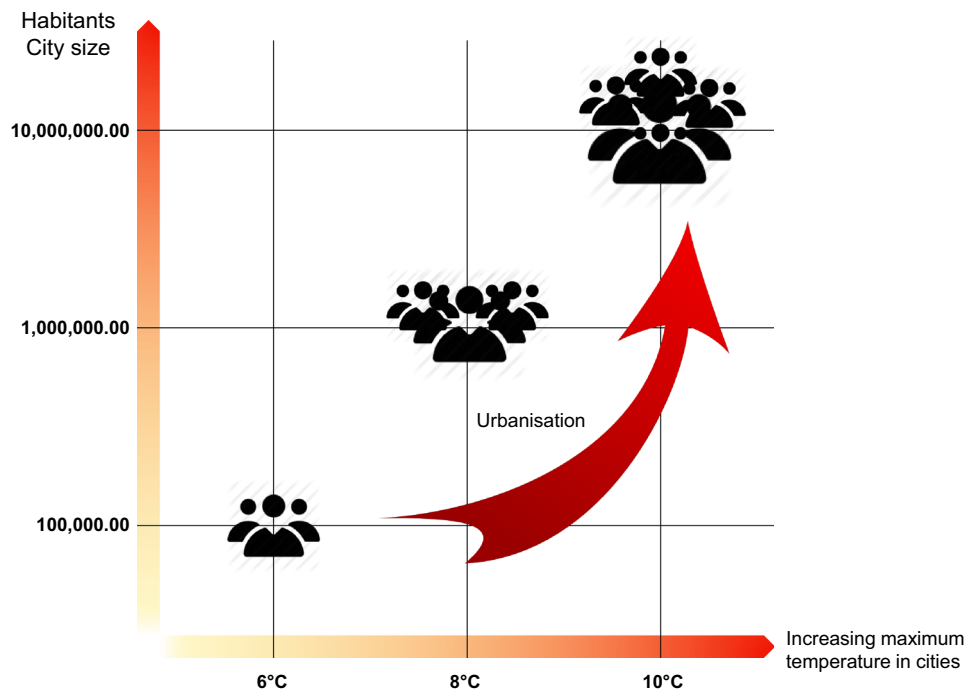
where:

$$E[I] = 1/(N-1) \tag{4}$$

$$V[I] = E[I^2] - E[I]^2 \tag{5}$$

Regarding other negative impacts, the increase in city size combined with an increasing number of dwellers cause a corresponding rise in urban air and surface temperatures, known as urban heat island (UHI), as shown in Fig. 6. A positive correlation has been deduced between impervious surfaces and land surface temperature (LST) in the sprawled areas [87, 90], where impervious surface areas become warmer than the surrounding areas. Two main factors cause the UHI effect. First, heat is absorbed from sunlight and subsequently released as thermal infrared radiation by dark surfaces such as pavements, roads and rooftops. The temperature of these surfaces can reach 28–39 °C higher than the surrounding air [7]. Second, there is a relative lack of vegetation cover in urban areas, especially trees, which work to cool air and balance the components of the environment.

Li and Yin [48] developed an approach to calculate urban heat island effect ratio (UHIER) that suggests urban areas have relatively higher temperature than the neighbourhoods surrounding the city. Senanayake et al. [70] identified UHIs and the distribution of LST by analysing vegetation cover using NDVI. Le-Xiang et al. [46] assessed the impacts of land-use and land-cover on LST, suggesting around 4.56 °C higher surface temperature in newly developed urban areas due to decreased vegetation caused by urban expansion.

Several studies have illustrated the use of RS data in analysing air pollution and its quality. Numerical simulations based on satellite data were performed to evaluate the effect of urban sprawl on air quality, surface temperature and their effects on people by De Ridder et al. [15]. In a recent study, Bechle et al. [5] evaluated the extent of the satellite data's ability to resolve urban-scale gradients in ground-level nitrogen dioxide (NO_2) within a large urban area. Wang et al. [85] derived high resolution aerosol optical thickness (AOT) from Terra-MODIS data by creating four models to analyse the relationship between AOT and PM2.5. Data from the same satellite were used by Nichol et al. [60] to assess 3D air quality over an urban landscape. Sifakis et al. [72] developed an approach to quantify AOT over urban areas by fusing different spectral bands of satellite imageries based on image processing techniques.

With regards to the evaluation of water quality and quantity, Chawira et al. [11] proposed a semi-empirical band ratio model to derive and quantify water quality parameters in two polluted lakes. They also identified the causes of pollution: domestic waste and raw industrial sewage, poor garbage collection, agriculture, and some mining activities, among others. Jay and Guillaume [33] used hyperspectral data for mapping depth and water quality. Trochta et al. [79] presented the identification of water types with different biogeochemical properties and drivers through an optical classification scheme based on RS data. Hunink et al. [27] studied the relationships between groundwater usage and crop type in irrigated

Table 4 Consequences of expansion of cities against observation variables, impacts, potential and limitations of urban remote sensing applications

	Consequences of the expansion of cities		
	Temperature	Air quality	Water quality
Observation variables or parameters	Dark surfaces (low albedo) The lack of vegetation	Ozone Nitrogen dioxide Sulphur dioxide PM2.5 and PM10 Carbon dioxide Dust aerosol	Turbidity Total suspended sediment Volatile suspended solids Polychlorinated biphenyls Chlorophyll
Impacts	Increased energy consumption & cost Elevated emissions of air pollutants (SO_2, CO and PM) and greenhouse gases (CO_2)—global warming Compromised human health and comfort Impaired water quality	Serious human health problems Inhibited plant growth Smog and acid rain Climate change	Change in colour More total runoff volume and flooded land, untreated or poorly treated sewage Surface water pollution Groundwater pollution Reduced storage capacity, flood control, light penetration in water—minimising fish yield Human health
Potential	Observe & map the surface urban heat island (SUHI) Identify the spatial patterns of upwelling thermal radiance Identify urban construction materials Time synchronised dense grid of temperature over a large area.	Monitor and map the compositions of air over the globe with high spatial and temporal coverage The combination of satellite observations with ground-based in situ for monitoring, modelling, simulating and forecasting the air quality and climate change Improve the quantification of air compositions	Assess surface water, subsurface water, soil moisture and groundwater with reasonable accuracy Assess pollutants spectrally and suspended sediments using regression based optical models Monitoring the vast spatial coverage and long-term, remotely recognition concentrations of both sediments & chlorophyll and detecting the presence of water beneath vegetation using the microwave spectrum
Limitations/considerations	Clouds (thermal imageries) Surface radiative properties Spectral wavelength	Cloud (the accuracy of air quality models) The lower levels of the atmosphere where exposure to pollution occurs Chemical and physical measurements through the atmosphere	Properties of scattering and absorption of suspended sediments and dissolved organic matter make it difficult to determine the intensity of reflected light Demand repeated monitoring on short time-scale Demand in situ measurements for calibration the estimation of water quality Poor retrieval of water constituents due to shadows cast on water bodies Correction for atmospheric influence on remote sensors is necessary to differentiate the patterns of water quality

areas. The realistic spatial distribution of air and water quality can help to define the urban landscape quality (ULQ). The use of census data alone to quantify ULQ can result in unreliable estimates as census data do not adequately capture the environmental factors such as water-borne diseases and various types of pollution (air, water, toxic chemicals, etc.). Satellite RS data can fill this gap and improve our understanding of the relationships between environmental factors and the urban landscape. Table 4 summarises the potential and shortcomings of remote sensing data for investigating the impacts of urban expansion.

Sustainable urban environments

Urban sustainability must be taken into account for planned urban growth to minimise our reliance on natural resources and non-renewable energy. City growth can mitigate the impacts of climate change by minimising ecological footprint, reducing pollution, increasing land-use efficiency, recycling waste, and increasing the use of sustainable materials, and by maximising renewable energy use. In essence, the aim of urban sustainability is to manage resources and to provide services through effective design and implementation of policies, which require access to detailed information on urban indicators. Remote sensing can offer cost-effective solutions for collecting vast amounts of data compared to resource-intensive conventional approaches such as survey and field monitoring. Figure 7 provides an overview of key urban sustainability applications of remote sensing when integrated with the available environmental, economic and social data.

Renewable energy resources in urban areas are highly sensitive to site and surroundings [55] and micro-climate [56], and are dependent on geographical constraints on development and regional economic policies [10]. Remote sensing is particularly suited to the geospatial assessment of the potential of renewable energy technologies (RET) such as wind, solar, wave, biomass and geothermal. Gooding et al. [22] estimated the physical and socio-economic potential for generating electricity from roof-mounted PV using digital surface models (DSMs) from LiDAR. Sun et al. [76] developed a regional model of solar

PV generation potential with its economic feasibility using digital elevation model (DEM). LiDAR data was used by Jakubiec and Reinhart [31] to create a map of solar photovoltaic (PV) potential of individual buildings.

Remote sensing can offer cost-effective means of identifying urban surfaces where solar PV can be installed. Kabir et al. [38] used QuickBird scenes to determine bright rooftops of Dhaka for PV applications by applying an object based image analysis (OBIA) approach. Wang and Koch [86] investigated the optimal locations of PV and the base electricity prices resulting from solar energy. Bergamasco and Asinari [6] computed the actual roof surface available for PV installations by classifying roof typologies. Baluyan et al. [4] discriminated rooftops from non-rooftops based on colour/grey level during image segmentation, support vector machine (SVM) classification, and the histogram method.

Jiang et al. [37] analysed the spatiotemporal properties of the wind field using the QuikSCAT satellite data to produce a wind resource map. Walsh-Thomas et al. [84] extended the use of satellite RS data to provide insights into the impacts of large scale wind farms on land surface temperature (LST). An extensive review of the potential of remote sensing techniques in examining geothermal resources was published by Van Der Meer et al. [82]. Ahamed et al. [2] reviewed the biophysical characteristics of biomass for managing energy crops at given sites. Rusu and Onea [68] evaluated wind and wave energy resources along the Caspian Sea. Based on the fused data from multiple satellites, Kaiser and Ahmed [41] derived the spatial distribution of hot springs, lineaments and geothermal localities for RET applications.
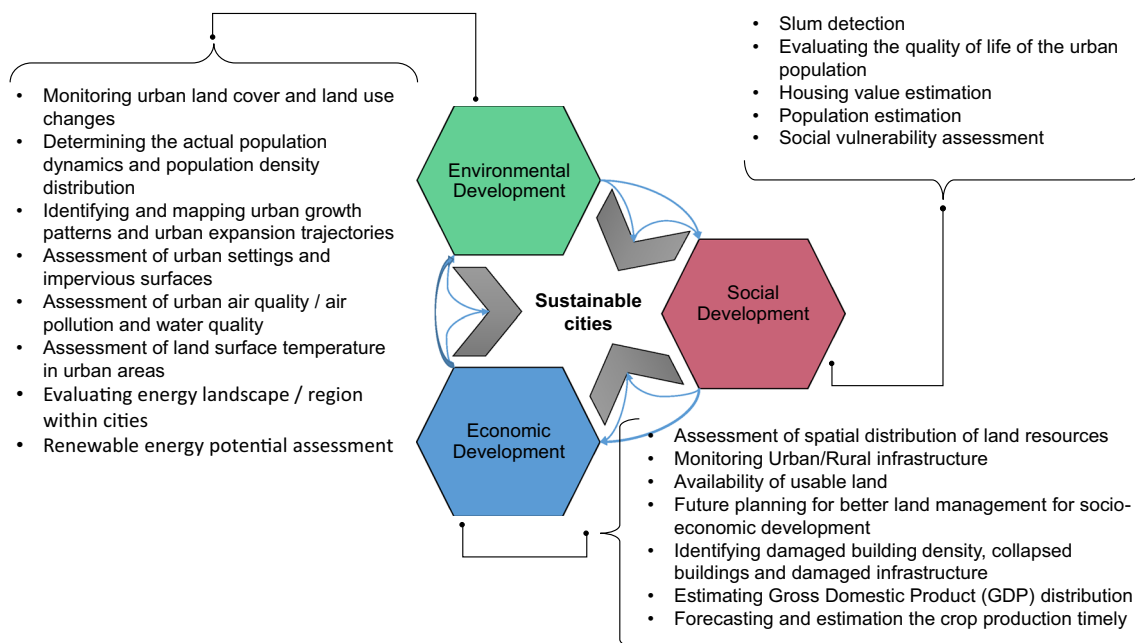
Fig. 7 Key urban sustainability applications of remote sensing

Trends and future research

Studies discussed in the previous sections demonstrate the significant potential of remote sensing in the assessment, monitoring and planning for urban sustainability. Figure 8 summarises the reviewed literature on urban growth, sprawl, and land-cover and land-use changes while Fig. 9 summarises previous work on slums, air and water quality, temperature assessment, and renewable energy. In addition, Table 5 presents the state-of-the-art in taxonomy, detection, extraction and pattern recognition in urban applications, focussing on machine learning algorithms such as neural network, decision tree, random forest, etc. The algorithmic aspects of data analysis for various urban applications are also summarised.

In the context of constrained resources, increasing urbanisation, rising vulnerabilities to climate change impacts, and ageing population, cities need to be sustainable, adaptable, smart and resilient [57]. Decisions need to be made based on the contextual evidence of performance of the urban environment, which needs to be collected at a higher resolution in a cost-effective manner. On the other hand, expanding urban areas affect the environment primarily by increasing energy consumption from buildings, transport and industry sectors [66], and by reducing albedo through

land-cover change from vegetation to built-up, resulting in increased LST [74]. Both can further reinforce the climate change drivers and act as a positive feedback loop; i.e. increased LST may result in more energy consumption, therefore, more warming, which in turn will result in further increases in LST. The potential of the use of remote sensing in tackling these urban challenges is summarised in Fig. 10.

In Table 6, we present the challenges and/or opportunities in three key research trends: (a) the integration of heterogeneous remote sensing data; (b) algorithms for extracting urban features; and (c) accuracy of urban land-cover and land-use classification. We highlighted the main benefits and limitations in each research trend for further investigations in the future.

Discussion and concluding remarks

We presented a review of the key applications of remote sensing in urban sustainability, and highlighted their potential to address problems associated with the expansion of cities. Nonetheless, there are still challenges and limitations in using remote sensing technology in urban studies. Challenges are related to the remote sensing data
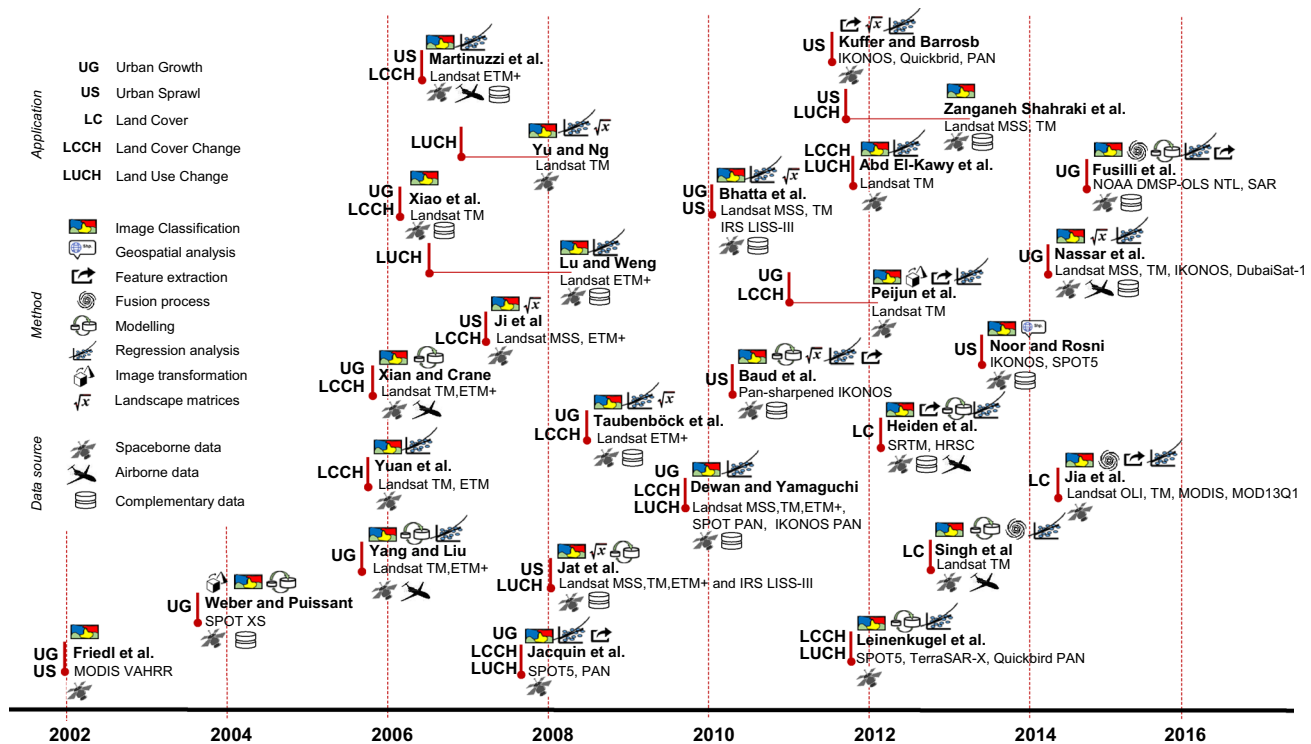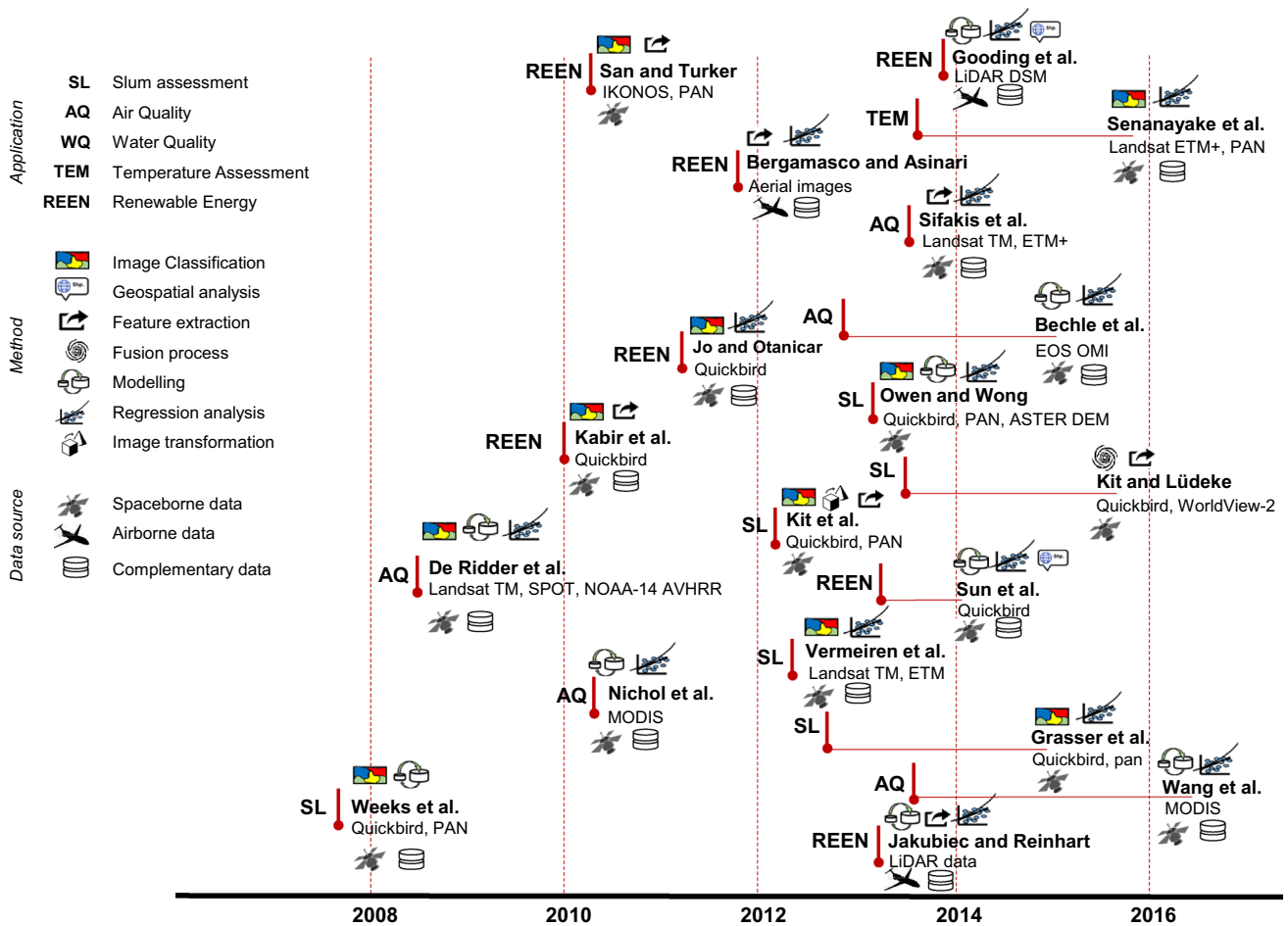

Fig. 8 Previous work on urban growth and sprawl, and land-cover and land-use changes

Fig. 9 Previous work on slums, air and water quality, temperature assessment, and renewable energy

itself, as well as its methods of calibration, such as those for dealing with the complex and heterogeneous urban environments. Although the accuracy of the extracted information in RS-based studies has improved, obtaining an accurate thematic map from RS-based classifications remains a challenge, due to: (a) the complexity of the urban landscape; (b) limitations of selected computer vision and image processing techniques; and (c) the complexities and nuances in integrating or fusing multi-source data. Spectral uncertainty still exists between the separated classes of the urban land-cover and land-use, such as bare soil and/or dry mud with impervious surfaces. Furthermore, the concentration of diverse built-up materials in a small area results in pixel generalisation, eventually leading to classification errors, which can be particularly problematic when working with low-resolution images.

The key advantage of remote sensing technology arises from the capability to integrate data from multiple sensors with similar or dissimilar spatial, spectral, or temporal resolutions to collate information on a common theme. However, there is a need for robust algorithms for fully automating the registration of data captured with many sensors, such as optical and radar, hyperspectral imagery and LiDAR data, which operate at disparate resolutions and use diverse acquisition approaches. Although the derived information from such sensors are potentially very useful for urban sustainability assessment, fusing their data is a real challenge using the conventional approaches of data processing. Additionally, techniques for object recognition, classification, segmentation, and change detection from the outputs of data fusion are still in their infancy. Therefore, to take full advantage of the diversity of remote sensing data within the urban environment, there is a need to develop new strategies and further refine existing techniques and approaches.

Table 5 The state-of-the-art in taxonomy, detection, extraction and pattern recognition in urban applications

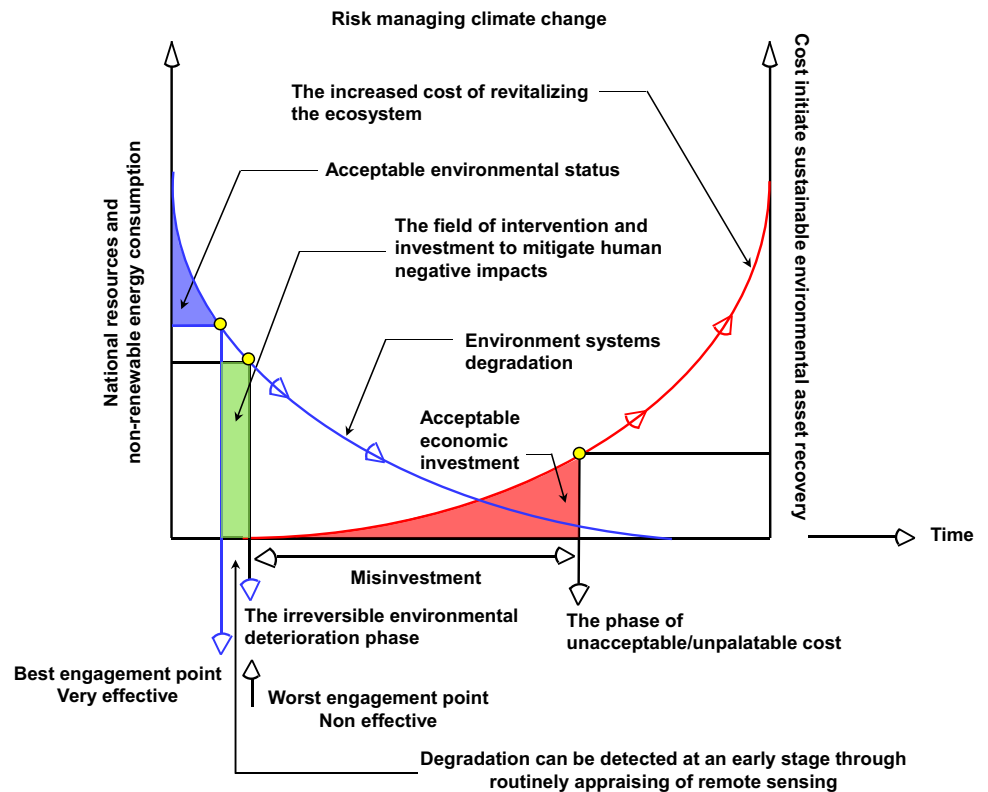| Application	Taxonomy/ quantification algorithms	Merits	Limitations	Example
Seismic building structural types (SBSTs)	Support vector machine (SVM) and random forest (RF)	Classify the combination of different remote sensing data Derive sets of valuable features to characterise the urban environment Model an effective earthquake loss and spatial distribution ABTSVM classifier outperforms other multi-class SVM classifiers	Hierarchical supervised classification scheme has uncertainties in separating SBSTs Performance depends on the ranked features Accuracy is subject to the addition of further features and subset based categories	Geiß et al. [21]
Urban change detection: land-use transitions	Scene classification with a bag-of-visual-words (BOVW)	Obtain semantic scene classes Effectively analyse land-use changes Satisfactory accuracy	Time-consuming Very difficult to achieve the direct selection of the "from-to" samples from the dataset Classification performance in certain cases is negatively affected by the redundancy of information	Wu et al. [91]
Urban land-cover and land-use classification	Binary tree SVM based on JM distance	Improve classification accuracy. Classify hyperspectral images adequately Ease of interpretation of urban classes	Confusion between road and bare soil classes Instability and complexity in the structure and parameters of the binary tree SVM	Du et al. [17]
Monitoring changes in impervious surfaces	MRGU	Integrate multiple endmember spectral mixture analysis (MESMA), analysis of regression residuals, spatial statistics (Getis Ord) with Moran's I, and urban growth theories in an effective manner Quantify and identify the magnitude of impervious surface changes and their spatial distribution.	Not universally applicable due to specific behaviour of maximum noise fraction (MNF) Difficult to use for quantifying changes in urban centres Performance (regression residuals) is subject to the structure of urban regions	Shahtahmassebi et al. [71]
Change detection	Unsupervised Neural network and feature transformation	Deep architecture (SDAE) for better representation of the relationships between feature- and pixel-pair Mapping based FCA and function learning to highlight change in a robust manner Denoising autoencoder	Uncertainty in the feature-pair High computational cost Complexity structures of stacked denoising autoencoders (SDAE) Many constraints are required to extract useful features	Zhang et al. [99]
Water quality, and sustainable water resources management	Integrated data fusion and mining (IDFM) and artificial neural network (ANN)	A near real-time monitoring and the early warning system Efficiency Forecasting reliability Potential for local adoption	Prediction accuracy may be effected by uncertainties in the fused data A large number of variables is required to overcome the uncertainty Not applicable for regional meteorology parameters	Imen et al. [28]

Table 5 continued

Application	Taxonomy/ quantification algorithms	Merits	Limitations	Example
Air temperature estimation	SVM	Fully automated method SVM regression is robust Regression errors can be modelled at the pixel level, improving accuracy estimation	Requires expert users to apply SVM Does not work well under non cloud-free conditions and require in situ measurements Regression error distribution is insufficient	Moser et al. [54]
Fine-scale population estimation for urban management, emergency response and epidemiological	RF and Linear regression modelling	Able to classify building types and extract their footprints in the heterogeneous urban areas Improved classification accuracy Ease of adoption	Subject to the accuracy of the selected morphology filter Use of large numbers of metrics and variables for building type classification Building background metrics do not show its advantage in the block classification Classification uncertainty for non-residential buildings	Xie et al. [94]
Renewable energy and urban feature extraction	Shadow detection and building geometry identification	Easy to apply Sufficient to generate 3D model of urban buildings Reliable analysis of the solar energy potential Identify the availability of 3D surfaces Flexibility and feasibility	Not fully automated Not suitable for dense urban areas Sensitive to the quality of satellite images	Kadhim et al. [39, 40]
Impervious surfaces estimation	SVM and RF	Increased classification accuracy Does not depend on combinations of features Data can be fused to optimise parameters efficiently Ease of application	Needs many texture matrices Inability to handle the confusion in shaded areas and bare soil Over-fitting	Zhang and Lin [98]

Apart from the challenges in the assimilation and integration of data, the methods and algorithms for extracting features and related information need to be considered for observing city growth and its environmental impacts. Some of these challenges relate to the information extraction from image texture; inference of contextual and semantic information using computer vision techniques; extraction of the geometric attributes of urban features such as 3D objects, and the enhancement of the degree of automation in accelerating the deduction of useful information from satellite images.

One of the goals of our research is to highlight the potential of remote sensing for tackling emerging environmental issues in countries without the vast environmental and land monitoring infrastructure typically found in Europe and the west. Countries and regions on the northern and southern shores of the Mediterranean are characterised by rapid urbanisation and environmental degradation, but are not well presented in the literature in terms of the development and applications of urban sustainability. The concern is that the region has experienced significant environmental changes in the past, and is

Fig. 10 The hypothetical deterioration of environmental systems and the potential of the use of remote sensing in their restoration Modified after Purkis and Klemas [66]

Table 6 Directions of future research

	Integration of heterogeneous data	Algorithms to identify urban features	Improve accuracy for spectral classification algorithms
Objective	Improve the spatial and spectral resolution Improve the classification accuracy Enhance the ability of features detection and display Promote the geometric precision Increase the capability of the change detection Refine, replace or repair the defect of image data Handle multi-source remote sensing data at the pixel, feature and decision of level fusion	Accelerate future processing and improve classification accuracy Automated processes for detecting, extracting, simulating, classifying and modelling urban features Capability of handling and fusing the large number of datasets Improve image objects segmentation Increase the reliability and precision of the feature extraction Mitigate the ambiguous and uncertainty	Capability of separating urban land-cover and land-use classes in an adequate manner. For a better visualisation and interpretation of urban landscape Performing a change detection analysis and pattern recognition Accurately characterise the model parameters for different urban remote sensing applications
Problems requiring solutions	A rescaling of multisource data of divers EO instruments Assessing the distortion of the spatial and spectral resolution Time-consuming and subjective The complexity and/or availability of a large training datasets for the deep learning features Manual or semi-automated the post-processing process Computation efficiency and effectiveness The quality of the distinguishing features With the fusion schemes, the optimal combining strategy of the current fusion algorithms is a challenging task and promising research that requires further investigations in the near future	Further developments for fusing LiDAR data with thermal, multispectral and hyperspectral imagery Reliable determination of the boundaries of urban objects in an automated manner Further improvements for addressing different characteristics of EO data Ability to cope with unpredictable environmental and illumination factors of diverse datasets Similarity in the characteristics of spectral, textural and geometrical-based between the urban objects and their background The problems in the occlusions and relief distortions Computational time to perform a task	Mixed pixels Uncertainty in the urban land-cover and land-use classes Mixed objects Promote pixel-based and object-based classification using contextual information Over-fitting can cause speckled results that are difficult to interpret An automatic labelling strategy is required for actual label sets in several applications Further refinements for the fusion of diverse data sources Integrate the derived urban features (e.g. building shadows) and/or spatial matrices with various classifier schemes Investigate the recent computer vision techniques for improving the accuracy

projected to be exposed to significant risks from climate change and increasing human impacts to its natural resources and ecosystems. Reviews on advances in remote sensing presented here are envisaged to encourage further adoption in urban sustainability applications, in particular in the countries and regions most affected by global environmental change.

Compliance with ethical standards

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