**Latest progress in space-borne optical remote sensing systems for monitoring global terrestrial ecosystems**

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**Abstract**

Since the launch of the first Landsat satellite in the early 1970’s, the field of space-borne optical remote sensing has made significant progress. Advances have been made in all aspects of optical remote sensing data including improved spatial, temporal, spectral and radiometric resolutions which have increased the uptake of these data by wider scientific communities. Flagship satellite missions like NASA’s Terra and Aqua and ESA’s Envisat with their high temporal (<3days) and spectral (15-36 bands) resolutions opened new opportunities for routine monitoring of various aspects of terrestrial ecosystems at global scale and have provided greater understanding of critical biophysical processes in the terrestrial ecosystem. Launch of new satellite sensors such as Landsat 8 and ESA’s Copernicus Sentinel missions (e.g. Sentinel 2 with improved spatial resolution (10-60m) and potential revisit time of 5 days) are set to revolutionise the availability and use of remote sensing data in global terrestrial ecosystem monitoring. Furthermore, the recent move towards use of constellations of nanosatellites (e.g. the the Flock missions by Planet Labs) to collect on-demand high spatial and temporal resolution optical remote sensing data would enable uptake of these data for operational monitoring. As a result of increase in data availability, i optical remote sensing data are now increasingly used to support a number of operational services (e.g. land monitoring, atmosphere monitoring, and climate change studies). However, many challenges still remain in exploiting the growing volume of optical remote sensing data to monitor global terrestrial ecosystems. These challenges include: ensuring the highest data quality both in terms of the sensitivity of sensors and the derived biophysical products, affordability and availability of the data and continuity of data acquisition. This review provides an overview of the developments in space-borne optical remote sensing in the past decade and discusses a selection of aspects of global terrestrial ecosystems where the data are currently used. It concludes by highlighting some of the challenges and opportunities of using optical remote sensing data in monitoring global terrestrial ecosystems.

1. **Introduction**

Global terrestrial ecosystems are important because they provide critical ecosystem services to society including but not limited to, food and fibre to human society, food and shelter for wildlife, sequestration of atmospheric carbon dioxide (a potential mechanism for mitigating climate change), and the renewal of the water cycle (Song *et al.,* 2013). Therefore, monitoring the state of global terrestrial ecosystems (i.e. their health, condition, extent and dynamics) is an important focus for global change research. This requirement has become more pertinent due to recent changes in the global climate system (IPCC, 2013), which is expected to have significant impacts on terrestrial ecosystems. Traditional approaches of monitoring terrestrial ecosystems through *in-situ* measurements, though offering detail and highly accurate information, are often inadequate at regional to global scales due to time constraints, high costs and sometimes non-replicability of measurements due to inconsistencies in protocol (Clark *et al.,* 2001). Satellite based remote sensing data acquisition, with its synoptic view and repetitive data collection capabilities, offers an improved capacity to monitor terrestrial ecosystems at regional to global scales (Turner *et al.,* 2006; Song *et al.,* 2013; Yang *et al.,* 2013; Gong *et al.,* 2013). Satellite remote sensing data acquisition involves recording reflected or emitted radiation by a sensor in one or more regions of the electromagnetic spectrum, and the data can then be processed and interpreted to gather information on Earth surface features. Remote sensing data acquisition can span the whole breadth of the electromagnetic spectrum; however, the two key regions often used in Earth observation remote sensing are the optical and microwave regions. This review focuses on the development and application of data from the optical remote sensing systems as these data are most widely used in monitoring global terrestrial ecosystems.

The launch of Landsat 1 in 1972 marked the first systematic and repetitive observation of large swathes of the Earth’s terrestrial surfaces in the optical domain of the electromagnetic spectrum. Landsat 1 enabled multispectral data to be acquired routinely over large areas and catalysed the expansion and development of digital image processing methodologies (Chander *et al.,* 2009). Since then, several other remote sensing satellite sensors which record data in one or more regions of optical spectrum have been launched (Table 1). Data from these sensors have been used to monitor various aspects of global terrestrial ecosystems including but not limited to: land use and land cover (Friedl *et al.,* 2002; Bartholome and Belward, 2005; Friedl *et al.,* 2010), terrestrial ecosystem primary productivity (Tucker *et al.,* 1981; Prince 1991; Prince and Goward, 1996; Ogutu *et al.,* 2013), crop production (Lobell, 2013), wildfire (Tansey *et al.,* 2004; Carmona-Moreno *et al.,* 2005; Hao and Larkin 2014), biodiversity monitoring and conservation (O’Connor *et al.,* 2015; Pettorelli *et al.,* 2014; Nagendra *et al.,* 2013; Pettorelli *et al.,* 2012; Duro *et al.,* 2007 ) vegetation condition and growth (e.g. phenology and biophysical variables) (Huete, 1988; Myneni *et al.,* 1997; Gower *et al.,* 1999; Dash and Curran, 2004;Jeganathan *et al.,* 2010; Dash *et al.,* 2010), and ecosystem services (Naidoo *et al.,* 2008).

Successful application of optical remote sensing data to monitor various aspects of global terrestrial ecosystems such as those highlighted above require the data to meet certain standards. For example, the remote sensing data should be acquired in sufficient resolution (i.e. spatial, temporal, radiometric and spectral resolution) to allow for accurate characterisation of the terrestrial ecosystem features and dynamics. These requirements have led to continuous development in both sensor technology and acquisition capabilities over last four decades. It is envisaged that satellite-based optical remote sensing will continue to provide the bulk of data needed for monitoring various aspects of global terrestrial ecosystems. Therefore, it is important to evaluate the progress that has been made in optical remote sensing systems since the launch of the first environmental remote sensing satellite (i.e. Landsat 1). The first section of this review highlights the progress that has been made in optical remote sensing, while the second section discusses a selection of areas of global terrestrial ecosystems where optical remote sensing data are currently used. The review concludes by highlighting some of the challenges and opportunities of using optical remote sensing data in monitoring global terrestrial ecosystems.

1. **Advances in satellite based optical remote sensing data acquisition**

Since the launch of Landsat 1 in 1972, a large number of optical remote sensing satellites have been launched (Table 1). Most of the optical remote sensing satellites are passive sensors, mostly recording reflected solar radiation from the Earth’s surface. The optical sensors can be categorised based on their sensitivity to various wavelengths of the electromagnetic spectrum as either multispectral or hyperspectral sensors. The initial optical remote sensing satellites (e.g. Landsat series, SPOT series, and AVHRR series) mainly collected data in a multispectral format, that is, by detecting radiation in a small number of broadband wavelengths within the visible and mid-infrared sections of the spectrum. Advancement in sensor technology such as spectral filtering techniques have enabled the observed scene radiance to be split into narrow distinct bands and improvement in detector array technology in the 1980s allowed the development of hyperspectral remote sensing which involves collection of data across a large number of contiguous narrow spectral bands (typically up to 200 bands) (Goetz, 2009; Bioucas-Dias *et al.,* 2013). Hyperspectral data offers a higher level of spectral and radiometric detail of features when compared to multispectral data (Ali *et al.,* 2013), thereby enabling not only improved distinctions between features, but also providing data to characterise the influence of atmosphere that can then be removed from the recorded radiance signal (Goetz, 2009). Even though hyperspectral remote sensing offers distinctive advantages over multispectral remote sensing, the relatively high costs of hyperspectral detectors, large data storage requirements and lack of appropriate algorithms to process the data (Plaza *et al.,* 2009) and to some extent a lack of appreciation of the capabilities of hyperspectral data (Goetz, 2009) has led to very few satellite based hyperspectral sensors being launched. Data from only two missions have been used in some selected applications, that is, the European Space Agency’s CHRIS PROBA-1 mission (which had the aim of exploring the capability of multi-angle imaging spectrometers; Barnsley *et al.,* 2004) and the NASA’s EO-1 Hyperion Imaging Spectrometer (which was also a technology demonstrator mission; Ungar *et al.,* 2003). Due to the limited availability of satellite based hyperspectral remote sensing data, multispectral remote sensing still forms the bulk of satellite based optical remote sensing data collection and information extraction. An area for future development in optical remote sensing would be a concerted effort to ensure that satellite based hyperspectral data can be acquired more routinely and made readily available for use by the scientific community so that its benefits can be fully realised. Achieving this will require improvement in the current limitations (i.e. reduction of costs, increased storage capacities and improved processing algorithms) of hyperspectral remote sensing data. One possible way of reducing costs include exploring the possibilities of using small/miniature satellites which have recently become available due to improved technology. A second suggestion that can mitigate the problem of data volume and processing demands is to encourage future missions to be designed to focus on specific narrow bands that have relevance to key biophysical processes in terrestrial ecosystems (e.g. the ESA- Fluorescence Explorer (FLEX) mission- designed to map vegetation fluorescence to quantify photosynthetic activities Kraft *et al.,* 2012) rather than collecting data in full hyperspectral mode. This will ensure that the processing demands for the data are lowered whilst the scientific capabilities of the mission are enhanced over the generalised multispectral missions. The shortcomings notwithstanding, two new missions are proposed that will provide hyperspectral data for monitoring terrestrial ecosystems: the Environmental Mapping and Analysis Program (EnMAP) hyperspectral satellite by German Aerospace Centre (DLR) (Kaufmann *et al.,* 2006) and the HyspIRI Mission by NASA (Green *et al.,* 2008; Mulla, 2013).

The usefulness of optical remote sensing data in monitoring global terrestrial ecosystems often depends on their spatial and temporal resolutions. In many applications, high spatial and temporal resolution is desired. However, due to limitations imposed by instruments field of view and swath width it is not often possible to achieve high spatial and temporal resolutions. Traditionally, sensors with high temporal resolutions (1-3 days) (e.g. NOAA AVHRR, Terra and Aqua Satellites) usually acquire data in coarse spatial resolutions (>250 m) owing to wide field of view, while those with medium spatial resolutions (<100m) with low field of view often acquire data at a coarse temporal resolutions (e.g. 16 day revisit time for the Landsat series) (Chander *et al.,* 2009). To overcome this limitation, programmable/tasking satellites have been launched in the past decade which can acquire data at both high temporal (1-3 days revisit time) and high spatial resolutions (1-30m) allowing focus on critical study areas. Examples of sensors capable of acquiring both high temporal and spatial resolution optical data include the satellite systems such asRapid Eye, QuickBird, WorldView, Pleiades (Gleyzes *et al.,* 2003; Longbotham *et al.,* 2015). Even though these sensors fulfil the requirement of high spatial and temporal resolution, the tasking requirement makes data acquisition expensive and not readily available for mass use. Furthermore, to achieve high spatial resolution, satellites carrying these sensors tend to be in lower orbit thereby reducing their swath width requiring more imagery to cover regional to global scale studies hence increasing the cost of using such data. The Disaster Monitoring Constellation International Imaging (DMCii) pioneered the concept of satellite constellations in optical remote sensing by launching a series of satellites sensors with exactly same specification but viewing the Earth surface at different times (Baker *et al.,* 2008). This was aimed at providing data at a quick revisit time, high spatial resolution and global coverage without going through the tasking process. The concept of constellation satellites was also used in the RapiEye sensors launched in 2008 making them able to provide daily coverage for any location on the globe and at high spatial resolution (6.5m) (Mulla, 2013). The European Space Agency, through the Sentinel missions, intends to use a similar constellation principle by launching a series of Sentinel satellites (Sentinel 2a (launched in June 23 2015) and 2b (to be launched in 2016)) which will provide optical data with a relatively fine spatial resolution (up to 10m), and with a high revisit times (5 days when the two satellites are operational) and at a large swath (290km) (Drusch *et al.,* 2012). In future, the use of satellite constellations could offer a way forward to address the challenges of achieving high spatial, high temporal and global coverage by optical remote sensing systems. This is especially important since optical remote sensing is often affected by weather (e.g. cloud cover) and having satellite constellations can ensure a high probability of data acquisition over areas prone to cloud cover.

A major challenge to the availability of satellite optical remote sensing data is the high cost of satellite missions. Traditionally, Earth observation satellites have tended to be big single missions carrying only one sensor (e.g. Landsat series, SPOT series) or even bigger multi-mission satellites (e.g. ENVISAT, Terra and Aqua missions) which are costly to fund and require many years to plan and execute. The DMCii pioneered the use of relatively smaller satellites which were cheaper and could be developed and deployed quickly to acquire remote sensing data at relatively lower costs (Underwood *et al.,* 2005). In the recent past, there has been a rise in the number of companies developing even smaller satellites (micro- or nano-satellites, sometimes called cube-sats) which are relatively cheap to build enabling mass production and deployment into orbit. Examples of these micro-satellites include the Skybox imaging Skysat satellites (Murthy *et al.,* 2014), Planet labs Dove satellites and UrtheCast satellites (Boshuizen *et al.* 2014, Hand, 2015). Due to the relatively cheap cost of assembling and deploying microsatellites, these companies have launched or intend to launch swarms of microsatellites, which by virtue of their large numbers will be able to revisit and photograph large swathes of Earth several times per day (Butler, 2014) but in limited spectral bands (typically visible and broadband near-infra-red capabilities only). Furthermore, compared to the conventional satellite sensors, these microsatellites acquire data at relatively high spatial resolution (ranging from 1-5m), allowing improved detail of the Earth surface features to be discerned from these data. Finally, as opposed to some of the conventional commercial imaging satellites that only collect images when tasked to do so, these microsatellites have the capacity to continuously collect data ensuring global coverage (Butler, 2014). However, there are some drawbacks which hinder that ability to fully use the data from the microsatellites to monitor and manage global terrestrial ecosystems. Firstly, these microsatellites are only acquiring data in broad visible spectral bands (e.g. the Planet Labs Doves), thus are mostly used as ‘photographs’ of Earth surface features rather than using the data to derive any quantitative biophysical variables. Secondly, there are some concerns about the quality of data acquired by the microsatellites, especially in their atmospheric, radiometric and geometric calibration which is not well-documented. Appropriate calibration ensures that data from satellites can be used to gain insight into the type and condition of the Earth surface feature of interest and is essential to ensure long-term monitoring capacity for scientific investigations (Chander *et al.,* 2010; Mishra *et al.,* 2014). Finally, the fact that the swath of each of the scenes acquired by microsatellites is often small (e.g. SkySat from Skybox has a swath width of 8km at nadir), which imply that to create large swath data, numerous scenes often need to be mosaicked together. This presents a challenge in ensuring that the data has an overall good quality, as the scenes may have been collected under different illumination and atmospheric conditions. If these challenges are addressed, the new generation of microsatellites have the potential to revolutionise optical remote sensing data acquisition. Furthermore, the mass collection of data will ultimately lead to reduction in costs of data thereby expanding the use of these data in monitoring various aspects of terrestrial ecosystems. Therefore, the future of optical remote sensing data acquisition may move away from government and national space agency backed big satellite missions which are expensive and take years to plan to small/micro-satellites run by the private sector which are cheap and can be readily deployed. The challenge of uptake of these data from the private sector will be whether they can be priced at a level which is affordable to many users.

1. **Application of optical remote sensing data and operational products in global terrestrial ecosystem monitoring**

Data from optical remote sensing are useful in monitoring various aspects of global terrestrial ecosystems either through developing specifically targeted outputs from the optical remote sensing data (e.g. production of land cover maps) or to deliver more specific biophysical products for monitoring ecosystem functions and conditions (e.g. Leaf Area Index, chlorophyll content). Examples of areas of application of optical remote sensing data include: land cover/use mapping and change detection, monitoring terrestrial vegetation condition and dynamics, climate change studies, biodiversity monitoring and conservation, habitat loss, wildfire studies, carbon exchange studies, and land-atmosphere interactions. Examples of areas where optical remote sensing data and related products have been used and developed for global terrestrial ecosystem monitoring and management are described in the following sections.

1. ***Land cover/ land use mapping and monitoring***

Land cover can be described as the composition and characteristic of land surface elements whereas land use is the functional dimension or socio-economic purpose of the land surface (Cihlar, 2000). Information about land cover/land use is important in many scientific research applications (e.g. climate change studies and biogeochemical cycle modelling), resource management (e.g. resource inventory, exploitation and evaluation), and policy applications (e.g. legislation, environmental management and planning). Since land cover/land use (LCLU) varies at a range of spatial scales from local to global and at temporal frequencies of months to millennia (Cihlar, 2000), its characterisation requires data at those spatial and temporal resolutions. Consequently, satellite based optical remote sensing has become the standard data source for mapping LCLU and studying their change at landscape to global scales (Friedl *et al.,* 2002; Bartholome and Belward, 2005). The basic principle of generating land cover maps from optical remote sensing data is that different land cover types within a feature space will exhibit different spectral behaviour that can be separated using various classification algorithms (Townsend and Justice 1988; Aplin, 2004). In one of the earlier reviews, Aplin, (2004), pointed out that there are two main areas of application of remote sensing-based LCLU data (i.e. environmental management and environmental understanding). Environmental management is defined as the control and use of land cover distributions to exploit land resources while safeguarding environmental concerns and environmental understanding as the scientific analysis of processes both natural and anthropogenic involved in determining LULC (Aplin, 2004).

Various agencies (both national and international) are currently engaged in deriving land cover products from optical remote sensing data (Table 2). Due to costs and data availability for producing land cover maps at regional to global scales, most of the existing regional to global land cover maps are often produced either as single year products (e.g. the GLC2000 map, Bartholome and Belward, 2005) or multiyear products (e.g. the CORINE land cover maps-, Bossard *et al.,* 2000, and the GLOBCOVER maps, Bontemps *et al.,* 2010). The majority of the global extent land cover maps (e.g. the GLC200, GLOBCOVER, and MODIS Land cover Product-Table 2) are produced at a coarse spatial resolution (>300m) (Table 2). However, in the recent past, a high spatial resolution (30m) global land cover product (i.e. the GlobeLand30) has been produced by the National Geomatics Centre of China (NGCC) using data from Landsat 5, Landsat 7 ETM and the China Environmental Disaster Alleviation Satellite using data from the HJ-1 sensor (Chen *et al.,* 2015). The GlobeLand30 product classifies the global land cover into ten classes (i.e. cultivated land, forest, grassland, shrub-land, water bodies, wetland, tundra, artificial surfaces, bare-land and permanent snow and ice) (Chen *et al.,* 2015). Its 30m spatial resolution offers a greater possibility of understanding landscape dynamics at the finer scales compared to the previous global land cover products with spatial resolutions greater than 100m (Table 2). Figure 1 shows the level of distinction between land cover types achievable from the 2010 GlobLand30 product compared with the 2009 GLOBCOVER product over a heterogeneous landscape in Heilongjiang province in Northern China. The high spatial (30m) resolution GlobeLand30 product is ‘less pixelated’ and provides a more detailed view of land cover variability compared to the coarse spatial resolution GLOBECOVER product. This enhanced detail is useful for providing accurate characterisation of land cover types and studying their dynamics over time.

Land cover data derived from remote sensing data has been used in various applications. Brink and Eva (2009) used land cover data derived from Landsat images to show a 57% increase in agricultural areas and a 21% reduction of natural vegetation over Africa between 1975 and 2000. Lunetta *et al.,* (2006) used land cover map derived from the MODIS sensor to identify a 0.7% annual rate of land cover change in the Albemarle–Pamlico Estuary System (APES) region of the US. Data from optical remote sensing has also been used in mapping urban sprawl (Ji *et al.,* 2005; Kasanko *et al.,* 2006). Kasanko *et al.,* (2006) used landuse data derived from high spatial resolution remote sensing images (e.g. IRS satellite) stored in the Monitoring LANd use/cover Dynamics-MOLAND database (maintained by the Joint Research Centre of the European Commission) to show the dispersion characteristics and level of compactness of 15 European cities. This study showed that the southern European cities are more compact compared to northern and eastern cities, while the western cities are midway between the two extremes. Ji *et al.,* (2005) used Landsat data to show a significant increase in built-up areas at the expense of vegetation cover in Kansas City, USA between 1970 and 2001. The recently released GlobeLand30 land cover product has successfully been used to show that globally, most land surface water is mainly distributed in the mid to high latitude areas of the northern hemisphere and the tropics and there has been a slight decrease in the area of land surface water (Cao *et al.,* 2014). Land cover data has also been used to characterise vegetation distribution in primary productivity models (Running *et al.,* 2004).

The usefulness of the land cover products is dependent on their accuracy, which depends on many factors (Coppin *et al.,* 2004; Rocchini *et al.,* 2013). One of the key sources of uncertainty in LCLU maps is the characteristics of the data used in deriving the LCLU maps. A number of challenges exist in using optical remote sensing data to generate accurate LCLU maps. Firstly, optical sensors are affected by weather conditions (e.g. clouds) which limit the amount of usable data especially in tropical areas which are prone to cloud cover. A high revisit time and use of satellite constellations can help improve the chances of getting cloud free data in areas that are prone to cloud cover. Furthermore, microwave/radar remote sensing data which are not affected by clouds can be used to overcome effects of weather on optical remote sensing data (DeFries, 2008). Secondly, most optical remote sensing data are acquired using multispectral sensors which collect data in broad-band wavelengths, which may not be sufficient for distinguishing between some land cover features (e.g. different vegetation species or crops). Hyperspectral optical remote sensing offers the promise of producing a more detailed land cover/use maps (Petropoulos *et al.,* 2012; Fagan *et al.,* 2015). However, the lack of a readily available satellite based hyperspectral data with a regular repeat cycle has hindered the use of hyperspectral data in mapping global LCLU. Thirdly, optical remote sensing data used for mapping land cover at regional to global scales are often at coarse spatial resolution (>300m). The coarse spatial resolution makes it difficult to distinguish between features on the land surface, hence reducing the accuracy of the derived land cover/use maps. However, the recent (22nd September 2014) release of the GlobeLand30 LCLU product by the Chinese government to the United Nations marked a milestone in the global LCLU mapping, whereby for the first time a global LCLU map has become available at a relatively high spatial resolution (30m). Furthermore, the recent move towards low cost micro-satellites which can collect global data at high spatial and temporal resolutions offers an opportunity to produce land cover/use maps even at higher spatial resolution(<10m). The high temporal resolution (i.e. 1-2 days) of data acquired by these microsatellites increases the chances of getting cloud free data in cloud prone areas to use in producing LCLU maps. Furthermore, the high temporal resolution data makes it potentially possible to extract phenological information which can be incorporated in the land cover/use classification process. This is particularly important as it has been shown that incorporating phenology information in land cover classification improves the accuracy of the classification output (Dudley *et al.,* 2015, Senf *et al.,* 2015, Simonetti *et al.,* 2015). As mentioned earlier, one drawback from the data collected by these microsatellites is that they are currently configured to collect data in broad-band multispectral mode which may not be ideal for distinguishing some land cover types (e.g. crop types) in a mapping exercise.

1. ***Terrestrial vegetation bio-geophysical variables monitoring***

Vegetation bio-geophysical variables (e.g. Leaf Area Index (LAI), Fraction of Absorbed Photosynthetic ally Active Radiation (FAPAR), Fraction of Vegetation Cover (FCOVER), phenology, leaf and canopy chlorophyll content) are useful variables in assessing terrestrial ecosystem function, condition and their role in biogeochemical cycle (Justice *et al.,* 2002). Traditionally, these variables are derived or estimated from field based measurements (Chen *et al.,* 1997; Ogutu *et al.,* 2011). However, these approaches are laborious, time consuming and often impractical to cover regional to global scales. Satellite based optical remote sensing offers a cost-effective way of acquiring data to derive these variables at global scales. The most common approaches of deriving these variables from optical remote sensing data include: use of band ratios (i.e. vegetation indices), developing empirical relationships, and inversion of radiative transfer models (Myneni *et al.,* 1997; Gower *et al.,* 1999; Jonckheere *et al.,* 2004; Ganguly *et al.,* 2008). The band ratio approach involves calculating a ratio between various bands (often bands in the visible and near infrared bands) recorded by the sensor to give an indication of the vegetation greenness and has been widely used since the launch of early terrestrial monitoring satellite sensors (Huete, 1988). A number of vegetation bio-geophysical parameters such as LAI, FAPAR, FCOVER, and canopy chlorophyll content can then be deduced from the band ratio indices (Huete, 1988; Myneni et al., 1997; Gower *et al.,* 1999; Dash and Curran, 2004). Empirical approaches involve deriving equations that relate reflectance values with known values (often from field measurements) of vegetation bio-geophysical variables (e.g. Leaf Area Index, chlorophyll content) and then using this equation to process a whole scene of remotely sensed data to derive the vegetation bio-geophysical variable of interest with a greater spatial coverage (Gower *et al.,* 1999). Finally, the use of inversion of radiative transfer models involves developing models which produce reflectance spectra under various atmospheric, view geometry and vegetated surface conditions and then using these spectra as a reference to be matched with remote sensing recorded reflectance spectra to predict the value of the vegetation bio-geophysical variable in question (e.g. Leaf area index) (Myneni *et al.,* 1997; Gower *et al.,* 1999).

Vegetation bio-geophysical variables derived from remote sensing data are important in monitoring many aspects of global terrestrial ecosystems. For example, vegetation phenology information such as phenological indicators of the start of growing season derived from optical remote sensing data have been used to show that the onset of growing season has been advancing by up to 20 days over last three decades, especially in the Northern Hemisphere, due to global warming (Badeck *et al.,* 2004; Chen *et al.,* 2005; White *et al.,* 2005; White *et al.,* 2009; Cong *et al.,* 2013; Dash *et al.,* 2010; 2013; Xu *et al.,* 2013). LAI from optical remote sensing data has been used to characterise vegetation condition in process based models used to understand changes in terrestrial ecosystems under changing climate conditions (Smith *et al.,* 2001; Sitch *et al.,* 2003). FAPAR is often used in diagnostic models to estimate vegetation productivity and carbon exchange (Running *et al.,* 2004; Ciais *et al.,* 2005; Ogutu *et al.,* 2013). Vegetation indices have been used to estimate crop production and the potential impacts of climate change on crop production (Bolton and Friedl, 2013; Kowalik *et al.,* 2014; Duncan *et al.,* 2015). Due to the significance of these vegetation bio-geophysical variables, a number of operational products have been generated from optical remote sensing data by the major space agencies and satellite operators (Table 3).

Even though data from optical remote sensing data has proved valuable in monitoring various vegetation bio-geophysical variables, a number of uncertainties still remain in using these data to effectively monitor terrestrial ecosystems. One key source of uncertainty is the robustness of the methods used to derive these vegetation biophysical variables. The empirical approaches are driven by experimental data collected in selected field locations. High costs and the labour intensiveness of *in-situ* data collection mean that not all sites can be sampled to develop globally representative and reliable empirical relationships between optical remote sensing data and the vegetation bio-geophysical variables (Colombo *et al.,* 2003; Liang, 2007; Houborg et al., 2007; Vuolo *et al.,* 2013). The relationships based on experimental data often perform better for conditions in which the data are collected (Liang, 2007, Houborg et al., 2007; Vuolo et al., 2013). For example, a study by Vuolo *et al (*2013) tested the transferability of empirically derived LAI models between sites in Italy and Austria and found that the accuracy of the models in predicting LAI in areas where they were not developed was reduced. In addition, Houborg et al., (2007) showed that the empirical relationship between vegetation indices and leaf area index tended to be site specific. This implies that the empirical relationships when applied globally, the uncertainty in the derived vegetation bio-geophysical variable increases. The inverse modelling approach of deriving vegetation bio-geophysical variables also has drawbacks, with the main one being the fact that the inverse problems are often multidimensional and ill-posed (i.e. the number of unknowns are often greater than the number of observations) (Combal *et al.,* 2003; Atzberger, 2004; Liang, 2007). This means that these models are often greatly affected by noise in the data and often the best solution for the inversion may never be achieved. This implies that the derived vegetation bio-geophysical variables always have some inherent uncertainties. Another source of uncertainty is caused by the difference between the information recorded by the sensor (i.e. radiance/reflectance) and the desired variable (e.g. leaf area index). This means that in some cases (e.g. when deriving LAI from remote sensing data) the desired vegetation bio-geophysical variable is often only an inference from the reflectance data. The consequence of this is that there will be uncertainties associated with the disparity between the measured data and the desired variable. For example, due to saturation of the reflectance values, the LAI derived from reflectance values may not reflect the entire range of LAI within a study site (Eriksson *et al.,* 2006; Heiskanen, *et al.,* 2013). Finally, data quality influences the level of accuracy of the derived bio-goephysical variables. For example, Morton *et al* (2014) showed that the seasonal greening of tropical vegetation in the Amazon reported by other researchers using the MODIS surface reflectance data, were probably due to artefact within then data rather than any changes in vegetation greenness in the tropical regions. In addition, a study by Guay *et al.,* (2014) on the vegetation productivity patterns across northern latitudes showed that disparities in estimates can result purely from the quality of data used. Therefore, adequate calibration and pre-processing (e.g. atmospheric correction) and product quality control is necessary to ensure that the data are as representative of the status of the bio-geophysical variables as possible. One way to improve accuracy is through adequate validation using ground-based observations (Porcar-Castell *et al.,* 2015; Balzarolo *et al.,* 211). A number of programmes (e.g. FlUXNET (Baldocchi *et al.,* 2001) and Spec Net(Gamon *et al.,* 2006) have been set up to provide data that can be used to comprehensively validate vegetation bio-geophysical variables derived from remote sensing data. Furthermore, the issue of scale mismatch between *in-situ* data and remote sensing measurements often reduce the accuracy of the vegetation bio-geophysical variables derived from remote sensing data. Initiatives such as the EUROSPEC (Porcar-Castell *et al.,* 2015) offer a way forward to addressing the issue of scaling between the *in-situ* and remote sensing based products.

1. ***Fire monitoring and products***

Burning of terrestrial ecosystems is a major source of greenhouse gases, aerosols, black carbon and atmospheric pollutants which have impacts on global climate and air quality. In addition, burning also leads to alteration of the vegetation structure and soil conditions (Hao and Larkin 2014). Consequently, monitoring the spatial and temporal extent of fires and the size of burnt area is important in the estimation of the levels of greenhouse gas emissions from fire events. Furthermore, data on the spatial and temporal distribution of fire emissions and the extent of burnt areas is important in modelling the dynamics of atmospheric photochemistry (Hao and Larkin 2014). Traditional approaches of monitoring fire events (e.g. the ground based fire reporting systems) are useful but inadequate in estimating and characterising large scale fire events. Satellite remote sensing based approaches of detecting burnt areas and active fires offer a cost effective way of quantifying the spatial and temporal extent of large scale fires (Giglio *et al.,* 2009). A number of methods have been devised to estimate fire events, burn severity and burnt areas from optical remote sensing data (Key and Benson, 1999; Roy *et al.,* 2008). A simple approach is the use of spectral indices (e.g. the Normalised Burn Ratio (Key and Benson, 1999)) to estimate burnt areas and burnt severity. A second approach uses the changes observed in thermal bands to detect any fires. For example, the bi-directional reflectance change in the MODIS sensor thermal band is currently being used to derive active fire products (Roy *et al.,* 2008).

Information on fire derived from optical remote sensing has been used to monitor various aspects of global terrestrial ecosystems. Langner *et al.,* (2005) used information derived from MODIS data to show that fire was a major contributor to forest degradation and deforestation in Borneo, Indonesia. Van der Werf *et al.,* (2003) used fire information derived from TRMM and Sea-viewing Wide Field of view Sensor (SeaWiFS) remote sensing data to estimate that about 2.6 PgCyr-1 of Carbon was emitted through fire and fuelwood use in tropical and subtropical ecosystems between1998-2001. Fire products derived from remote sensing data have also been used to monitor the contribution of vegetation fire emissions to air pollution and climate change through changes in albedo from black carbon from fire events and changes in solar irradiance due to aerosol particles (Langmann *et al.,* 2009). A number of fire monitoring products are currently produced from remote sensing data (Table 4). These products can be categorised into two groups: spatio-temporal maps of active fires and burnt area/burn scar maps. The burnt area products have been produced either as single year or multiple year products. The notable single year products include: the GLOBSCAR product (Simon *et al.,* 2004), and the Global Burnt Area-2000 (Tansey *et al.,* 2004). Examples of multiple year products include: the Global Burnt Surface Dataset (82-99) (Carmona-Moreno *et al.,* 2005), the L3JRC product (Tansey *et al.,* 2008), MODIS Burnt area product (MOD45A1) (Roy *et al.,* 2005) and the Global Fire Emissions Database (GFED4) (Giglio *et al.,* 2013). The second fire products derived from optical remote sensing data are the active fire databases. The key active fire products include the MODIS active fire products (i.e. MOD14 and MYD14) (Giglio *et al.,* 2006; Giglio 2010) and the Fire Radiative Power (FRP) derived from the MSG SEVIRI sensor (Wooster *et al.,* 2005; Wooster *et al.,* 2015).

The availability of data from optical remote sensing has undoubtedly improved the mapping and monitoring of global fire events. However, there are uncertainties which still need to be addressed in these products. For example, most of the fire products have been found to fail in accounting for small fires (Sa *et al.,* 2007) or low intensity fires such as those used in shifting cultivation (Miettinen *et al.,* 2007). Furthermore, these products have been shown to have accuracies of between 70-80% (Schroeder *et al.,* 2008) and can sometimes go below 40% in some biomes (Giglio *et al.,* 2009). The key source of these uncertainties is the spatial resolution of the data used to derive the fire products. Most of the fire products are derived using global remote sensing data at coarse spatial resolution (>250m) (e.g. NOAA-AVHRR, MODIS and SPOT VEGETATION) resulting in omission of small and low level fires. Furthermore, fires which occur between the times of consecutive satellite overpass are missed. The weather conditions (especially presence of clouds) have also been shown to reduce the robustness of the algorithms used to generate fire products from remote sensing data (Giglio *et al.,* 2009; Giglio *et al.,* 2010). One way of improving the fire monitoring products from remote sensing data could be to perform inter-comparison between the products to identify biomes/areas where there are agreements and disagreements and to help refine the algorithm used to derive the products. Furthermore, use of high spatial resolution data and data integration to monitor global fire events could be explored. Currently, the development and improvement of fire products is ongoing through characterisation of sources of uncertainties in the products (Padilla *et al.,* 2015). These efforts, together with the launch of new optical remote sensing satellites will ensure that better and more accurate fire products can be generated continuously in future.

1. ***Ecosystem productivity monitoring and products***

Terrestrial ecosystem primary productivity, defined simply as the production of organic matter through photosynthesis (Prentice *et al.,* 2000), is an important component of the global carbon cycle. Consequently, information on the status of terrestrial ecosystem primary productivity is important in understanding the dynamics of the global carbon cycle. This information has become even more critical with the realisation that increase in atmospheric carbon dioxide due to anthropogenic activities is leading to climate change through global warming (IPCC, 2013). This is because terrestrial ecosystems primary productivity plays a key role in regulating the carbon cycle and hence the problem of timing and magnitude of possible climate change. Traditional approaches of estimating terrestrial ecosystem primary productivity range from use of allometric equations developed through field measurements to modelling approaches which include simple statistical-climate correlation models to mechanistic ecophysiological models (Ruimy *et al.,* 1994; Goetz *et al.,* 1999; Veroustraete *et al.,* 2002; Running *et al.,* 2004; Gitelson *et al.,* 2008; Ogutu *et al.,* 2013). The models often operate on point measurements that are extrapolated spatially, though such spatial scaling of point measurements to the landscape or regional scale is often problematic owing to great landscape heterogeneity relative to sampling density (Goetz *et al.,* 1999; Gamon *et al.,* 2006; Porcar-Castell *et al.,* 2015).

To overcome some of these problems, attempts were made in the early 1980s to use optical remote sensing data which were becoming readily available to estimate terrestrial ecosystem primary productivity (Tucker *et al.,* 1981; Prince 1991; Prince and Goward, 1995). One approach of estimating vegetation productivity from optical remote sensing data involves developing empirical relationships between vegetation indices with vegetation productivity and applying those relationships regionally or globally (Sims *et al.,* 2008). This approach requires experimental data with a large coverage of different vegetation types and climatic conditions which is often unavailable for regional or global studies. The second approach for estimating vegetation primary productivity from optical remote sensing data is through the use of the light use efficiency (LUE) concept proposed by Monteith (1972).

The light use efficiency concept states that gross primary productivity (GPP) is linearly related to the amount of absorbed photosynthetically active radiation- APAR (derived as a product of FAPAR and incident PAR) and a parameter representing the efficiency of plant production (i.e. light use efficiency term), which represents the rate at which absorbed PAR is converted to dry matter (Monteith, 1972). The FAPAR term can be derived from optical remote sensing data, making the implementation of the LUE approach of estimating primary productivity achievable at regional to global scales. A number of optical remote sensing based primary productivity products have been generated following this approach. These include: the MODIS GPP/NPP product (MOD17) which is derived using data from MODIS sensor (Running *et al.,* 2004) and the GEOSUCCESS NPP product derived using the C-Fix Model using the VGT data from SPOT satellite (Veroustraete *et al.,* 2002). These GPP/NPP products have been used to study various aspects of terrestrial ecosystems from understanding the dynamics of vegetation productivity and carbon exchange due to climate change (Reichstein *et al.,* 2007) to studying impacts of fire events on ecosystems (Yi *et al.,* 2013). Even though the LUE based approach has been used to successfully estimate vegetation productivity, a number of issues have been identified with the approach. Firstly, there is often a lack of consensus on what should be the correct LUE term in the models and how it should be derived. It has been argued that LUE can be constant for specific biomes due to ‘ecosystem functional convergence’ (Goetz and Prince 1999), while other research show that LUE term varies even within specific biomes (Ruimy *et al.,* 1994; Song *et al.,* 2009). To address the problem of generating the appropriate LUE term at global scales, attempts have been made to derive it directly from remote sensing data using a vegetation index (i.e. the photochemical reflectance index (PRI)) which has been shown to closely track photosynthetic activity and hence LUE in plants (Gamon *et al.,* 1992; Nichol *et al.,* 2000, Drolet et al., 2005; Garbulsky *et al.,* 2011). Another approach of deriving LUE from remote sensing data has involved tracking and estimating chlorophyll fluorescence, which has been shown to be closely related to LUE (Liu and Cheng, 2010; Joiner *et al.,* 2010). This effort has been boosted by the recent selection of the Fluorescence Explorer (FLEX) mission by the European Space Agency to be its eighth Earth Explorer mission, planned for launch in 2022. Data from this mission will be important in attempts to derive LUE from satellite data. If successful, the derivation of LUE from satellite data would eliminate a major uncertainty in modelling global terrestrial ecosystem productivity. In addition to the uncertainties associated with the LUE term, the variables derived from remote sensing such as FAPAR also have been shown to contain inherent errors (Weiss *et al.* 2007; McCallum *et al.* 2010 Ogutu *et al.,* 2014). For example, the FAPAR generated from remote sensing data often encompass FAPAR for the whole canopy rather than just the green FAPAR used in photosynthesis process (Hanan *et al.,* 2002; Ogutu and Dash 2013). To address this issue attempts have been made to derive only green FAPAR using *in-situ* data and upscaling this to global scale using optical remote sensing data (Ogutu and Dash 2013). Consequently, a new primary productivity model which uses only the green FAPAR (i.e. The Southampton Carbon Flux Model- SCARF model; Ogutu *et al.,* 2013) has been developed. The model uses the quantum yield approach to predict primary productivity from optical remote sensing data and was shown to result in relatively accurate predictions of primary productivity in various biomes (Ogutu *et al.,* 2013). A schematic diagram of the operational procedure of the SCARF model is shown in figure 2.

A final approach of deriving vegetation productivity using remote sensing data involves the use of non-LUE based process models (Running and Gower, 1991; Sitch *et al.,* 2003; Best *et al.,* 2011). These models simulate vegetation productivity based on photosynthesis theories and uses optical remote sensing data (e.g. Leaf Area Index) to characterise the status of vegetation in the models (Crammer *et al.,* 1999; Sitch *et al.,* 2003; Best *et al.,* 2011). These models are important in predicting future changes in terrestrial vegetation characteristics and productivity under various climate scenarios (Sitch *et al.,* 2003; Best *et al.,* 2011; Scheiter *et al.,* 2013; Sitch *et al,* 2015). Traditionally, process-based models used limited amounts of remote sensing data, but with the increased availability of these data, new generation of process based models are staring to routinely include these datasets in their parameterisation (Best *et al.,* 2011; Scheiter *et al.,* 2013). Apart from being used in parameterising the process based models, the relatively long availability of optical remote sensing data has also led to these data being used in data assimilation processes aimed at improving performance of land surface models (Zobitz *et al.,* 2014). Overall, a recent study that compared vegetation primary production (represented as above ground biomass) derived using remote sensing data with estimates from inventory based methods highlighted considerable inconsistencies (Hill *et al.,* 2013). This implies that improvements are still needed in the methods used to derive primary production from remote sensing data. A key area pointed out by this research for improvement is how uncertainties in the data, methods and results are characterised and reported (Hill *et al.,* 2013). Furthermore, the authors propose setting up of network of ground comparison sites with common measurement protocols and ensuring that data from these sites are not used in the development, parametrisation and testing of models (Hill *et al.,* 2013).Programmes such as FLUXNET (Baldocchi et al., 2001), SpecNet (Gamon *et al.,* 2006) and EUROSPEC (Porcor-Castell *et al;.,* 2015) are already using a standard protocol and can be used to meet these objectives.

1. ***Land –atmosphere interaction and products***

Land-atmosphere interactions include a variety of complex processes and feedbacks between radiative, hydrological, and biogeochemical processes resulting in critical exchanges of energy and matter that influence the overall Earth system and its climate (Fernandez-Prieto *et al.,* 2013). The key biophysical variables controlled by the land-atmosphere interaction include: albedo, emitted infrared radiation, sensible heat, water vapour, evapotranspiration, and carbon flux. Estimation of these biophysical variables at local to global scales is critical in understanding how they impact the global terrestrial ecosystems. Satellite based optical remote sensing provides a means of estimating some of these land-atmosphere interaction biophysical variables at regional to global scales (Fernandez-Prieto *et al.,* 2013). The approaches used to derive these variables include the use of empirical equations and the use of inverse modelling (Justice *et al.,* 2002; Gao and Kaufman, 2003; Cleugh *et al.,* 2007; Moody *et al.,* 2005; Wan, 2008). A number of products which represent aspects of land-atmosphere interaction are currently being routinely generated from optical remote sensing data. These include: land surface temperature/emissivity (Justice *et al.,* 2002), land surface albedo (Moody *et al.,* 2005), evapotranspiration (Cleugh *et al.,* 2007), and water vapour (Gao and Kaufman, 2003).

These land-atmosphere interaction products have been used to monitor various aspects of global terrestrial ecosystems. For example, Jin *et al* (2005) used MODIS albedo and land surface emissivity data to show how global urbanization impacts on global climate, through alteration of the surface albedo and surface temperatures. Myhre *et al.,* (2005) used MODIS surface albedo product to show that anthropogenic land cover changes have led to a reduction of radiative forcing by about -0.09Wm-2 since pre-agriculture times. MODIS Albedo and BRDF product has also been used to show increase in surface albedo, especially in the spring season, after fire events in boreal forests (Lyons *et al.,* 2008). Even though these products have been used to study aspects of terrestrial ecosystems, they still contain uncertainties. For example, Velpuri *et al.,* (2013) showed that the MODIS evapotranspiration product had uncertainties of up to 50% at point scale and 25% at a basin scale. The algorithms used to derive the land-atmosphere products needs to be refined, for example, through validation and inter-comparison exercises. Initiatives such as the SpecNet (Gamon *et al.,* 2006), FLUXNET (Baldocchi *et al.,* 2001) and EUROSPEC (Porcar-Castell *et al.,* 2015) are important in providing data necessary to not only validate the algorithms used to derived the land-atmosphere interaction variables, but also to bridge the scaling gap between the *in-situ* measurements and remote sensing data. Finally, currently the land-atmosphere interaction products are generated form data collected by coarse spatial resolution (>250m) sensors (e.g. the MODIS sensor) which would also increase the levels of uncertainties in the data. With the launch of new satellites sensors (e.g. the Sentinel missions (Drusch *et al.,* 2012)) future work should continue on the possibility of generating these variables at high spatial resolutions.

# Discussion and conclusion

From this review, it is evident that optical remote sensing data has been useful in monitoring and managing various aspects of global terrestrial ecosystems. This trend is expected to continue with the launch of new improved satellites (e.g. the ESA Sentinel missions) and the drive to make Earth observation data freely accessible to the wider public (e.g. recent availability of all Landsat archive data and free data policy of Sentinel missions). However, there are still challenges to be addressed and opportunities to be exploited to achieve the full potential of using these data.

The challenges of using optical remote sensing data in global terrestrial ecosystem management include but not limited to: (i) data quality, availability and accessibility of data at necessary spatial and temporal scales, (ii) data continuity due to relatively low lifespan of satellite missions and uncertainty in funding for future missions, and (iii) the cost of data analysis (including logistical requirements, hardware, software and training of qualified analysts). Good quality Earth observation data is fundamental in monitoring and management of global terrestrial ecosystems. The current key challenges of ensuring good quality EO data include appropriate radiometric and geometric calibration and validation of these data. To ensure that data acquired through optical remote sensing is representative of Earth surface features, good radiometric calibration of the sensors is necessary. Radiometric calibration is often done through pre-launch instrument characterisation, on-board calibration, vicarious calibration and inter-instrument cross-calibration (Liang, 2007; Chander *et al.,* 2010; Mishra *et al.,* 2014). However, it has been shown that satellites do not retain their sampling characteristics at launch after a period of time in orbit (mostly due to orbital drift with time and altitude), which can introduce errors in the recorded data (Latifovic *et al.,* 2012). Using such data without further radiometric calibration could lead to inaccurate results when monitoring global terrestrial ecosystems. Therefore, continuous efforts to ensure that the data are adequately corrected for radiometric errors are necessary. Perhaps cross space agency radiometric calibration activities such as Radiometric Calibration Network of Automated Instruments (RadCalNet), should be encouraged to ensure continuity of measurements at ground calibration targets to ensure good radiometric calibration of satellite data.

The geometric integrity of EO data is equally important, especially, as many global terrestrial ecosystem monitoring applications often use EO data from multiple time periods with varying spectral, spatial and angular characteristics (Liang, 2007; Chander *et al.,* 2010; Mishra *et al.,* 2014). The aim of geometric correction is to ensure that the EO data projection is representative of a specific location projection on the Earth’s surface. Accurate geometric correction would ensure that when using such datasets to monitor global terrestrial ecosystems, the features occurring in the same location can be studied or compared over time. The final data quality issue that needs to be addressed when using EO data is the validity or accuracy the data, especially, the products derived from them. It is important to ensure that the EO derived products (e.g. LAI, FAPAR, FCOVER,, canopy chlorophyll content and land cover maps) accurately represent the specific biophysical variable. It is also worth noting that substantial amount of processing is often needed to turn raw satellite data into meaningful and useable data, involving several assumptions. This implies that the same raw data can lead to entirely different records of a particular terrestrial ecosystem variable. Therefore, validation of the algorithms used to derive these products, and the products themselves is critical if these products are to be used to effectively monitor and manage terrestrial ecosystems (Morisette *et al.,* 2002; 2006). A number of validation exercises (e.g. the BigFoot validation project, Cohen *et al.,* 2000; the VALERI project, Baret *et al.,* 2003) have been undertaken to ensure that most of the products derived from optical remote sensing data are representative of specific Earth surface features. Further efforts should focus on a standard validation protocol to ensure robustness of this process and good representation of validation dataset across space and time. Initiatives such as such as FLUXNET (Baldocchi et al., 2001), SpecNet(Gamon *et al.,* 2006) and EUROSPEC(Porcor-Castell *et al;.,* 2015) can be used to achieve this objective. In addition, the work undertaken by the Committee on Earth Observation Satellites (CEOS) Land Product Validation Subgroup is important in achieving this goal.

A second challenge to using optical remote sensing data in monitoring terrestrial ecosystems is the availability of data at necessary spatial and temporal scales. It is often the case that the EO data scale/resolution differs with what is required in monitoring terrestrial ecosystem properties. For example, one may need to monitor variation of a biophysical variable at species level in forests, but this is not easily achieved with the current optical satellite remote sensing datasets (Pettorelli *et al.,* 2014). The use of hyperspectral remote sensing data could improve the distinction between different land cover features, but their availability from satellite sensors is limited. Efforts should be made to ensure hyperspectral imagery can be acquired more routinely and made readily available to users. There is a promise of increased availability of hyperspectral data with the planned launch of EnMAPand the HyspIRI Mission. The current frequency of data acquisition may also not be appropriate for monitoring certain terrestrial ecosystem phenomena. For example, monitoring of diurnal variation in light use efficiency by plants is not possible with the current repeat times of optical remote sensing data (Song *et al.,* 2013). Furthermore, there is often a temporal mismatch between data availability and user request (that is, data is often released days or even months after acquisition, making it impossible to monitor changes terrestrial ecosystems in near real time). Related to the availability of data at appropriate temporal and spatial scales is the ease of accessing available remote sensing data. A number of remote sensing data are currently freely available, but a good number are not, especially the high resolution datasets acquired by commercial satellites. To encourage uptake of these datasets a model of partnership between governments and the private sector could be encouraged to ensure that these datasets can be acquired cheaply and made available to the public for use in monitoring terrestrial ecosystems. Programmes such as the satellite applications CATAPULT initiated by the UK government is an example of initiatives that would see increased uptake of satellite data. International collaborations such as the international Charter on ‘Space and Major Disasters’ which consist of several international space agencies are useful platforms for ensuring guarantee coverage of Earth observation datasets for monitoring natural disasters.

A third concern of using optical remote sensing data for monitoring terrestrial ecosystems is data continuity. Satellite missions often have a low lifespan (about 5-10 years) meaning that when these missions end without follow-up missions, there could be gaps in data acquisition which may lead to discontinuation of certain terrestrial ecosystem products. A compounding factor to this is the uncertainties surrounding funding for future missions. To ensure continuity of EO data adequate plans should be put in place to design and deploy similar sensors before the end of the lifespan of current sensors. The need for this approach was made obvious by the loss of European Space Agency’s ENVISAT in 2012, before the SENTINEL follow-up missions were ready for launch. Even though the need for data continuity should be considered when designing new sensors, it should not limit the development of new sensors with better spatial and radiometric resolutions (Boyd and Foody, 2011). One approach of dealing with the problem of data continuity and perhaps to solve the issue with fit for purpose of adequate spatial resolution is to integrate /fuse data from various satellite missions. Data fusion involves combining data from multiple sources to improve their potential values and application in monitoring a phenomenon (Zhang, 2010). Data fusion and synergy also enables the extension periods of observation by ensuring that it is possible to use data from different sensors operating at different time steps to monitor terrestrial ecosystems. As mentioned in the previous sections, the use of microsatellites such as the Planet labs Dove satellites (Boshuizen *et al.* 2014, Hand, 2015) and Skybox imaging Skysat satellites (Murthy *et al.,* 2014) which are relatively cheap could offer a way forward by availing optical remote sensing data with global coverage at high spatial and temporal resolution in a continuous manner.

A final challenge of effectively using optical remote sensing data for monitoring terrestrial ecosystems is the cost of data analysis. Optical remote sensing data analysis can be expensive given the logistical requirements, hardware, software, and training of qualified analysts. This can hinder the uptake of these datasets for monitoring terrestrial ecosystems especially in low income countries. In terms of training, approaches such as online courses could be encouraged to bridge the gap of lack of qualified remote sensing data analysts. In terms of software there has been a rise in open access software which can be used by those who cannot afford commercial software. The drawback of most open access software is that some are complex, change rapidly and lack appropriate documentation which reduces their adequate use. However, if these are addressed, they offer a chance of increased uptake of remote sensing data in the management and monitoring of various aspects of global terrestrial ecosystems. Cloud computing and access to community clusters of high performance computing (HPCs) (for example, the CEMS in the UK and NEX system in NASA) offers a potential solution to the requirement by users to invest in costly hardware needed for processing optical remote sensing data (Lee *et al.,* 2011). If harnessed properly, cloud computing could reduce the costs of installing expensive hardware needed to process EO data leading to an increase in the uptake and use of optical remote sensing data in monitoring terrestrial ecosystems, especially in low income countries.

To conclude, even with the challenges highlighted above, optical remote sensing will continue to provide the bulk of data for monitoring global terrestrial ecosystems, mainly due to the synoptic view of remote sensing satellites and the ability of repeat acquisition of these datasets cost-effectively. A number of satellite missions are planned to be launched in the near future (e.g. the ESA SENTINEL missions) which will provide improved acquisition capability and continuity of recent terrestrial monitoring products. Data fusion and synergy also offers an opportunity to integrate different datasets and ensure data continuity, thereby expanding the length of observation records achievable form a single mission. While in the past most satellite missions were run by space agencies supported by governments, currently, there has been an upsurge in private sector entities getting involved in launching Earth observation satellites. The key future question is how these data will be made available to user communities at affordable cost to ensure their seamless integration in existing terrestrial ecosystem monitoring projects. A second debate on the acquisition of Earth observation data revolves around the nature of future satellite missions. For example, should these missions be ‘big’ missions where one satellite carries several instruments (e.g. ENVISAT) or ‘small’ missions which can be deployed quickly with only few instruments on board (e.g. the DMCii). There has also been an upsurge in the area of microsatellites which are relatively cheaper to manufacture and several can be launched at a time. It is expected that the next decade will see further innovation in optical remote sensing capabilities, especially the radiometric and spectral integrity of sensors on-board microsatellites, which will lead to improvement in the way global terrestrial ecosystems are characterised, monitored and managed.

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**Table 1: Timeline depicting launch date of major satellite platforms operating in the optical spectrum for monitoring global terrestrial ecosystems**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Year of Launch** | **Satellite** | **Sensor on-board** | **Spatial resolution** | **Temporal resolution(Revisit time)** | **Spectral range** |
| 1972 | ERTS(Landsat-1) | Multispectral Scanner (MSS) | 60m | 18 days | 0.5-1.1μm |
| 1975 | Landsat-2 | MSS | 60m | 18 days | 0.5-1.1μm |
| 1978 | Landsat-3 | MSS | 60m | 18 days | 0.5-1.1μm |
| 1978 | NOAA-6 | Advanced Very High Resolution Radiometer (AVHRR) | 1.1km | 1day | 0.58-11.5μm |
| 1981 | NOAA-7 | AVHRR | 1.1km | 1day | 0.58-12.5μm |
| 1982 | Landsat-4 | MSS and Thematic Mapper(TM) | 30m, 120m | 16 days | 0.45-12.5μm |
| 1983 | NOAA-8 | AVHRR | 1.1km | 1day | 0.58-11.5μm |
| 1985 | Landsat-5 | MSS, TM | 30m,120m | 16 days | 0.45-12.5μm |
| 1985 | NOAA-9 | AVHRR | 1.1km | 1 day | 0.58-12.5μm |
| 1986 | SPOT-1 | High-resolution Visible(HRV) | 10-20m | 1-3days | 0.51-0.89μm |
| 1986 | NOAA-10 | AVHRR | 1.1km | 1day | 0.58-11.5μm |
| 1988 | NOAA-11 | AVHRR | 1.1km | 1day | 0.58-12.5μm |
| 1988 | IRS-1A | Linear Imaging Self-Scanning(LISS I, LISS II) | 36-72m | 22days | 0.46-0.86μm |
| 1990 | SPOT-2 | HRV | 10-20m | 1-3days | 0.51-0.89μm |
| 1991 | NOAA-12 | AVHRR | 1.1km | 1day | 0.58-12.5μm |
| 1991 | IRS-1B | LISS I, LISS II | 36-72m | 22days | 0.46-0.86μm |
| 1993 | SPOT-3 | HRV | 10-20m | 1-3dys | 0.51-0.89μm |
| 1994 | IRS-P2 | LISS | 36m | 24 days | 0.46-0.86μm |
| 1994 | NOAA-14 | AVHRR | 1.1km | 1day | 0.58-12.5μm |
| 1995 | ObView-1 | Optical Transient Detector-(OTD) | 10000m | 2days | 0.77μm |
| 1995 | IRS-1C | LISS III | 5.8-70m | 24 days | 0.52-1.7μm |
| 1996 | IRS-P3 | Modular Optical Scanning Spectrometer(MOS) | 520m | 5 days | 0.4-1.65μm |
| 1997 | IRS-1D | LISS III, WiFs | 5.8-70m | 25 days | 0.52-1.7μm |
| 1997 | Obview-2 | Sea viewing Wide Field Sensor(SeaWiFS) | 1.1km | 16 days | 0.4-0.88μm |
| 1998 | SPOT-4 | HRVIR, VEGETATION | HRVIR =10-20m; VEGETATION=1.15km | 2-3days | 0.43-1.75μm |
| 1998 | NOAA-15 | AVHRR | 1.1km | 1day | 0.58-12.4μm |
| 1999 | Landsat-7 | Enhanced Thematic Mapper (ETM+) | 15-60m | 16 days | 0.45-12.5μm |
| 1999 | IKONOS-2 | High Resolution Sensors | 0.82-4m | ~3days | 0.45-0.853μm |
| 1999 | IRS-P4 | Ocean Colour Monitor(OCM) | 360m | 2 days | 0.4-0.86μm |
| 1999 | KOMPSAT-1 | Ocean Scanning Multi-spectral Imager-OSMI | 850m | 28days | 0.4-0.88μm |
| 1999 | Terra | MODIS, ASTER | MODIS:250-1000m  ASTER:15-90m | MODIS: 24hrs  ASTER:16 days | MODIS (0.459-14.385μm)  ASTER(0.60-11.65μm) |
| 2000 | NOAA-16 | AVHRR | 1.1km | 1day | 0.58-12.4μm |
| 2000 | EO-1 | Hyperion, Advanced Land Imager(ALI) | ALI: 10-30m;  Hyperion= 30m | 16 days | ALI= 0.48-2.35μm; Hyperion=0.4-2.5 |
| 2001 | Quickbird | High Resolution Sensors | 65cm-2.9m | 1-3.5days | 0.45-0.9μm |
| 2001 | PROBA | Compact High Resolution Imaging Spectrometer (CASI) | 18m | 7days | 0.43-1.035μm |
| 2002 | SPOT-5 | HRG, VEGETATION | HRG = 5- 20m; VEGETATION=1.15km | 2-3days | 0.43-1.75μm |
| 2002 | ENVISAT | Medium Resolution Imaging Spectrometer(MERIS) | 300m | 35days | 0.4-0.9μm |
| 2002 | AQUA | MODIS | Varied: 250-1000m | 24hrs | 0.459-14.385μm |
| 2002 | NOAA-17 | AVHRR | 1.1km | 1day | 0.58-12.4μm |
| 2003 | UK-DMC | SLIM-6 | 32m | 4 days | 0.52-0.9μm |
| 2003 | Obview-3 | Obview-3 | 1- 4m | 3days | 0.45-0.9μm |
| 2003 | IRS-P6/ ResourceSat-1 | LISS-3 | 23m | 24 days | 0.52-1.7μm |
| 2005 | NOAA-18 | AVHRR | 1.1km | 1day | 0.58-12.4μm |
| 2006 | ALOS | AVNIR-2 | 10m | 46days | 0.4-0.89μm |
| 2006 | KOMPSAT-2 | Kompsat-MSC | 1-4m | 28days | 0.5-0.9μm |
| 2007 | WorldView-1 | WV-1 | 0.5m | 1.7dyas | 0.4-0.9μm |
| 2008 | GeoEye-1 | GIS-MS | 0.46m-1.84m | 2-8days | 0.45-0.92μm |
| 2008 | RapidEye | REIS | 6.5m | 5.5days | 0.44-0.85μm |
| 2009 | WorldView-2 | WV-110; WV60 | 0.46m | 1.1days | 0.45-1.04μm |
| 2009 | UK-DMC | SLIM-6-22 | 22m | 3 days | 0.52-0.90μm |
| 2009 | NOAA-19 | AVHRR | 1.1km | 1day | 0.58-12.4μm |
| 2011 | Pleiades-1A | VHR | 50cm-2m | 1day | 0.48-0.95μm |
| 2011 | ResourceSat2 | LISS-3&LISS-4 | LISS-3: 56m;  LISS-4: 5.8m | 24 days | 0.52-0.86μm |
| 2012 | SPOT-6 | New AstroSat Optical Modular Instrument (NAOMI) | 2.2.-8.8m | 1-5 days | 0.45-0.89μm |
| 2012 | Pleiades-1B | VHR | 50cm-2m | 1day | 0.48-0.95μm |
| 2012 | KOMPSAT-3 | Advanced Earth Imaging Sensor-AEISS | 0.7-2.8m | 28days | 0.45-0.9μm |
| 2013 | Landsat-8/LDCM | OLI, TIRS | 15-30m | 16 days | 0.43-12.51μm |
| 2013 | Skysat-1 | Skybox Image Sensor | 0.9- 2m | 1.8per day | 0.45-0.9μm |
| 2014 | Skysat-2 | Skybox Image Sensor | 0.9- 2m | 1.8per day | 0.45-0.9μm |
| 2014 | SPOT-7 | NAOMI | 2.2-8.8m | 1-5days | 0.45-0.89μm |
| 2014 | WorldView-3 | WV-3 | ~0.3m | 1-4.5 days | 0.45-2.245μm |
| 2015 | KOMPSAT-3A | AEISS | 0.7-2.8m | 28days | 0.45-0.9μm |
| 2015 | Sentinel-2A | MultiSpectral Instrument (MSI) | 10-60m | 10 days | 0.443-2.19μm |
|  |  |  |  |  |  |

Table 2: Main regional to global land cover products derived from optical remote sensing data

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Product** | **Satellite** | **Sensor** | **Spatial resolution** | **Extent/Coverage** |
| GLC2000 | SPOT | VGT | 1km | Global and Regional |
| GLOBCOVER 2005 and 2009 | ENVISAT | MERIS | 300m | Global and Regional |
| MODIS Land Cover Type (MCD12Q1) | Aqua, Terra | MODIS | 500m | Global |
| FAO-Global Land Cover SHARE | Landsat | TM/ETM | 1km | Global |
| CORINE | IRS/Rapid Eye | LISS-III, LISS-IV, AWIFS, RapidEye | 100m, 250m | Regional |
| GlobeLand30 | Landsat  China Environmental Disaster Alleviation Satellite | Landsat 5 and ETM  HJ-1 | 30m | Global |

Table 3: Operational vegetation bio-geophysical products derived from optical remote sensing data

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Product** | **Satellite** | **Sensor** | **Spatial resolution** | **Coverage/extent** |
| ***LAI and FAPAR*** |  |  |  |  |
| * CYLOPES LAI/FAPAR | SPOT | VGT | 1km | Global |
| * GLOBCARBON LAI/FAPAR | ENVISAT, SPOT 4, SPOT 5 | MERIS,VGT | 1km to 0.5° | Global |
| * MODIS LAI/FAPAR | Terra and Aqua | MODIS | 1km | Global |
| * POLDER FAPAR/LAI | POLDER-1, POLDER-2 | ADEOS-1, ADEOS-2 | 6km | Global |
| * SEVIRI LAI/FAPAR | MSG | SEVIRI | 3km | Global |
| ***FCOVER*** |  |  |  |  |
| * CYCLOPES FCOVER | SPOT | VGT | 1km | Global |
| * MODIS Vegetation Continuous Fields | Terra and Aqua | MODIS | 250m | Global |
| ***Vegetation Indices*** |  |  |  |  |
| * MERIS Terrestrial Chlorophyll Index-MTCI | ENVISAT | MERIS | 1- 4.63 | Regional and Global |
| * AVHRR NDVI | NOAA | AVHRR | 1-8km | Global |
| * MODIS NDVI | Terra and Aqua | MODIS | 250m to 0.5° | Global |
| * MODIS EVI | Terra and Aqua | MODIS | 250m to 0.5° | Global |
| * MERIS Global Vegetation Index-MGVI | ENVISAT | MERIS | 1.2km | Global |

Table 4: Fire products derived from optical remote sensing data

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Product** | **Satellite/Sensor** | **Spatial resolution** | **Coverage/extent** | **Source** |
| GLOBSCAR | ERS-2-ATSR-2 | 1km | Global | Simon *et al.,* 2004 |
| GFED | Terra/Aqua-MODIS; ERS/ATSR; VIRS | 0.5degrees | Global | Giglio *et al.,* 2010 |
| Globcarbon | SPOT/VEGETATION; ATSR-2, AATSR | 1km, 0.25 or 0.5 | Global | Plummer *et al.,* 2006 |
| Global Burnt Surface (GBS) | NOAA-AVHRR GAC | 8km | Global | Carmona-Moreno et al., 2005 |
| MCD45A1 | Terra/Aqua-MODIS | 500m | Global | Roy et al., 2008 |
| L3JRC | SPOT/VEGETATION | 1km | Global | Tansey *et al.,* 2008 |
| GBA2000 | SPOT/VEGETATION | 1km | Global | Tansey *et al.,* 2004 |
| FRP | METEOSAT-SEVIRI | 1 degree | Global | Wooster et al., 2005; Wooster et al., 2015 |
| MYD14/MOD14 | Terra/Aqua-MODIS | 1km | Global | Giglio *et al.,* 2006; Giglio, 2010 |

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**Figure 1**

**\\soton.ac.uk\ude\PersonalFiles\Users\jadu\mydocuments\PAPER_ OTHER\progress in physical geography\Revised3\Figure 2.tif**

**Figure2**