Assessing sustainable development prospects through remote sensing: A review

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ARTICLE INFO

ABSTRACT

The Earth's ecosystems face severe environmental stress from unsustainable socioeconomic development linked to population growth, urbanization, and industrialization. Governments worldwide are interested in sustainability measures to address these issues. Remote sensing allows for the measurement, integration, and presentation of useful information for effective decision-making at various temporal and spatial scales. Scientists and decision-makers have endorsed extensive use of remote sensing to bridge gaps among disciplines and achieve sustainable development. This paper presents an extensive review of remote sensing technology used to support sustainable development efforts, with a focus on natural resource management and assessment of natural hazards. We further explore how remote sensing can be used in a cross-cutting, interdisciplinary manner to support decision-making aimed at addressing sustainable development challenges. Remote sensing technology has improved significantly in terms of sensor resolution, data acquisition time, and accessibility over the past several years. This technology has also been widely applied to address key issues and challenges in sustainability. Furthermore, an evaluation of the suitability and limitations of various satellite-derived indices proposed in the literature for assessing sustainable development goals showed that these older indices still perform reasonably well. Nevertheless, with advancements in sensor radiometry and resolution, they were less exploited and new indices are less explored.

1. Introduction

The success of sustainable development in any region depends upon what is known regarding resource management and hazards in the area (Tabor and Hutchinson, 1994). Although several approaches and techniques are available to monitor natural resources and hazards, remote sensing (RS) technology has been particularly popular since the 1970s because of its low acquisition costs and high utility for data collection, interpretation, and management. Over the past few decades, RS tools and techniques have been deployed for several purposes at various time scales (Jensen, 1996). RS provides both archived and near-real-time information on Earth systems (Jensen, 1996; Jensen and Cowen, 1999). RS is applied to obtain spatial information in various fields in Earth system science. The ability of RS to monitor Earth systems at various spatial and temporal scales makes it suitable for addressing global environmental, ecological, and socioeconomic challenges. RS can

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provide a synoptic view of spatial information at local, regional, and global scales, thus facilitating swift decision-making and action (Jensen and Cowen, 1999). As information can be obtained directly through RS, it is the main surveying technology employed for collecting data in inaccessible and remote locations.

Several benchmark studies have been carried out on the role of RS in sustainable development, covering a variety of sub-topics within the fields of environmental assessment, natural hazards, and socioeconomic development, among others (Avtar et al., 2013; Dudhani et al., 2006; Holloway and Mengersen, 2018). For instance, Franklin (2001) used RS to aid for sustainable forest management. Huete et al. (1997) developed a global vegetation index that could be used to monitor the dynamic behavior of plant growth. Wilson et al. (2003), among other researchers, evaluated the influence of zoning on vegetation indices and temperature in urban ecosystems using RS, and Dudhani et al. (2006) mapped water resources in a plain, as well as in a hilly and mountainous region, using RS as the primary data source. Van Westen (2000) reviewed the utility of RS for natural disaster management and concluded that although no satellite was specifically designed for use in disaster mitigation, most orbital satellites provided useful information that contributed to disaster prevention, preparedness, and relief efforts.

RS has been increasingly applied over the last three decades to assess sustainable development efforts. Advancements in RS technology and the availability of large volumes of data have led to vast improvements in data analysis, especially when combined with geographic information system (GIS) and machine learning (ML) algorithms. ML techniques, such as convolutional neural networks, random forests, and support vector machines, have been used to analyze RS data for environmental assessments and monitoring of socioeconomic developments since the early 1990s (Lary et al., 2016; Singh et al., 2017; Merghadi et al., 2020). These algorithms are likely to play a crucial role for maximizing the benefits of geospatial data. Due to the paucity of images with fine spatial and temporal resolution, these methods were not always efficient and accurate when used to monitor sustainable development efforts. However, the development of new platforms and interfaces, such as graphics processing units, open data sources (e.g., USGS Earth Explorer, Copernicus Data Hub, Bhuvan, Open Topography), and cloud platforms (e.g., Google Earth Engine) over the past decade has greatly improved the mapping and monitoring of sustainable development activities. Another reason for the upsurge in the use of RS to assess sustainable development over the past decade is the increase in global collaborations among members of the RS community, which has been facilitated in part by discussions on various social media forums such as Facebook, LinkedIn, Quora, Stack Exchange, and GitHub. An increase in the availability of numerous sophisticated analytical tools and open-source RS software (e. g., SAGA, QGIS, SNAP, SeaDAS, LAS) has also contributed to the increased use of RS to capture data for monitoring natural resources and the environment.

Today, RS, which can be considered as a scientific tool, is applied in almost every field of Earth and environmental science. Considering the importance of sustainable development in the 21st century, this review aims to assess how advancements in RS technology have affected three important areas of sustainability. First, we review how RS is used to monitor, develop, and manage natural resources. Second, we summarize how RS is applied for environmental assessments and hazard monitoring. Third, we assess the utility of RS for improving transportation planning, population estimations, and quality of life. In this review, we attempted to provide an overview of the concept of sustainable development and the roles RS and GIS play in achieving sustainability in the face of intensifying human activities and climate change.

2. Focus and structure of the review

This study focused to review the literature related to the use of RS for sustainable development applications. Table 1 summarizes the major developments in remote sensing technology in the sustainable development field over the last two decades. It considers the published review paper in various journals of remote sensing. A rapid evaluation was done of published review papers to reveal quantitative information about the categories that are formulated in this section.

We explored the published articles indexed in the Scopus, Web of Science, and Google Scholar for mainly three broader themes viz. Natural resources management and development, environmental assessment and hazard monitoring, and socio-economic development. These three categories were further subdivided into ten specific segments and the *keywords search* was conducted (Appendix Table A-1) for the following entities i.e. Biodiversity, Water Resources, Mineral Resources, Environmental Assessment, Flood Hazard Forecasting and Assessment, Landslide mitigation and management, High-mountain hazard management, Transportation, Population and the Quality of Life. Fig. 1 illustrates the flowchart of the study with concepts and applications of RS in sustainability science.

After the identification of related articles, the abstracts were scanned to screen-out the irrelevant items. A special emphasis was laid on the case studies related to the development of remote sensing-based spectral indices and their applications in different disciplines. To keep the scope of assessment wide with more granularity, the search was supplemented by additional papers about the environment, water, biodiversity, landslide, flood, and related subjects. Full papers were reviewed carefully by the authors with a key focus around the applied nature of remote sensing on sustainability for a conclusive database of the papers. The assessments of each article, as well as the classification method of the selected papers, were discussed among the authors and other academic collaborators to reach a consensus. Then the major findings of each paper were noted, together with their research scale, methodology deployed, the illustration of sensor development, and limitations. It helped in the extraction of the main application of remote sensing in natural resource management and allied sectors. The issues of category-overlapping were encountered among the identified papers. As a single paper in many instances was found connected to more than one category. For instance, one paper could address both groundwater and population variables; and a paper on flood hazards has overlapped with high-mountain hazard management. In these circumstances, the papers were clustered and analyzed with the indexes suggested by the authors in addressing the ten classified issues as per the literature survey.

Fig. 2 shows the trend of review articles published in various research categories from January 1, 2001, to May 15, 2020. It reveals the increasing trend in the number of published review articles. The total number of published review articles in two decades from 2000 to 2010 and 2011–2020 is 319 and 752, respectively. The trend of published review articles has increased two folds. The number of published articles in the population category is increasing significantly.

The surveyed literature in the three broad segments of sustainability science was then classified into ten sub-categories (Fig. 3). Section 3

Table 1
Review articles with proportion to the total published papers in different research categories.

Research Categories	All Published Papers	Review Articles	Percentage of review papers
Population	9189	360	3.9
Environmental Assessment	6092	226	3.7
Biodiversity	3430	177	5.2
Quality of Life	1015	81	8.0
Groundwater	3669	79	2.2
Transportation	3063	52	1.7
Landslide mitigation and management	2881	46	1.6
Mineral Resources	1970	44	2.2
Flood Hazard Forecasting and Assessment	1984	38	1.9

Source: Authors Scopus Database search between January 1, 2001, to May 15, 2020
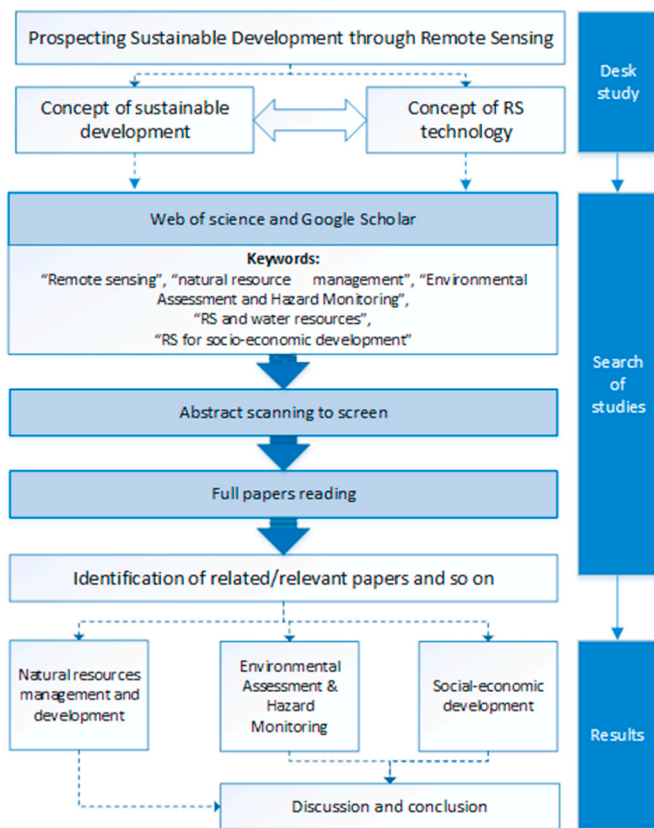
Fig. 1. Flowchart for selection of review papers in Application RS and GIS in sustainable development.

discusses the natural resource management and development segment engage with the biodiversity challenges (both direct and indirect approaches) and exploration of key mineral and water resources. Section 4 deals with the environmental assessment and hazard monitoring segment deal with a comprehensive evaluation of environmental impact by flood h, landslide, and environmental assessment in general. And section 5 focuses on the socio-economic development segment covers the factors like transport or mobility, population estimation and allocation; and the quality of life.

3. Natural resource management and development

RS is applied in diverse ways for natural resource management and development. The applications of RS technology for natural resource management and development, especially in the context of sustainable development, are briefly presented in the following sub-sections.

3.1. Biodiversity

Biodiversity and ecosystem services are critical for life on Earth, as they facilitate provisioning, supportive, regulatory, and cultural services (Millennium Ecosystem Assessment, 2005; Avtar et al., 2017). Thus, it is important to monitor and conserve biodiversity for current and future generations. Several field-based methods and techniques have been developed to support biodiversity conservation. However, they are usually limited in terms of scale and effectiveness. For instance, conventional land use and land cover (LULC) maps acquired from field surveys have failed to comprehensively classify and monitor biodiversity and ecosystems, especially those in inaccessible and larger geographic areas. Given these limitations, the development of effective techniques to capture information under non-ideal conditions is necessary. RS techniques are better for observing and monitoring

environmental changes, as well as providing baseline information over extensive areas, and consistently produce precise and accurate data (Duro et al., 2007; Xie et al., 2008).

RS is widely used to explore a range of ecological functions, as well as natural and anthropogenic drivers of landscape changes (Gould, 2000; Kerr et al., 2001; Kerr and Ostrovsky, 2003; McDermid et al., 2009). For instance, RS can be used to identify the biophysical characteristics of species habitats, distributions, and locations, in addition to spatial variation in species richness. Over the past few years, RS has been further enhanced and improved to deal with emerging challenges. RS can be directly applied for biodiversity monitoring, such as by using airborne and satellite sensors to capture information about species assemblages in ecological communities or individual organisms (Table 2). RS can also be indirectly applied via the extraction of environmental parameters for use as proxies (e.g., indicators of potential habitats for different plant/animal species; Duro et al., 2007; Turner et al., 2003) (Table 2). Field surveys to determine plant traits are usually limited to smaller areas and a small number of species. However, with the advancement of RS techniques, time-series information can be collected from large areas within a short survey period (Homolova et al., 2013).

RS can also be used to directly monitor land cover, producing information that directly supports sustainable development efforts. The Landsat Thematic Mapper (TM), Compact Airborne Spectrographic Imager, and narrow-bandwidth visible and near-infrared spectroradiometer sensors have been used to directly capture images of vegetation cover for several decades (Haboudane and Miller, 2002; Hou et al., 2013; Menon and Bawa, 1997). Based on these RS data, forest fragmentation, land use and cover, and species distributions have been mapped and monitored over time (Kerr et al., 2001; Menon and Bawa, 1997). LULC data are especially useful for detecting the distributions of individual species, species assemblages, and species richness over broad areas (Kerr and Ostrovsky, 2003). Key indicators of biodiversity that can be obtained from Earth observation data include productivity, richness, spatial and temporal distribution, disturbance, composition, topography, heterogeneity, biomass, and structure (Buermann et al., 2008; Cord et al., 2014; Foody and Cutler, 2006; Haboudane and Miller, 2002; Hou et al., 2013; Menon and Bawa, 1997; Saatchi et al., 2008; Viña et al., 2008; Waring et al., 2010; Zald et al., 2014).

RS can also be used to derive environmental parameters or indices indirectly, to in turn map species patterns and diversity (Turner et al., 2003). Such parameters are thought to be drivers of biodiversity, and those that are frequently estimated for determining species richness and distribution patterns include (i) primary productivity, (ii) climate variables, and (iii) habitat structure (Abdalla, 2012). These three types of parameters facilitate assessment of the diversity of various species at any given location and time (Turner et al., 2003). Parameters can first be estimated from data obtained by advanced RS sensors; then, both local and global species availability, richness, and diversity can be inferred.

3.1.1. Primary productivity

Species primary productivity has been estimated in several studies based on multispectral RS data. This is typically done by deriving the normalized difference vegetation index or similar vegetation indices and determining the quantitative relationship between the derived vegetation index and plant phenology (Turner et al., 2003). Hazarika et al. (2005) applied an integrated approach using leaf area index data derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor as input for the Sim-CYCLE ecosystem model. They then improved estimates of the net primary productivity (NPP) of species in tropical and boreal forest biomes. Multi-decadal time-series estimates of oceanic and phytoplankton-biomass NPP were calculated by Kahru et al. (2015) using spectral reflectance data derived from multiple ocean-color satellites. MODIS was used by Nightingale et al. (2007) to estimate the gross primary production of forest species in the United States, and the estimates agreed well with the results from a simple process-based model. The relationship between primary productivity and species

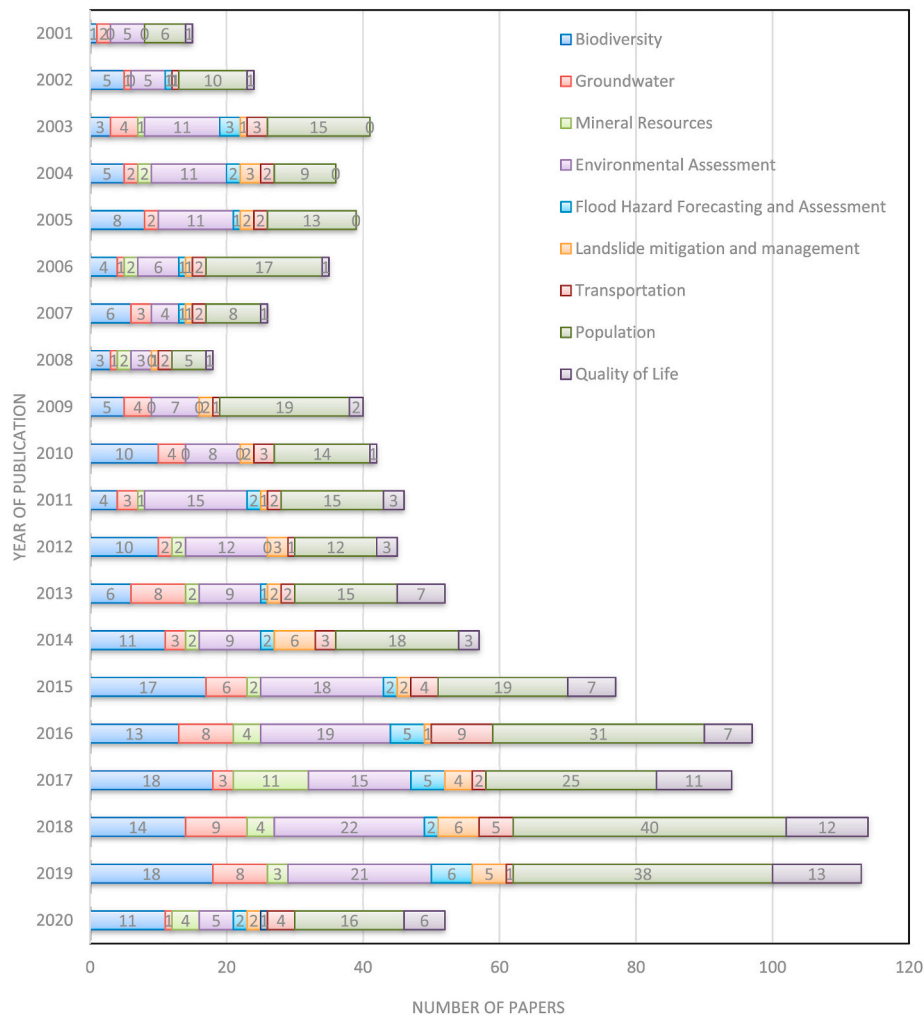**Review Articles Published between January 2001 to May 2020**

Fig. 2. Trends of review articles published under nine defined research categories.
(Source: Authors Scopus Database search between January 1, 2001, to May 15, 2020)

richness requires further exploration. However, it is widely accepted that primary productivity can be used for assessing species diversity at various spatial scales (Worm et al., 2002).

3.1.2. Climate

Climate data captured via RS techniques are useful for understanding spatial patterns of microclimatic behavior and their relationships with biodiversity. Several variables, including temperature, relative humidity, and soil moisture, are determining factors with respect to the survival and productivity of many species (Turner et al., 2003). In recent years, many satellites from which climate parameters can be derived have been launched. For example, in 1999 and 2002, the United States launched the TERRA and AQUA satellites, respectively. TERRA has five onboard sensors designed to monitor the Earth's environment and changes in climate, as follows: (i) the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), (ii) Clouds and the Earth's Radiant Energy System (CERES), (iii) Multi-angle Imaging Spectroradiometer (MISR), (iv) MODIS, and (v) Measurements of Pollution in the Troposphere (MOPITT). AQUA has six onboard sensors for water studies: (i) the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E), (ii) MODIS, (iii) Advanced Microwave Sounding Unit (AMSU-A), (iv) Atmospheric Infrared Sounder (AIRS), (v) Humidity Sounder for Brazil (HSB), and (vi) CERES. These

sensors collect information on the Earth's water cycle, including evaporation from oceans, water vapor in the atmosphere, clouds, precipitation, soil moisture, sea ice, land ice, and snow cover on land and ocean. Radiating energy fluxes, aerosols, vegetation cover, phytoplankton, and water temperature are also measured. These parameters help us to understand the relationship between climate data and biodiversity.

3.1.3. Habitat structure

By understanding species habitat structures, insights into species patterns and distributions can be obtained. In this regard, RS technologies have proven to be indispensable. Goetz et al. (2007) examined the heterogeneity of bird habitats in temperate forests in Maryland, USA, using light detection and ranging (LiDAR) technology. LiDAR data were used to derive the canopy height, topography, and vertical distribution of canopy elements, with the latter being an indicator of bird species richness in trees. The results of the vertical distribution analysis correlated with those of bird surveys. Hyde et al. (2006) mapped forest habitat structure using multiple RS sensors. Data from LiDAR, synthetic aperture radar/interferometric synthetic aperture radar (SAR/InSAR), Landsat-7, and QuickBird were integrated and compared to estimate forest structural parameters such as canopy height and biomass. This study revealed that the use of multi-sensor data provided more accurate results than LiDAR data alone.
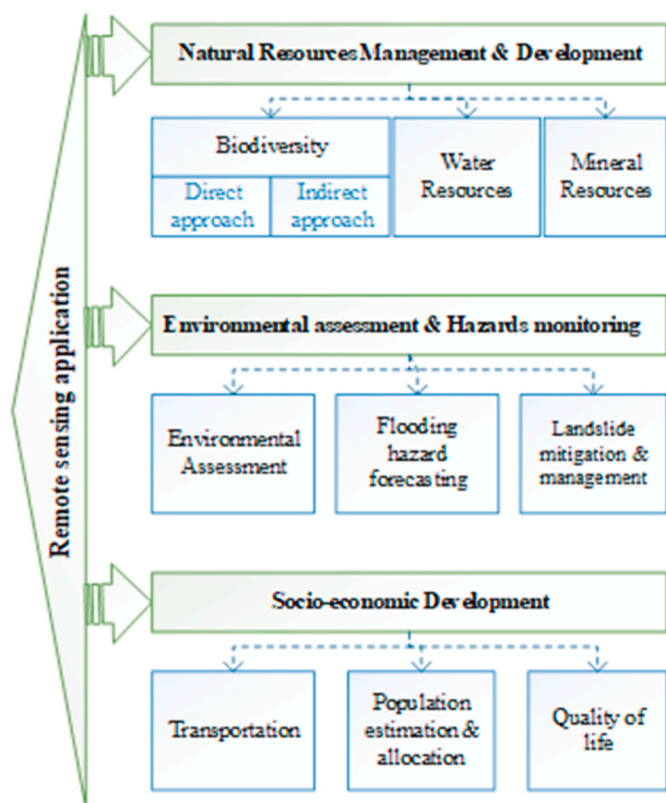
Fig. 3. Remote sensing applications in the study.

3.2. Water resource mapping and monitoring

Water is essential for human life. Climate change, urbanization, and industrialization have severely impacted water resources. Surface water is susceptible to pollution; thus, further exploitation of groundwater resources is inevitable (Avtar et al., 2013a,b; Minh et al., 2019). In addition to being a source of clean drinking water, groundwater also sustains rivers, wetlands, and lakes, which are ecologically and agriculturally important in both developing and developed countries (Jha et al., 2007; Thakur et al., 2017). A number of studies have been performed to detect surface water resources and elucidate their spatiotemporal distributions based on satellite images (Rokni et al., 2014). Several algorithms have been developed to detect water bodies in RS images, such as the normalized difference water index (NDWI; McFeeters, 1996), modified NDWI (Xu, 2006), and automated water extraction index (Feyisa et al., 2014). Changes in the surface area and volume of water bodies were estimated using these water indices coupled with bathymetric datasets. Furthermore, satellite sensors such as Landsat, ASTER, SPOT, and MODIS are routinely used for water quality monitoring (e.g., of turbidity, primary productivity, nutrients, harmful algae, etc.) and mapping (Mishra et al., 2013). Yunus et al. (2020) recently applied RS to quantify the improvement in ambient water quality during the COVID-19 lockdown period and reported a 15% decrease in suspended particulate matter in Vembanad Lake (India). Kamerosky et al. (2015) monitored the 2011 super algal bloom in the Indian River Lagoon (Florida, USA) using MERIS images. Other researchers have detected oil spills in water bodies using MODIS images (Pisano et al., 2015) and mapped seasonal variation in colored dissolved organic matter in Barataria Bay (Louisiana, USA) using Landsat images (Joshi and D'Sa, 2015).

Although RS is employed directly for monitoring surface water resources, indirect techniques are used for mapping and exploring groundwater resources. Geophysical and geological maps can be coupled with RS-derived thematic data to quickly provide information

Table 2
Application of Remote Sensing in Biodiversity using Direct Approach.

Satellite	Indicators	Applications
Vegetation cover Landsat, Moderate-resolution imaging spectro-radiometer (MODIS)	Normalized Difference Vegetation Index (NDVI); Enhanced Vegetation Index (EVI); surface reflectance; land surface temperature (LST); Maximum Entropy Algorithm	-to determine the healthiness, distribution, and richness of forest ecosystems (Gould, 2000; Krishnaswamy et al., 2009); -to map the spatial distribution of plant and animal species, model species distribution (Buermann et al., 2008; Cord et al., 2014; Saatchi et al., 2008; Viña et al., 2008); -to understand characterizing ecosystem functions (Pettorelli et al., 2005); -this in comparison with categorical land cover classification obtained from species distribution models reveals a better model performance (Cord et al., 2014).
Forest cover IRS 1D-III, PAN, Shuttle Radar Topographic Mission (SRTM), digital elevation model (DEM), Landsat, MODIS	Net primary productivity (NPP), Gross primary productivity (GPP)	-to monitor the changes in the forest cover over a period of time to detect activities of deforestation caused by natural or anthropogenic activities (Duro et al., 2007; Menon and Bawa, 1997; Nandy et al., 2011); -to generate maps for determining slope-wise forest degradation (Nandy et al., 2011); -to track areas undergoing deforestation activities as well as the rate and extent of deforestation for appropriate conservation practices (Wiens et al., 2009).
Biomass estimation MODIS, QSCAT, SRTM, TRMM, Landsat	Above Ground Biomass (AGB)	- to establish linkages between variations in species richness, habitat heterogeneity and/or climatic energy (Kerr et al., 2001; Saatchi et al., 2008); it also has helped to establish that high species richness resides in immensely heterogeneous habitats (Kerr et al., 2001); -Leaf area density, nitrogen/chlorophyll content, maximum photosynthetic capacity, above-ground structure, and biomass (Haboudane and Miller, 2002; Waring et al., 2010).
Flora and Fauna Light Detection and Ranging (LiDAR), Interferometric Synthetic Aperture Radar (InSAR), Airborne	Radar vegetation index (RVI) The global forest/non-forest map (FNF)	- to predict above-ground plant growth and forest composition and structure (Waring et al., 2010; Zald et al., 2014);

(continued on next page)

Table 2 (*continued*)

Satellite	Indicators	Applications
laser scanning, airborne CIR, ALOS AVNIR-2		-to obtain relevant and useful information about the spatial and temporal distribution of animals; -to show the relationship between fauna and forest characteristics, assess the habitat of forest-dwelling species and wildlife and its suitability (Graf et al., 2009; Martinuzzi et al., 2009), -to delineate forest stands based on species composition, timber size, stem density, canopy closure, growing stock, and site type among others (Hou et al., 2013).

on probable areas for detailed groundwater exploration. This is especially useful where drilling is not possible, such as in fully urbanized or inaccessible areas. RS can rapidly identify potential groundwater zones based on factors that govern groundwater formation, including geology, lithology, geomorphology, faults/fractures, drainage patterns, land use, and soil type (Schultz and Engman, 2000). The use of RS data for exploring the suitability of groundwater resources for various developmental purposes has been well-documented (Abdalla, 2012; Jha et al., 2007; Lee et al., 2012; Singh et al., 2011). In particular, RS data provide a synoptic view and large area coverage, exhibit multi-temporal and multi-purpose capabilities, and are highly cost-effective (Avtar et al., 2017). Nevertheless, although the effectiveness of satellite imagery for delineating potential groundwater zones has been demonstrated (Chowdhury et al., 2003), the effectiveness of other RS methods, and of integrating different methods, still needs to be validated.

Typically, RS is employed in groundwater exploration to delineate geomorphology and map lineaments, surface lithological characteristics, slopes, pediplains, and LULC (Avtar et al., 2010; Ganapuram et al., 2009; Jha et al., 2007). Recently, these factors were integrated with other subsurface factors and thematic layers associated with groundwater flow and storage in GIS analyses, to identify potential groundwater zones (Abdalla, 2012; Lee et al., 2012). In many places, RS and geophysical data are combined for detailed exploration of groundwater resources, with the aim of developing these resources (Arafa-Hamed, 2013; Khan et al., 2014). Numerical modeling based mainly on RS data has been used to identify groundwater recharge and discharge zones (Schultz and Engman, 2000). Most groundwater studies employed RS data from different optical satellites to explore various groundwater-associated factors (Crossman et al., 2012).

Although groundwater exploration is important, the assessment of surface water quality and quantity cannot be overlooked. RS plays a vital role in the assessment of water quality parameters such as suspended sediments, chlorophyll, and temperature. For example, Ritchie et al. (2003) used optical and thermal sensors to monitor these parameters, whereas Chang et al. (2015) used RS to monitor surface water quality and ecosystem status as they relate to nutrient cycles over a period of 40 years. RS is widely used to quantitatively assess surface water bodies, and RS data are useful for monitoring changes in surface water extent due to climate and anthropogenic factors. Huang et al., 2018 reviewed the current status of detection and monitoring of surface water bodies using optical remote sensing data and noticed that remote sensing data along with in-situ observation can help to model spatio-temporal dynamics of surface water bodies. However, integrated used of multisource data can improve global to regional water monitoring. Pekel et al. (2016) used Landsat archive data to quantify changes in global surface water over the past 32 years. They reported that permanent water bodies

disappeared, and new ones appeared from 1984 to 2015. Such information may aid water management and policymaking. Zhang et al. (2002) studied the hydrological cycle in the Tibetan Plateau by examining lake areas, levels, and volumes using Landsat data from 1970 to 2015. Their findings contributed to knowledge on groundwater storage and recharge in the area. These studies provide vital information on water gains and losses in different continental areas based on RS data and could help improve future water management practices.

3.3. Mineral resource exploration and development

For many countries, mineral resources are the major contributor to state revenue. These mineral resources are concentrated in different regions of a country. The exploration of these hidden earth resources for national economic development requires the use of modern exploration technologies, such as geology, geophysics, drilling, and remote sensing. Remote sensing has been particularly effective in detecting surface manifestation of mineral deposits beneath the earth. The use of remote sensing to interpret geologic features in the early years (during World War II) began with the analysis of aerial photographs. Different scientific and applied technological progress from digital image processing, micro-electronics, computer processors to cryogenic engines cumulated towards developing comprehensive capabilities for establishing remote sensing satellites into the earth's orbit. The leading space programs of the United States of America (USA), European Union (EU), Russia (formerly U.S.S.R during the Cold War), Japan, China, and India have worked immensely independently as well as in collaboration towards various applications of remote sensing. Several countries have collaborated to bring different satellite platforms in specific orbits with remote sensing sensors. These platforms and sensors further provide information about Earth's abundant resources with higher levels of granularity and precision (Belward and Skøien, 2015; Sabins, 1999).

The capability of remote sensing application for mineral exploration was started from the passive satellite sensors to active sensors. In the past decades, several studies have been done towards (1) The mapping of geology and structures (the faults and fractures) that hosts ore deposits; (2) Identifying hydrothermally altered rocks based on their spectral signatures; (3) Mapping surface distribution of rocks and its mineral constituents (Sabins, 1999). Sabins (1999) reviewed use of Landsat, SPOT, and AVIRIS data for mineral exploration and various spectral characteristics. Due to the higher spectral resolutions of Hyperspectral images, it is possible to detect signals from different minerals within the electromagnetic wavelengths. Thus it draws the attention of geologists and other scientists concerned with mineral exploration (Kodikara et al., 2012; Van der Meer et al., 2012; Vicente and de Souza Filho, 2011). RS can also be used to map hydrothermal alteration (Kodikara et al., 2012; Van der Meer et al., 2012; Vicente and de Souza Filho, 2011). For example, Pour et al. (2013) used Landsat-7 Enhanced Thematic Mapper (ETM) and Hyperion data to identify zones of hydrothermal alteration and the associated structural elements, which are closely related to gold mineralization in the Sarawak region of Malaysia.

In another study involving Hyperion imagery, Zadeh et al. (2014) used sub-pixel mapping techniques to discriminate and map "diagnostic alteration minerals" around porphyry copper deposits in Iran. They were able to identify minerals such as biotite, muscovite, illite, kaolinite, goethite, hematite, jarosite, pyrophyllite, and chlorite, which are associated with the presence of porphyry copper deposits. Gabr et al. (2010) used multiple ASTER images to locate alteration zones related to gold deposits in Abu-Marawat, which is in the southern part of the North-Eastern Desert in Egypt. The researchers developed new band ratios (4/8, 4/2, and 8/9 in RGB) for mapping alteration minerals that will be useful for future gold exploration. Finally, Carrino et al. (2018) used airborne hyperspectral and geophysical data to generate an alteration map that effectively characterized mineral assemblies in southern Peru.

4. Environmental assessments and hazard monitoring

4.1. Environmental assessments

RS is now being used extensively for monitoring global warming and related phenomena, including changes in snow and ice cover, solar radiation, and land inundation/reclamation. The Advanced Very High-Resolution Radiometer has been measuring sea surface temperature (SST) since the 1970s and recorded an average SST increase of 0.28 °C from 1984 to 2006 (Yang et al., 2013a). Such data complement ground-based measurements in global warming research. Measuring changes in snow and ice cover is crucial for assessing/estimating sea-level rise and changes in Earth's albedo. The snow cover extent (SCE) in the Northern Hemisphere has been routinely monitored since 1967 using visible-band and passive microwave-band sensors. The SCE in this region decreased by 0.8 million km^2 per decade from 1970 to 2010 (Brown and Robinson, 2011).

Bolch (2007) used RS and GIS data to track changes in glacier cover on the Zailiyskiy and Kungey Alatau mountain ridges of the Northern Tien Shan, and was able to delineate glacier cover in the study area by merging a Landsat ETM + TM4/TM5 ratio image with ASTER/SRTM3-DEM data. When the results were compared to historic glacier data, taking into account other relevant parameters such as temperature and precipitation recorded over five decades, glacier extent was shown to have decreased significantly, by more than 32%, between 1955 and 1999. Immerzeel et al. (2009) also used RS to monitor snow cover in Himalayan river basins and concluded that accelerated glacial melting is taking place, because discharge into rivers was higher than expected given the precipitation during the simulation period.

It is important to measure solar radiation to determine whether natural deviations therein have contributed to global warming. Measurements of total solar irradiance (TSI) started in 1978 using active-cavity electrical-substitution radiometers. TSI was reported to have a limited influence on the current global warming (Vignola et al., 2019; Yang et al., 2013b). On the other hand, aerosols create a cooling effect across the Earth. Using a technique for measuring aerosol optical depth based on visible and infrared spectra, aerosol concentrations have been shown to change over time. Since the 1980s, aerosol concentrations have been decreasing in North America and Europe but increasing in Asia (Manktelow et al., 2007).

Land reclamation is needed to support human activities, infrastructure and industrial development. However, it has multifarious and long-term consequences on the environment. RS has been used to assess the impact of land reclamation on land cover and coastal resources. Nakagawa and Yasuoka (2001) estimated the concentrations and distribution of suspended solids after land reclamation off Isahaya, Japan using Landsat-TM, ADEOS/AVNIR, and TERRA/ASTER data. They found that suspended-solid concentrations in the water increased significantly after the land-reclamation project. Ranade (2007) studied the environmental impact of open limestone mining on surrounding land area in India using IRS LISS-III data, and reported that the mine provided ancillary activities and employment for the local population. Karan et al. 2016 used various Landsat based indices to determine whether the rehabilitation of land degraded by coal mining in Jharia (India) was successful and reported that RS data can be used to effectively monitor rehabilitation by providing information on vegetation cover and soil moisture.

4.2. Flood Hazard Forecasting and Assessment

Floods are among the most devastating natural hazards, causing considerable damage to human life and livelihoods globally every year. In mountainous areas, landslides may also accompany floods, resulting in significant damage to nearby communities. These hazards are being exacerbated by the increased intensity of precipitation, together with greater uncertainty around precipitation events in many areas due to climate change (Daoud et al., 2016). RS data can be used to effectively predict floods, landslides, subsidence, and ground instability, thus contributing to risk assessment and mitigation planning (Carrasco et al., 2003). In flood forecasting, RS is used in conjunction with *in-situ* observations and hydrologic models. RS data are mostly used to construct digital elevation models that include catchment geometry, hill-slope angles, measurements of rainfall intensity and duration, and measurements of soil moisture to quantify and model flood hazards (Yan et al., 2013). Fig. 4 shows the data required for hydrologic models, and the satellite platforms that could potentially provide such data (CEOS Disaster Management Support and Wood, 2003).

Remote sensing satellites record the seasonal land cover changes and climatic behavior (Singh et al., 2015). This recorded data is used as an input parameter in the hydrodynamic models. The seasonal land records of vegetation provide data for the model such as water interception potential, soil strength assessment, permeability, and erosion potential. The climate behavior data provides further information on the severity of flood hazards or the extent of the inundated area. Techniques to retrieve this climate information require passive and active sensing, which uses thermal and microwave sensors and several instruments that include the spectrometer, spectro-radiometer, synthetic aperture radar, and gravimeter (Gray et al., 2011). Several remote sensors (InSAR, GPS, laser altimetry, and microwave imaging) help both in hazard monitoring (like flood and landslide) and post-disaster response (Gili et al., 2000; Malet et al., 2002).

In some areas such as mountainous areas in developing countries with a lack of *in-situ* measurement devices. It is difficult to simulate hydrodynamic models due to a lack of data. Nonetheless, data from satellite remote sensing in the upstream stretches of rivers can be used directly for downstream river discharge forecasting (Hirpa et al., 2013). The study of Hirpa et al. (2013) used upstream satellite remote sensing data for downstream discharge nowcasting and its future forecasting in major rivers in South Asia. This study showed that the well-correlated satellite-derived flow signals enabled the detection of the propagation of river flow waves. Flash floods are very difficult to forecast due to the associated short time of rainfall occurrence and high intensity. However, the integration of radar rainfall nowcasting into Numerical Weather Prediction (NWP) models and hydrodynamic models can help to extend the forecasting lead time for extreme flash floods (Rossa et al., 2010). Remote sensing data can be used to monitor inundated areas accurately (Munasinghe et al., 2018). It can help in disaster risk management during the emergency response to rapidly assess the extent of flood damages. Table 3 shows a summary of the studies relevant to flood hazard assessment.
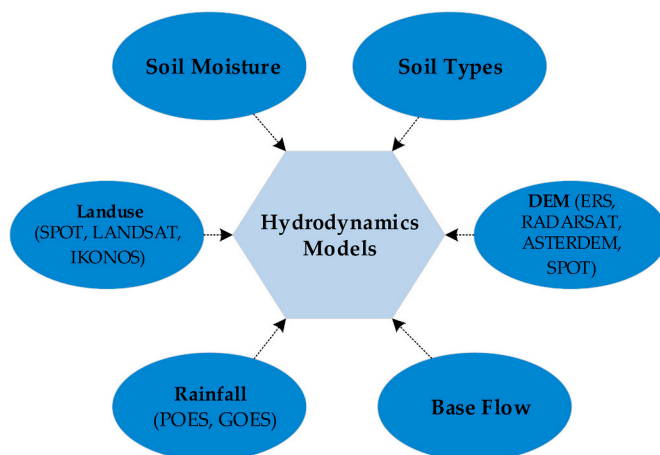

Fig. 4. Hydrodynamics models application.

4.3. Landslide mitigation and management

Landslides are one of the most destructive natural hazards occurring worldwide, particularly in the mountainous regions. The damages from landslides, whether induced through earthquake or rainfall, can have a staggering effect on the peoples' lives and property. Fan et al., 2020 reviewed formation and impact of landslide dams worldwide to evaluate landslide dam stability criteria and geomorphic indices. Marano et al. (2010) reported that about 5% of the fatalities caused during an earthquake event are a direct consequence of the coseismic landslides. In a recent case, about 80% of the total fatalities from the Hokkaido Eastern Iburi earthquake in Japan were caused due to the subsequent landslides (Japan Times, 2018). A similar account can also be noticed for rainfall-induced debris flows. The United States Geological Survey (USGS) reported that, on average, 25–50 people are killed by landslides each year in the United States. This number is considerably larger in several other parts of the world. For instance, between 2004 and 2010,

there were more than 30,000 deaths caused by landslides, and the majority of them are reported in south-western India and eastern Asia (Petley, 2012). The estimates of potential landslide risk in any region are a function of the topography, climate, tectonic events, and occurrence of previous landslides. Such detailed information can be of great value to a wide range of decision-makers. Landslide inventory mapping is the primary step for landslide investigation, mitigation and management. Guzzetti et al. (2012) noted that "*Preparing landslide maps is important to document the extent of landslide phenomena in a region, to investigate the distribution, types, pattern, recurrence and statistics of slope failures, to determine landslide susceptibility, hazard, vulnerability and risk, and to study the evolution of landscapes dominated by mass-wasting processes*". Landslide inventory maps have been made with the help of high resolution aerial and satellite images such as Landsat TM, ETM+, OLI; Sentinel-2, and very recently with the help of Planet data (Fig. 5). The Google Earth platform and the supported images have also helped greatly in the inventory mapping. In forested areas, the LiDAR elevation data have proved to be an useful technique to detect and map landslides

Table 3

Application of remote sensing in environmental assessment and hazard monitoring.

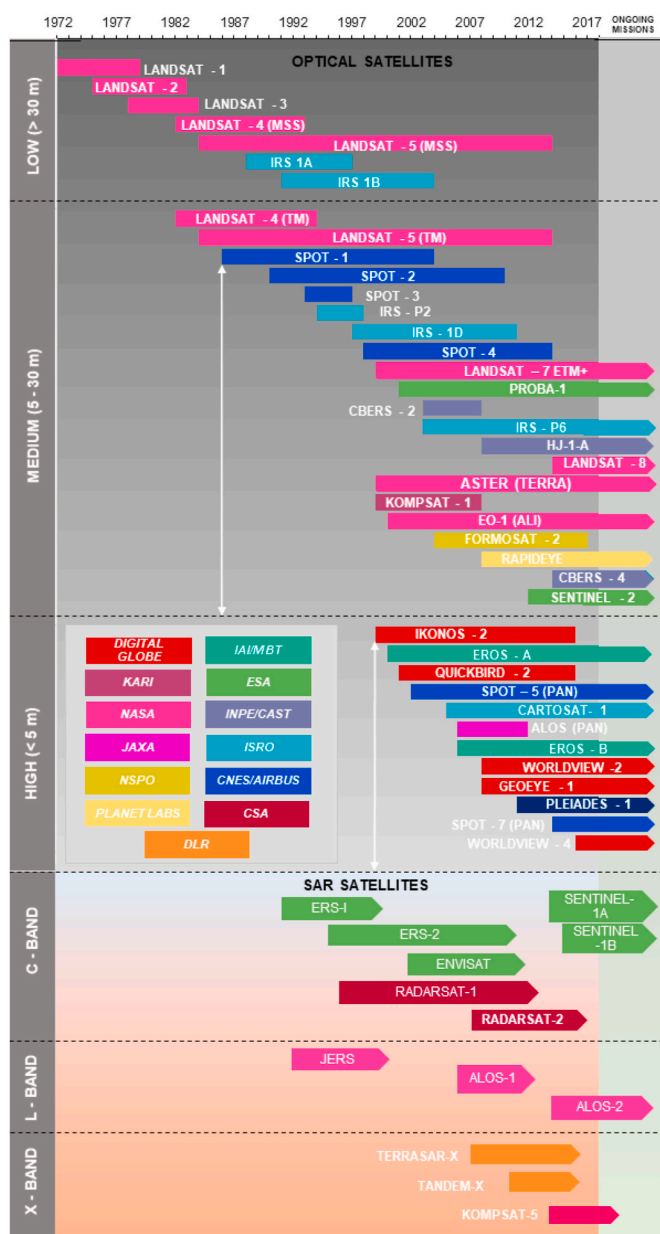| Satellite types	Indicators	Applications
Environmental Assessment		
Landsat ETM Scene merged ASTER/SRTM3-DEM; NASA Global Inventory Monitoring and Modeling Systems (GIMMS)	snow cover extent (SCE); TM4/TM5 ratio image; cloud condensation nuclei (CCN); ice nuclei (IN); AVHRR NDVI dataset from GIMMS; Accumulated growing degree days (AGDD) and Accumulated humidity (ARHUM)	-Impact of climate change on glaciers, snow cover (Bolch, 2007; D. Brown and Robinson, 2011) -Impact of climate change on cropping patterns, land use planning (Nakagawa and Yasuoka, 2001; Ranade, 2007) -Effect of aerosols on the environment at regional and global levels Manktelow et al., 2007) -Measurement of solar radiation (Vignola et al., 2019) -macro-scale impact of climate change (Yang et al., 2013a)
Flooding Hazard Forecasting and Assessment		
InSAR, GPS, visible and near-infrared/thermal infrared (VNIR/TIR) imaging, multi-parameter, Synthetic Aperture Radar, laser altimetry, microwave imaging	Numerical Weather Prediction (NWP) models; hydrodynamic models for catchment geometry, hill-slope angles, measurements of rainfall intensity and duration, and measurements of soil moisture	-Hazard zoning for landslides and torrential floods (Carrasco et al., 2003; Gili et al., 2000; Malet et al., 2002) -Socioeconomic Scenario planning and disaster management through satellite data (CEOS Disaster Management Support and Wood, 2003; Daoud et al., 2016) -Seawater monitoring and impact on coastal areas (Gray et al., 2011; Yan et al., 2013) -Surface and river water discharge forecasting and monitoring (Hirpa et al., 2013; Rossa et al., 2010)
Landslide Mitigation and Management		
Landsat-1; Synthetic Aperture Radar (SAR) sensors; Interferometric Synthetic Aperture Radar (InSAR); Object-Based Image Analysis (OBIA)	Differential and Persistent Scatterer SAR Interferometry (DInSAR and PSI) and Object-Based Image Analysis (OBIA)	-Mapping and monitoring of landslide (Casagli et al., 2016; Guzzetti et al., 2012; Williams et al., 2017) -Earthquake and landslides causality assessment (Marano et al., 2010; Petley, 2012; Singhroy et al., 2002)

Fig. 5. Optical and radar remote sensing satellites used in landslide mapping and mitigation studies.

(Görüm, 2019).

The management and mitigation of landslide-related disasters can be improved with the remote sensing technology. Over the years, many governmental, public, and private agencies benefitted by applying timely and high-quality information derived from remote sensing observations, especially in response to emergencies (Casagli et al., 2016). Previously, there existed difficulties in estimating the landslide risk for various reasons such as non-availability of landslide inventory maps, uncertainty in rainfall projections, and problems associated with transforming a model into reality. The optical remote sensing data of earth resource monitoring became available with the launch of Landsat-1 (Earth Resource Technology Satellite) in the year 1972. Since then, many satellite sensors with advanced capabilities have been launched, and are increasingly used to support, landslide risk management (Fig. 5). The chronological developments in the remote sensing satellites and their classification based on different bands is very important for landslide mapping and the landslide mitigation. The use of remote sensing data from a variety of satellites has become possible because of their multispectral capabilities, high temporal cycle, high spatial resolution, and wide-area coverage (Casagli et al., 2016; Singhroy et al., 2002).

There are certain challenges related to the use of optical satellites in some regions. Although optical satellites are extensively used, the frequent cloud cover over equatorial regions and in the tropics pose a challenge in quick inventory mapping, as optical satellites cannot observe the Earth's surface when clouds are present. In cases where mapping efforts are hampered by widespread cloud cover, satellite-borne Synthetic Aperture Radar (SAR) sensors can be used for landslide detection (Williams et al., 2017). The most commonly used wavelength bands in which SAR operates are L, C, and X that corresponding to ~20, ~5, and ~3 cm, respectively. The SAR polarimetry allows us to separate landslides from those of the surrounding forested areas based on backscattering properties. Nolesini et al. (2016) successfully applied radar images to monitor slopes in mines and highways (transport). Additionally, surface deformations can be detected at millimeter precision using InSAR techniques (Casagli et al., 2016; Guzzetti et al., 2012). RS derived data can be used to support the details of landslide inventories mapping. It can further help in disaster risk management during the emergency response to rapidly assess the extent of landslide damages due to ground motion. Table 3 shows a summary of the studies relevant to landslide management.

4.4. Forest fire

Since the advent of remote sensing, imaging data has become a primary data source for forest fire mapping and monitoring in inaccessible forest regions Xiao-rui et al., 2005. Because of the requirement of high temporal resolution in case of forest fires, the Moderate Resolution Imaging Spectroradiometer (MODIS) data are often a primary choice owing to their daily repetitive coverage and ability to detect fires in remote regions. On the other hand, the risk to forest fire are estimated based on meteorological data or from vegetation indices. The satellite based evapotranspiration rates are a good estimate of fire risk assessment (Vidal et al., 1994). Satellite sensors such as SPOT, Landsat TM, ETM+ and OLI, AVHRR, ERS2, RADARSAT etc. Have been used to map the burned areas, change detection, damage and risk assessment. Yuan et al. (2017) recently presented the applicability of UAV mounted infrared (IR) imaging systems for the automatic detection of fires in forested regions. Vegetation indexes including Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Normalized Burn Ratio (NBR) and Normalized Difference Vegetation Index (NDVIreXn) that implements red edge spectral bands showed high competence in mapping post-fire scenarios (Navarro et al., 2017).

Data mining applications such as convolutional neural network, fuzzy metaheuristic ensembles, genetic algorithms etc. become popular to set optimal combination of forest fire related variables and modeling

forest fire susceptibilities (Hong et al., 2018). In these models, variables of meteorological, topographic and vegetation indexes derived from satellite products are incorporated as factors to obtain the necessary details of soil moisture conditions and evapo-transpiration conditions.

5. Socio-economic development

The remote sensing application has seen an extensive use towards the socio-economic development through specific data retrieval. Hereon, the socio-economic qualities have been discussed including transportation, population estimation and allocation, and quality of life assessment. Remote sensing has a clear place in the future of socioeconomic development studies because it offers greater insights into the manifestations of human activity through high resolution and low-cost data.

5.1. Transportation

Transportation deals with the flow of people and goods between two geographically separated locations. To achieve sustainable growth and development in any country, effective transportation systems are very important. An efficiently flowing transportation system would not only aid in the proficient movement of goods and services but also reduce carbon emissions. It can further encourage local, national, and regional economic integration and enhance sustainable development (Arampatzis et al., 2004). Sustainable transportation is one of the important action agenda of the UN's sustainable development goals (SDG). Various remote sensing technologies can be applied to monitor transportation infrastructure (Hoppe et al., 2016). These technologies hold more promise for the long-term phenomenon by changing the daily practice in the various transportation fields. Despite the challenges (e.g. availability of data, cost, licensing, image-processing software, user conservatism, training, database management, real-time imagery, currency, and communication issues) involved in applying remote sensing data in transportation, much success has been chucked through the usage of these advanced technologies.

In the use of GIS linked sensor technologies for an intelligent transport system, the use of loop detectors and road tubes, are being increasingly operationalized as road sensors (Guerrero-Ibáñez et al., 2018). The remote sensing from space and air offers the potential for wide-area coverage, synoptic views, rapid deployment, and flexible maneuverability (McCord et al., 2003). The use of remote sensing in the transport sector allows the synoptic observation and analysis of urban growth while providing a greater understanding of changes in land use and land cover. The use of high spatial resolution imageries such as *Quickbird* and *GeoEye* makes it possible to have a clearer picture of the impact transportation poses to the environment (Hester et al., 2008). Various case studies have been presented on the success chucked due to the use of remote sensing technologies. For instance, panchromatic 1m imagery obtained from sensors carried on the IKONOS satellite was utilized in the year 2000 by a transportation company to quantify truck traffic on I-25 near Denver, Colorado, with special emphasis on long trucks (Anderson and Young, 2001). The long trucks (>60 ft) served as an indicator of interstate truck traffic, providing a piece of information that is not readily available from other sources.

The aerial photographs have been used to study traffic congestion on freeways and major arterials in the metropolitan area of Phoenix, Arizona for transportation planning and management (Center, 1999). This was done through the collection of aerial photographs of peak-period traffic congestion from a fixed-wing aircraft for different locations and time intervals. This study can be useful to estimate the delay at the intersection. On freeways, vehicle densities were determined directly from the aerial photographs for well-defined segments. Different classes of vehicles (passenger cars, trucks, tractor-trailers, and buses) were considered, and passenger-car equivalent factors were applied to determine a density measure of passenger cars per lane per mile. The

density value generated was then used with the Highway Capacity Manual (by the Transport Research Board of the U.S.A) to determine the freeway level of service (Council, 2000). This led to the conduction of separate studies of the general-purpose lanes and the high-occupancy-vehicle lanes. It shows the potential use of aerial photography. Vehicle velocities are also among the flow-related parameters of most interest to transportation planners, engineers, enforcement agencies, and policymakers. Ground-based sensors have been used to estimate vehicle velocities at locations on a highway during a time interval from airborne imagery. The ground cameras and a GPS-equipped floating car were used to produce ground-based velocity estimates of moving vehicles by determining the number of other flow parameters (Angel et al., 2002; Angel and Hickman, 2002).

Commercially available remote sensing technologies such as SAR data acquired from the Italian COSMO-SkyMed satellite have been used to monitor the feasibility of transportation networks in the City of Staunton. The SAR is known to provide millimeter-level surface displacement by measuring small changes in phase angle of the return signal (Hoppe et al., 2016) through the usage of InSAR technique. InSAR has become a standard tool for remote sensing-based displacement measurements (Fletcher et al., 2007). The principle behind the usage of the InSAR is the acquisition and processing of phase shift information obtained from a series of complex SAR images. In this case, every pixel element from each image is processed and the elevation at its centroid is established based on signal phase response and the satellite altitude information (Rosen et al., 2000).

The availability and use of the InSAR technology for millimeter-scale remote sensing of deformation offers potential new opportunities for effective implementation in transportation monitoring and geohazard assessment. Besides, the level of accuracy generated through its usage increases with the number of frame acquisitions, as random atmospheric errors become progressively minimized (Hoppe et al., 2016). Another study conducted by Zhou and Wei (2008) explored the use of remote sensing in transportation (pavement construction, operations, planning, and analysis). The high-resolution satellite imagery (e.g., IKONOS) was used to monitor pavement construction and evaluate management in some parts of the USA. The use of satellite images has been found useful to observe/monitor the road condition, such as loss of oily components, pavement condition deterioration, exposing the rocky components of the pavement, structural damages like cracking etc. (Zhou and Wei, 2008).

Ayalew et al. (2003) identified spatial and spectral requirements for successful large-scale road feature extraction, and further examined the benefits of using hyper-spectral imaging over traditional methods of roadway maintenance and rehabilitation for pavement management applications. Spagnolini and Rampa (1999) used the monostatic ground penetrating radar (GPR) for pavement profiling, such as layer thickness whilst Guo et al. (2007) developed an algorithm for suburban road segmentation in high-resolution aerial images. The research has demonstrated that information acquired from the interpretation of satellite imagery can play a significant role in the planning, management, and implementation of highway maintenance or rehabilitation (Zhou and Wei, 2008).

Vehicle detection through the use of high-resolution optical imagery is of great significance because of its wide applications in transportation control, road verification, visual surveillance, traffic safety, etc. (Yu and Shi, 2015). They deployed a new methodological approach that involves the transformation of a panchromatic image to a "fake" hyperspectral form to aid in vehicle detection. Over the past two decades, different approaches have been employed for vehicle detection in remote sensing. These approaches mainly fall into two categories. First, the statistics-based methods which involve algorithms such as PCA. Second, the Bayesian model as well as threshold segment methods (Sharma et al., 2006) and feature-based methods such as histogram of oriented gradients, local binary patterns, Haar-like features, etc. (Grabner et al., 2008). For example, Leitloff et al. (2010) developed a sophisticated model for

typical traffic situations in urban areas. Table 4 shows summary of the studies relevant to applications of remote sensing in transportation.

5.2. Population estimation and allocation

An important aspect of sustainable development is the understanding of the dynamics of the population within a community and across national boundaries. This information assists in resource sharing and allocation, environmental impact and risk assessment, industrialization, and socio-economic development. The population also plays a substantial role in our ability to measure the extent of human influence on the environment. Demographic data is measurable and quantifiable, which lends itself to applications in remote sensing. From an economic perspective, the population is one of the determinants of demand. An increase in the population invariably increases the aggregate demand within a country. There are a few ways to go about using remote sensing techniques to count the population. Jensen and Cowen (1999) showed that high-resolution satellite imagery is capable of identifying housing

Table 4

Application of remote sensing in socio-economic development.

Satellite types	Indicators	Applications
Transportation		
IKONOS; InSAR time series; SAR interferometry; Envisat; RADARSAT	Single and two ellipse methods; CORINAIR methodology; Doppler centroid values; high radar cross-section (RCS); signal-to-clutter ratio (SCR)	-Traffic flow pattern and management, travel time estimation (Anderson and Young, 2001; Angel et al., 2002; Fletcher et al., 2007; Grabner et al., 2008; Hoppe et al., 2016; McCord et al., 2003; Sharma et al., 2006) -Decision support system for urban transportation policies (Arampatzis et al., 2004; Ayalew et al., 2003; Center, 1999; Council, 2000; Guo et al., 2007; Leitloff et al., 2010; Spagnolini and Rampa, 1999; Zhou and Wei, 2008) -Advanced technologies for intelligent transport system (Hester et al., 2008; Rosen et al., 2000; Yu and Shi, 2015)
Population Estimation and Allocation		
IKONOS; Landsat ETM+	Combining satellite imageries with census data and inclusion of textures, temperatures, and spectral responses	-measurement of socio-economic patterns like population density, infrastructure, the cover of land use land change, etc. (Jensen and Cowen, 1999; Li and Weng, 2005; Liu et al., 2006; Meyer and Turner, 1992)
Quality of Life		
Landsat; Ikonos; AVIRIS	Ground Instantaneous Field of View (GIFOV)	-Measuring quality of life through parameters like poverty and risks to natural hazards in the habitations (Hall et al., 2008; Lo and Faber, 1997; Rogers et al., 2006) -Inferences about life expectancy based on spatial information (Tsimbos et al., 2011) -Exploratory analysis of land use land cover through population density (Pozzi and Small, 2001)

structures and differentiating duplex, triplex, and condominium units. This development lends itself to the method of image classification wherein housing structures are identified though accurate results yet can be impeded by tree cover and hence the necessity to differentiate housing structures from other classifications such as industrial or commercial structures.

On the other hand, Liu et al. (2006) compared data obtained from IKONOS satellite imagery against population census data. They found that high-resolution satellite images do not correlate strongly enough with the population data to serve as a proxy for population data. They also only found a weak correlation between landscape textures and population density. As census data is already being collected through surveying methods on the ground, there is less necessity for remote sensing applications in population estimation. There is a clear distinction in the literature between allocation and estimation. Despite the prevalence of population census data, this type of information does not give significant insight into how these people are spatially arranged. The population has been recognized as an indirect driver of land-use change though its effect cannot be explicitly stated (Meyer and Turner, 1992). Shi et al. (2014) evaluated the role of nighttime light data in the estimation of Gross Domestic Product and electricity consumption in China. Sutton et al. (1997) noticed a strong relationship between the nighttime light data and population density in the United States.

An increasing population density has been observed concurrently with swelling land-use change and diminishing forest cover (White et al., 2012). Most studies refer to the lack of accurately sensed data being one of the main obstacles to pinpointing the direct effect of population on land-use change. There are various methods of going about population allocation modeling. In the point-based model, scientists often implement density functions in their modeling of how the population of a city is spatially constructed. It functions on the principle that people tend to cluster, and in the model, the population density is greatest at the center and tends to disperse as we move farther away from the point. Li and Weng (2005) combined Landsat ETM + imagery with census data to estimate the population density of Indianapolis, Indiana. They found that remote sensing-based models that stratified the population according to density levels increased the accuracy of the model. They cited the issue that the census data is of a lower resolution than the remotely sensed data. They also found that the inclusion of textures, temperatures, and spectral responses greatly increased the accuracy of estimation.

The remotely sensed data must be combined with *in-situ* data to ensure accuracy. However, literature seems to agree that, measurements of population density using remote sensing have not been carried out consistently due to the large degree of variation between communities. More technologically developed countries can remotely sense population allocations. Japan, for example, has access to positioning data obtained from smartphones. This knowledge was applied when the 2011 Tohoku Earthquake struck, providing insight as to where the highest concentrations of people were in real-time in the midst of the disaster. However, the use of this type of remotely sensed data has raised a lot of concerns if it is to be used in the field of research because for many people it represents a privacy breach. Table 4 shows a summary of the studies relevant to applications of remote sensing in population estimation and allocation.

5.3. Quality of life

Although it does not have a precise definition, quality of life refers to the general well-being within a country or a region. Since many factors are believed to exert an impact on it, there are limits to which quality of life can be quantified. Still, attempts have been made by several studies to measure it to some extent. The Standard of living is not to be used interchangeably with quality of life, as the former is a subset of quality of life and refers specifically to the level of wealth and income statistics. Other aspects of quality of life include the quality and availability of water, housing, environmental quality, health care, safety, and energy consumption. In some cases, the climatic or atmospheric temperature may play an important role in determining the quality of life as they exert an effect on the surrounding environment. Remote sensing has found some success in wealth and poverty mapping. However, it is difficult to derive precise estimates of income distribution. Hall et al. (2008) used infant mortality rates as a dummy variable for poverty. They endeavored to create a map showing the relationship between natural hazards and environmental vulnerability against poverty rates. One of the issues that they experienced is that poverty occurs for different reasons, so the true causes and definition of poverty must be properly identified, and it is likely that they differ from place-to-place.

Extending the studies on poverty, in recent years, scientists have seen the need to shift away from a static poverty mapping model and move towards a more dynamic one. Rogers et al. (2006) mapped poverty in Uganda under the assumption that poverty is a function determined by environmental conditions, agricultural activities, human and animal disease, natural resource availability in tandem with household survey information. There have been attempts to connect demographic data such as life expectancy to the spatial area. A study by Tsimbos et al. (2011) measured the spatial characteristics of life expectancy in Greece by creating a spatially weighted matrix to compare regional patterns of life expectancy. Although there is some evidence that about the spatial trend as shown by high levels of contiguity in three clusters: the Peloponnesian region, the islands of the Dodecanese and Crete. This study was not conclusive, yet it highlights one of the main issues of socio-economic applications of remote sensing. Still, accurately attributing a precise number of people to a small spatial designation has been observed consistently and needs further investigation.

In some literature, environmental quality has been used interchangeably with the quality of life. This refers to the perception of the quality of the natural environment is integrated into the human environment such that the human population actively interacts with and perceives. Lo and Faber (1997) were able to show that there is a linkage between income, population density, and forest amenities measured by leaf area. They found that higher levels of greenness were positively correlated with income and median home data and negatively correlated with population density. Pozzi and Small (2001) suggested that using greenness to determine levels of affluence can lead to ambiguous results because greenness can be indicative of either high or low levels of affluence. At this point, they agree that the stratification between urban, rural, and suburban locals greatly increases the accuracy of results.

6. Satellite-derived indices in sustainable development

Over time, a wide variety of spectral indices have been developed with the help of remote sensing products to effectively map and monitor the resources and hazards (Ban et al., 2017; Wang and Qu, 2007). Utilizing spectral indices and spectral transformation methods are prominently used in agriculture, the response of changing environmental conditions, water (flooding), soil moisture and in various other fields of sustainable management of resources and hazard monitoring fields (Ban et al., 2017; Rouse et al., 1974; Van Westen, 2000; Xiao et al., 2004). These spectral transformation methods are very effective for the interpretation and analysis of phenomena and processes related to the dynamics of change of the main components of the Earth surface. Table 5 illustrates the list of the major spectral indices developed over the last few decades from various remote sensing products that are applied in the field of sustainable development. There were several publications in the development of new indices before the year 2000 and most of these indices have a high citation (>1000). However, these indices mainly focus on vegetation properties as compared to water and soil (Table 5). The number of published papers and the development of new indies is less after the year 2000 with less citation (<1000). The development of new indices of water and soil is also good in proportion to vegetation after the year 2000 (Table 5). These indices have been extensively used

Table 5
Major spectral indices developed using remote sensing data for applications in sustainable development.

Sl No.	Indices	Application	Author(s) [Reference]	Publication Year	Citations
1.	Normalized difference water index (NDWI)	Water	McFeeters, 1996 (McFeeters, 1996)	1966	3056
2.	Ratio Vegetation Index (RVI)	Vegetation	Jordan 1969 (Jordan, 1969)	1969	1935
3.	Leaf Area Index (LAI)	Vegetation, Forestry	Jordan et al., 1969 (Jordan, 1969)	1969	1934
4.	Normalized Difference Vegetation Index (NDVI)	Vegetation, Forestry, Agriculture	Rouse et al. 1974 (Rouse et al., 1974)	1974	7179
5.	Difference Vegetation Index (DVI)	Vegetation	Richardson et al., 1977 (Richardson and Wiegand, 1977)	1977	1628
6.	Perpendicular Vegetation Index (PVI)	Vegetation	Richardson and Wiegand 1977 (Richardson and Wiegand, 1977)	1977	1613
7.	Tasseled Cap	Soil, Water, Vegetation	Kauth et al., 1976 (Kauth and Thomas, 1976)	1976	2069
8.	Soil-Adjusted Vegetation Index (SAVI)	Soil, Agriculture, Vegetation, Forestry	Huete, 1988 (Huete et al., 1997)	1988	5510
9.	Enhanced Vegetation Index (EVI)	Vegetation, Forestry	Liu and Huete, 1998 (H. Q. Liu and Huete, 1995)	1988	754
10.	Moisture stress Index (MSI)	Vegetation	Hunt Jr and Rock 1989 (Hunt Jr and Rock, 1989)	1989	1029
11.	Transformed Soil adjusted vegetation index (TSAVI)	Soil, Vegetation	Baret et al., 1989 (Baret et al., 1989)	1989	553
12.	physiological reflectance index (PRI)	Vegetation	Gamon et al., 1992 (Gamon et al., 1992)	1992	1730
13.	Atmospherically Resistant Vegetation Index (ARVI)	Vegetation, Agriculture,	Kaufman and Tanre, 1992 (Kaufman and Tanre, 1992)	1992	1134
14.	photochemical reflectance index (PRI)	Vegetation in coniferous forest	Gamon et al. 1992 (Gamon et al., 1992) {1006}	1992	1006
15.	Global environment monitoring index (GEMI)	Vegetation	Pinty & Verstraete 1992 (Pinty and Verstraete, 1992)	1992	681
16.	Normalized Difference Index (NDI)	Vegetation	McNairn and Protz 1993 (McNairn and Protz, 1993)	1993	152
17.	Modified Soil adjusted vegetation index (MSAVI)	Soil, Vegetation	Qi et al., 1994 (Qi et al., 1994)	1994	2059
18.	Chlorophyll index (CI)	Chlorophyll content	Gitelson and Merzlyak 1994 (Gitelson and Merzlyak, 1994)	1994	899
19.	Chlorophyll Absorption Ratio Index (CARI)	Agriculture	Kim et al. 1994 (M. S. Kim et al., 1994)	1994	228
20.	Normalized Difference Moisture Index (NDSI)	Snow	Hall et al., 1995 (Hall et al., 1995)	1995	1126
21.	Optimized soil-adjusted vegetation indices (OSAVI)	Soil, Vegetation	Rondeaux et al., 1996 (Rondeaux et al., 1996)	1996	1558
22.	Green atmospherically resistant vegetation index (GARI)	Vegetation	Gitelson et al., 1996 (Gitelson et al., 1996)	1996	1519
23.	Green-Normalized difference vegetation index (GNDVI)	Vegetation	Gitelson et al., 1996 (Gitelson et al., 1996)	1996	1519
24.	Modified Simple Ratio (MSR)	Vegetation	Chen 1996 (Chen, 1996)	1996	601
25.	Soil and Atmosphere Resistant Vegetation Index (SARVI2)	Vegetation	Huete et al. 1997 (Huete et al., 1997)	1997	1514
26.	Modified Chlorophyll Absorption in Reflectance Index (MCARI)	Vegetation	Daughtry et al., 2000 (Daughtry et al., 2000)	2000	1702
27.	Specific Leaf Area Vegetation Index (SLAW)	Vegetation	Lymburner et al., 2000 (Lymburner et al., 2000)	2000	124
28.	Anth reflectance Index (ARI)	Anthocyanin spectral features of leaves	Gitelson et al., 2001 (Gitelson et al., 2001)	2001	631
29.	Aerosol free Vegetation Index (AFRI)	Vegetation	Karnieli et al., 2001 (Karnieli et al., 2001)	2001	184
30.	Global Vegetation Moisture Index (GVMI)	Vegetation moisture	Ceccato et al., 2002 (Ceccato et al., 2002)	2002	601
31.	Transformed difference vegetation index (TDVI)	Vegetation	Bannari et al., 2002 (Bannari et al., 2002)	2002	67
32.	shortwave infrared water stress index (SIWSI)	Soil moisture	Fensholt and Sandholt 2003 (Fensholt and Sandholt, 2003)	2003	388
33.	Normalized Difference Built-up index	Built-up area	Zha et al., 2003 (Zha et al., 2003)	2003	1219
34.	Wide Dynamic Range Vegetation Index (WDRVI)	Vegetation	Gitelson, A. (2004) (Gitelson, 2004)	2004	690
35.	Normalized Difference Moisture Index (NDMI)	Soil, Water	Xiao et al. 2004 (Xiao et al., 2004)	2004	607
36.	Radar Vegetation Index (RVI)	Vegetation, Forestry	Kim and Zyl 2004 (Y. Kim and Zyl, 2004)	2004	180
37.	Modified normalized difference water index (MNDWI)	Water	Xu, 2006 (Xu, 2006)	2006	514
38.	Normalized Multi-band Drought Index (NMDI)	Soil and vegetation moisture	Wang and Qu 2007 (Wang and Qu, 2007)	2007	230
39.	Enhanced Vegetation Index-2 (EVI2)	Vegetation	Jiang et al., 2008 (Jiang et al., 2008)	2008	991
40.	Triangular Chlorophyll Index (TCI)	Vegetation	Haboudane et al., 2008 (Haboudane et al., 2008)	2008	216
41.	Crop Water Stress Index (CWSI)	Agriculture	Berni et al. 2009 (Berni et al., 2009)	2009	267
42.	Anthocyanin reflectance index (ARI)	Vegetation	Gitelson et al., 2009 (Gitelson et al., 2009)	2009	113
43.	Canopy chlorophyll content index (CCCI)	Vegetation	El-Shikha et al., 2009 (El-Shikha et al., 2008)	2009	47
44.	Greeen-Red NDVI (GRNDVI)	Vegetation	Glenn et al., 2010 (Glenn et al., 2010)	2010	163
45.	Enhanced Built-Up and Bareness Index (EBBI)	Built-up and bareland	As-syakur et al., 2012 (As-syakur et al., 2012)	2012	166
46.	Automated water extraction index (AWEI)	Water	Feyisa et al. 2014 (Feyisa et al., 2014)	2014	592
47.	Water Index (WI)	Water	Fisher et al. 2016 (Fisher et al., 2016)	2016	141

for various research categories as mentioned in section 3, 4 and 5. The popularity of the use of Indices in remote sensing is high mainly because it's simple and easy to use with multiple satellite data and it can provide quick information about a phenomenon or object.

It can be seen from Table 5 that most of the indices applied in sustainable developmental studies were developed a long time ago when the sensor radiometric resolution and spatial resolution was lower than the present ones. Despite that, these indices performed well such as NDVI, EVI, and LAI, etc. Today a large number of satellites orbiting outer space today with a narrower range of radiometric resolution. It provides an improved spatial resolution and increased availability of SAR data in multiple frequencies. However, lesser attempts have been made for developing new spectral indices capable of retrieving more accurate information from remote sensing products. Therefore, there is a need to

explore new indices for continued development in attaining sustainable development through remote sensing techniques. The newly developed indices can derive better information about an object or area from the latest sensors to improve Earth's monitoring.

7. Research challenges

- The biggest challenges associated with the remote sensing itself is the availability and distribution of data. Lack of freely available high-resolution remote sensing data makes the remote sensing research community debilitated despite the fact that advanced remote sensing tools have become available for processing and analyzing the data. In cases, where the high-resolution data is available commercially, their cost is not affordable to many researchers, especially those from economically weaker countries.
- Lack of effective national spatial data infrastructures (SDI) in developing countries prevent access to data and information for analysis and validation.
- Due to the inherent shortcomings of remote sensing devices in measuring the underground conditions directly, inferential methods are sometimes adopted, however, such methods suffer from limited accuracy in many cases, especially in groundwater exploration.
- Mapping of lake bodies in glaciated areas using various indices are still difficult because of the similar behavior of reflectance from adjoining areas.
- Since turbidity varies largely between the aquatic systems, generic algorithms for water quality mapping introduces error value of more than 10% in low to moderately turbid waters. The error in highly turbid water is much more.
- Use of hyperspectral data for mineral mapping has high potential, however the availability of hyperspectral sensor data is limited.
- Mapping of surface mineralogy with remote sensing under forest canopy in tropical rainforests region of the world remains difficult.
- Although there are advanced algorithms for mapping snow cover, remote sensing of snow can be extremely difficult due to mixed pixels arising from cloud cover.
- Availability of clouds free satellite data during the event of floods is still challenging in tropical region. High-temporal resolution SAR remote sensing is the viable solution.
- Apart from mapping the flood extent and water depths, derivation of flood water characteristics such as flow velocity, sediments load, warning time and awareness, winds and duration of inundation from the integration of satellites imageries and hydraulic model are difficult due to their heterogeinities both in space and time (Merz et al., 2010).
- More accurate and open-access precipitation, discharge, boundary data and topography at the global level are needed to increase dependability of flood hazard modeling.
- Lack of ground data for validation in data scarce regions often affect the reliability of satellite-based rainfall data.
- Satellites that currently employ rainfall measurements are available only at coarser resolution, which limits the rainfall threshold – landslide initiation mapping in the ungauged catchments.
- Separating the landslide initiation and deposition areas are challenging even with 3 m resolution Planet images (Wang et al., 2019).
- Estimation of income distribution from remote sensing data still remain a challenge in understanding the quality of life.
- Population estimation using remote sensing data without ground measurement remain a difficult task.
- Sustainable transportation mapping and analysis in developing countries is greatly affected by the availability, cost, licensing and access to high resolution real-time imageries and image processing software.
- Effective communication between remote sensing experts and decision makers on the effective use of remote sensing for human welfare issues is lacking in most developing countries.

8. Conclusions

This paper reviewed how RS technologies have been used to support several aspects of sustainable development, including (1) natural resource monitoring, development, and management; (2) environmental assessments and hazard monitoring; and (3) socioeconomic development. RS has several advantages, including the ability to provide global-scale coverage, high-resolution data, and multi spatio-temporal coverage with optical, SAR, thermal and LiDAR sensors. It provides large volume of data and recent development in ML algorithms can handle large volume of geospatial data to extract beneficial information. Here, we discussed the use of RS for sustaining the Earth and human life. With the development of new and improved satellite and airborne sensors, data with increasingly higher spatial, spectral, and/or temporal resolution will become available for researchers, governments private agencies, and policymakers, thus facilitating planning and decision-making in many areas of sustainable development. Accordingly, the United Nations highlighted RS as an indispensable tool for achieving its Sustainable Development Goals (SDGs). RS can be used not only to develop comprehensive policies promoting sustainable development, but also for effective implementation, monitoring, and decision-making. However, for RS to be effective and reliable, adequate information has to be obtained from other sources. In particular, the development of new spectral indices based on improved sensor technology is key for achieving sustainable development goals.

Spatial data from RS and other sources can be integrated using GIS, among other spatial-integration tools, to analyze global environmental processes and change. During the COVID-19 global crisis, the contribution of remote sensing data has been widely discussed in a wide variety of applications including monitoring water and air pollution, management of the threat, monitoring traffic patterns, measuring human and economic activities, and socio-economic restriction. Several new studies and applications of remote sensing are emerged during the pandemic and are becoming significant case studies for sustainability applications.

For developing countries, however, obtaining RS data for research and development purposes is difficult; thus, it is not efficient to use RS technology to support sustainable development in such countries. As counters strive to achieve the SDGs, more data acquisition platforms should be created and made available to researchers in developing nations to enable them to actively use RS data to support national, regional, and global sustainable development. RS techniques are still not widely employed in developing countries, which are more vulnerable to natural hazards. There may also be conflicts of interests in terms of security and privacy between governments and other entities associated with RS use. Additional collaborations between policy think tanks, decision-making bodies in developing countries, and countries or organizations with ready access to GIS resources are needed.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Appendix

Table A 1
Queries run on the Scopus Database for ten broad classifications of the literature survey.

Sl. No.	Query Details	Query String
1.	Biodiversity	((TITLE-ABS-KEY(Biodiversity) AND TITLE-ABS-KEYv(remote sensing)) AND (LIMIT-TO (DOCTYPE,"re")))
2.	Groundwater	((TITLE-ABS-KEY (Groundwater) AND TITLE-ABS-KEY (remote sensing)) AND (LIMIT-TO (DOCTYPE,"re")))
3.	Mineral Resources	((TITLE-ABS-KEY (Mineral Resources) OR TITLE-ABS-KEY (Mineral Exploration) OR TITLE-ABS-KEY (Mineral Resources Exploration) AND TITLE-ABS-KEY (remote sensing)) AND (LIMIT-TO (DOCTYPE,"re")))
4.	Environmental Assessment	((TITLE-ABS-KEY (Environmental Assessment) AND TITLE-ABS-KEY (remote sensing)) AND (LIMIT-TO (DOCTYPE,"re")))
5.	Flood Hazard Forecasting and Assessment	((TITLE-ABS-KEY(Flood Hazard Forecasting) OR TITLE-ABS-KEY(Flood Hazard Assessment) OR TITLE-ABS-KEY(Flood Forecasting) OR TITLE-ABS-KEY(Flood Assessment) AND TITLE-ABS-KEY (remote sensing)) AND (LIMIT-TO (DOCTYPE,"re")))
6.	Landslide mitigation and management	((TITLE-ABS-KEY (Landslide mitigation and management) OR TITLE-ABS-KEY (Landslide mitigation) OR TITLE-ABS-KEY (Landslide management) OR TITLE-ABS-KEY(Landslide) AND TITLE-ABS-KEY (remote sensing)) AND (LIMIT-TO (DOCTYPE,"re")))
7.	Transportation	((TITLE-ABS-KEY (Transportation) AND TITLE-ABS-KEY (remote sensing)) AND (LIMIT-TO (DOCTYPE,"re")))
8.	Population	((TITLE-ABS-KEY(Population) OR TITLE-ABS-KEY (Population Estimation) OR TITLE-ABS-KEY (Population Allocation) AND TITLE-ABS-KEY (remote sensing)) AND (LIMIT-TO (DOCTYPE,"re")))
9.	Quality of life	((TITLE-ABS-KEY (Quality of Life) AND TITLE-ABS-KEY (remote sensing)) AND (LIMIT-TO (DOCTYPE,"re")))

Source: Authors Scopus Database search between January 1, 2001 to May 15, 2020

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2020.100402.

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