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There is a global consensus that carbon dioxide and other greenhouse gas emissions must be reduced as a response to global climate change. Remote sensing satellite data have become an important means of monitoring carbon emission due to its unique advantages such as availability, high resolution, and wide coverage, and remote sensing data are playing an increasingly important role in carbon monitoring and fixation. This article summarizes the main applications of remote sensing satellite data in reducing carbon emissions and prospects for future research.

Advantages of remote sensing satellite data

In response to global climate change caused by emission of greenhouse gases, most countries worldwide have made commitments to reduce such emissions. At the 75th session of the United Nations General Assembly, China proposed to scale up its nationally determined contributions, strive to peak carbon dioxide emissions before 2030 and achieve carbon neutrality before 2060. The Climate Ambition Summit held in December 2020 reviewed the achievements of countries in implementing the Paris Agreement and further renewed a new climate change response plan. The 26th UN Climate Change Conference of the Parties (COP26), originally scheduled to be held in 2020, was postponed due to the coronavirus pandemic, but the climate crisis has not abated. According to Forster et al. (2020), although the measures taken by various countries to deal with the coronavirus pandemic have caused global carbon emissions to drop significantly in the short term, with the end of world closures, carbon emissions will rebound and may increase rapidly.

Environmental issues have been widely discussed by many scholars (Fu and Zhang, 2011; Cheng, 2020), and the topics are quite broad, such as the relationship between economic growth and pollution emissions, environmental efficiency, etc.

(Llorca and Meunié, 2009; Färe et al., 2014; Ma et al., 2018). However, most of the environmental indicators measured by the above-mentioned studies are derived from statistical data, so that the update is slow and there are many human factors. Implementing these commitments requires the accurate scientific monitoring of the concentrations and sources of greenhouse gases. Satellite data have become an important means of monitoring carbon emission due to the following advantages. First, the biggest advantage of remote sensing satellite data is its wide availability. For example, after the occurrence of natural disasters such as fires or earthquakes, it is difficult to know the situation on the ground due to the accessibility challenges. However, satellite data can help experts make accurate assessments of the damage caused by these natural disasters. For example, Shi, Sasai, and Yamaguchi (2014) used MODIS burned-area products in multi-source remote sensing and field surveys to obtain parameters such as fuel capacity and combustion efficiency to estimate carbon emissions from fires in Southeast Asia from 2001 to 2010.

Second, remote sensing data sources are available at a substantially higher degree of spatial resolution than the traditional data. At present, most publicly available remote sensing satellite images are based on 30×30 m grid units; some are even based on 0.5×0.5 m units, allowing more detailed analyses. Hansen et al. (2013) used Landsat TM/ETM+ multi-temporal remote sensing images with a spatial resolution of 30 m to draw the first high-resolution map of changes in global forest cover from 2000 to 2012, based on which the loss or increase in natural resources could be evaluated.

Third, the geographic coverage of remote sensing satellite data is wider than traditional data and is not restricted by political, climatic, and geographical boundaries. It is essentially the only method to obtain realistic data on a large scale (Nagendra 2001;

Kerr and Ostrovsky 2003). For example, Song (2018) used multiple global land-cover data sets to study the value of global ecological services.

Fourth, remote sensing satellite data can trace historical changes. Traditional carbon emission monitoring relies on ground stations. The number of stations positioned in some areas is small; thus, the representativeness and coverage of monitoring sites are limited, and data-quality uniformity between different sites can be difficult to control. Therefore, it is challenging for researchers to trace past carbon emissions conditions. However, the emergence of remote sensing satellite data has significantly expanded researchers' ability to track the past emissions data of carbon dioxide. Zheng et al. (2020) constructed a high-temporal-resolution dynamic inversion technology for carbon emission monitoring that combined satellite remote sensing data and emissions source information, revealing that the drivers of China's carbon emissions changed under COVID-19.

Fifth, combining remote sensing satellite data with artificial intelligence can expand its applicability and value. Artificial intelligence empowers remote sensing technology to process and analyze heterogenous massive multi-source heterogeneous data and shares it with other applications, thereby greatly shortening the interpretative cycle of remote sensing data, improving interpretation accuracy, and spawning new remote sensing technologies and applications. Chen et al. (2020a) adopted a particle swarm optimization-backpropagation (PSO-BP) algorithm to unify DMSP/OLS and NPP/VIIRS satellite images for the calibration of night-time light data, thus obtaining stable, high-quality, long-term night-time light data. Therefore, the incorporation of artificial intelligence not only represents an advancement in the field of remote emissions sensing but is also promising for the prediction of future population distributions, GDP forecasting, and pollutant estimation.

Applications of remote sensing satellite data for carbon emissions reduction

Although researchers in several fields have investigated the use of remote sensing satellite data for research on carbon emissions reduction, several studies have focused on estimating the volume of above-ground biomass and its carbon storage, the relationship between productivity and carbon storage, estimating soil carbon storage, and the relationship between land use and carbon emissions. Here, we overview the current state of relevant literature in these fields.

[Insert Table 1 here.]

Estimation of above-ground biomass and carbon storage

Biomass refers to the total amount of organic matter contained in an ecosystem at a given time and is the main component of the vegetation carbon pool within the carbon reserves of terrestrial ecosystems (Muukkonen and Heiskanen 2007; Eckert 2012). Thus, its volume and characteristics must be accurately estimated to understand the distribution of vegetation carbon reserves and carbon sources (Le Toan et al. 2011). Researchers have long applied satellite data for the dynamic monitoring of above-ground biomass in grasslands and woodlands (McDaniel and Haas 1982; Roy and Ravan 1996).

The most commonly used optical remote sensing data sources include NOAA/AVHRR, MODIS, Landsat TM/ETM+, and QuickBird. Table 1 summarizes the main remote sensing satellite resources used in carbon emission reduction. Biomass can also be estimated using radar data or by combining radar data with traditional optical remote sensing data (Englhart, Keuck, and Siegert 2011; Berninger et al. 2018) to compensate for optical sensors affected by severe weather (Thomas et al. 2017). Regarding research methods, the vegetation index, leaf area index (LAI), absorbed photosynthetically active radiation (APAR), and other parameters are mainly obtained using remote sensing satellites to estimate biomass (Ribeiro et al. 2008; Propastin et al. 2012; Fernández-Martínez et al. 2014; Li et al. 2018). Commonly used remote sensing data extraction methods include visual interpretation (Shalaby and Tateishi 2007; Zhang and Zhu 2011), the maximum likelihood method (Jia and Richards 1994; Erbek, Özkan, and Taberner 2004), the object-oriented classification method (Wang, Sousa, and Gong 2004; Myint et al. 2008), and the support vector machine method (Heumann 2011; Singh et al. 2014).

Table 1. Remote sensing satellite resources used to combat carbon emissions

Type	Platform	Spatial resolution (m)	Revisit period (days)	Temporal coverage
Optical: high spatial resolution	QuickBird	Multi-spectral: 2.44 Panchromatic: 0.61	1–6	2001–2013
	Ikonos	Multi-spectral: 4 Panchromatic: 1	1.5–3	1999–2015
	ALOS	PRISM: 2.5 AVNIR-2: 10	2	2006–2011
	SPOT 4	Panchromatic: 10	26	1986–2013
	SPOT 5	Multispectral: 10 Panchromatic: 2.5-5	26	2002–2015
	Worldview 2	Multi-spectral: 1.8 Panchromatic: 0.5	1.0–4.5	2009–
	Worldview	Multi-spectral: 1.24	1.1–3.7	2014–

	3	Panchromatic: 0.31		
Optical：medium spatial resolution	Landsat 5	Multi-spectral: 30	16	1984–2013
	Landsat 7	Multi-spectral: 30 Panchromatic: 15	16	1999–
	Landsat 8	Multi-spectral: 30 Panchromatic: 15	16	2013–
	Sentinel-2	Multi-spectral: 10/20/60	10	2015–
	MODIS	Terra: 250/500/1000 Aqua: 250/500/1000	1–2	Terra: 1999– Aqua: 2002–
	ASTER	Visible:15 Infrared: 30 Thermal infrared: 90	16	1999-
SAR	ALOS	PALSAR: 10–100	46	2006-2011
	ALOS-2	Spotlight: 1–3 Stripmap: 3/6/10	16	2014–
	Sentinel-1	Interferometric Wide Swath: 5 Stripmap: 5	12	2014–
LiDAR	Airplane, UAV	0.1	mobilized to order	2000–

Estimation of productivity and carbon storage

Vegetation productivity

Vegetation net primary productivity (NPP) is a key parameter of the carbon cycle process in an ecosystem, reflecting the ability of vegetation to fix atmospheric CO_2 via photosynthesis (Cai et al. 2010; Chen et al. 2020b). The application of remote sensing to measure ecosystem productivity is mainly realized in two ways. One is a statistical model based on a remote sensing vegetation index; the other is a light-energy utilization model based on remote sensing data. Commonly applied examples of the methods include the CASA model (Liu, Dong, and Liu 2015), MODIS-GPP (Turner et al. 2003), CENTURY model (Peng and Apps 1999), and VPM model (Xiao et al. 2004), among others.

Marine productivity

The CO_2 entering the ocean is fixed by phytoplankton and photosynthetic bacteria into organic carbon via photosynthesis and thus, enters the marine ecosystem. The carbon fixation capacity of plankton can be expressed by their primary productivity. Certain parameters in ecological mathematical productivity models are often acquired through remote sensing. After appropriate processing, this remote sensing data can be used to estimate ocean primary productivity. Commonly used ecological mathematical models include the Bedford Productivity Model (BPM) (Longhurst, Sathyendranath, and Caverhill 1995), Laboratoire de Physique et Chimie Marines (LPCM) model (Antoine, André, and Morel 1996), and the Vertically Generalized Production Model

(VPGM) (Behrenfeld and Falkowski 1997).

Estimation of soil carbon storage

Soil is the largest carbon pool in terrestrial ecosystems (Jobbágy and Jackson 2000; Scharlemann et al. 2014), and relatively small changes in the soil can cause fluctuations in the atmospheric CO_2 concentration. Two methods are commonly used to estimate soil carbon storage. One is to directly use different bands provided by remote sensing satellite to establish a soil organic carbon spectrum model to estimate soil organic carbon (Chen et al. 2000). However, this method can only be applied to bare surface-level soil, and other characteristics of the soil can affect the accuracy of the estimation. The other method is to use indirect parameters measured by remote sensing satellites, such as vegetation status, soil water content, biomass, and temperature to build a data-driven model to evaluate soil properties (Mondal et al. 2017; Huang et al. 2020).

Land-use and carbon emissions

Carbon emissions related land-use types and changes

Some scholars have used satellite data to estimate the biomass associated with different land-use and cover types to calculate carbon storage and its historical changes, thereby estimating the current status and changes in carbon storage on regional, national, and even global scales (Houghton et al. 2012; Zhang et al. 2015). For example, using a series of field measurements and satellite data, Wang et al. (2020) reported that the huge carbon sink of China's terrestrial ecosystem is mainly attributable to carbon sequestration by China’s major forests. Thus, these findings point to the success of China's efforts to restore natural forest vegetation and strengthen plantation cultivation over the past 40 years.

Carbon emissions from human activities associated with various land-use types

Sources of carbon emission include energy consumption in settlements and exhaust emissions from vehicles. For example, Chen et al. (2020a) drew on the high correlation between night-time light data and human activities to retroactively estimate CO_2 emissions in 2,735 Chinese counties from 1997 to 2017 using two sets of night-time light data (DMSP/OLS and NPP/VIIRS Data) provided by the National Geophysical Data Center (NGDC).

Further research

With the rapid development of remote sensing platforms and sensor technologies, future remote sensing monitoring platforms will become more diverse, and the technical methods to collect and analyze remote sensing data will become more detailed. In future studies, the following two aspects deserve attention:

First, remote sensing satellite data will play an important role in future research on the reduction in large-scale carbon emissions. The rapid development of remote sensing technology has made satellite data more widely used in the field of carbon emission reduction. Research on a large regional scale has already taken advantage of advancements in remote sensing technology. However, on the global scale, high-quality estimates of carbon emissions and carbon fixation remain insufficient. Therefore, the use of remote sensing satellite data for large-scale analyses, such as estimates of global vegetation carbon sequestration capacity, global blue-carbon habitat mapping, and carbon sequestration potential assessments, should be further explored. Such studies could be highly significant for the identification of global carbon peaks and the achievement of carbon neutrality, and assist countries in meeting the "Paris Agreement" and United Nations Intergovernmental Panel on Climate Change (IPCC) emissions reduction targets.

Second, the GEE (Google Earth Engine) platform and artificial intelligence technology are powerful tools for large-scale remote sensing data analysis. In recent years, the spatial, temporal, spectral, and radiation resolution of remote sensing data have improved continuously, and the types of data available have increased. However, traditional image processing tools such as ENVI (The Environment for Visualizing Images) face challenges when dealing with extremely large data volumes. However, Google's GEE cloud platform possesses PB-level data processing capabilities on a global scale and has greatly improved the processing and information mining capabilities available for big Earth observation data (Gorelick et al. 2017). Moreover, this powerful platform, is a promising tool for large-scale data analyses in the future, particularly in conjunction with new developments in artificial intelligence technology that could serve as a powerful instrument for information extraction and image analysis.

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