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Remote Sensing Intelligent Interpretation for Mine Geological Environment

From Land Use and Land Cover
Perspective

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Foreword

Although mining industry has been the cornerstone for global economic growth, numerous mine-related geo-environmental issues have become a great concern for many countries. The so-called mine geo-environment refers to the environmental system encompassing the range of mineral deposits (mined or under mining or to be mined) which consists of the ore bodies, the host rocks, the groundwater, and the soils. During and after mining activities, the system experiences dynamic changes both in structure and in function. Therefore, it is critical to strengthen the monitoring of the mine geo-environment to better characterize the changes and thus find out best solutions to sustainable mining with minimal impact on the environment and the health of a livable Earth.

Remote sensing (RS) technology has been widely used in various areas and sectors, mainly by combining interactive human-computer visual interpretations and field verifications. The traditional RS technology is characterized by low efficiency, strong subjectivity, and a low degree of intelligence. In recent decades, the advancement of Earth Sciences has become increasingly dependent on technological innovation. The paradigm of scientific research is undergoing profound changes, and transdisciplinary integration has become increasingly important for innovations. This is particularly the case for the fields of observation, detection, and simulation technologies for high-precision, multi-scale, and big data. The integration of new generation artificial intelligence techniques in Earth Sciences has generated new research methods and technical tools for geoscientists. The intelligent interpretation of remote sensing data of the mine geo-environment involves convergent research of four different disciplines: geoscience, remote sensing science, computer science, and intelligence science, promoting development of “intelligence + geoscience” studies, with a broad range of content and multiple challenges.

The lead author of this book, Prof. Weitao Chen, my former Ph.D. student, has been actively involved in RS studies, and this book was designed to summarize the results of his group’s recent work on mine geo-environment. This book takes the multi-level interpretation task of “pixel, target, and scene primitives” as the main objective, focusing on problems related to the mine geo-environment, with a close focus on land use and land cover issues within a mining area. Additionally, the

book offers a detailed presentation of the principles and methods of deep learning technology, constructs a multi-scale mining area dataset, and establishes a theoretical framework for the intelligent interpretation of remote sensing data for land use and land cover in mining areas.

This book adds new ideas and tools to theoretical framework of the intelligent interpretation of remote sensing for complex geological settings. It also improves our understanding of the artificial intelligence techniques in Earth Science, accelerates the application of results from theoretical research on in-depth learning, and promotes the process of the “intelligence + geoscience” transdisciplinary integration. I sincerely congratulate the publication of the book and look forward to reading the authors’ forthcoming publications in “intelligence + geoscience” studies.

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Preface

Mining exploitation significantly alters both natural and anthropogenic systems, which has been considered one of the most intensive forms of terrestrial landscape change mediated by humans. Although remote sensing technique has been widely used in mining information extraction in the past two decades, there are multiple challenges associated with the spatial, temporal, and spectral characteristics of mining land covers that need to be addressed, such as creating effective remote sensing features and improving the ability of intelligent interpretation and so on.

Based on mine geological environment effect, this book constructs a set of systematic remote sensing dataset focusing on the multi-level task with the system of “mine remote sensing target detection→scene classification→semantic segmentation”, and carries out the research on the theory and method of remote sensing intelligent interpretation based on deep learning.

Taking Hubei Province of China as an example, this book focuses on four aspects: 1. construct the multiscale remote sensing dataset of mining area, including mine target remote sensing dataset, mining (including non-mining areas) remote sensing scene dataset, and semantic segmentation remote sensing dataset of mining area land cover. The three datasets are the basis of intelligent interpretation based on deep learning; 2. research on mine target remote sensing detection method based on deep learning; 3. research on remote sensing scene classification method of mine and non mine areas based on deep learning; 4. research on the fine-scale classification method of mining land cover based on semantic segmentation.

Chapter 1 was written by Weitao Chen and Lizhe Wang and assisted by Gaodian Zhou. Chapter 2 was written by Weitao Chen and Xianju Li, with the assistance of Jiahui Xu and Peiwen Ye. Chapter 3 was written by Xianju Li and Weitao Chen and assisted by Jingyan Zhang and Qian Hu. Chapter 4 was written by Weitao Chen and Shubing Ouyang and assisted by Min Liu and Cong Wang. Chapter 5 was written by Weitao Chen, Xianju Li, and Lizhe Wang, with the assistance of Gaodian Zhou, Min Liu, Cong Wang, Haoyi Wang, and Wei Qin. Chapter 6 was written by Weitao Chen and Xianju Li and assisted by Min Liu and Jiaxuan Zheng. Chapter 7 was written by Weitao Chen and Xianju Li and assisted by Cong Wang. Chapter 8 was written by Xianju Li and Weitao Chen, with the assistance of Gaodian Zhou, Haoyi Wang, and

Wei Qin. The experiments of the book were designed by Weitao Chen, Xianju Li, and Lizhe Wang and completed by Min Liu , Jiakuan Zheng, Cong Wang, and Qin Wei. The work of the whole book was completed by Weitao Chen, Xianju Li, and Lizhe Wang.

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The book is intended for undergraduate and graduate students who are interested in mine environment, remote sensing, and artificial intelligent. It can also be used as a reference book for relevant scientific and technological workers.

Wuhan, China

Weitao Chen
Xianju Li
Lizhe Wang

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Chapter 1

Mine Geo-Environment: An Overview



1.1 Definition of Mine Geo-Environment

The geo-environment is an important part of the human environment, and includes the geological background, processes, and space; as such, it is also referred as the geological environment system (Eremenko et al. 2018; Frye 1967; Arias-Maldonado and Trachtenberg 2019). The geo-environment is the product of the Earth's evolution. Following a lengthy geological evolution, the lithosphere, hydrosphere, and atmosphere have reached a relatively stable state through material exchange and energy transfer (Guo et al. 2013; Robertson and Dixon 1984; Bai et al. 2007). This stable natural system is the basis for the survival and development of humans and other organisms. During the evolution of life, the geo-environment also underwent continuous changes (Powell and McKirdy 1973; Judd et al. 2002).

The mine geo-environment includes all natural geological conditions, geographic and topographic conditions, social and cultural conditions, and other factors in mining areas that have been discontinued, are being produced, or will be produced in future. The mine geo-environment is based on the lithosphere; during mine operation, this environment continuously affects the balance between soil, water, atmosphere, and lithosphere (Xu 2005, 2008; Cao et al. 2007; Hai-qing and Chen 2011).

1.2 Issues in the Geo-Environment Related to Mining

The non-standard exploitation and utilization of mineral resources induces various problems in the mine geo-environment (Marschalko et al. 2012; Ogola et al. 2002). These problems involve different types of pollution, damage, and geological disasters caused by mining on the surrounding geo-environment, mainly manifesting as soil erosion, water and soil losses, and desertification. Other notable issues include land cracking, subsidence, collapse, mountain collapse, landslide and debris flow, pollution of the surrounding water and soil owing to the discharge of waste residues

and wastewater, the destruction of wildlife habitats and the natural landscape, and harm or risks to human health and property (Kondolf 1997; Sengupta 2021; Plumlee 1999; Zhao et al. 2008).

1.3 Mine Geo-Environment of Open-Pit Mining

In general, the mining techniques utilized include open-pit, underground, and combined open-pit and underground mining. Different types of minerals are associated with various mining techniques. As tectonic positions vary, the same minerals experience variations in the tectonic uplift amplitude after mineralization, resulting in different levels of mining difficulty and applications of different mining techniques (Zhengfu et al. 2010; Langer 2013; Hustrulid et al. 2001).

Non-metallic mines largely adopt the open-pit mining technique because of the wide distribution of these resources and the high surface exposure. The key non-metallic minerals include limestone, granite, bentonite, quartzite for glass, and sandstone for construction. Although various mining techniques are used for metal ores, open-pit mining is adopted for rare earth metals, a few tungsten placers, and for some iron and manganese ores (Schippers et al. 2013; Spitz and Trudinger 2019). Several lead–zinc mining areas also adopt open-pit mining during the early stages, before converting to underground mining. Prior to the 1980s, nickel mainly relied on open-pit mining; afterwards, underground mining techniques became more popular. There are various types of gold deposits and associated mining techniques; open-pit mining is mainly used for placer gold deposits, while rock gold deposits are extracted using the combined open-pit and underground mining technique (Brierley 1982; Aryee et al. 2003; Weige 1998; Crowson 2012; Hartman and Mutmanský 2002).

Although the elements of the geo-environment of open-pit mines for various mineral resources differ, they all include a ground transportation system, waste disposal system, production workshop, office and living buildings, buildings for crushing, beneficiation, and smelting, and a tailings pond (Monjezi et al. 2009; Karavaeva et al. 2019; Galperin et al. 2017). The key difference between open-pit and underground mining is that the developed mining area is above the surface for the former, while the surface system for the latter only consists of wellhead buildings and facilities (Triantafyllidis and Psarraki 2020; Xuan et al. 2013; Pan et al. 2017).

Based on the rapid development and wide application of remote sensing technology, the modern mine remote sensing survey technology has gradually been developed on the basis of traditional mine surveys. Compared with traditional mine surveys, mine remote sensing is able to survey target objects within a short time and can rapidly provide survey results. Additionally, the available tools, wide area of application, and comprehensiveness of remote sensing technology ensures that the comprehensive survey of an area does not include the errors that often occur in traditional mine surveys. Mine remote sensing also ensures the objectivity and impartiality of survey results, and remote monitoring reduces or eliminates laborious field investigations, with greater resolution and timeliness (Mallupattu and Sreenivasula

Reddy 2013; Tong et al. 2015; Francioni et al. 2015; Schmidt and Glaesser 1998; Thompson 1996).

Remote sensing surveys of the geo-environment of open-pit mines have been conducted owing to these advantages, aimed at the above-ground content within the mine geo-environment, utilizing one or more types of remote sensing data (Francion et al. 2015; Schmidt and Glaesser 1998; Thompson 1996; Cai et al. 2009).

The issues related to the geo-environment of open-pit mines can be categorized into three major groups. First, geological disasters and potential hazards caused by mineral production, including landslides, debris flows, and ground collapses and fissures. Second, the destruction of landforms and landscapes largely caused by changes to the original landform and the geomorphic characteristics of the mining area, which can result in mountain damage, rock exposure, vegetation damage, and other phenomena. Third, the destruction of land resources mainly caused by changes to the land use, soil pollution status, land cover, and other phenomena (Fleurisson 2012; Lesin et al. 2015; Monjez et al. 2009; Kahrman 2002; Wang et al. 2018).

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Chapter 2

Multimodal Remote Sensing Science and Technology



2.1 Multimodal Remote Sensing Data Sources

2.1.1 *High-Resolution Optical Satellite Remote Sensing Images*

With the development of remote sensing sensor technology, many satellites can provide high-resolution images, wherein the resolution may reach the sub-meter level. These high-resolution data allow the opportunity to observe the Earth's surface, and offer data support for various remote sensing-related research fields.

High-resolution data generally refers to images with a spatial resolution exceeding 10 m, which are clear, detailed, and textured. This means that information on a small-scale ground object can be collected accurately. As the details of ground objects can be clearly visualized in high-resolution images, this technology has been widely used for image interpretation, urban planning, disaster relief, mapping, and other fields. High-resolution data generally includes the red, green, and blue bands of visible light. With the development of technology, current high-resolution satellites can acquire data for even more wavebands while ensuring a high spatial resolution. Table 2.1 presents parameter information for specific high-resolution satellites.

2.1.2 *High-Resolution Radar Satellite Remote Sensing Data*

Radars are often used in active remote sensing methodology. It is advantageous as radars have a specific degree of penetration and are able to acquire high-resolution ground images without being affected by weather. Radar satellites are also able to provide multiple polarization images such as single, double, and full polarization images. By combining and processing different polarization methods, rich ground feature information can be extracted. Moreover, radar images provide clear textural

Table 2.1 Parameters for specific high-resolution satellites

Satellite	Band (μm)	Spatial resolution (m)	Wide width (km)	Visit cycle (days)
SPOT5	Pan: 0.49–0.69	5 or 2.5	60 * 60	26
	G: 0.49–0.61 R: 0.61–0.68 NIR: 0.78–0.89	10		
	SWIR: 1.58–1.78	20		
FORMOSAT II	Pan: 0.45–0.90	2	24 * 24	1
	B: 0.45–0.52 G: 0.52–0.60 R: 0.63–0.69 NIR: 0.76–0.90	8		
EROS-B	Pan: 0.50–0.90	0.7	7 * 7 7 * 140	5
CartoSAT-1(P5)	Pan: 0.50–0.85	2.5	30 * 30	5
KOMPSAT-2	Pan: 0.50–0.90	1	15 * 15	3
	B: 0.45–0.52 G: 0.52–0.60 R: 0.63–0.69 NIR: 0.76–0.90	4		
WorldView-1, -2	Pan: 0.45–0.80	0.5	30 * 30 or 60 * 60	1.1–3.7
	B: 0.45–0.51 G: 0.51–0.58 R: 0.63–0.69 NIR: 0.77–0.895 COAST: 0.40–0.45 YELLOW: 0.585–0.625 RED EDGE: 0.705–0.745 NIR2: 0.86–1.04	2.4		
RapidEye	B: 0.44–0.51 G: 0.52–0.59 R: 0.63–0.685 RED EDGE: 0.69–0.73 NIR: 0.76–0.85	5.8	77 * 77	Every day
Pleiades-1A, 1B	Pan: 0.48–0.83	0.5	20 * 20 100 * 100 20 * 280	Every day
	B: 0.43–0.55 G: 0.49–0.61 R: 0.60–0.72 NIR: 0.75–0.95	2		
SPOT6, SPOT7	Pan: 0.455–0.745	1.5	60 * 60	2–3

(continued)

Table 2.1 (continued)

Satellite	Band (μm)	Spatial resolution (m)	Wide width (km)	Visit cycle (days)
	B: 0.455–0.525 G: 0.53–0.59 R: 0.625–0.695 NIR: 0.76–0.89	6		
WorldView-3	Pan: 0.45–0.80	0.31		
	B: 0.45–0.51 G: 0.51–0.58 R: 0.63–0.69 NIR: 0.77–0.895 COAST: 0.40–0.45 YELLOW: 0.585–0.625 RED EDGE: 0.705–0.745 NIR:0.86–1.04	1.24		
	SWIR	3.7		
	CAVIS	30		
KOMPSAT-3A	Pan: 0.40–0.90	0.31		
	B: 0.45–0.52 G: 0.52–0.60 R: 0.63–0.69 NIR: 0.76–0.90	2.2		
	MWIR	5.5		
Beijing II	Pan: 0.50–0.80	1		
	B: 0.45–0.52 G: 0.52–0.59 R: 0.63–0.69 NIR: 0.77–0.89	4		
Gaojing I	Pan: 0.45–0.89	0.5	12 * 12	4

Pan panchromatic, *NIR* near-infrared, *SWIR* short-wave infrared, *CAVIS* atmospheric instrument which stands for cloud, aerosol, water vapor, ice, snow, *MWIR* middle-wave infrared

information and are sensitive to small changes in specific parameters related to ground objects. In summary, radar data plays an important role in various qualitative and quantitative remote sensing techniques. Table 2.2 provides examples of radar satellite parameters.

Table 2.2 Parameters for some radar satellites

System	Band	Polarization	Wide width (km)	Resolution (m)	Period (days)	Orbital (cm)	Acceptance mode
ERS-2	C	VV	100	25	35	30	Stripmap
RADASAT1	C	VV	10–500	10–30–100	24	> 100	Stripmap ScanSAR
TerraSAR-X	X	Full	5–10–30–100	1–3–16	11	10	Spotlight Stripmap ScanSAR
Cosmo-skymed	X, L	Full	10–30–200	1–3–15	1–16	10	Spotlight Stripmap ScanSAR
RADASAT2	C	Full	10–500	3–100	1–24	10	Spotlight Stripmap ScanSAR
ALOS-2	L	Full	25 × 25 50 50 70 350 490	1 × 3 3 6 10 60 100	14		Spotlight Stripmap ScanSAR
Sentinel-1A Sentinel-1B	C	Full	250 20 × 20 80 400 × 400	5 × 20 5 × 5 5 × 5 20 × 40	12		Wideswath Wave Strip map Extra wide-swath
GF-3	C	Full	10–650	1–500			12 imaging models

2.1.3 Hyperspectral Satellite Remote Sensing Data

Hyperspectral remote sensing overcomes the limitations associated with traditional single band, multispectral remote sensing in terms of band number, band range, and fine information expression. It is able to utilize a very narrow electromagnetic wave segment to acquire relevant data from research objects. Table 2.3 provides some hyperspectral satellites and their parameters.

Data Features

The data features of hyperspectral remote sensing include:

- (1) Provision of numerous bands: the imaging spectrometers provide data on tens and potentially hundreds of bands in the visible and near-infrared (NIR) spectral regions;

Table 2.3 Some hyperspectral satellites and their parameters

Satellite	Sensor	Band (number/range)	Spatial resolution (m)
EOS AM-1	Modis	2/620–890 nm	250
		5/459–2155 nm	500
		29/405–14,385 nm	1000
EO-1	Hyperion	35/VIS	30
		35/NIR	
		172/SWIR	
GF-5	AHSI	330/400–2500 nm	30
PRISMA	PRISMA HSI	239/400–2500 nm	30
HysIS	HysIS	70/VIS ~ NIR	30
		256/SWIR	
ADEOS-2	GLI	34/380–11,950 nm	250, 1000
PROBA-1	CHRIS	80/400–1050 nm	17, 34
HJ-1A	HSI	115/450–950 nm	100

- (2) High spectral resolution: the imaging spectrometer sampling interval is generally < 10 nm, and this fine spectral resolution reflects the subtle characteristics of ground matter spectra;
- (3) Large amount of data: the data acquired exponentially increase with the number of bands;
- (4) Increased information redundancy: the high correlation of adjacent bands increases information redundancy;
- (5) Provision of spatial and spectral domain information (i.e., “atlas in one”): spectral profiles obtained from imaging spectrometers may be compared to those of congeners measured at the ground level.

Application Areas

The application areas of hyperspectral remote sensing include:

- (1) Geology

The diagnostic characteristics of hyperspectral remote sensing, such as absorption and the reflection of rocks and minerals, are often exploited in geological research. The application of hyperspectral data in geology largely includes lithology mapping, the identification and exploration of mineral resources, and environmental monitoring of the mining area (Peyghambari and Zhang 2021).

Hyperspectral data has a high spectral resolution; hundreds of continuous spectral bands may be used to extract pixel spectral features and identify minerals and rocks. The spectral absorption characteristics of different minerals are mainly related to the vibration of chemical bonds and ionic components in visible, NIR, and short-wave infrared bands. As such, these spectral differences can be used to analyze

the lithology and create a lithology composition map. Each lithologic unit itself is composed of non-linear, micro-scale mixtures of different minerals with varying spectral characteristics. Additionally, the rock surface of the survey area may be partially covered by soil, weathered layers, and vegetation, increasing the complexity and difficulty of lithology mapping via remote sensing (Pal et al. 2020).

Minerals are a precious geological resource. Hyperspectral remote sensing provides a method to identify and explore mineral resources by retrieving data on the object surface composition, mineral types, and abundance distribution, and offering guidance for mining work (Van der Meer et al. 2012). For instance, Carrino et al. (2018) used hyperspectral data for mineral exploration in southern Peru. Bishop et al. (2011) carried out mineral exploration in Pulang of Yunnan Province, China by combining ASTER and Hyperion data.

However, mining activities also cause serious pollution in the environment surrounding the mine. Lead, zinc, cadmium, and specific toxic minerals, alongside the waste generated by mining, pollute the surrounding water and soil, poison flora and fauna, affect human health, and ultimately cause major ecosystem damage. Hyperspectral data could potentially be used to monitor the content of mineral elements in the mine, and then evaluate and prevent pollution. As such, these data assist in locating pollution in the surrounding environment in a timely manner, identifying the source, and facilitating its rapid treatment, thereby ensuring the health of the ecosystem while allowing the continuation of mining work (Pour et al. 2021). Martín-Crespo et al. (2020) found that mine tailings cause toxic metal pollution in riverbed alluvium. Ma et al. (2020) investigated the dust diffusion characteristics of the Kuancheng mining area in Hebei Province, analyzed the impact of dust on the canopy spectrum in surrounding vegetation, and provided decision-making support for dust management.

(2) Agriculture

Remote sensing is a useful tool to monitor the spatio-temporal changes in crop morphology and physiological state, and to support precision agricultural practices. Compared with multispectral imaging, hyperspectral imaging purports to be a more advanced technique for acquiring detailed spectral responses of target features. The application of hyperspectral imaging in agriculture mainly manifests in the rapid and precise acquisition of a range of information on crop growth status and environmental stresses. These data may be used to adjust the volume of input materials to reduce waste, increase yield, and protect agricultural resources and environmental quality.

Hyperspectral remote sensing has been utilized in five key research areas related to agriculture. First, spectral characteristics have been extracted from multi-temporal hyperspectral data to identify and classify different vegetation and crops. Second, hyperspectral remote sensing has been used to estimate the leaf area index (LAI), biomass, total nitrogen, total phosphorus, and other biophysical parameters of vegetation. Third, hyperspectral imaging has been used in research on various remote sensing information models including those for clarifying the heat diffusion coefficient, soil water content, crop drought estimates, soil erosion, and land production potential. Fourth, hyperspectral imaging has been used alongside vegetation indices

to analyze land cover or monitor crop growth. For example, using the National Oceanic and Atmospheric Administration (NOAA)-Advanced Very High Resolution Radiometer (AVHR) data and normalized vegetation index (NDVI), the land cover index model was established to regionally differentiate land cover and its seasonal variations. Fifth, hyperspectral remote sensing has been used to monitor crop growth. Based on the large amount of data generated by remote sensing and the use of advanced computer and network technology, remote sensing information systems have been applied in many fields. These systems are able to monitor crop growth regularly. They can also rapidly monitor and evaluate flood and drought disasters that may affect regional grain production.

To summarize, hyperspectral imaging has been widely used in agriculture, with applications including the estimation of crop biochemical (e.g., chlorophyll, carotenoids, and water content) and biophysical properties (e.g., LAI and biomass). This information can help understand the physiological state of vegetation, predict yield, assess crop nutritional status (e.g., nitrogen deficiency), monitor crop diseases, and investigate soil properties (e.g., soil moisture, organic matter content, and carbon).

(3) Atmosphere and the environment

Atmospheric molecular and particulate components strongly respond to the solar reflectance spectrum; these components include water vapor, carbon dioxide, oxygen, ozone, clouds, and aerosols. Water vapor is the main absorption component. A narrow hyperspectral band can identify spectral differences from changes in atmospheric composition, allowing the detection of fine atmospheric absorption characteristics.

The application of hyperspectral remote sensing in the atmosphere has two main aspects. First, the determination of greenhouse gases in the Earth's atmosphere, including carbon dioxide, ozone, methane, and pollutant gas compositions. Second, the determination of atmospheric temperature and the vertical distribution of water and air, the study of atmospheric processes, and analysis of the Earth's surface composition, which mainly apply to meteorology. Atmospheric detection requires a high spectral resolution, and hyperspectral remote sensing provides clear advantages in this regard.

Based on the spectral characteristics of the ocean, the environmental protection departments of countries can effectively conduct marine resource exploration and detect changes in the marine environment. This could be carried out while concurrently identifying the inputs of harmful wastewater, crude oil leakage, and other marine pollutants across a large spatial range, rapidly and accurately.

As environmental problems have become increasingly important, research on this aspect is also developing. For example, in coastal and terrestrial water bodies, hyperspectral imaging has been used to detect chlorophyll, phytoplankton, dissolved organic matter, and the local or distant transport of suspended matter. In terms of environmental monitoring, surface components that directly or indirectly harm the environment (e.g., acid rain and heavy metals), can be detected, and the migration of harmful minerals can be monitored.

Hyperspectral imaging may also be used for the quantitative analysis of the surrounding environment (e.g., for environmental pollution), and to investigate environmental risk factors (e.g., precisely identify hazardous waste minerals, compile unique alteration mineral distribution maps, evaluate wildfire risk, and identify and probe combustion areas).

(4) Vegetation

Once corresponding technological treatments are adopted for vegetation hyperspectral remote sensing data from different sources, they could be used for vegetation parameter estimation and analysis, and potential long-range vegetation monitoring and estimation.

Hyperspectral data is rich in spectral information, which may be used for vegetation classification and mapping. For example, in some areas with rich vegetation types [e.g., coastal wetlands and mountains (Marcinkowska-Ochtyra et al. 2018)], hyperspectral data is essential for vegetation classification (Adam et al. 2010; Liu et al. 2020). Some studies have also been conducted on the fine classification of surface vegetation using unmanned aerial vehicle (UAV) hyperspectral data (Ishida et al. 2018; Yan et al. 2019).

Some scholars have used specific band combinations to construct vegetation indices in various studies; this has largely been conducted for vegetation growth monitoring and the quantitative inversion of vegetation parameters.

Gao et al. (2020) used the NDVI and other vegetation indices to extract vegetation areas and investigate vegetation coverage. This coverage provides an indirect evaluation of ecological health from the perspective of forest land distribution. Pettorelli et al. (2005) found that NDVI may be used to predict the ecological impact of environmental changes on ecosystem function, animal population dynamics and distribution, and to better understand the impact of humans on the environment.

Tan et al. (2020) combined the NDVI and Beer–Lambert Law to quantitatively invert the wheat LAI and monitor wheat growth. Blackburn (2007) identified that vegetation pigment could be quantitatively detected by hyperspectral imaging, and the vegetation pigment concentration may be used to diagnose various physiological processes of vegetation. This is significant for monitoring vegetation health, the broader ecosystem, and climate change.

Xue and Su (2017) reviewed more than 100 vegetation indices, analyzed their applicability, and stated that new indices could be established with the development of hyperspectral technology. This will broaden the research field, making hyperspectral technology one of the most important fields of aerospace remote sensing for the near future.

2.1.4 Survey Satellite Remote Sensing Data

Survey satellites investigate and monitor the Earth's resources and environment using remote sensing technology. Different types of sensors are utilized on satellites