review

Utilizing Geospatial Information to Implement SDGs and Monitor their Progress

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Abstract: It is more than four years since the 2030 agenda for sustainable development was adopted by the United Nations and its member states in September 2015. Several efforts are being made by member countries to contribute towards achieving the 17 Sustainable Development Goals (SDGs). The progress which had been made over time in achieving SDGs can be monitored by measuring a set of quantifiable indicators for each of the goals. It has been seen that geospatial information plays a significant role in measuring some of the targets, hence it is relevant in the implementation of SDGs and monitoring of their progress. Synoptic view and repetitive coverage of the Earth's features and phenomenon by different satellites is a powerful and propitious technological advancement. The paper reviews robustness of Earth Observation data for continuous planning, monitoring and evaluation of SDGs. The scientific world has made commendable progress by providing geospatial data at various spatial, spectral, radiometric and temporal resolutions enabling usage of the data for various applications. This paper also reviews the application of big data from earth observation and citizen science data to implement SDGs with a multi-disciplinary approach. It covers literature from various academic landscapes utilizing geospatial data for mapping, monitoring, and evaluating earth's features and phenomena as it establishes the basis of its utilization for the achievement of the SDGs.

Keywords: sustainable development goals, geospatial data and techniques, geographic information system, remote sensing, and indicators

1. Introduction

The Sustainable Development Goals (SDGs) are a universal call for action to end poverty, hunger, protect the planet, and ensure that all people enjoy peace (United Nations & Nations, 2015). The success of the Millennium Development Goals (MDGs) has encouraged us to achieve 2030's Agenda for 17 SDGs which lead the world to prosperity and sustainability. To monitor the progress for each goal, a set of quantifiable indicators, targets, and observable data specific to each goal has been devised (Tomás, Svatava, & Bedrich, 2016). This requires systematic data observations at the local community level and subsequent decisions, which include the collaboration of various stakeholders. The United Nations has highlighted issues of data quality and data collection abilities to optimally measure various indicators and has emphasized the need for a Data Revolution to enhance the data quality (Kharas, Homi. Gerlach, Karina. Elgin-Cossart, 2013). Geospatial data is one of the most promising data sources. It can be applied for monitoring progress in achieving the SDGs. The role of big data in analyzing SDG indicators has been discussed by MacFeely (2019). It has been pointed out that conventional data sources are not sufficient. Therefore, the possibility of using big data for SDG monitoring has been studied. This paper presents the issues and challenges in compiling SDG indicators. A review of methods for translating SDG interconnected goals into a policy action has been given by Breuer, Janetschek, & Malerba (2019). Here, the existing framework for the conceptualization of SDGs and the interconnections among the 17 goals is presented. Also, the advantages and limitations of several used frameworks have been studied. A study by Allen, Metternicht, & Wiedmann (2019) presented a novel integrated method to prioritize SDG targets through study cases from 22 countries in the Arab region. A multi-attribute decision method has been adopted for the study basing on the level of urgency, systemic impact, and policy gap.

The earth observation data gathers information about the physical, chemical, and biological systems of the planet that can be detected via remote-sensing technologies which are useful in achieving the SDGs (Masó, Serral, Domingo-Marimon, & Zabala, 2019). Moreover, *in-situ* sensors can be installed to measure these variables at the local scale with a higher frequency. There are numerous satellite sensors, each with particular characteristics, which are essential tools in monitoring and visualizing local and global level changes (various satellite sensors and their characteristics are given in Annexure 1). The RS and Geographic Information Systems (GIS) techniques utilize satellite data that provides a synoptic view with global and local coverage at various spatial resolutions. These approaches, in addition to field surveying data, can also be used to monitor the impact of climate change on different components of aquatic and terrestrial ecosystems (Avtar, Takeuchi, & Sawada, 2013). The study by Koch & Krellenberg (2018) pointed out the targets for SDGs which need to be translated into a national context. SDG indicators and monitoring systems need to be altered depending on the national context.

Geospatial data and techniques can be used very effectively for monitoring most of the SDGs. Furthermore, the scientific results provided through the use of geospatial technologies can provide a strong basis for policymaking to promote sustainable development in communities at local and regional levels (United Nations Secretary, 2016). For example, the visualization of indices generated from census data may indicate the spatiotemporal changes in poverty (SDG 1: end poverty). Similarly, visualization of schools, literacy, green space in cities, usage of natural resources, GHGs emissions over product life cycle, cases registered against violence, and many more likewise would help communities in the preliminary survey thereby to take concrete actions to achieve SDG 1, SDG 4, SDG 11, SDG 12, and SDG 16, respectively within the stipulated time frame. The impact of climate change can be witnessed in all the sectors from health to the terrestrial ecosystem. The recent GIS technologies utilizing spatial statistics for analyzing spatial distributions and patterns can be used for controlling diseases by monitoring water quality and sanitation for different areas (SDG 3, SDG 6 and SDG 14). Geospatial data and techniques can be used very effectively for monitoring most of the SDGs, but in some SDGs, it can be used as proxy data. However, the use of geospatial data is arguably not yet plausible for all SDGs. The selected SDGs and use of geospatial data and techniques to generate relevant data for monitoring the progress of various indicators of the goals is illustrated in Figure 1. Figure 1 also shows the various RS and GIS based methods for implementing SDGs. In this paper, we focus on the following goals: SDG 1: no poverty, SDG 2: no hunger, SDG 3: good health, SDG 6: clean water and sanitation, SDG 11: sustainable cities and communities, SDG 13: protect the planet, SDG 14: life below water, and SDG 15: life on land.

This paper provides a systematic review of the scientific literature concerning the use of geospatial data for achieving the SDGs. Specifically, this paper highlights: (i) the various SDG indicators, (ii) which indicators can be monitored using geospatial data and their progress, (iii) how to improve the monitoring techniques with advanced sensors, citizen science, and big data.

Figure 1. Utilization of geospatial data for SDGs (Modified from: Sustainable Development Knowledge Platform)

2. Methodology

For this review paper, the following keywords were used in Google Scholar to gather relevant papers from 2015 - 2019: "Sustainable Development Goals"; "remote sensing AND SDGs"; "remote sensing AND GIS AND SDGs"; "geospatial data AND SDGs"; "monitoring SDGs"; and "monitoring the progress of SDGs". These keywords displayed various literature depending on various factors such as exact keywords (put in double quotes), search period (anytime and since 2015), Boolean operators used (AND, OR, NOT), etc. as summarized in figure 2. Figure 2 shows the flowchart of literature review to develop this review paper on the use of remote sensing techniques for SDGs' implementation.

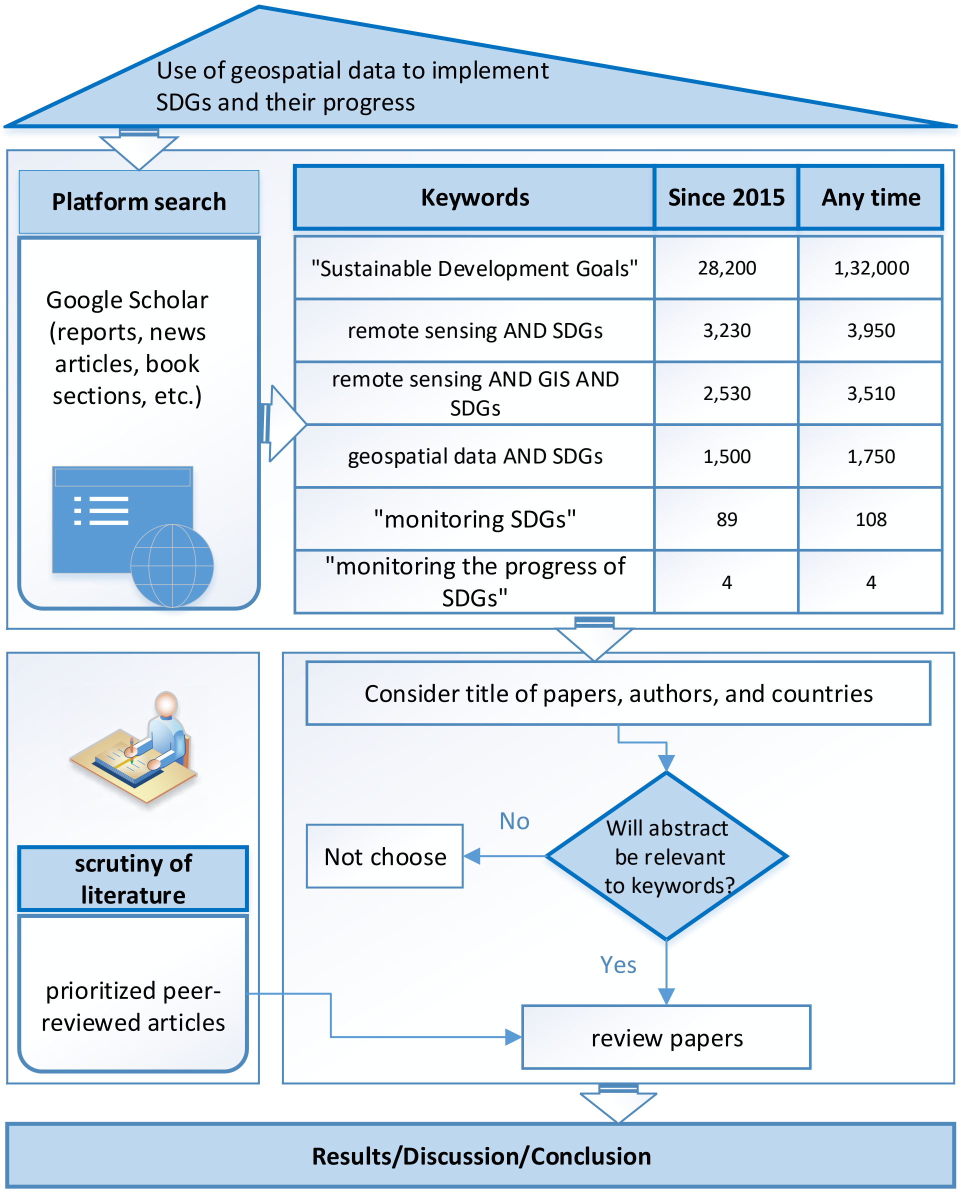

Figure 2. Flowchart of review paper on application of remote sensing techniques to implement SDGs.

Resulting literature was scrutinized in two phases. In the first phase, only abstracts with relevant keywords were examined to determine whether to choose the paper for further analysis or not. To reduce the biases, the first selection was based on the title of the paper with the pertinent keywords regardless of the authors' names and countries. We prioritized peer-reviewed articles in the first phase of scrutiny. During the second phase of literature scrutiny, reports, news' articles, book sections, etc. were also included. A critical appraisal of the selected papers through the second phase of scrutiny was carried out.

3. Geospatial data for Sustainable Development Goals (SDGs)

3.1. Sustainable Development Goal 1: no poverty

The spatial information from satellite data can help to acquire backdated census data at a global scale, especially for developing countries. The United Nations has defined 7 targets and 14 indicators for SDG-1. The traditional method to measure poverty relies on census data, which typically has a repeat cycle of 5 or 10 years as it is difficult to update the data yearly. In some of the low and middle-income countries, census data is unavailable; or if available, it is outdated. Therefore, the use of alternative techniques based on GIS and mobile mapping can help in updating and filling up such data gaps (Tatem et al., 2017). The poverty maps based on geospatial data provide information on inequality within a country and hence divulge the spatial disparities related to the various indicators of SDG 1 (Kuffer et al., 2018). These maps are becoming an important tool for the development of effective policies, aiming to reduce inequalities within countries by implementing social protection programs. These programs include allocating subsidies, effective resource use, disability pension, unemployment insurance, old-age pension, etc. Multi-temporal poverty maps can be used to see the change in poverty by implementing social protection programs. The use of geospatial information can give information about potential hotspots where the international community must work together to reduce poverty. Mobile phone data has also been used as an indicator of poverty, for example: the use of monthly credit consumption, the proportion of people using mobile phones, movement of mobile phones, etc. (Eagle, Macy, & Claxton, 2010; Soto, Frias-Martinez, Virseda, & Frias-Martinez, 2011). There are numerous studies where GIS tools are leveraged towards implementing policies to achieve SDGs, some of which are discussed below.

Gallo and Ertur studied the distribution of regional GDP per capita in Europe from 1980-1995 and found clear evidence of global and local spatial autocorrelation (Gallo, J. L. & Ertur, 2003). Minot & Baulch (2005) investigated spatial patterns of poverty in Vietnam, which reveals that most of the poor people do not live in the poorest districts but in the lowland deltas, where poverty incidence is intermediate. Therefore, governments should consider poor people, not poor areas. Kuffer et al. (2016) reviewed literature related to slum area mapping using remote sensing data, emphasizing the role of high-resolution satellite data and object-based image analysis (OBIA) for robustness across cities and imagery. Asensio focused on the targeting aspect of poverty alleviation (Asensio, 1997). In this work, census data were used alongside aerial-photo interpretation within a GIS environment. Numerous and varied indicators which revolved around unemployment rate, health-infant mortality rate, ethnicity, educational attainment of female household heads, housing quality, etc. were used. The level of data aggregation was the building block. The use of GIS-based poverty maps can integrate data from various sources in defining and describing poverty. This can generate reliable poverty indicators at district and sub-district levels. The application of GIS can provide an insightful idea of the census data, which seems underutilized in developing countries.

In Indonesia, Poverty Reduction Information System for Monitoring and Analysis (PRISMA) has been widely used to conduct spatial analysis of poverty in relation with other variables in the GIS platform (Sugiyarto, 2007). Okwi et al. (2007) mentioned in their study that acquisition of various thematic data such as slope, soil type, distance, travel time to public resources, elevation, type of land use, and demographic variables can be useful to explain spatial patterns of poverty (Okwi et al., 2007). Elvidge et al. (2009) derived a global poverty map using a poverty index calculated by dividing population count by the brightness of satellite observed night time light (DMSP nighttime light data). They used land cover, topography, population settlement, as well as DMSP nighttime light data and estimated that the numbers of individuals living in poverty are 2.2 billion, slightly under the world development indicators (WDI) estimation of 2.6 billion. This information can be updated easily with the use of multi-temporal satellite data. Blumenstock et al. (2016) demonstrated that policymakers in the world's poorest countries are often forced to make policies with data insufficiency especially in the African region (Blumenstock et al., 2016). Therefore, the use of high-resolution satellite imagery and machine learning can fill the gap of data insufficiency. Multi-dimensional poverty index (MPI) based on mobile call details, ownership, call volume, as well as satellite-based nighttime light data has been used in Rwanda with high accuracy (Njuguna & McSharry, 2017). This study shows that mobile and satellite-based big data can be effectively used for evaluating spatiotemporal poverty. The use of high-resolution satellite data to estimate variation in poverty across small local areas by analyzing features such as the density of paved and unpaved roads, building density, roof types, and farmland types have been conducted in Sri Lanka (Engstrom, 2016). Geospatial data can be effectively used as a tool to provide updated data as well as to monitor the progress or growth due to the implementation of current policies. One study developed a transfer learning approach using convolutional neural networks (CNN), where night-time light intensities are used as a data-rich proxy to predict poverty in Africa (Xie, Jean, Burke, Lobell, & Ermon, 2015). This approach can easily be generalized to other RS tasks and has great potential to solve global sustainability challenges. One of the recent studies demonstrated how mobile phone and satellite data can be utilized as a mapping tool for poverty (Tatem et al., 2017). The findings indicate the feasibility to estimate and continually monitor poverty rates at high spatial resolution in countries with limited capacity to support traditional methods of data collection. Hence, it can be concluded from the above-discussed literature review that geospatial techniques are effective means to reach out to the most vulnerable groups to better execute the policies aimed at poverty elimination.

3.2. *Sustainable Development Goal 2: no hunger*

Remote Sensing based estimation of agricultural yield can be used to avoid hunger. According to the United Nations Food and Agriculture Organization (FAO), there is more than enough food produced in the world to feed everyone. But recent data shows that the estimated number of undernourished people has increased from 777 million in 2015 to 815 million in 2016 (FAO IFAD UNICEF, 2017). Tackling the hunger problem is not an easy task and it needs international cooperation among countries. Knowing the problem of malnutrition in an area, projecting future crop production and water availability could help us to mitigate the problem in the future since we would make needful plans in a timely manner. The satellite data can contribute to achieving the goal of zero hunger by providing timely data on agriculture yield and market demand using modeling techniques. The use of unmanned aerial vehicles (UAVs) in precision agriculture can also support sustainable agriculture production by precision farming (Paganini et al., 2018). Nhamo et al. (2018) studied improving the estimation of irrigated area using Landsat data in Limpopo province, South Africa with the use of UAV-based information. Arroyo et al. (2017) estimated the yield of corn using UAV data as well as the optimization of fertilizer use.

RS and GIS could be used to detect key areas struggling to ensure enough food. One study analyzed the current situation of the distribution of underweight children in Africa and found the highest prevalence rate around the border between Nigeria and Niger, Burundi, and central/northern Ethiopia (Nubé & Sonneveld, 2005). They indicated that the regional characteristics, as well as national policies and circumstances, play a role in high causation as well as prevention. Liu et al. (2008) also analyzed hotspots of hunger along with the climate change scenario for the subnational level of Sub-Saharan Africa. The authors found that existing problems in Nigeria, Sudan, and Angola would be mitigated by improving the domestic food security situation through gaining economic power, but some regions in Tanzania, Mozambique, and DR Congo would face more serious hunger problems if climate change continues to progress. Basing on the projections, SDG-2 can be achieved for these countries only if the international community could work together to help struggling countries. Geospatial data can be used to forecast the agricultural yield at the national, regional, and global levels with the use of ground-based observation and weather data in a timely and accurate manner. Satellite data can provide useful information about poor growing seasons and years of low crop productions. Group on Earth Observations Global Agricultural Monitoring (GEOGLAM) is one of the seminal agencies that use geospatial data for agriculture forecasting. Raising agricultural productivity and climate resilience are necessary to feed the growing population by adopting advanced technologies (World Bank, 2016).

3.3 Sustainable Development Goal 3: good health

Spatial analysis techniques can help in examining healthcare systems as well as estimating the path of infectious diseases. Improving sanitary conditions such as access to clean water is crucial in maintaining good health. Therefore, SDG-3 is feasible if SDG 6 (*clean water and sanitation*), is achieved. It is worth mentioning here that all the 17 goals of SDGs are not independent, rather these goals are interconnected. The WDI data and the World Water Development Report by UN-Water provide us the percentage of the population with access to clean water using GIS maps (UN Water, 2018). The maps show a cluster in

Africa telling that the situation must be improved in the future for the attainment of SDGs. Similar to its use for detecting hunger problems, GIS plays an important role in assisting decision-makers to improve the situation.

In addition to sanitation, maintaining good health requires access to the healthcare system. GIS can be used to analyze healthcare conditions nationally and internationally. One study analyzed the condition of healthcare in Costa Rica by measuring its spatial access within the country (Rosero-Bixby, 2004). His findings provide important information to achieve SDG 3 in Costa Rica because it clearly points out certain communities without adequate access to healthcare. Together with other healthcare indicators such as child mortality rate, if the regional differences are revealed, the government could intensively allocate the budget and human resources in areas lagging behind others to improve the situation for achieving SDG 3. A similar analysis is useful for Sub-Saharan countries to show the precise location seeking help from the international community.

Gaugliardo (2004) studied the situation of the primary care by measuring the distance to a healthcare facility and found the differences in accessibility of primary care in Washington DC. Some areas have more than 70 medical service providers for 100,000 children while others have less than 20. Wang and Luo (2005) studied to find areas, which suffered from the shortage of healthcare workers in Illinois and found that disadvantaged areas were widespread all over the state, except big cities such as Chicago. Both studies implied that GIS can also be used in medical geography to depict social inequality in developed countries. Also, improving social conditions contributes to achieving both SDG 3 and SDG 10: *reduced inequalities*.

The effectiveness of GIS is not limited to the general healthcare system. We could utilize it for epidemiology studies to prevent future pandemics. Maude et al. (2014) analyzed the spatial and temporal data on clinical malaria in Cambodia, and depicted the distribution of the disease and village malaria workers. Timo Lüge (2014) prepared a case study to report how GIS was used to combat the recent Ebola outbreak in Guinea. In countries like Guinea, it is quite challenging to tackle communicable diseases because a lot of basic information including geographic and social data is missing. Quick responses are crucial to control outbreaks. A medical humanitarian organization, Medicine Sans Frontier, needed to start from collecting geographic data to know how streets connect residential areas as well as where the cases were reported. Jones et al. (2008) studied global temporal and spatial patterns of emerging infectious diseases (EIDs) and found that the origin of EIDs is significantly correlated with socio-economic, environmental, and ecological factors. The study revealed that the fragile regions due to EIDs in the world include developed countries, and the risk map would help us to prepare for future outbreaks. EIDs include zoonosis, which is common to both humans and animals. Outbreaks of zoonosis such as avian/swine influenza, Ebola, and rabies would significantly impact both human health and national economies, especially if livestock is a major industry. Preventing infectious diseases through monitoring is necessary for SDG-3. With the current trends of global warming and globalization, the infected area is expanding into new areas as mosquitos move along with human and material flows. Therefore, controlling infectious diseases will be challenging to all countries. The recent outbreak of the Zika virus in South America has already spread widely to North America, Europe, and Asia. Furthermore, the impact of the disease is especially significant for pregnant women and newborn babies. Therefore, for SDG 3, analyzing the origin, tracking the outbreak and preventing the disease from invasion is an important process for which GIS is an effective tool. Orimoloye et al. (2018) studied about changes in land surface temperature and radiation due to urbanization in South Africa using Landsat data and radiation risks to heatstroke, skin cancer, and heart disease (Orimoloye, Mazinyo, Nel, & Kalumba, 2018). Strano et al. (2018) proposed a tool for supporting the design of disease surveillance and control strategies through mapping areas of high connectivity with roads in the African region (Strano, Viana, Sorichetta, & Tatem, 2018).

3.4 Sustainable Development Goal 6: clean water and sanitation

SDG 6 addresses the issues related to clean water and sanitation. It has seven targets to be achieved by 2030 ranging from water resources to the hygiene of people. The application of geospatial techniques like remote sensing and GIS promises to achieve each of the seven targets. *Target 1 is to achieve universal and equitable access to safe and affordable drinking water for all by 2030.* The study "Assessment of Groundwater Potential in a Semi-Arid Region of India Using RS, GIS and Multi-Criteria Decision Making Techniques" (Machiwal, Jha, & Mal, 2011) provides a very good insight to achieve this target. In this study, the authors proposed a standard methodology to delineate groundwater potential zones integrating RS, GIS, and Multi-Criteria Decision Making (MCDM) techniques. Using each of these techniques, they have generated a groundwater map and demarcated four groundwater potential zones as good, moderate, poor, and very poor based on groundwater potential index in the Udaipur district of Rajasthan, Western India. On the basis of hydrogeology and geomorphic characteristics, four categories of groundwater prospect zones were delineated. Another study in the drought-prone Bundelkhand region also showed the importance of RS, GIS, and ground survey data to identify groundwater potential zones. This study can be used to address drought mitigation and adaptation (Avtar et al., 2010).

Target 2 of the SDG 6 is to achieve access to adequate and equitable sanitation and hygiene for all and end open defecation paying special attention to the needs of women, girls, and those in vulnerable situations. Open defecation is a very common sight in developing countries due to inaccessibility to infrastructure and facilities. Various information on land cover and infrastructure derived from satellite data can be used for geographical analysis in the planning of infrastructure development (Paulson, 1992). Information like land-cover derived from satellite imagery combined with land ownership, slope, soil type, and visibility indicators in GIS can be used to design infrastructure facilities (Tatem et al., 2017). These techniques are also important for assessing the environmental impact and cost of construction (Kuffer et al., 2018). Another type of application is the zoning of cities according to the physical and socio-economic attributes for infrastructure planning. The zones can be used for different purposes such as sanitation, housing, etc. Information about population density and area can also be used to calculate the approximate number of users and hence building costs.

The study on water pollution and management in Tiruchirappalli Taluk (District), Tamil Nadu, India used IRS LISS-III (Linear Imaging Self Scanning Sensor), satellite imagery, and

SRTM (Shuttle Radar Topography Mission) data integrated with water level data, canal inflow, and groundwater condition to generate a map showing the distribution of water pollution in the area (Alaguraja, Yuvaraj, & Sekar, 2010). Another study conducted in the Alabata community (Nigeria), which is a community without basic infrastructure facilities, revealed the importance of RS-GIS based techniques in the bacteriological examination of water supply to the rural communities. Data on sanitation, health, water sources, and water sampling points were taken and plotted in GIS and a base map was generated in this study. Development of the RS-GIS system allows the overlapping of the spatial location of water sources and bacteriological quality data as well as the generation of a map for the planning and management (Shittu et al., 2015).

Over-exploitation of groundwater resources can also be monitored by RS-GIS techniques. The study on integrated RS-GIS application for groundwater exploitation and identification of artificial recharge sites provides a very good example to support this argument. In this study, IRS-LISS-II data and other relevant datasets were used to extract information on hydro-geomorphic features of hard rock terrain. This study was conducted in Sironj area of Vidisha district of Madya Pradesh (India). IRS-LISS-II data has been integrated with DEM, as well as drainage and groundwater data analysis in GIS. This study has helped in designing an appropriate groundwater management plan for a hard rock terrain (Saraf & Choudhury, 1998). Satellite data with multiple applications can be useful to monitor clouds, precipitation, soil moisture, groundwater potential, inland water bodies, change in the river, surface water levels, etc. (Paganini et al., 2018).

Target 5 of SDG 6 is protecting and restoring water-related ecosystems, including mountains, forests, wetlands, rivers, aquifers, and lakes by 2020. The availability of water depends on several factors such as forests, wetlands, mountain springs, etc. Therefore, protecting them and restoring them plays a vital role in achieving SDG 6. The study was done by Reusing (2000) on change detection of natural high forests in Ethiopia using RS and GIS techniques set a very good example. The author has done a countrywide change detection analysis of Ethiopia's natural high forests using multi-temporal LANDSAT-TM satellite images. Wetlands are important in mitigating and controlling floods - a hazard which brings lots of negative impacts on the poor communities due to the widespread of waterborne diseases, destroying properties and agricultural fields. Therefore, restoring and protecting existing wetlands is a timely necessity and RS and GIS can be incorporated in this. Rebelo et al. (2009) have developed a multiple purpose wetland inventory using integrated RS-GIS techniques and specific analysis at different scales in response to past uncertainties and gaps. Furthermore, they have quantified the conditions of wetlands along the western coastline of Sri Lanka using satellite data and GIS to describe trends in land use due to the changes in agriculture, sedimentation, and settlement patterns.

3.5 Sustainable Development Goal 11: sustainable cities and communities

There has been accelerated progress made on global spatial data collection and processing because of advancements in technologies and computer science. Therefore, increased investment and technical applications are needed to expand on the progress being made to integrate geospatial data into the global goal of implementing sustainable cities and human settlements. UN-Habitat is already engaging research institutions to develop a representative dataset of urban areas that would make possible the monitoring of urban land-use efficiency, land-use mix, street connectivity, and other key factors of sustainable urban development (Habitat, 2015). Consequently, adopting SDG 11 is also transformational in the sense that it targets the sequential progress of urban planning, the complex provision of public space, access to basic services and transportation systems by the growing population in this digital world of uncertainties.

United Nations Regional Cartographic Conference for Asia-Pacific (2015) emphasized the importance of an integrated approach to sustainable development, including the need for quality data and information for decision making (Lehmann et al., 2017). The high need for geographic data was then first captured in a global sustainable development dialogue. The report of the summit, under the 'means of implementation' theme called for member states to inter-alia: promotion of development and wider use of earth observation technologies including satellite RS, global mapping and geographic information systems, to collect quality data on environmental impacts, land-use and land cover changes, etc. Also, it echoed urgent action at all levels of data access, exploring the use of geographic information by utilizing the technologies of satellite RS for further development as far as urbanization is concerned. How geographic information would be applied to sustainable development challenges or be implemented was not clarified. There was simply no apex intergovernmental mechanism in existence that could suitably address the production and use of geographic information within national, regional, and global policy frameworks – or how they could be applied to sustainable development challenges. There are various sectors in a city that really need the application of geospatial information. Acquiring data on these indicators will contribute a lot to the implementation of the sustainable cities through SDG 11 achievements by 2030. For example, the application of RS data in wastewater monitoring can clearly assist us to identify the flow and can be used as an indicator for monitoring the proportion of wastewater safely treated (Ulugtekin et al., 2005). There is a similar situation on the population density, land use, land cover and many other data needed for the achievement of SDG 11. If this data is integrated with other geospatial layer, and administrative data of high-resolution satellite images which can document the location of treatment facilities in a city, can help to estimate the wastewater generation potential as well as their impacts. The use of geospatial data in the implementation of SDG 11 will contribute a lot to filling most of the knowledge gaps. It will place many demands on national statistical systems, as well as cost-effective gains on monitoring in general.

Geospatial information and analysis significantly enhances the effectiveness of the SDG 11 indicators in monitoring and guiding sustainable development from global to local scales. The value of statistical and geospatial data compilation for the implementation and monitoring of the 2030 Agenda and SDG 11 constitutes an important basis for the continued collaboration between the geospatial field and many other sectors involved in achieving the implementation of the sustainable cities goal. However, this will require us not only to promote the use of statistical and geospatial data as reporting and monitoring tools for achieving the SDG 11 but to further support capacity building in the intersection of various disciplines in a transdisciplinary approach ((ISO) & (IHO), 2015).

This review paper has recognized the need for the global geospatial information community, particularly for the implementation of SDG 11 through the utilization of national geospatial information agencies. There is an opportunity to integrate geospatial information into the sustainable cities goal in more accurate ways to gather, measure, and monitor the targets and indicators of SDG 11. For example, through an approach called Backcasting, conceptually developed to support sustainable decisions in the energy sector (Haslauer, Biberacher, & Blaschke, 2012). Backcasting works backward from the envisioned future goals to the present, setting milestones to achieve the desired objective. These milestones are small interim scenarios along the way between the future scenario (usually 20–50 years ahead) and the present situation. The use of the Backcasting methodology, if implemented in a modeling environment of many cities, as well as the urban planning process based on GIS using the scripting language Python will play a major part in implementing SDG 11. Most importantly, in order to achieve this outcome, national geospatial information institutes need to collaborate more with the national statistical and earth observatory professional communities.

The governments need to ensure unity between institutions having similar goals and objectives both at national and global perspectives. Institutions are required to deliver the same data, as practical as possible and depending on national circumstances and functions usefulness of the geospatial data in the implementation of the SDG 11 is concerned. Urban centers/cities contribute around 80% of global greenhouse gas (GHG) emissions, especially in most developing nations where urban centres and cities are spaced with no effective means of urban transport systems. Therefore, sustainability indicators can provide new ideas and solutions to the planning and expansion occurring globally. The decisions for sustainable cities planning and management should be taken on an evaluation of their consequences. Correspondingly, each strategy needs to design the right tools of study, analysis, and prediction (Martos et al., 2016). For this reason, the integration of RS and geospatial tools like GIS and many modeling and projection tools will have an effective impact to implement and monitor achievement of the sustainable city goal. An urban transport indicator for SDGs has been discussed by Brussel et al. (2019). It has been argued that the urban transport indicator has many limitations. Out of several limitations, the major limitation is supply oriented. The indicators for this study have been collected using geoinformation for the city of Bogota in Columbia. The mapping, modeling, and measurements of urban growth can be analyzed using GIS and RS-based statistical models. While achieving safe, resilient, sustainable cities and communities surely present the global community with a set of significant social, environmental, and economic challenges where geospatial information can provide a set of science and time-based monitoring solutions. As noted at the second session of United Nations Initiative on Global Geospatial Information Management (UN-GGIM) in August 2012, “all of the issues impacting sustainable development can be analyzed, mapped, discussed and/or modeled within a geographic context” (Scott & Rajabifard, 2017). The use of Geo-information will effectively reduce the network load and the building modeling cost as well. This will contribute substantially to the achievement of sustainable and low carbon cities by saving three quarters of manpower, time and cost during the implementation of most construction projects (Rau & Cheng, 2013). A case study on GIS based methods for assessing the environmental effects in informal settlements in Cuiaba, Central Brazil has been carried out by Zeilhofer & Piazza (2008). The reason for the rise in informal settlements in Cairo, the capital of Egypt, has been studied by El-Batran & Arandel (2005). The sustainable informal settlements in Dharavi, Mumbai from India; Santa Marta favela, Rio de Janeiro from Brazil; Tondo, Manila from the Philippines have been studied by Dovey (2015). The author explains that the informal settlements for shelter and community have risen globally and are legally unjustifiable. The informal settlements in Kisumu, Kenya have been described by Karanja (2010). In conclusion, whether collecting and analysing satellite images or developing geopolitical policy, geography provides the integrative approach necessary for global collaboration and consensus decision making towards the achievement of SDG 11 on safe, resilient and sustainable cities.

3.6 Sustainable Development Goal 13: climate action

The key to understand our dynamic climate is creating a framework to take many different pieces of past and future data from a variety of sources and merge them together in a single system using GIS (Dangermond & Artz, 2010). A particular technological measure, which was specifically identified by national development targets and strategies of most countries all over the world is the use of RS, particularly on climate monitoring and analysis. For instance, Indonesia has initiated the development of its National Satellite Development Programme to aid the application of satellite RS on the issues of climate change and food security in the country. Also, countries like the Philippines are pushing for the capacity building of technical people to earn needed expertise on the use and application of new and sophisticated tools such as GIS. It goes without saying that RS has become a pre-requisite for reliable information bulletins on climate change which was relied on by decision-makers. Various pieces of literature pointed out the following reasons why RS has become a very important ingredient in climate change study and decision making related to it:

- Many regions in the world are characterized by the lack of a dense network of ground-based measurements for Essential Climate Variables (ECVs).
- Some parameters can only be observed from space or can be observed with better accuracy from space (e.g. top of atmosphere radiation budget).
- RS provides climate variables with a large regional coverage up to global coverage.
- Assimilation of satellite data has largely increased the quality of reanalyzed data.
- Satellite-derived products have the potential to increase the accuracy of gridded climate datasets gained from dense ground-based networks.

At present, the application of RS in dealing with the issue of climate change has been very useful. It is noteworthy to mention one of the earliest and globally important contributions of RS in climate change study, which is the discovery of the ozone hole over Antarctica. It was discovered by a British scientist and was confirmed by the Nimbus-7 Total Ozone Mapping Spectrometer (TOMS) launched in 1978. Since then, the TOMS make maps of daily global ozone concentration. These data were used as scientific pieces of evidence in the First Montreal Protocol, where 46 nations agreed to reduce the use of chlorofluorocarbons (CFCs) by 50% by 1999. However, like many other great things, it is also being hurdled by some issues and criticisms including (i) there are types of data which are not accurate when downscaled to a more human scale of meters (e.g., while standing in the field), (ii) requires highly technical expertise, (iii) involve the use of costly/expensive equipment, (iv) accuracy is highly dependent on the source data. This pushed different organizations (i.e., NASA, ESRI) to strive for future directions in RS and global change, including international cooperation, dataset management, and distributed computing. Recent developments in RS opened up new possibilities for monitoring climate change impacts on the glacier and permafrost-related hazards and threat to human lives and infrastructure in mountainous areas (Kaab et al., 2006). Previous studies show the importance of RS and GIS in the assessment of natural hazards in mountainous regions, therefore, it will play a major role in the sustainability of the region in the near future (Kääb, 2002; Quincey et al., 2005).

3.7 Sustainable Development Goal 14: life below water

This goal addresses the sustainable use and conservation of oceans, seas, and marine resources. This goal consists of several targets addressing marine pollution, protection of marine and coastal ecosystems, minimizing ocean acidification, regulating and managing fishing activities, prohibiting overfishing, increasing economic benefits to the small island via the sustainable use of marine resources, developing research capacity, and implementing international laws which support sustainable utilization of marine resources. Geospatial techniques provide an enhanced interface to achieve these targets in numerous ways. One good example can be taken by the study done by Dahdouh-guebas (2002). The author has studied the sustainable use and management of important tropical coastal ecosystems such as mangrove forests, seagrass beds and coral reefs using integrated RS and GIS. He determined the ecosystem resilience and recovery followed by an adverse impact using these techniques. The author stressed that there is a need for more comprehensive approaches that deal with new RS technologies and analysis in a GIS environment, and that integrate findings collected over longer periods with the aim of future prediction. Another study done for seagrass meadows in North Carolina, USA supports the significance of geospatial techniques in the sustainable use of the ocean and its resources. Seagrass meadows are vulnerable to external environmental changes and they provide a habitat for coastal fisheries. Therefore, monitoring and conserving seagrass is key to a healthy ocean environment. Spatial monitoring of seagrasses can improve coastal management and provides a change in location and areal extent through time (Ferguson & Korfmacher, 1997).

Oil spills are a common problem in oceans mainly associated with shipping activities. In recent years, the frequency of oil spills has increased due to the development of marine transportation. Oil spills can significantly affect the primary productivity of ocean and marine ecosystems including fisheries, marine animals, corals, etc. RS based algorithm has been used widely to detect oil spills. There is a significant improvement in the oil spill detection with the use of microwave remote sensing techniques (Yu et al., 2017). For example, Satellite-based oil pollution monitoring capabilities in the Norwegian waters were demonstrated in the early 1990s by using images from the ERS-1 satellite (Wahl et al., (1994). With the advancement of RS technologies, Synthetic Aperture Radar (SAR) plays an important role in oil-spill monitoring (Brekke & Solberg, 2005). Arslan (2018) reported that Sentinel-1 SAR and Landsat-8 data can be effectively used to highlight the oil spill area.

Global fish production was relatively stable during the past decade, whereas aquaculture production continued to rise (FAO (Food & Agriculture Organisation), 2012). Both sectors are very important in global food security and there is an increasing threat to their sustainability. Some of the challenges are overfishing, degradation of keystone species, and climate change. On the other hand, aquaculture faces problems like competition for space, disease outbreak, labor, and impacts of climate change. The solutions to some of these problems can involve applying satellite remotely sensed (SRS) information (Saitoh et al. 2011). RS can be used to detect ocean temperature, sea surface height anomaly, ocean color etc. which are very important in operational oceanography. In pelagic fisheries, there are mainly two RS applications. One is for the identification of potential fishing zones, and the other one is for the development of management measures in order to minimize the catch of endangered species. For example, Howell et al. (2008) demonstrated a tool that facilitated the avoidance of loggerhead turtle (*Caretta caretta*) by catch, while fishing for swordfish (*Xiphias gladius*) and tuna (*Thunnus* spp.) in the North Pacific (Howell et al. (2008).

3.8 Sustainable Development Goal 15: life on land

Forest plays a major role in regulating the global carbon cycle at regional to the global scale. According to the MEA (2005) report, (Finlayson, 2016), 335- 365 Gigatonnes of carbon is locked up by forests each year. Any significant alterations or reduction in the forested area due to any or many of the following reasons, namely changes in land use and land cover, the practice of selective logging, forest fires, pest, and diseases, would definitely lessen the productive functioning of the forest. The previous studies concluded that it is highly important to reduce greenhouse gas (GHG) emissions from deforestation and forest degradation as a step towards mitigating climate change (Angelsen et al., 2012; Instituter & Meridian Institute, 2009).

Climate change is a growing concern that has led to international negotiations under the United Nations Framework Convention on Climate Change (UNFCC) (Sustainable Development Solutions Network (SDSN), 2014). The REDD+ concept emphasizes reducing emissions from deforestation and forest degradation, promoting sustainable forest management, as well as enhancing carbon sinks are all integrated and regarded as mitigating GHG emissions. Forest degradation heavily impacts small communities, who are dependent on the forest as a source of income and food. Destruction of the forest also affects soil and water quality in the immediate area and can adversely affect biodiversity over a range of connected ecosystems. There has been a lot of ambiguity in the definition of forest degradation. According to FAO report (FAO, 2011), forest degradation has been defined as; changes within the forests which negatively affect the structure or functions of the stand or site, and thereby lower the capacity to supply products and/or services. While REDD+ defines degradation as a long-term loss (persisting for x years or more) of at least *y%* of forest carbon stocks since time *T,* and not qualifying as deforestation which is conversion of forest land to another land use category. Thus, it is highly essential to decide the definition, the indicators on the basis of which a nation's trajectory towards the achievement of SDGs could be monitored. Once, the international organizations decide the common indicators, the phenomenon or feature can be monitored by geospatial techniques.

Looking into the grave problem that stands right in front of humanity, is the need to accurately monitor, map and estimate the net forest cover, monitor deforestation, and degraded forest area and quantify the Above Ground Biomass (AGB). RS technique which offers comprehensive spatial and temporal coverage has been used for the same in past decades. Many types of research and monitoring programs have been carried out to map deforestation and forest degradation using optical RS. For instance, Reddy et al. (2016) quantified and monitored deforestation in India over eight decades extending from 1930 to 2013 using grid cell analysis of multi-source and multi-temporal dataset. The satellite imageries were acquired from cloud-free Landsat Multispectral Scanner System (MSS) from 1972-1977, IRS 1A/IB LISS I (1995), IRS P6 Advanced Wide Field Sensor (AWiFS) (2005) and Resources at-2 AWiFS (2013) with an overall accuracy of forest cover more than 89%. Another study by Ritters et al. (2016), who assessed global and regional changes in forest fragmentation in relation to the change of forest area from 2000 to 2012. The study utilized global tree cover data to map forest and forest interior areas in 2000 and concluded that forest area change is not necessarily a good predictor of forest fragmentation change. Thus, we see that there are still some gaps between our understanding of the ecological processes and finding using geospatial techniques. It is required that basic science, technology, and policy evolve and develop hand-in-hand.

Regional-scale studies do provide insights into general trends in space and time domain over the entire country and are important for designing a national-level policy to stop the progress of deforestation and degradation. But, they do tend to overlook the changes at a local level, which will require the usage of high-resolution satellite imagery. The choice of usage of satellite imagery depends on the objective of the study. For instance, WWF Indonesia Tesso Nilo Programme (2004) (Kusumaningtyas et al., (2009) used ASTER satellite image procured on 24 July 2003 covering a part of Tesso Nilo National Park, Riau Province, Sumatra Island to monitor the illegal logging practices in the area. In conjunction with the satellite data, they collected other information like GPS location of each logging operation and time when trucks with illegal logs left the site of investigation and likewise. The study could find out the company involved in illegal logging on the site. Such studies at the local level surely help to monitor the activities of private companies and thereby a strong monitoring system will help to stop deforestation and forest degradation. But, the use of satellite working in the optical range is constrained by the unfavorable weather conditions. In such a case, microwave RS is a more preferred option. The data is available in around the year with its penetration capability to clouds thus, providing data even in rainy and cloudy conditions. Shimada et al. (2014) generated four global forest/non-forest mosaics of Advanced Land Observing Satellite (ALOS) Phased Arrayed L-band Synthetic Aperture Radar (PALSAR). The maps provided a new global resource for documenting the changing extent of forests and offer opportunities for quantifying historical and future dynamics through comparison with historical (1992–1998) Japanese Earth Resources Satellite (JERS-1) SAR.

Green plants uptake carbon from the atmosphere via the process of photosynthesis. The removal of carbon from the atmosphere, referred to as carbon sequestration is a function of the terrestrial ecosystem, for instance, the authors (Jaramillo, Kauffman, Rentería-Rodríguez, Cummings, & Ellingson, 2003) found that forest ecosystems sequester more carbon per unit area than any other land type. Another factor playing a vital role in carbon sequestration is the quantity of biomass (Brown, Schroeder, & Kern, 1999). Therefore, it is important for each country to assess above-ground biomass accurately, which has a prime role in quantifying carbon stored in the forest. From the usage of destructive techniques to highly accurate non-destructive techniques, the world has witnessed tremendous growth of technology in the way of quantifying AGB. The forest biomass has been estimated using PolInSAR coherence based regression analysis of using RADARSAT-2 datasets covering Barkot Reserve Forest, Doon Valley, India (Singh, Kumar, & Kushwaha, 2014).

Achievement of targets under Sustainable Development Goal 15 which basically focuses on sustainable management of all types of forest will require each nation to establish a transparent, consistent, and accurate forest monitoring system. The implication of the present human activities along with the policies developed and practiced are the factors, which will certainly shape the future of the forest ecosystem. Thus, it is critically important to forecast future scenarios. One key component of these systems lies in satellite RS approaches and techniques to determine baseline data on forest loss against which future rates of change can be evaluated. Advances in approaches meeting these criteria for measuring, reporting and verification purposes are therefore of tremendous interest. Thapa et al. (2015) carried out research to generate future above-ground forest carbon stock in Riau Province, Indonesia. The study utilized ALOS PALSAR-2 Mosaic data at a 25m spatial resolution to generate a baseline and generated future scenarios in correspondence to the IPCC Assessment Report (AR 5). The three policy scenarios were analyzed: BAU, corresponding to the 'business as usual policy', G-FC indicating the 'government-forest conservation policy', and G-CPL, representing the 'government-concession for plantations and logging policy'. It was found that if the currently practiced policies are continued then, the place will lose the forest cover and thereby impact carbon sequestration. Such studies play a paramount role in designing and analyzing the current policies and their implications on the future. Thus, it is evident that the use of an objective specific geospatial technique is essentially important for the implementation and achievement of SDG 15.

4. Discussion

The progress being made in achieving SDGs can be measured by several quantifiable indicators. The role of RS techniques in the measurement to monitor the roadmaps for achieving SDGs has been significant in terms of its capacity to use sensor data in order to augment the census data. Several studies, which use one kind of RS technique or others, have shown that RS methods play a major role in the monitoring of SDGs. Citizens, science and big data have also been found useful for measuring and monitoring SDG indicators. The data generated by citizens is data that people or their organizations produce to directly monitor, demand, or drive changes on issues that affect them. It is generated by using surveys, messages, phone calls, emails, reports, social media, etc. The produced data can be quantitative or qualitative in various formats (DataShift, 2017). The lessons learned from the Millennium Development Goals (MDGs) showed the engagement of citizens and civil societies can play a critical role for an inclusive, transparent, and participatory SDGs accountability framework (Romano, 2015). Public participation at all levels should be prioritized as per Post-2015 agenda to ensure inclusive development. It can help to bring the most marginalized voices to the table with the rights to freedom of expression, association, peaceful assembly, and access to information (Romano, 2015). Citizen-driven data could play a major role in monitoring and driving progress of SDGs implementation in real-time. Citizen-driven data has a high potential to fill the existing gaps by providing real-time, prioritized or precise data. It can ensure transformational changes that are required to tackle the huge global challenges to implement SDGs (DataShift, 2017). Citizen science can contribute to the implementation of SDGs in various ways such as additional data and capacity, fulfilling commitments to multi-stakeholder partnerships, driving innovation and capacity building, broad ownership and accuracy of data, strengthening accountability, shadow monitoring, etc. The authors in Cronforth Jack (2015) said "SDG monitoring should be rigorous, based on evidence, time, reliability and disaggregation by different groups in society. All citizens generated data can make a crucial contribution to make a reality". Some of the examples for the above points can be already seen affecting our everyday life in the form of Google Maps or Google Earth, data addition, and analysis with geotagging and image uploads by individuals all over the world. Not only do others have the practical aspect of the situation; they also keep the system updated. With the massive interest of highly complex data available from satellites all over the world and presented in a simple form and easily understandable format of Google Earth, people are encouraged to make astonishing discoveries e.g. largest rain forest in Southern Africa or identification of unusual cave systems that lead to the discovery of a New Human Ancestor (Nobre et al., 2010). These are a few examples of citizen data, as well as making a contribution to the betterment of the system and increasing scientific curiosity & making discoveries (Santens, 2011). A study by Global Pulse on mining citizen feedback data for enhancing local government decision making in 2015 demonstrated the potential utility of near real-time information on public policy issues and their corresponding locations within defined constituencies, enhanced data analysis for prioritization and rapid response, and deriving insights on different aspects of citizen feedback (UN Global Pulse, 2015). Forest Watchers "proposes a new paradigm in conservationism based on the convergence of volunteer computing with free or donated catalogs of high-resolution Earth imagery" (Gonzalez D. L., 2012). It involves volunteer citizens and scientists from around the globe, who help monitor levels of deforestation. By reviewing satellite images of forested regions, local residents, volunteers, non-governmental organizations, and governments can help in the assessment of these regions. Moreover, this initiative encourages local citizens and provides the rights of ownership to help in implementing SDGs. Flückiger & Seth (2016) suggested that data from civil-society can be crowdsourced to implement and monitor the progress of SDGs. United Nations

Environmental Program (UNEP) is involved in capacity development, environmental awareness, and information exchange programs to foster a generation of environmentally conscious citizens that can help ecosystem renewal in Kenya (UNEP, 2017). The use of citizen, science, and data/information can provide transparency in a system with updated and real-time information that can change the course of our future with a political will. A positive example for such political and citizen, science and data movements is the accessibility to free satellite data such as Landsat, Sentinel, MODIS for scientific purposes. It has led to a tremendous increase in research studies and monitoring of areas ranging from busiest metropolitans to the most remote location on the plant ushering a new era of scientific research backed by satellite data analysis.

Over the last decade, big data has become an interesting field of research with an increase in attention attracting the interest of academia, industries, governments, and other organizations. The authors in (Kitchin, 2014) have suggested it to be a predominant source of innovation, competition, and productivity. The recent development in computer science with the high-performance computer, storage capacity, and the growth of high-resolution satellite data is dramatically increasing by several terabytes per day. Scientists are considering RS data as “Big Data” because of the continuation in controlling global earth observation for environmental monitoring (Skyland, 2012). The RS big data do not merely refer to the volume and velocity of data but also to the variety and complexity of data. This diversity and complexity in data make the access and processing significantly difficult especially for the layman (Ma et al., 2014). Annexure1 shows various satellites and their specifications. These satellites have sensors with different spatial, temporal, and spectral resolution resulting in multi-sensor complex data. The use of a multi-sensor approach can overcome the limitations of one sensor with the use of other sensor data from local to global scale (Ma et al., 2014). The opportunity of big data for SDGs lies in leveraging new/non-traditional data sources and techniques to better measure or monitor progress for the achievement of the SDGs. Moreover, with the interest in big data in the global SDG discourse, attempts have been made to identify ongoing regional and country-specific activities. It is important to understand the applicability of big data in relation to the SDGs by identifying how big data can help to implement and monitor potential targets. The use of urban big data for advancing more innovative targets and indicators relevant to the SDGs has been studied by Kharrazi, Qin, & Zhang, 2016. The SDG for any government can be challenging to understand and even more difficult to put a system in place for the achievement of such goals. The initiation of government interest for Big data mining can be on various fronts and for a variety of purposes. The first step for any government is to make the life of the citizen of that country/region better than before and ensure sufficient resources for the future generation. For example, the benefits of big data mining done by governments intended for the improvement for citizen services can potentially be the determination of eligibility of beneficiaries, using advanced analytical tools, to plan and track welfare schemes to ensure that benefits reach only eligible citizens, identify deceased, invalid, and duplicate persons to eliminate duplicate benefit payments. While these benefits are just a few to start with, it is just an example of the broad spectrum of impacts in all aspects of any nation. Further, to achieve these development targets in a sustained manner, converged governance efforts are required at the grassroots, which in turn would inevitably result in the generation of continuous baseline data. The use of structured baseline data and unstructured citizens' data can be combined and analyzed by the application of big data analytics and emerging Information and Communication Technologies (ICTs). There is a need to raise awareness of the potential of big data for public purposes and invest in institutional capacity building as well as data-driven regulation and policy-making (Development, 2017). The use of big data analysis in medicine and healthcare practices is on the rise, and we are already seeing legal proposals such as the draft Electronic Data Records standards in order to both enable and govern the collection of medical data. The pooling of medical data for identification, diagnosis, and treatment of a wide range of health problems is one such example of everyone benefiting from data pooling. The study by Lu et al. (2015) suggested five priorities for the SDGs viz. devise metrics, establish monitoring mechanisms, evaluate progress, enhance infrastructure, standardize, and verify data. The authors Maurice (2016) measure the progress of SDGs by using data from the 2015 edition of the global burden of diseases, injuries and risk factor study. The authors of Jotzo (2013) discuss that big data should be selected in such a way that it can be used to test different aspects for sustainable production of energy, food security, water security, and eliminating poverty.

5. Concluding remarks

The 17 SDGs have been set for improvement of human well-being, protecting natural resources, and mitigating the impact of human activities on the planet for future generations. Unlike the previous MDGs, the SDGs are meant for both developed and developing countries. Considering the broad themes and areas of the SDGs, monitoring is crucial for their successful accomplishment by 2030, as well as to revise the existing policies for better functioning and precise targeting. Geospatial data can visualize regional differences. Hence, it is useful to detect social and economic inequalities at both national and local levels. Many studies have revealed that geospatial data is an effective tool to monitor the SDGs' achievement and progress to make effective future plans. However, it is not fully applied in the monitoring and evaluation of global problems and targets. For the success of SDGs, the monitoring process should be standardized for all countries with the cooperation of the scientific and political communities. Considering the broad range of SDGs' targets, geospatial information is one of the most important tools for monitoring their achievement. It will also pave the way for the successful accomplishment of SDGs. Based on this observation, it is still necessary to develop geospatial techniques for the implementation and monitoring of SDGs 5, 8, 10, and 17 where very limited research has been done.

Achieving the SDGs undoubtedly demands massive global concerted efforts to efficiently make use of data sharing, processing, and aggregation in a highly multidisciplinary framework. National geospatial information agencies will need to collaborate closely with national statistical and earth observation professional communities to deliver consistent and reliable data to fit into the formulation of wide-ranging sustainable development policies. This review paper also discussed the role of citizen science and big data for the success of SDGs' implementation. Participation and transparency are the key components for a robust, effective, and accountable mechanism for SDGs from local to a global scale. By the potential use of Google Earth Engine, it is evident that many future opportunities exist for the real-time processing of satellite data. The integrative approach of partnership, capacity-building, and big data can result in sustainable solutions for SDGs' implementation.

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Annexure-1

Satellite sensors and their characteristics

S. No.	Sensors	Spatial resolution (m)	No. of Spectral bands	Radiometric resolution (bit)	Band range (µm)	Swath width (km)	Revisit cycle (days)
A.	**Coarse Resolution Sensors**						
1	AVHRR	1000	4	11	0.58-11.65	2900	daily
2	MODIS	250, 500,1000	36	12	0.62-2.16	2330	daily
B.	**Multi-Spectral Sensors**						
3	Landsat-1, 2, 3	MSS 56X79	4	6	0.5-1.1	185	16
4	Landsat-4, 5 TM	30	7	8	0.45-2.35	185	16
5	Landsat-7 ETM+	30	8	8	0.45-1.55	185	16
6	Landsat-8	30	11	16	0.43-2.29	185	16
7	ASTER	15, 30, 90	15	8	0.52-2.43	60	16
8	ALI	30	10	12	0.433-2.35	37	16
9	SPOT-1, 2, 3, 4, 5	2. 5-20	15	16	0.50-1.75	60	3 - 5
10	IRS 1C, 1D	23.4 (SWIR 70.5)	4	7	0.52-1.7	141/140	24
11	IRS 1C, IRS 1D	188	2	7	0.62-0.86	810	24
12	IRS 1C, IRS1D	5.8	1	6	0.50-0.75	70	24
13	IRS P6	5.8	3	10	0.52-0.86	70/23 (mono)	24
14	IRS P6	56	4	10 and 12	0.52-1.7	737/740	24
15	Cartosat-1 (PAN)	2.5	1	10	0.5-0.85	30	5
16	Cartosat-2 (PAN)	0.8	1	10	0.5-0.85	9.6	5
17	CBERS-2	20 m pan,		11	0.51-0.89	113	26
18	Sentinel-2	10, 20, 60	13	12	0.44-2.2	290	5
19	Sentinel-3	Full resolution 300m	21	12	0.44-1.02	~1270	27
C.	**Hyper-Spectral Sensor**						
1	Hyperion	30	196	16	0.427-0.925	7.5	16
D.	**Hyper-Spatial Sensor**						
1	SPOT-6	1.5 (PAN)	4	12	0.455 - 0.89	60	daily
2	RAPID EYE	6.5	5	12	0.44-0.89	77	1 - 2
4	WORLDVIEW	0.55	1	11	0.45-0.51	17.7	1.7-5.9
5	FORMOSAT-2	2 - 8	5	12	0.45-0.90	24	daily
6	KOMPSAT-3A	0.55 (PAN)	6	14	0.45 - 0.9	12	28
7	Pleiades -1A	0.5 (PAN)	5	12	0.43 - 0.94	20	daily
8	GeoEye	0.46 (PAN)	5	11	0.45 -0.92	15.2	3
9	IKONOS	1 - 4	4	11	0.445-0.853	11.3	5
10	QUICKBIRD	0.61-2.44	4	11	0.45-0.89	18	5
E.	**Synthetic Aperture Radar Sensor**						
1	ERS -1	5.3 (C-band)	VV	100	30	30	35
2	JERS -1	1.275 (L-band)	HH	75	18	18	44
3	RADARSAT-1	5.3 (C-band)	HH	50-500	9-147	6-147	24
4	ENVISAT	5.33 (C-band)	HH, VV	56.5 - 104.8	30-100		35
5	ALOS (PALSAR)	1.27 (L-band)	single, dual, quad	20 - 350	10 - 100		46
6	RADARSAT-2	5.3 (C-band)	Full polarimetric	125	4.6-7.6	3.1-10.4(Wide multi-look)	24
7	TerraSAR-X	9.65 (X-band)	Single and dual	100 (scanSAR)	0.24	0.9-1.8 (Spotlight)	11
8	RISAT-1	5.35 (C-band)	single, dual	25 (stripmap-1)	3	2 (stripmap-1)	25
9	TanDEM-X	9.65 (X-band)	single, dual	30	1.7-3.4	1.2 (spotlight)	11
10	PALSAR-2	1.27 (L-band)	single, dual	25-350	1	3 (spotlight)	14
11	Sentinel-1	5.405 (C-band)	single or dual	80 (strip mode)	4.3 - 4.9	1.7 - 3.6 (strip mode)	12