Review

Integrating Geospatial Information into the implementation and monitoring of roadmaps for achieving SDGs

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Abstract: It has been around four years since the 2030 agenda for sustainable development was adopted by the United Nations in September 2015. Several efforts are being made by member countries to contribute towards achieving 17 Sustainable Development Goals (SDGs). The progress 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 has played a significant role in measuring some of the targets and hence in implementation and monitoring the roadmaps for achieving SDGs. It is evident from this review study that the synoptic view and repetitive coverage of the earth's feature or phenomenon provided by remote sensing (RS) data is one of the most powerful and propitious technological advancements in science and technology. 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 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, evaluation, thereafter, and 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 human wellbeing

1. Introduction

The Sustainable Development Goals (SDGs) are a universal call to 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) encouraged us to take a step forward by making effort in achieving 17 SDGs which lead the world towards prosperity and sustainability. In order to monitor the progress made over time on each goal, a set of quantifiable indicators of various targets specific to each goal need to be measured (Tomás, Svatava, & Bedrich, 2016). This requires systematic data observations at the local community level and subsequent decisions, which includes the collaboration of various stakeholders. The United Nations addressed the issues of existing poor data collection abilities and insufficient data quality in order to optimally measure the indicators. Hence, the need for a revolution in data collection to enhance the data quality of national datasets was emphasized (Kharas, Homi. Gerlach, Karina. Elgin-Cossart, 2013). In this task, geospatial data represents one of the most promising data sources, which can be applied towards implementing the roadmaps and monitoring the progress in achieving the SDGs. Some indicators need studying interesting processes and dynamics of the earth such as climate change, carbon fluxes, water dynamics and biodiversity treats. The earth observation data gathers information about the physical, chemical, and biological systems of the planet via remote-sensing technologies which are useful in achieving the SDGs (Masó, Serral, Domingo-Marimon, & Zabala, 2019). Although, *in-situ* sensors can be installed on the ground to measure these variables these sensors can provide earth data at small scale and that too at a regular frequency. On the contrary, Earth Observation (EO) satellites provide earth data on a large scale. Though the spatial coverage area increases significantly but the data collection frequency is limited depending on the revisiting period of satellites. While most of the national statistical data sources have become centralized, national spatial information is still fragmented and uncoordinated. To establish national and international baselines, we need to improve the collection and sharing of data. Specifically, data collection with the help of the local community, the participation of local people is essential in building capacity development and for transforming data into practice. The result was obtained by Fukuda-Parr (2019) showed SDG 10 (reduced inequalities) within as well as between countries. The paper concludes that political and technical considerations are intertwined and transparency in policy strengths and weaknesses of measurement choices are important. The role of big data in analyzing SDG indicators has been discussed in (MacFeely, 2019). It has been pointed out that conventional data sources are not sufficient and the possibility of using big data for SDG monitoring has been studied. The paper presents issues and challenges in compiling SDG indicators. A review of methods for translating SDG interconnected goals into policy action has been given in (Breuer, Janetschek, & Malerba, 2019). The existing framework for the conceptualization of SDGs and the interconnections among 17 goals is presented. Also, the advantages and disadvantages of several frameworks used have been studied. The monitoring of SDGs in Poland has been investigated using dynamic analysis method in (Raszkowski & Bartniczak, 2019). It has been concluded that the implementation of SDGs in Poland is satisfactory. The study presents that out of the analysis of a total of 73 indicators, 57 indicators show contribute towards sustainable development. An urban transport indicator for SDGs has been discussed in (Brussel, Zuidgeest, Pfeffer, & van Maarseveen, 2019). It has been argued that urban transport indicator has many limitations. Out of several limitations, the major limitation is supply oriented. The indicators for the study has been collected using geoinformation for the city of Bogota in Columbia. The study in (Allen, Metternicht, &

Wiedmann, 2019) presents a novel integrated method for prioritizing of SDG targets. the study area is 22 countries in the Arab region. A multi-attribute decision method has been adopted for the study. the study also discusses benchmarks for indicators. The study (Koch & Krellenberg, 2018) points out that targets for SDGs are needed to be translated into a national context. SDG indicators and monitoring systems are needed to be altered depending on the national context. The authors present that indicators and targets for SDG 11 need to be altered a lot in the German context. A gendered analysis for SDG 8 has been carried out in (Rai, Brown, & Ruwanpura, 2019). The authors argue that the focus of SDG 8 on economic growth is not adequate. The authors also argue that gender supports SDG 8 if decent work is realized. SDG synergy between forestry and agriculture in food, water, energy and income nexus has been presented in (van Noordwijk et al., 2018). The authors categorize SDGs into three main groups. Application of RS and Geographical Information System (GIS) methods for change detection in Ethiopia forests has been discussed in (Reusing, 2000b). Forest monitoring has been done using an airborne and satellite-based RS. Satellite images captured during 1973-1976 were used to analyze change detection and land degradation neutrality (Wunder, Kaphengst, & Frelih-Larsen, 2018). A framework for the assessment of SDG target 15.3 on land degradation neutrality has been outlined. A case study exploring how locally managed marine areas in Mozambique contributes to SDGs for food security and poverty elimination has been presented in (Diz et al., 2018). The concept of fiscal space developed for the health sector in the SDG context has been studied in (Barroy et al., 2018). The authors in (Asi & Williams, 2018) conclude that SDGs are complicated even in stable environment scenarios. Marine spatial planning has been discussed for connecting SDG 14 with the rest of the SDGs in (Ntona & Morgera, 2018). The relationship of climate change actions in the food system to SDGs has been discussed in (Bruce M et al., 2018). The authors in (Diaz-Sarachaga, Jato-Espino, & Castro-Fresno, 2018) analyze the suitability of applying an integrated index for assessing the SDGs.

The visualization of indices generated from census data may indicate the spatiotemporal changes in poverty (SDG 1: end poverty). Similarly, map visualization of schools, literacy, green space in the cities, usage of natural resources and emissions over product life cycle, cases registered against violence and many more likewise would help communities to reconnaissance and thereby, taking concrete actions to achieve SDG 1, SDG 4, SDG 11, SDG 12 and SDG 16 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 of areas (SDG 3, SDG 6 and SDG 14). The satellite sensors are essential tools in monitoring and visualizing local and global level changes. The various satellite sensors and their characteristics are given in Annexure 1. The summary of the sensors is useful to understand the characteristics and applications of these sensors in various fields without repeating the details about the sensor. The RS and GIS are indispensable tools which provide a synoptic view with global to local coverage at various spatial resolutions and in addition to field surveying data, they can monitor the impact of climate change on different components of the aquatic and terrestrial ecosystem (Avtar, Takeuchi, & Sawada, 2013). Scientific results and conclusions can provide a strong basis for the policymakers to formulate best policies for promoting sustainable development of their respective communities (United Nations Secretary, 2016). 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. Figure 1 highlights the SDGs for which the use of geospatial data is plausible. Highlighted goals mean geospatial data and techniques are enough to implement these goals and to monitor the progress of various indicators. We still need to develop techniques and data for the implementation and monitoring the SDG 5, SDG 8, SDG 10 and SDG 17.

This review paper examines the effectiveness of RS and GIS in achieving SDGs. Specifically, the paper focuses on goals directly related to human wellbeing viz. SDG 1: no poverty, SDG 2: no hunger, and SDG 3: good health, and goals related to a safe planet viz. 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. The paper provides a systematic review of the scientific knowledge about the use of geospatial data for implementing and monitoring roadmaps for achieving SDGs. The geospatial data is becoming an asset and important resource because of its multiple applications. We highlighted the studies from the literature that summaries (i) what are the various indicators for SDGs, (ii) what indicators can be monitored using geospatial data, (iii) how to measure and analyze the progress made over time in achieving SDGs, and (iv) how to improve the monitoring techniques with the advanced sensors and modeling techniques. To achieve the above objectives, the selected literature was reviewed systematically with the focus on multi-sensor RS techniques.

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

2. Methodology

This review is focused on papers that used geospatial data to monitor the progress of implementing the pathways to achieve SDGs. The keywords such as "Sustainable Development Goals", "remote sensing AND SDGs", "remote sensing AND GIS AND SDGs", "geospatial data AND SDGs", "monitoring SDGs", "monitoring the progress of SDGs" were used in Google Scholar to gather relevant papers on this study. These keywords brought a varying number of results 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 Table 1.

Table 1. Search results for different keywords

Search Keywords	Search Platform	Search Period	Number of Papers
"Sustainable Development Goals"	Google Scholar	Anytime	1,32,000
		Since 2015	28,200
remote sensing AND SDGs	Google Scholar	Anytime	3,950
		Since 2015	3,230
remote sensing AND GIS AND SDGs	Google Scholar	Anytime	3,510
		Since 2015	2,530
geospatial data AND SDGs	Google Scholar	Anytime	1,750
		Since 2015	1,500
"monitoring SDGs"	Google Scholar	Anytime	108
		Since 2015	89
"monitoring the progress of SDGs"	Google Scholar	Anytime	4
		Since 2015	4

In the first phase, only abstracts with relevant keywords were briefly analyzed to decide whether or not to choose the paper for further analysis. To reduce the biases, the first selection was based on the title of the paper with the pertinent keywords regardless of the author name and country. During the second phase of scrutiny of literature, we prioritized peer-reviewed articles, however, reports, news articles, book sections, etc. were also included. A critical appraisal of the papers selected 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 RS images can help to backdated data of census 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 developing effective policies aimed at reducing inequalities within countries by implementing social protection programs which include allocating subsidies, effective resource use, disability pension, unemployment insurance, oldage 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. The use of mobile phone data has been used as an indicator of poverty, for example, use of monthly credit consumption, the proportion of people with the use of 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 these studies are discussed below.

Le Gallo and Ertur studied the distribution of regional GDP per capita in Europe and found that the spatial autocorrelation (Gallo, J. L. & Ertur, 2003). The finding of the authors matches with those of Minot and Baulch (Minot & Baulch, 2005) since poverty often existed in the clustered form. The numeric values of indicators are important, but GIS enables us to see the problem obviously in bird's eye view. Asensio focused on the targeting aspect of poverty alleviation (Asensio, 1997). In his work, census figures 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 and housing quality, etc. were used. The level of data aggregation was the building block. The use of GIS-based poverty map 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 to other variables in the GIS platform (Sugiyarto, 2007). Okwi et al. mentioned in their study that acquisition of various thematic data such as slope, soil type, distance and 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. derived a global poverty map using a poverty index calculated by dividing population count by the brightness of satellite observed lighting (DMSP nighttime lights) (Elvidge et al., 2009). They have used land cover, topography, population settlement and DMSP nighttime light data. They 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. 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 night 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, farmland types has 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. Xie et al. 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 the most vulnerable groups to reduce poverty.

3.2. *Sustainable Development Goal 2: no hunger*

Estimation of agricultural yields based RS data which can be used to prevent hunger issue. 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). The tackling with hunger problem is not an easy task and it needs international cooperation in concert. Knowing the problem of undernutrition in an area, projecting future crop production and water availability could help us to mitigate the problem in the future since we would make a plan in advance. The satellite data can contribute to zero hunger by providing timely data on agriculture yield, market demand using modelings. The use of unmanned aerial vehicles (UAVs) in precision agriculture can also support sustainable agriculture production by precision farming (Paganini et al., 2018). The RS and GIS could be used to detect problem areas struggling for ensuring enough food. Nube and Sonneveld 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 the 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. also analyzed hotspots of hunger along with the climate change scenario for the subnational level of Sub-Saharan Africa (Liu et al., 2008). 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. Based on the projections, SDG 2 would be achieved for these countries only if the international community could work together to help struggling countries. Geospatial data can be used to timely and accurately forecast the agricultural yield at a national, regional and global level with the use of ground-based observation and weather data. 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 the agriculture productivity and climate resilience are needed to feed the growing population by adopting advanced technologies (World Bank, 2016).

3.3 Sustainable Development Goal 3: good health

Spatial analyses techniques can help in examining such a healthcare system 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 only if SDG 6: *clean water and sanitation*, is achieved. It is worth to mention 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 clean water access using GIS maps. 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. Rosero-Bixby studied the condition of healthcare in Costa Rica measuring the 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 behind the others to improve the situation for achieving SDG 3. A similar analysis is useful for Sub-Saharan countries to show clear signs for the international community.

Gaugliardo studied the situation of the primary care by measuring the distance to a healthcare facility and found the differences in the accessibility of primary care in Washington DC (Gaugliardo, 2004). Some areas have medical service providers over 70 for 100,000 children while others have less than 20. Wang and Luo 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 (Wang & Luo, 2005). Both studies imply 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 study to prevent a future pandemic of diseases. Maude et al. analyzed the spatial and temporal data on clinical malaria in Cambodia, and the distribution of the disease and village malaria workers were depicted (Maude et al., 2014). Luge prepared a case study to report how GIS was used to combat the recent Ebola outbreak in Guinea (Timo Lüge, 2014). 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. Although quick responses are crucial to containing the pandemic and the epidemic, a response tends to be slow and ineffective. 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 studied global temporal and spatial patterns of emerging infectious diseases (EIDs) and found that the origin of EIDs is correlated with socio-economic, environmental and ecological factors (Jones et al., 2008). The study revealed the fragile regions due to EIDs in the world including developed countries, and the risk map would help us to prepare for the future outbreaks. EIDs include zoonosis, which is common to both human and animal. Outbreaks of zoonosis such as avian/swine influenza, Ebola, and rabies would significantly impact on both human health and national economies, especially if the livestock industry is a major industry. Preventing infectious diseases through monitoring is necessary for SDG 3. The current trend of global warming as well as globalization, the infected area is expanding into new areas as mosquitos move along with human and material flows, and controlling infectious diseases will be challenging to all countries. The recent outbreak of Zika virus in South America has already widespread to North America, Europe, and Asia, and 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, and GIS is an effective tool for this process. Orimoloye et al. studied about change 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. 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).

The GIS is also an effective tool to monitor the progress of achievement as well as to make future plans for SDGs, and many studies have revealed its effectiveness (Sustainable Development Solutions Network (SDSN), 2014). GIS is, however, not fully incorporated in the monitoring and evaluation process for global problems and targets. For the successful ending of SDGs, the monitoring process could be standardized for all countries, and the GIS could be incorporated into the process aiming for redressing regional differences in a country. Science and political communities would need to cooperate to make an effective monitoring system for SDGs

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 applications of geospatial techniques like remote sensing and GIS has promised for achieving 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 RSGIS 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 using integrated RS, GIS and Multi-Criteria Decision Making (MCDM) technique. 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 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 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, Singh, Shashtri, Singh, & Mukherjee, 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 and girls and those in vulnerable situations. Open defecation is a very common sight in developing countries due to inaccessibility to infrastructure 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 properties of infrastructure planning. The zones can be for different purposes such as sanitation, housing etc. By using the information of population densities and area it can be also used to calculate the approximate number of users and costs.

The study on water pollution and management in Tiruchirappalli Taluk, Tamil Nadu, India using IRS LISS-III (Linear Imaging Self Scanning Sensor), satellite imagery and SRTM (Shuttle Radar Topography Mission) data integrated with water level data, canal inflow, groundwater condition to generate distribution of water pollution map in the area (Alaguraja, Yuvaraj, & Sekar, 2010). Another study conducted in Alabata community (Nigeria), which is a community without basic infrastructure facilities revealed the importance of RS-GIS based techniques in the bacteriological examination of rural community water supply. 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 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, Akpan, Popoola, Oyedepo, & Oluderu, 2015).

Over-exploitation of groundwater resources can 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 are 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, drainage and groundwater data analysis in GIS. This study has helped to design 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 and 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. Availability of water depends on several factors like 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 on change detection of natural high forests in Ethiopia using RS and GIS techniques set a very good example for this (Reusing, 2000a). The author has done countrywide change detection analysis of Ethiopia's natural high forests using multi-temporal LANDSAT-TM satellite images. Wetlands are important in mitigating and controlling flood 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., have developed a multiple purpose wetland inventory using integrated RS-GIS techniques and specific analyses at different scales in response to past uncertainties and gaps (Rebelo, Finlayson, & Nagabhatla, 2009). 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 advancement in technologies and computer science. Therefore, increased investment and technical application are needed to expand on the progress being made to integrate geospatial data into the implementation of sustainable cities and human settlements global goal. UN-Habitat is already engaging research institutions to develop a representative dataset of urban areas that would make possible monitoring of urban land-use efficiency, land-use mix, street connectivity and other key factors of sustainable urban development (Habitat, 2015). Consequently, adopted 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 to the growing population in this digital world of uncertainties. Furthermore, working towards the achievement of higher-level outcomes in other goals (e.g. poverty eradication, water and sanitation, food security and energy efficiency), which strongly reflects cities as arenas of implementation, and places where projects strong foundations are to be built.

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 a 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-use changes, including through urgent actions at all levels of access, explore 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 SDG 11 achievements by 2030. For example, the application of RS data in wastewater monitoring can clearly assist us to identify the flow and be used as an indicator for monitoring the proportion of wastewater safely treated (Ulugtekin, Bektas, Dogru, Goksel, & Alaton, 2005). There is a similar situation on the population density, land use, land cover and many other data needed in the achievement of SDG 11. If this data is integrated with other geospatial, survey and administrative data of high-resolution satellite images can document the location of treatment facilities in a city, estimate the wastewater generation potential, release 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, help on the lack of capacity for additional monitoring and well it also has cost-effective gains on monitoring in general.

Geospatial information and analysis significantly enhance 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 the implementation structure of sustainable cities goal achievement. 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 further support the capacity building in the intersection of various disciplines in a transdisciplinary approach ((ISO), And, & (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 the 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 Backcasting methodology, if implemented in a modeling environment of many cities, urban planning process based on Geo-Information-System (GIS-based) using the scripting language Python, will play a major part in the implementation process of the 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 the unity between institutions having similar goals and objectives both at national and global perspectives. The institutions are required to deliver the same data, as much as practical and depending on national circumstances and functions usefulness of the geospatial data in the implementation of the SDG 11 is concerned. Urban cities contribute around 80% of global greenhouse gas (GHG) emissions, especially in most developing nations where urban centers and cities are very much spaced, with no effective means of urban transport systems. Therefore, sustainability indicators can provide new ideas and solutions to the planning and expansion happening 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, Pacheco-Torres, Ordóñez, & Jadraque-Gago, 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 sustainable city goal. 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, geospatial information can provide a set of science and time-based monitoring solutions to these challenges. 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. Which contribute substantially to the achievement of the 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 methods for assessing the environmental effects in informal settlements in Cuiaba, Central Brazil has been carried out in (Zeilhofer & Piazza Topanotti, 2008). The reason for the rise in informal settlements in Cairo, the capital of Egypt has been studied in (El-Batran & Arandel, 2005). The sustainable informal settlements in Dharavi, Mumbai, India, Santa Marta favela, Rio de Janeiro, Tondo, Manila, Philippines have been studied in (Dovey, 2015). The author in (Dovey, 2013) 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 in (Karanja, 2010). In conclusion, whether collecting and analyzing satellite images or developing geopolitical policy, geography provides the integrative approach necessary for global collaboration and consensus decision making towards the achievement of SDG Goal 11 on safe, resilient and sustainable cities.

3.6 Sustainable Development Goal 13: climate action

The key to understanding 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 in aid of the application of satellite RS on the issues of climate change and food security in the country. Also, countries like the Philippines is pushing for the capacity building of its technical people to earn needed expertise on the use and application of new and sophisticated equipment such as the 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 reanalysis 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 shreds 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 down 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, ENVISAT, and distributed computing. Recent developments in RS open 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, Huggel, & Fischer, 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 for 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 ocean, 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 Geubas (2002) (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. The author 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 prediction. Another study done for seagrass meadows, North Carolina, USA supports the significance of geospatial techniques in the sustainable use of ocean and its resources. Seagrass meadows are vulnerable to external environmental changes and they provide 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). RS and Landsat TM were used in this study to detect these changes.

Oil spills are a very common sight in oceans. They are mainly associated with the shipping routes. Oil spills can significantly affect the marine animals by coating on them and suffocating them to death. Furthermore, it can inhibit sunlight falling on the ocean and inhibit primary production. RS can be used to detect these oil spills easily. Microwaves are commonly used for the detection of ocean pollution. 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, Anderssen, & Skøelv, 1994). With the advancement of RS technologies Synthetic Aperture Radar (SAR) plays an important role in oil-spill monitoring (Brekke & Solberg, 2005).

Global capture fisheries 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, 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, and wind which are very important in operational oceanography. In pelagic fisheries, there are mainly two RS applications. One is for 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*) bycatch, while fishing for swordfish (*Xiphias gladius*) and tuna (*Thunnus* spp.) in the North Pacific (Howell, Kobayashi, Parker, Balazs, & Polovina, 2008). This proved the feasibility of designing near-real-time fishery management boundaries using SRS SST (sea surface temperature), modeled data, and thermal habitat signatures from pop-up satellite tags (Saitoh et al., 2011).

3.8 Sustainable Development Goal 15: life on land

Forest plays a major role in regulating the global carbon cycle at regional to a global scale. According to 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 which may be due to any or many of the following reasons; 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 authors in (Angelsen, Brockhaus, Sunderlin, & Verchot, 2012; Instituter & Meridian Institute, 2009) have concluded that it is highly important to reduce greenhouse gas (GHG) emissions from deforestation and forest degradation as a step towards mitigating climate change.

Global 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 on 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 emergency income and food during famine or destruction of the forest also affects soil and water quality in the immediate area and can adversely affect on biodiversity over a range of connected ecosystem. 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 affects the structure or functions of the stand or site, and thereby lower the capacity to supply products and/ or services. While REDD+ defines degradation is 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 that 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 which stands right in front of humanity, it is the need of an hour to accurately monitor, map and estimate the net forest cover, monitor deforestation, and degraded forest area and quantifies 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. (2015) (Sudhakar 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 used were 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). The overall accuracy of the forest cover maps derived for the years 1975, 1985, 1995, 2005 and 2013 was 89.2%, 90.5%, 92.4%, and 93.2% respectively. Another study by Ritters et al. (2015) (Riitters, Wickham, Costanza, & Vogt, 2016) 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 national-level policy designing to stop the progress of deforestation and degradation. But, they do tend to overlook the changes at a local level, which shall 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, Kobayashi, & Takeda, 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 local level surely help to monitor the activities of private companies and thereby a strong monitoring system shall 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. The authors in (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 provide 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.

The 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 a type of terrestrial ecosystem existing, for instance, the authors in (Jaramillo, Kauffman, Rentería-Rodríguez, Cummings, & Ellingson, 2003) found that forest ecosystem to 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. 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 in (Singh, Kumar, & Kushwaha, 2014).

Achievement of targets under Sustainable Development Goal 15 which basically focuses on sustainable management of all types of the forest by the year 2020 shall require each nation to establish a transparent, consistent and accurate forest monitoring system. The implication of the human activities in present 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. The authors in (Thapa, Motohka, Watanabe, & Shimada, 2015) carried 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 impacting carbon sequestration. Such kinds of studies play a paramount role in designing and analyzing the current policies and their implication on the future. Thus, it is evident that the use of an objective specific geospatial technique is essentially important for implementation and achievement of Sustainable Development Goal 15. An analytical framework for SDGs is given in Figure 2.

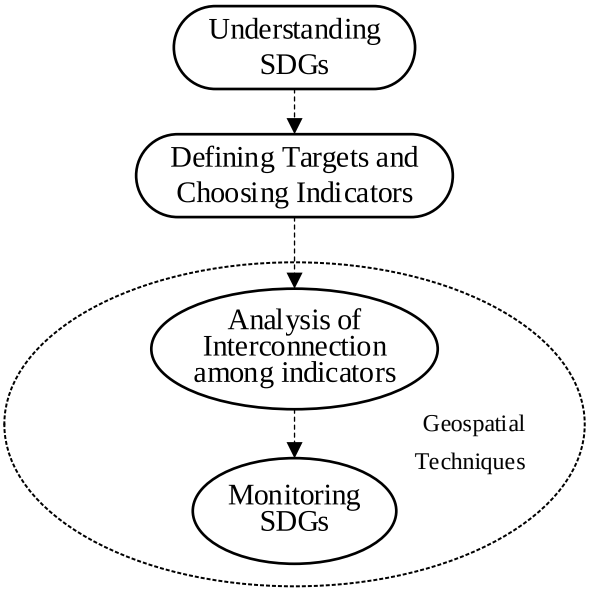

Figure 2. Analytical Framework for SDGs

4. Discussion

The progress being made in achieving SDGs can be measured by several quantifiable indicators. The role of RS techniques in the measurement of various indicators for monitoring the roadmaps for achieving SDGs has been significant in terms of its capacity to use sensor data for augmentation of the census data. Several studies which make use of one kind of RS technique or other have shown that RS methods play a major role in the monitoring of SDGs. The citizen science and big data have also been found useful for measuring and monitoring SDG indicators. Citizen generated data 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. and the data produced can be quantitative or qualitative in various formats (DataShift, 2017). Lessons learned from Millennium Development Goals (MDGs) shows 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 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 wards implementation of SDGs in various ways such as filling data gaps and capacity, fulfilling commitments to multi-stakeholder partnerships, driving Innovation and build capacity, 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, timely, reliable and disaggregated by different groups in society all of which the citizen generated data can make a crucial contribution to making a reality". Some of the examples for the above points can be already seen taking effect in 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 others get to have the practical aspect of the situation but also keeps the system up to date. With the massive interest of highly complex data available from satellites all over the world and presented into simple form and easily understandable format of Google Earth has encouraged people 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 not only making a contribution to the betterment of the system but also increasing scientific curiosity & making discoveries (Santens, 2011). A study by Global Pulse on mining citizen feedback data for enhanced 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 citizen scientists from around the globe, who help monitor levels of deforestation. By reviewing satellite images of forested regions local residents, volunteers, non-governmental organizations governments can help in the assessment of these regions. Moreover, this initiative encourages local citizens and provide the rights of ownership to help and implement SDGs. The authors in   (Flückiger & Seth, 2016) suggested data from civil-society can be crowdsourced to implement and monitor the progress of SDGs. United Nations Environmental Programme (UNEP) is involved in capacity development, environmental awareness, and information exchange program to foster a generation of environmentally conscious citizens that can help ecosystem renewal in Kenya (UNEP, 2017). Use of citizen science data/information can provide transparency in a system with updated and real-time information that can change the course of our future with political will. A positive example for such political and citizen science data movement is accessibility to Landsat, Sentinel, MODIS data for scientific purpose to anyone who wants to use 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 increasing 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 and storage capacity, 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 continues monitoring of global earth observation for environmental monitoring (Skyland, 2012). The RS big data does not merely refer to the volume and velocity of data but also the variety and complexity of data. This diversity and complexity in data makes the accessing and processing the data significantly difficult especially for the layman (Ma et al., 2014). Annexure1 shows various satellites and their specification. These satellites have sensors with different spatial, temporal and spectral resolution will result in multi-sensor complex data. 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 the Sustainable Development Goals (SDGs) lies in leveraging new/non-traditional data sources and techniques to better measure or monitor progress towards 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 in (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. The initiation of government interest for Big data mining can be on various fronts and for a variety of purposes. This can be attained to even more over the already established systems and for the betterment of the existing system. For Example, the benefits of big data mining done by governments intended for the betterment 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. 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 authors in (Lu, Nakicenovic, Visbeck, & Stevance, 2015) suggest five priorities for the SDGs viz. devise metrics, establish monitoring mechanisms, evaluate progress, enhance infrastructure, standardize and verify data. The authors of (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 seventeen goals of SDGs have been set for improving human well-being, protecting natural resources and lessening the impact of human activities on the earth for the future generation. Unlike the previous Millennium Development Goals, the Sustainable Development Goals are meant for both developed and developing countries, and considering the broad themes and areas of the SDGs, monitoring is a crucial process for the successful accomplishment by 2030. Monitoring is a necessary step 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 in both national and local levels. It requires numeric data to create a GIS database, meaning the data must be physically obtained. However, connecting the numeric data and geography provides clearer shreds of evidence of regional differences and spatial correlations. On another front, RS can also visualize the surface of the earth; hence it is useful to detect environmental problems. Considering the broad range of SDGs' targets, geospatial information is one of the most important tools for monitoring the achievement and it will pave the way towards successful accomplishment of SDGs.

Achieving the SDGs undoubtedly demand a massive global effort in concert to efficiently make use of data sharing, processing, and aggregation in a highly multidisciplinary framework. National geospatial information agencies will need to collaborate more closely with national statistical and earth observation professional communities, be more unified with similar national to global objectives and aspirations, be delivering consistent and reliable data that is fit-for-purpose, and demonstrate the functionality and value of the geospatial data by integrating it into the wider sustainable development policy process. This 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. In the future, the demand for real-time processing of satellite data has high opportunities that can be noticed by the potential use of

Google Earth Engine. The integrative approach of partnership, capacity-building, and big data can bring a sustainable solution 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