As the technology of remote sensing has advanced over the last two decades, the scientific potential of the data that it produces has greatly improved. To better serve society’s needs, the immense amounts of aggregated satellite data need to be transferred into high-level products in order to improve the predictive capabilities of global and regional models at different scales and to aid in decision making through various decision support systems. A general trend is that the data centers are distributing more high-level products rather than simply the raw satellite imagery.

An increasing number of researchers from a diverse set of academic and scientific disciplines are now routinely using remotely sensed data products, and the mathematical and physical sophistication of the techniques used to process and analyze these data have increased considerably. As a result, there is an urgent need for a reference book on the advanced methods and algorithms that are now available for extracting information from the huge volume of remotely sensed data, which are often buried in various journals and other sources. Such a book should be highly quantitative and rigorously technical; at the same time, it should be accessible to students at the upper undergraduate and first-year graduate student level.

To meet this critical demand, we have identified and organized a group of active research scientists to contribute chapters and sections drawn from their research expertise. Although this is an edited volume with multiple authors, it is well designed and integrated. The editors and authors have made great efforts to ensure the consistency and integrity of the text.

In addition to the introductory chapter, this book consists of five parts: (1) data processing methods and techniques; (2) estimation of land-surface radiation budget components; (3) estimation of biophysical and biochemical variables; (4) estimation of water cycle components; and (5) high-level product generation and application demonstrations. The titles and authors of the individual chapters are as follows:

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(Continued)
Chapter 1 presents introductory material and provides an overview of the book. From the system perspective, it briefly describes the essential components of the remote-sensing system, ranging from platforms and sensors, modeling approaches, and information extraction methods to applications.

Part 1 includes four chapters on data processing. Chapter 2 is the only chapter that presents the methods and techniques for handling geometric properties of remotely sensed data. These include the calibration of systematic errors, geometric correction, geometric registration, digital terrain model generation, and digital ortho-image generation.

Chapter 3 seeks to reconstruct spatial and temporal continuous high-quality imagery. As the temporal resolution of satellite observations greatly increases, images are more often contaminated by clouds and aerosols that partially or completely block the surface information. Two groups of techniques are presented. The first group deals with composite methods for aggregating the fine temporal resolution (say, daily) to the coarse resolution (say, weekly or monthly), and the second discusses smoothing and gap-filling methods to eliminate the impacts of clouds and aerosols at the same temporal resolution.

Chapter 4 introduces the basic principles and methods of data fusion for integrating multiple data sources on the pixel basis, which have
different spatial resolutions, and are acquired from different spectra (optical, thermal, microwave). This chapter focuses mainly on low-level data products. (The methods for integrating high-level products are introduced in Chapter 22.)

Chapter 5 introduces methods for correcting the atmospheric effects of aerosols and water vapor on the optical imagery. Other atmospheric correction methods are discussed in Chapter 8 for thermal-IR data and in Part 4 for microwave data.

Part 2 focuses on estimation of surface radiation budget components. The surface radiation budget is characterized by all-wave net radiation \( R_n \) that is the sum of shortwave \( S_n \) and longwave \( L_n \) net radiation

\[
R_n = S_n + L_n = (s \downarrow - s \uparrow) + (L \downarrow - L \uparrow) = (1 - \alpha)S \downarrow + (L \downarrow - L \uparrow)
\]

where \( S \downarrow \) is the downward shortwave radiation (discussed in Chapter 6), \( S \uparrow \) is the upward shortwave radiation, \( \alpha \) is the surface shortwave albedo (discussed in Chapter 7), \( L \downarrow \) is the downward longwave radiation, and \( L \uparrow \) is the upward longwave radiation. Longwave net radiation \( L_n \) can be also calculated by

\[
L_n = \varepsilon L \downarrow - \varepsilon \sigma T_s^4
\]

where \( \sigma \) is the Stefan-Boltzmann constant, \( \varepsilon \) is surface thermal broadband emissivity, and \( T_s \) is surface skin temperature. Estimation of \( \varepsilon \) and \( T_s \) is discussed in Chapter 8, and \( L \downarrow \) and \( L_n \) are covered in Chapter 9.

Part 3 focuses on the estimation of biochemical and biophysical variables of plant canopy. Chapter 10 introduces the various methods for estimating plant biochemical variables, such as chlorophyll, water, protein, lignin and cellulose. The biophysical variables discussed in this book include leaf area index (LAI) in Chapter 11, the fraction of absorbed photosynthetically active radiation by green vegetation (FPAR) in Chapter 12, fractional vegetation cover in Chapter 13, vegetation height and vertical structure in Chapter 14, above-ground biomass in Chapter 15, and vegetation production in terms of gross primary production (GPP) and net primary production (NPP) in Chapter 16. Various inversion methods are introduced in this part, including optimization methods (Section 11.3.2), neural networks (Sections 11.3.3, 13.3.3 and 15.3.4), genetic algorithms (Section 11.3.4), Bayesian networks (Section 11.3.5), regression tree methods (Section 13.3.3), data assimilation methods (Section 11.4) and look-up table methods (Section 11.3.6). Part 3 also discusses multiple data sources besides optical imagery, such as Synthetic Aperture Radar (SAR) and Light Detection and Ranging (Lidar), and polarimetric InSAR data.

Part 4 is on estimation of water balance components. A general water balance equation is expressed by:

\[
P = Q + E + \Delta S
\]

where \( P \) is precipitation (discussed in Chapter 17), \( Q \) is runoff that is currently difficult to estimate from remote sensing, \( E \) is evapotranspiration (discussed in Chapter 18), and \( \Delta S \) is the change in storage to which three chapters are related: soil moisture in Chapter 19, snow water equivalence in Chapter 20, and surface water storage in Chapter 21. In addition to optical and thermal data, microwave data are dealt with extensively in all chapters except in Chapter 18. The gravity data with the GRACE data are also briefly introduced in Chapter 21.

Part 5 deals with high-level product generation, integration, and application. Chapter 22 presents different methods for integrating high-level products of the same variable (e.g., LAI) that may be generated from different satellite data or different inversion algorithms. The data fusion methods for integrating low-level products are discussed in Chapter 4. Chapter 23 describes the typical procedures for producing high-level products from low-level satellite data and for developing a data management
system that is used for effectively handling a large volume of satellite data. The last chapter demonstrates how remote-sensing data products can be used for land-cover and land-use change studies, particularly on mapping the extent of three major land-use types (urban, forest, and agriculture), detecting changes in these land-use types, and evaluating the environmental impacts of these land-use changes.

One important feature of this book is its focus on extracting land-surface information from satellite observations. All relevant chapters follow the same template: introduction to basic concepts and fundamental principles, review of practical algorithms with a comprehensive list of references, detailed descriptions of representative algorithms and case studies, surveys of current products, spatiotemporal variations of the variable, and identification of future research directions. The book includes almost 500 figures and tables, as well as 1700 references.

This book can serve as a text for upper-level undergraduate and graduate students in a variety of disciplines related to Earth observation. The entire book may be too lengthy for a one-semester or one quarter class, but most chapters in Parts 2–5 are relatively independent, and using a subset of them will be useful in such classes.

The text can also serve as a valuable reference book for anyone interested in the use and applications of remote-sensing data. Ideally, those using this book will have taken an introductory remote-sensing course, but we have written it at such a level that even those who have had little or no prior training in remote sensing can easily understand the overall development of this field.
List of Contributors

Jinshan Cao School of Remote Sensing and Information Engineering, Wuhan University, 129 Luoyu Road, Wuhan 430079, China

Erxue Chen Institute of Forest Resources Information Technology, Chinese Academy of Forestry, 1 Dongxiaofu, Beijing 100091, China

Zhuoqi Chen State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China and College of Global Change and Earth System Science, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Jie Cheng State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China and College of Global Change and Earth System Science, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Cuicui Dou Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, 73 East Beijing Road, Nanjing 210008, China and School of Earth Sciences and Engineering, Hohai University, 1 Xikang Road, Nanjing 210098, China

Jinyang Du State Key Laboratory of Remote Sensing Science, Jointly Sponsored by the Institute of Remote Sensing Applications of Chinese Academy of Sciences and Beijing Normal University, 20 Datun Road, Beijing 100101, China

Robert E. Dickinson Department of Geological Sciences, University of Texas, Austin, TX 78712, USA

Wenjie Fan Institute of RS and GIS, Peking University, 5 Yiheyuan Road, Beijing 100871, China

Hongliang Fang Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 11A Datun Road, Beijing 100101, China

Qiaoni Fu Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, 73 East Beijing Road, Nanjing 210008, China and School of Earth Sciences and Engineering, Hohai University, 1 Xikang Road, Nanjing 210098, China

Tao He Department of Geographical Sciences, University of Maryland, 2181 LeFrak Hall, College Park, MD 20742, USA

Wenli Huang Department of Geographical Sciences, University of Maryland, 2181 LeFrak Hall, College Park, MD 20742, USA

Shunping Ji School of Remote Sensing and Information Engineering, Wuhan University, 129 Luoyu Road, Wuhan 430079, China

Bo Jiang State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China; School of Geography, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and Department of Geographical Sciences, University of Maryland, 2181 LeFrak Hall, College Park, MD 20742, USA

Lingmei Jiang State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China; Beijing Key Laboratory for Remote Sensing of Environment and Digital Cities, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and School of Geography,
Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Zengyuan Li Institute of Forest Resources Information Technology, Chinese Academy of Forestry, 1 Dongxiaofu, Beijing 100091, China

Shunlin Liang State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China; College of Global Change and Earth System Science, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and Department of Geographical Sciences, University of Maryland, 2181 LeFrak Hall, College Park, MD 20742, USA

Qiang Liu State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China

Suhong Liu State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China

Jinmei Pan State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China

Yong Pang Institute of Forest Resources Information Technology, Chinese Academy of Forestry, 1 Dongxiaofu, Beijing 100091, China

Ying Qu State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China

Yonghua Qu State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China

Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China; Beijing Key Laboratory for Remote Sensing of Environment and Digital Cities, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and School of Geography, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China
Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and School of Geography, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Huazhong Ren State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China; Beijing Key Laboratory for Remote Sensing of Environment and Digital Cities, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and School of Geography, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Jiancheng Shi State Key Laboratory of Remote Sensing Science, Jointly Sponsored by the Institute of Remote Sensing Applications of Chinese Academy of Sciences and Beijing Normal University, 20 Datun Road, Beijing 100101, China

Jinling Song State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China; Beijing Key Laboratory for Remote Sensing of Environment and Digital Cities, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and School of Geography, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Ping Song Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, 73 East Beijing Road, Nanjing 210008, China and Graduate University of Chinese Academy of Sciences, 19A Yuquan Road, Beijing 100049, China

Guoqing Sun State Key Laboratory of Remote Sensing Science, Jointly Sponsored by the Institute of Remote Sensing Applications of Chinese Academy of Sciences and Beijing Normal University, 20 Datun Road, Beijing 100101, China and Department of Geographical Sciences, University of Maryland, 2181 LeFrak Hall, College Park, MD 20742, USA

Wanxiao Sun Department of Geography and Planning, Grand Valley State University, 1 Campus Drive, Allendale, MI 49401-9403, USA

Xin Tao Department of Geographical Sciences, University of Maryland, 2181 LeFrak Hall, College Park, MD 20742, USA

Dongdong Wang Department of Geographical Sciences, University of Maryland, 2181 LeFrak Hall, College Park, MD 20742, USA

Jindi Wang State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China; Beijing Key Laboratory for Remote Sensing of Environment and Digital Cities, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and School of Geography, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Kaicun Wang College of Global Change and Earth System Science, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Wenhui Wang I.M. Systems Group at NOAA/NESDIS/STAR, 5200 Auth Road, Camp Springs, MD 20746, USA

Jianguang Wen State Key Laboratory of Remote Sensing Science, Jointly Sponsored by the Institute of Remote Sensing Applications of Chinese Academy of Sciences and Beijing Normal University, 20 Datun Road, Beijing 100101, China

Zhiqiang Xiao State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China; Beijing Key Laboratory for Remote Sensing of Environment and Digital Cities, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and School of Geography, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Chuan Xiong State Key Laboratory of Remote Sensing Science, Jointly Sponsored by the Institute of Remote Sensing Applications of Chinese Academy of Sciences and Beijing Normal University, 20 Datun Road, Beijing 100101, China
LIST OF CONTRIBUTORS

Chunyan Yan School of Earth Sciences and Resources, China University of Geosciences, Beijing, 29 Xueyuan Road, Beijing 100083, China

Guangjian Yan State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China; Beijing Key Laboratory for Remote Sensing of Environment and Digital Cities, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and School of Geography, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Jinghui Yang Chinese Academy of Surveying and Mapping, 28 Lianhuachi West Road, Beijing 100830, China

Xiang Yu School of Remote Sensing and Information Engineering, Wuhan University, 129 Luoyu Road, Wuhan 430079, China

Wenping Yuan State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China and College of Global Change and Earth System Science, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Xiuxiao Yuan School of Remote Sensing and Information Engineering, Wuhan University, 129 Luoyu Road, Wuhan 430079, China

Jixian Zhang Chinese Academy of Surveying and Mapping, 28 Lianhuachi West Road, Beijing 100830, China

Lixin Zhang State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China; Beijing Key Laboratory for Remote Sensing of Environment and Digital Cities, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China and School of Geography, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Xiaotong Zhang State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China and College of Global Change and Earth System Science, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Xin Zhang State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China and School of Geography, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Zhiyu Zhang State Key Laboratory of Remote Sensing Science, Jointly Sponsored by the Institute of Remote Sensing Applications of Chinese Academy of Sciences and Beijing Normal University, 20 Datun Road, Beijing 100101, China

Xiang Zhao State Key Laboratory of Remote Sensing Science, Jointly Sponsored by Beijing Normal University and the Institute of Remote Sensing Applications of Chinese Academy of Sciences, 19 Xinjiekouwai Street, Beijing 100875, China and College of Global Change and Earth System Science, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, China

Xiaosong Zhao Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, 73 East Beijing Road, Nanjing 210008, China

Xiufang Zhu Department of Geographical Sciences, University of Maryland, 2181 LeFrak Hall, College Park, MD 20742, USA
CHAPTER 13

Fractional Vegetation Cover

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Abstract

Fractional vegetation cover (FVC) is an important biophysical parameter describing the Earth’s surface system. This chapter summarizes various methods used for the field measurement and remote-sensing retrieval of FVC, including visual estimation, sampling and the use of optical measuring instruments, regression modeling, mixed pixel decomposition, and computer learning methods. Some frequently used methods are described in detail, and actual examples and discussions are given in the section describing field measurement. Finally, the principal remote-sensing products and algorithms are briefly introduced, and possible further improvements of FVC estimation are presented.

13.1. INTRODUCTION

Fractional vegetation cover (FVC) is generally defined as the ratio of the vertical projection area of vegetation (including leaves, stalks, and branches) on the ground to the total vegetation area. FVC is an important parameter used to measure surface vegetation cover; additionally, it is an important index for researching the aerosphere, pedosphere, hydrosphere, and biosphere as well as their interactions. FVC is an important biophysical parameter for simulating the exchange between the land surface and the atmospheric boundary level using the soil-vegetation-atmosphere transfer model (Chen et al., 1997). Accurate estimation of the FVC is required for research on land-surface processes, climate change, and numerical weather prediction (Zeng et al., 2000). Moreover, FVC is extensively applied in agriculture, forestry, resource and environmental management, land use, hydrology, disaster risk monitoring, and drought monitoring.

In most of these applications, the FVC of healthy vegetation is required, and the absorption and emission of carbon and water, which are performed by the vegetation and are the foundation for the Earth’s biosphere, are emphasized. However, in some applications, the withered and necrotic part of the vegetation is considered, such as studies on water and soil conservation, in which the interception of rainfall by vegetation needs to be determined. In these studies, the focus is on the physical properties of the vegetation.

Field measurement and remote-sensing retrieval are two approaches used to obtain FVC accurate values. Field measurement is a conventional approach to extract FVC and includes visual estimation and photography. Remote-sensing retrieval can be divided into two methods: the empirical-model method and the physical-model method. Using an empirical model, FVC is calculated by either a simple statistical model or a regression relationship. Typically, an empirical relationship between the normalized difference vegetation index (NDVI) and the FVC is established, and then the FVC is calculated from the NDVI. The physical model considers the complex canopy radiative transfer process, which involves reflectance, transmittance, and absorption by leaves and other elements. Therefore, the FVC is difficult to directly calculate using the physical-model method and must be obtained using a look-up table or by simplifying the retrieval process with other machine-learning methods. A machine-learning method is a type of retrieval process in which the required knowledge is acquired through sample data training for rapid physical-model simulation, thus accomplishing information transmission. Because sample data are usually acquired in large quantities through complex physical-model simulations, the machine-learning method can be categorized as a physical-model method. This chapter introduces the methods used to obtain FVC and the available remote-sensing products.

13.2. FIELD MEASUREMENTS OF FVC

In the past, field measurement was the most commonly used method to obtain FVC.
However, with the extensive application of remote-sensing techniques for monitoring vegetation, field measurement is losing its dominance. Regardless, field measurement continues to play a nonnegligible role by providing basic data for the remote-sensing estimation of FVC. Zhou believes that an ideal field measurement of FVC should have the following features: (a) instruments with operational ease and economical utilization, (b) available, accurate, and objective land-surface observation records, (c) a short measurement duration, and (d) negligible impact from human factors. Most field measurement methods are unable to meet all four requirements, although digital photography is widely applied in the field measurement of FVC because it can satisfy all four requirements (Zhou et al., 2001).

13.2.1. Visual Estimation

In visual estimation, FVC is estimated based on the estimator's experience. This method is characterized by its simplicity and operational ease; however, it is highly subjective and random because the estimation precision is closely associated with the estimator's experience. The following methods are included:

13.2.1.1. The Traditional Method

Several sample plots covering a given area are selected based on specific statistical requirements. The FVC of the sample plots is directly estimated based on experience.

13.2.1.2. The Digital Image Method

First, the vegetation within the sample plots is vertically photographed; then, the photos are visually estimated. To improve the estimation precision, reference images are interpreted by personnel in accordance with certain standards, and the average value is taken. In this method, a FVC standard image series must be generated, and the training of survey personnel is required. Images that contain a fractional amount (from 5 up to 95%) of vegetation cover are printed and subsequently coded by survey personnel. Special measurement and calculation software is employed to estimate the FVC. Several colored images are randomly selected each time for the visual estimation of the FVC by trained staff based on standard images. Finally, the results of the visual estimation and those provided by the software are compared to determine the error in visual estimation. Generally, training objectives require that the visual estimation error is less than 10%.

13.2.1.3. The Grid Method

The grid method is an improvement on traditional visual estimation. In this method, the sample plot is divided into several subquadrats of equal area based on vegetation type. Then, the FVC of each subquadrat is estimated using the traditional method of visual estimation. The mean value of the FVC is taken as the FVC of the sample plot. Research indicates that the grid method is easier to perform and has a higher precision than the traditional method. The grid method for visual estimation is essentially a spatial sampling method that uses equal spacing.

13.2.2. The Sampling Method

The sampling method is also known as the probability calculation method. In this method, the occurrence probability of vegetation in the sample plot is calculated using measurement methods based on statistical principles. The calculated probability is taken as the FVC of the sample plot. This method has the disadvantages of operational complexity, long measurement duration, a large number of limitations, and low efficiency; however, the method provides high precision. Some sampling methods are listed below.
13.2.2.1. The Quadrat Sampling Method

A square sample plot is marked off in the research area as the quadrat. The FVC is measured on two diagonals of the quadrat (measured only once for the overlapped section). The arithmetic mean is determined as the FVC of the quadrat.

13.2.2.2. The Belt-Transect Sampling Method

Two perpendicularly crossed rectangular-belt transects are selected. The FVC of the sample plot is defined as the ratio of the plant length that is in contact with the belt transect to the total length of the belt transect. For example, to measure the forest canopy closure, the trees located on the two diagonals of the quadrat are the objects of investigation. The forest canopy closure is defined as the ratio of the number of times that a canopy is visible overhead to the total number of times that the head is raised.

13.2.2.3. The Point Count Sampling Method

Needles are vertically placed in the vegetation, and the FVC is defined as the ratio of the number of needles in contact with leaves to the total number of needles.

13.2.2.4. The Shadow Sampling Method

The shadow sampling method is also termed the meter-stick method. A meter stick is placed on the land surface parallel to the crop rows. The stick is moved forward a set distance, and the length of shadow on the stick is read; the ratio of shadow length on the stick to the total length of the stick is recorded as the FVC. This method is generally used for row crops, and high noon is considered the optimal time for measurement.

13.2.3. Optical Measuring Instruments

As science and technology have developed, new measuring instruments are now being applied to FVC measurement. For example, electronic equipment is used to record the flux of intercepted sunlight, which is then compared to the level of direct sunlight at that location. From these data, the vegetation gap fraction is obtained. For these measurements, the FVC is calculated as \((1 - \text{the vertical vegetation gap fraction})\). Other methods include direct imaging, such as digital photography, which is the most extensively applied method. The proportions of various vegetation types that are present are calculated using image classification. Common measurement techniques include the following:

13.2.3.1. Spatial Quantum Sensor (SQS) and Traversing Quantum Sell (TQS)

SQS and TQS are used to calculate FVC based on the amount of sunlight that is intercepted by vegetation as measured by a sensor. However, these methods have not been extensively applied in practice because specialized sensors are usually needed, resulting in field operation difficulties.

13.2.3.2. Digital Photography

Digital photography is performed in a vertical and downward manner. FVC is the ratio of the number of vegetation pixels to the total number of pixels in the digital images. Digital photography is used extensively in the field measurement of FVC because it is free of the subjectivity of other measurements, has high precision and good stability, and is easy to use. In recent years, some progress has been made in estimating FVC using digital photography. Zhou et al. (1998) acquired FVC digital images using a digital camera to test the consistency of this method. Gitelson et al. estimated the FVC of wheat in Nebraska, in the United States, using digital photography (Gitelson et al., 2002). Michael et al. conducted long-term monitoring of the FVC of an arid ecosystem in the United States using an agricultural digital camera, with accurate and effective results (Michael et al., 2000). Based on a comparison of the
various techniques used to obtain field measurements of FVC, White et al. (2000) claimed that digital photography was the easiest and most reliable technique to test and verify the extraction of remote-sensing information. Hu et al. acquired photographs of sample plots in a research area and extracted FVC information from digital images of the area through classification. The information extracted was later used to verify the FVC of the entire research area obtained using remote-sensing estimation (Hu et al., 2007).

Despite the extensive application of digital photography, which is due to its easy operation and high efficiency, certain problems are encountered in obtaining FVC. Two major issues affect FVC extraction precision, and these factors require certain skills to deal with them. The first issue arises from the methods used for measurement and photography and includes the problem of image edge distortion. The most frequently used solution is to cut the image edge to remove this influence. The other issue, which is more striking and deserves more attention, is the method used to extract FVC information from digital images. Supervised and unsupervised classifications are adopted to solve this problem, and FVC is calculated as the proportion of classified vegetation. All the traditional methods are unable to extract the FVC from digital images rapidly and automatically, thus lowering the practicability of digital photography. However, some researchers have proposed methods that are more convenient to extract the FVC from digital images (Liu and Pattey, 2010; Liu et al., 2011).

### 13.2.3.3. LAI-2000 Indirect Measurement

LAI-2000 is a more delicately designed measuring instrument and is mainly intended to measure the leaf area index (LAI) (see Section 11.1.2 in Chapter 11). Moreover, LAI-2000 can calculate FVC based on the measured vegetation gap fraction. LAI-2000 uses a camera with a fish-eye lens for observation and imaging, and the image is divided into several rings with variable radii by viewing the zenith angles of 7°, 23°, 38°, 53°, and 68°. During FVC measurements, the observed area in the ring with the minimum zenith angle (7°) is approximated as the zenith observation, and the FVC is calculated as (1—the gap fraction for the ring with the minimum zenith angle (7°)) (Rautiainen et al., 2005). This measurement shares similar principles with digital photography. In addition, White et al. (2000), when measuring FVC using LAI-2000, first measured the plant area index and then obtained the FVC through conversion. Compared with the method where only the ring with the minimum zenith angle is involved, this method has the advantage of expanding the spatial range for measurement by utilizing a greater number of multiangle observations in a wide field of view using a fish-eye lens. However, this method also has the disadvantage of incorporating a greater number of uncertain factors.

As with the application of digital photography for FVC measurement, early morning and evening are the optimal measuring times; the measurement should not be conducted in direct sunlight. Generally, the use of LAI-2000 is not as convenient as digital photography for measuring FVC.

### 13.2.4. Examples of Field Measurement

#### 13.2.4.1. Examples of Noninstrumental Measurements

Some examples of field measurements of FVC are given below. Depending on the types and features of the vegetation studied, the point sampling, shadow sampling method and canopy projection method are used.

1) Grassland

The point count sampling method is used to measure grassland FVC. In the research plot,
1 m × 1 m subquadrats are selected. Needles are used as markers every 10 cm (φ = 2 mm), that is, the needles are successively and vertically inserted in the subquadrat above the grassland at 10-cm intervals. The points where the needles come into contact with grass are counted, and the points where there are no contacts are not counted. The FVC is the ratio of the number of contact points to the total number of points, as shown in Figure 13.1. The mean value of the measured FVC for three subquadrats at three different positions is recorded as the FVC of the quadrat.

2) Forested land

For tall vegetation, such as trees in forested land, the forest canopy closure is generally used to indicate the cover as expressed in Equation (13.1):

\[ D = \frac{fd}{fe} \times 100\% \] (13.1)

Here, \( D \) is the forest canopy closure (or the FVC of shrub land) expressed as a percentage; \( fe \) is the area of quadrat (units, m²), and \( fd \) is the vertical projection area of the tree canopy (or grass canopy) in the quadrat (units, m²).

Forest canopy closure can also be measured using the tree canopy projection method, which is only applicable to forested land. This method is similar to the grid method for visual estimation; therefore, it is not specifically introduced here. A 20 m × 20 m sample plot is typically selected and divided into 5 m × 5 m grids with a measuring tape. The position of each tree in the grid is measured, and the projection length of the canopy of each tree is measured in the north–south and east–west directions using the measuring tape and a compass. The canopy projection is plotted on grid paper on an appropriate scale. The areas of canopy projection and the sample plot are calculated based on the grid; from these data, the forest canopy closure can be derived as shown in Figure 13.2.

3) Shrubbery

The shadow sampling method is usually adopted for measuring the FVC of shrubbery. A rope or measuring tape is extended over the quadrat of shrubbery, and the length of that...
shadow that is cast on the measuring rope is measured. The FVC of the shrubbery is the ratio of the length of shadow cast by the shrub to the total length of the rope or the quadrat. This procedure is repeated three times at three different positions on the quadrat, and the mean value is the FVC of shrubbery in the quadrat. The area of quadrat can be as small as 10 m × 10 m.

13.2.4.2. Examples of Digital Photography Measurement

1) Selecting the photography environment

First, illumination conditions must be selected. The vegetation should be photographed on a cloudy day or in the morning or evening when the effect of shadows is minimal. However, because morning dew might also affect the photography, the morning is not recommended. Artificial lighting equipment can be used in the dark during the evening. In short, the spectral difference between the vegetation and the soil background should be as strong as possible, and interference from shadows should be prevented. Figure 13.3 shows images taken with a digital camera in various environments; in (a), a flashlight was used during the night; in (b), the image was taken in direct sunlight; and in (c), the image was taken during a cloudy day.

In field measurements, a long stick with the camera mounted on one end is beneficial to conveniently measure various species of vegetation, enabling a larger area to be photographed with a smaller field of view. The stick can be used to change the camera height; a fixed-focus camera can be placed at the end of the instrument platform at the front end of the support bar, and the camera can be operated by remote control. Figure 13.4 shows a simple observation platform designed by one of the authors during the field measurement of FVC.

The photographic method used depends on the species of vegetation and planting pattern:

- Low crops (<2 m) not in rows
The observation platform is used directly where the height of the installed camera above the canopy of vegetation far exceeds the crown diameter of the vegetation. Sampling is conducted along the diagonals of the quadrat; finally, the arithmetic average is taken. This method is similar to the quadrat sampling method.

Low crops (<2 m) in rows

In a situation with a small field of view (<30°), rows of more than two cycles should be included in the field of view, and the side length of the image should be parallel to the row. If there are no more than two complete cycles, then information regarding row spacing and plant spacing are required. The FVC of the entire cycle, that is, the FVC of the quadrat, can be obtained from the number of rows included in the field of view.

High crops (>2 m) not in rows

Sampling along the diagonals, as in the quadrat sampling method, can also be conducted. During the photography session, if the sampling points fall on the low vegetation between plants, then the observation platform is used; if the sampling points fall on the tree crown and the observation platform can be maintained above the crown of the vegetation as high as possible, then the observation platform can also be used to obtain photographs. However, if the height is excessively great, then the images should be taken in a bottom-up manner from beneath the crown. Meanwhile, the low vegetation is photographed in a top-down manner beneath the crown to obtain the total FVC of the region near the tree.

High vegetation in rows (>2 m)

Through the top-down photography of the low vegetation underneath the crown and the bottom-up photography beneath the tree crown, the FVC within the crown projection area can be obtained by weighting the FVC obtained from the two images. Next, the low vegetation between the trees is photographed, and the FVC that does not lie within the crown projection area is calculated. Finally, the average area of the tree crown is obtained using the tree crown projection method. The ratio of the crown projection area to the area outside the projection is calculated based on row spacing, and the FVC of the quadrat is obtained by weighting.

2) FVC extraction from the classification of digital images

Many methods are available to extract the FVC from digital images, and the degree of automation and the precision of identification are important factors that affect the efficiency of field measurements. For example, supervised classification has high precision but low efficiency, whereas unsupervised classification has high efficiency but low precision due to errors of commission and omission. Thus, the defects in these methods restrict their application to a certain extent.

Figure 13.5 illustrates the results of the automatic and rapid extraction of FVC from digital images. This method, which is proposed by Liu et al. (2011), has the advantages of a simple algorithm, a high degree of automation and high precision, as well as ease of operation. More rapid classification methods with a higher degree of automation and greater accuracy are required to maximize the superiority of digital photography.

13.3. THE REMOTE-SENSING RETRIEVAL

The development of remote-sensing technology facilitates the acquisition of multitemporal and multiscale data to continually monitor FVC on a large or global scale. Accordingly, many FVC estimation methods are also
being developed. The most extensively applicable method involves establishing the relationship between FVC and vegetation index (such as NDVI) to retrieve FVC. The commonly used remote-sensing methods of FVC retrieval are mainly divided into two categories: empirical model methods and pixel decomposition model methods. Additionally, many researchers have adopted machine-learning methods, such as those that employ neural networks, to estimate FVC.

13.3.1. Regression Models

Regression models are also called empirical models and are constructed through the regression of remote-sensing data collected using a specific wave band, several wave bands, or a remotely sensed vegetation index (VI) to measure FVC. This model can be extended to FVC estimations on a larger scale.

The VI method is most frequently applied. Based on an analysis of the spectral features of vegetation, this method selects the VI that
correlates well with FVC and then establishes the conversion relationship between VI and FVC for FVC estimation. Generally, the VI varies depending on area and vegetation species. The most extensively applied NDVI is expressed using Formula (13.2).

\[
\text{NDVI} = \frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + \rho_{\text{red}}} \quad (13.2)
\]

where \(\rho_{\text{nir}}\) is the reflectance of vegetation in the near-infrared band and \(\rho_{\text{red}}\) is the reflectance of vegetation in the red band. The extensive application of NDVI, which can be used to indicate the growth status of vegetation, stems from the considerable difference in the reflectance of normal vegetation in the red band and the near-infrared band.

Previous research suggests that FVC is closely correlated with the VI and that the correlation between the two can be either linear or nonlinear. Therefore, the regression model can also be linear or nonlinear, and the regression model method can be subdivided into the linear and nonlinear regression model methods.

**13.3.1.1. The Linear Regression Model Method**

In the linear regression model method, the linear regression of the actual FVC and remotely sensed VI are determined to establish the estimation model for FVC in the research area. The linear regression model of NDVI and FVC provides a simple method to estimate FVC; thus, it has achieved widespread application (Hurcom et al., 1998). For instance, Xiao and Moody, through the linear regression of 60 points selected from a Landsat ETM + NDVI image and FVC (considered as the actual surface FVC), extracted a high-resolution (0.3 m) true color ortho-image and found a strong linear relationship between NDVI and FVC \((R^2 = 0.89)\). They then applied this formula to estimate the FVC of all of the pixels in the Landsat ETM + image (Xiao & Moody, 2005).

For both dense and sparse vegetation, the FVC of a remote-sensing pixel can be defined as having a linear relationship with the VI if the influence of multiple scattering is omitted:

\[
FVC = a \cdot \text{VI} + b \quad (13.3)
\]

where FVC is the FVC of the mixed pixel, VI is the VI of the mixed pixel and \(a\) and \(b\) are the regression coefficients of FVC and VI, respectively. **Figure 13.6** shows the expression for the linear regression of soil-adjusted VI and FVC established by Choudhury et al. (1994).

Some attempts have been made to grade the value of NDVI such that different grades indicate different FVCs. For instance, Mohammad et al. categorized NDVI after some conversion \((\text{NDVI} = (\text{NDVI} + 0.5) \times 255)\) into six grades, namely, 5, 5–50, 50–100, 100–150, 150–200 and 200–250, which represented the FVC of six situations, namely, 0%, 20%, 40%, 60%, 80%, and 100%, respectively (Mohammad et al., 2002). However, this method of segmentation with discretization of NDVI still utilizes a linear or nonlinear relationship between VI and FVC.

**FIGURE 13.6** The linear regression relationship between soil-adjusted VI and FVC. (Choudhury et al., 1994, Fig. 12(a))
13.3.1.2. The Nonlinear Regression Model Method

By fitting NDVI and FVC, the nonlinear regression model can be established and applied to calculate the FVC of an entire research area. Research by Carlson and Ripley indicates that for some values of FVC where LAI was 1–3, a higher clumping index of vegetation would result in a better nonlinear correlation between the VI and FVC (Carlson et al., 1997).

Choudhury et al. (1994) found that FVC was related to scaled NDVI in a quadratic manner. Based on this finding, the authors estimated the FVC of a coniferous forest in the U.S. Pacific Northwest. The results indicated that although NDVI is the most commonly applied method, it did not have the strongest correlation with the FVC of trees. Meanwhile, based on remote-sensing data from NOAA AVHRR, Choudhury and coworkers estimated the FVC of a coniferous forest using the NDVI and scaled NDVI. They found that the correlation coefficient was 0.55 at a confidence interval of 99% (Choudhury et al., 1994). Gillies & Carlson et al. obtained a quadratic relationship between the FVC and scaled NDVI using various methods and datasets (Gillies et al., 1997; Carlson et al., 1997).

Some researchers have studied the VI method using both the linear and the nonlinear regression method. For instance, Gitelson et al. conducted a regression of three types of VIs, namely, the NDVI, the Green NDVI, and the visible atmospherically resistant index (VARI) with the FVC of wheat (Figure 13.7). Nonlinear regression was used for the NDVI and Green NDVI, and linear regression was used for the VARI. A comparative analysis indicated that the VARI was very sensitive to FVC within the range of 0-10% and that it could minimize the sensitivity to atmospheric influence. It was suggested that the VARI should be utilized in the linear regression model to estimate FVC (Gitelson et al., 2002). Either a strong linear relationship (Ormsby et al., 1987) or a nonlinear relationship (Li et al., 2005) was found between the VI and FVC, depending on the specific landscape type. Both the linear and nonlinear models have difficulties with mixed vegetation. Even when the FVC is 100%, the VI depends on the vegetation species that are present due to the

**FIGURE 13.7** The expression for the regression relationship between VI and FVC. (Gitelson et al., 2002, Fig. 7 (B))
differences in their chlorophyll content and canopy structure. It has been reported that even when the actual FVC of different vegetation species is basically the same in a research area, the values of FVC directly calculated from the NDVI can deviate from each other by as much as 40% as a result of the difference in chlorophyll content between natural and artificial vegetation (Glenn et al., 2008).

The estimation precision of FVC can be improved if the features and species of the vegetation are determined by field measurement. Previous researchers have used the average leaf inclination angle corresponding to different vegetation species under various land-surface conditions to predict the FVC from the VI (Anderson, 1997).

Non-VI forms can also be used to establish an empirical regression relationship with FVC. Graetz et al. conducted a linear regression analysis on measured FVC data from the fifth channel of Landsat MSS. The regression model obtained was later applied to estimate the FVC of sparse grassland (Graetz et al., 1988). Peter used ATSR-2 remote-sensing data in four channels (555, 670, 870, and 1,630 nm) to study the linear regression of FVC with reflectance. The results indicated that applying the linear regression model based on the data from four channels was superior to application of VI alone for estimating FVC (Peter, 2002).

Due to its simplicity, the regression model method has been widely applied in FVC estimations on a regional level with high precision. Nevertheless, it has been demonstrated that the empirical regression model has its own limitations, as it is only applicable to the FVC estimation of specific vegetation species in specific regions. For instance, Graetz’s linear regression model is only applicable to sparse grassland, and his nonlinear regression model was proposed specifically for the study of degraded grassland (Graetz et al., 1986). In addition, due to its regional limitations, the regression model is not suitable for extensive applications, and the empirical model (on the regional level) might be invalid if it is used to estimate FVC on a large scale.

### 13.3.2. The Linear Unmixing Model

The linear unmixing model is based on the principle that each pixel in an image is composed of several components, and each pixel contributes separately to the information observed by remote sensors. Through decomposition of the remote-sensing information (channel information or VI), the pixel decomposition model can be used to estimate FVC. This model can be either linear or nonlinear; however, thus far, most of the studies on the mixed pixel decomposition model focus on the linear unmixing model. This section, therefore, mainly concentrates on application of the linear unmixing model to the remote-sensing calculation of FVC.

The linear unmixing model is the most extensively applied model among the mixed pixel decomposition models. In this model, pixel information is assumed to result from the linear synthesis of the information of each component. The linear unmixing model involves the assumptions that the photon reaching the sensor acts upon only one component and that the components are mutually independent and do not interact. If the photon acts upon several components, then nonlinear mixing occurs. In fact, the linear and nonlinear mixing methods are based on a single concept; that is, linear mixing occurs as an exception from nonlinear mixing when multiple reflections are ignored. To obtain a convenient solution, the number of regional land feature types, and the major land feature types in particular, should not exceed the number of remote-sensing channels; otherwise, \( n + 1 \) unknown variables would have to be solved using \( n \) equations; this constitutes the largest limitation of the linear unmixing model. The linear unmixing model is able to calculate and extract the FVC for each pixel in the image.
Suppose that each component contained in a pixel contributes to the pixel information received by the satellite sensors and that the value of the spectral characteristics of the vegetation in each component is taken as a factor. Then, the linear mixing model is established using the area of this specific component as the weight of this factor, which can be mathematically expressed as:

\[ R_b = \sum_{i=1}^{n} f_i r_{i,b} + e_b \]  (13.4)

where \( R_b \) is the reflectance of the pixel in channel \( b \), \( f_i \) is the proportion of the number of subpixel \( i \) to that of the mixed pixel, \( r_{i,b} \) is the reflectance of subpixel \( i \) in channel \( b \), \( n \) is the number of subpixels, and \( e_b \) is the fitting error of channel \( b \) (Van der Meer, 1999).

The proportion of each component in a mixed pixel can be solved using the least-squares method. The FVC is then calculated based on the proportion of each vegetation component present. The precision of this solution depends mainly on the selection of each pure component (Lu and Weng, 2004).

Among the various linear unmixing models, the simplest assumes that each pixel is composed of only two components, that is, vegetation and nonvegetation, and that the spectral information results from linear mixing of the two components. The proportional area of each component in the pixel is the weight of each component. The proportional area of vegetation is the FVC of the pixel, as mathematically expressed using Formulas (13.5) and (13.6):

\[ \text{NDVI} = f \times \text{NDVI}_v + (1-f) \times \text{NDVI}_s \]  (13.5)

and then,

\[ f = \frac{\text{NDVI} - \text{NDVI}_s}{\text{NDVI}_v - \text{NDVI}_s} \]  (13.6)

where \( f \) is the proportion of vegetation area in the mixed pixel (i.e., FVC), \( \text{NDVI} \) is the NDVI of the mixed pixel, \( \text{NDVI}_v \) is the NDVI of the vegetation and \( \text{NDVI}_s \) is the NDVI of bare soil.

It is clear from this equation that this dimidiate pixel model is a linear regression model for VI. To obtain the FVC of mixed pixels, the NDVIs of vegetation and of bare soil should be determined. However, the determination of \( \text{NDVI}_v \) and \( \text{NDVI}_s \) is affected by many factors, such as soil, vegetation type, and chlorophyll content. Nevertheless, these parameters can be determined through statistical analysis of spatial and temporal NDVI data. Time-series NDVI data are analyzed statistically, and the maximum time-series NDVI is used as the NDVI of vegetation, whereas the minimum time-series NDVI is used as the NDVI of bare soil (Gutman et al., 1998; Zeng et al., 2000). Some researchers directly select the maximum and minimum NDVIs of the research area as the NDVI values for vegetation and bare soil, respectively (Xiao & Moody, 2005).

The dimidiate pixel model is extensively applied because of its simple form. Figure 13.8 illustrates the global seasonal FVC estimated by Gutman and coworkers based on the dimidiate model of FVC and NDVI. Using cluster analysis, the optimal maximum and minimum values of NDVI were selected from the maximum and minimum values of NDVI for each season. Gutman et al. proposed that the FVC estimated using this model has a maximum error of 0.35, which might be derived from estimation of the maximum and minimum values of NDVI (Gutman et al., 1998). Qi et al. used the dimidiate model in their study of the spatial and temporal variation of vegetation in the San Pedro Basin in the U.S. Southwest based on NDVI data. Landsat TM, SPOT4 VEGETATION, and aerial photography data were also used to study this method. The results indicated that the model was able to estimate the dynamic variation of vegetation reliably, even without atmospheric correction (Qi et al., 2000). Leprieur et al. used SPOT data after atmospheric correction to calculate NDVI and applied this model to estimate the FVC in the Sahel (Leprieur et al., 1994).
As the model requires pixels representing pure vegetation and bare soil, low-resolution remote-sensing data are not applicable. For many regions, pixels representing pure vegetation are difficult to obtain in low-resolution data. Gutman et al. obtaining FVC using the pixel decomposition model based on the dimidiate pixel model (Gutman et al., 1998). Depending on the vegetation distribution features located in a mixed pixel, the pixels were divided into uniform and mosaic pixels, and the latter were further classified into dense, nondense and variable-density vegetation pixels. Different FVC models were constructed for different subpixel structures.

In a sense, an essential part of the mixed pixel decomposition model is extracting pure pixels to realize the conversion of remotely sensed spectral signals to physical vegetation parameters. Xiao and Moody estimated the FVC within an area of approximately 4000 km² in New Mexico (Xiao & Moody, 2005) using various methods. In their report, they presented a comparative analysis on the estimation of FVC by two methods: the mixed pixel decomposition model based on spectral data (SMA3, SMA4, SMA5, and NDVI-SMA) and the linear regression model based on NDVI. The analyses of SMA3, SMA4, and SMA5 included a discussion on whether the sum of the proportions of each component in each mixed pixel should be constrained to 1. Figure 13.9 shows the relationship between the FVC values that were estimated using various methods and the actual FVC. Figure 13.10 presents the FVC values of a research area that was estimated using various methods.

Xiao and Moody reported that the NDVI-based method of estimating the FVC of arid and semiarid areas was appropriate and relatively easy. They also noted that the NDVI-based estimation of FVC was particularly sensitive to soil reflectance. Therefore, overestimating the NDVI of an area of sparse vegetation would lead to overestimating FVC. The selection of the number of components in mixed pixels and the selection of each end member, which depends on the vegetation structure and the distribution of vegetation in the research area, are the major factors affecting FVC estimation in the mixed pixel decomposition.
FIGURE 13.9 The relationship between the FVC that estimated using various methods and the actual FVC: (a) SMA3 without constraint; (b) SMA3 with constraint; (c) SMA4 without constraint; (d) SMA with constraint; (e) a situation based on the expression for regression with NDVI; (f) NDVI–SMA; (g) SMA5 without constraint; (h) SMA5 with constraint; the solid line is 1:1. (Xiao & Moody, 2005, Fig. 4)
method. Xiao and Moody found that SMA 5 was more suitable for FVC estimation in their research area (Xiao and Moody, 2005).

13.3.3. Machine Learning Methods

As computer technology develops, an increasing number of machine-learning methods, such as neural networks, support vector machines, and decision trees, are being used in the theoretical study and application of remote-sensing technology. Support vector machines and decision trees are mainly used either for land-cover classification or for extraction of the vegetation cover from pixels.

13.3.3.1. The Neural Network Method

A neural network is an intelligent computer-based technology that imitates the learning process of human brains and serves as a general computing tool in solving complex problems. A neural network is composed of a series of simple processing units connected by weighting coefficients determined by specific mechanisms, as shown in Figure 13.11. Through continuous learning with training data, a neural network is capable of outputting optimal results with high computational efficiency.

A neural network can be used to retrieve various features of vegetation from remote-sensing
However, these studies usually employ ordinary neural networks or multi-layer perceptrons. Other types of neural networks might possess greater potential. However, many issues need to be considered if neural networks are to be applied, as the middle layer of neural networks is a black box. Consequently, it is difficult to control the retrieval of the parameters.

Based on a comparison of multivariable regression analysis, the VI method, and the neural network method, Boyd et al. found that a neural network was the most applicable to the FVC estimation of a forest in the U.S. Pacific Northwest. Three types of neural network methods—namely, the multilayer perceptron, the radial basis function, and the generalized regression neural network—were also compared. The multilayer perceptron was finally selected to determine the FVC of the research area. Using this method, 40 iterations were performed on six black boxes using a backpropagation algorithm. Within a 99% confidence interval, the results demonstrated that this method estimated the FVC of the forest with higher precision than the multi-element regression analysis or the VI method; the coefficient of determination with respect to the actual FVC of the forest was 0.57 (Boyd et al., 2002). Voorde et al. proposed using a multilayer perceptron to randomly select 3037 pixels from an ETM + image for training, followed by mixed pixel decomposition, to estimate the FVC of subpixels. Moreover, to compare the results with those estimated using a neural network, regression analysis and the linear unmixing model were also used to estimate the FVC of the research area. Figure 13.12 shows the estimates of the FVC of the research area obtained using various methods, whereas Figure 13.13 shows the error in the FVC estimation using various methods (Voorde et al., 2008).

**13.3.3.2. The Decision Tree Method**

Natural land features are diverse and constantly change; this change is becoming more complex due to human and natural factors. Therefore, it is a common phenomenon that one land feature generates different spectra or different land features share the same spectrum in remote sensing. This creates difficulties for identifying and classifying remote-sensing images. Therefore, it is necessary to study the inherent rules and associations of apparently disordered and intricate land features; then, based on the rules and associations discovered, a tree structure, or a decision tree, is established. This decision tree functions as the basis for identifying and classifying land features. To ensure the accuracy and objectivity of the classification,
decision functions for remote-sensing data or non-remote-sensing data are constantly involved in the classification process. Other information includes expert knowledge and relevant data (such as boundary conditions and classification parameters) that are used to improve the classification conditions and precision. This involvement of decision functions ensures that the results generated by the classification tree method are reasonable and that these results can be satisfactorily obtained by forming an optimal logical decision tree.

A decision tree is generally applied to land-cover classification and for the FVC estimation of sub-pixels. MODIS Vegetation Continuous Fields (VCFs; Hansen et al., 2003) use a decision
tree to estimate the FVC of trees and grass on the global scale. Other studies (e.g., Hansen et al., 2002; Huang et al., 2003; Yang et al., 2003; Xu et al., 2005; Gessner et al., 2009) have also used a decision tree to solve problems related to remote-sensing subpixels. A decision tree is a parameter-free classification method.

The advantages of the decision tree method, which include the lack of parameterization and the absence of a need to assume the normal distribution or homogeneity of input data, facilitate its extensive application in various fields. Rogan et al. adopted a decision tree that was designed to identify and classify the input data. First, multitemporal spectral mixture analysis (MSMA) was performed to extract four types of endmembers of green vegetation (GV), non-photosynthetic vegetation (NPV), shade, and soil. Next, using the designed decision data, the four types of endmembers were identified step-wise and classified. When the intercategory deviation was the greatest, a classification threshold was required to separate the two categories at each step. Based on the classification results, four categories of endmembers were calculated, and the user precision of the FVC of each endmember was determined to be approximately 76% (Rogan et al., 2002).

13.4. CURRENT REMOTE-SENSING PRODUCTS

A validation report of FVC products for the MSG/SEVIRI sensor summarizes currently available remote-sensing land-surface analysis vegetation products (Validation Report of Land Surface Analysis Vegetation products, 2008, URL: http://landsaf.meteo.pt/GetDocument.do?id=301) as shown in Table 13.1. Satellite data used in current products mainly come from SPOT/VEGETATION, ENVISAT/MERIS, and ADEOS/POLDER, which are polar-orbiting satellite sensors, and MSG/SEVIRI.

FVC and LAI products for POLDER use the neural network method, and the radiative transfer model by Kuusk (Lacaze et al., 2003) has been adopted as the training model. LAI products are directly outputted through the neural network method. The FVC products are derived from
the LAI products based on the exponential relationship between the two using the following formula: 
\[ FVC = 1 - \exp(-0.5 \times LAI) \].

A MERIS sensor on the ENVISAT platform, which is also based on a neural network, is able to capture multiangular and multispectral data. Unlike POLDER, FVC products are not directly obtained from LAI products. In addition, FVC products, LAI products, and the fraction of absorbed photosynthetic active radiation (FAPAR) products are generated by inputting observations from 13 channels simultaneously. The training of the neural network uses the PROSPECT + SAIL model (Baret et al., 2006), and Bacour et al. (2006) have validated the products.

CYCLOPES products, which use SPOT/VEGETATION (VGT) data to generate FVC, also have adopted the neural network method. Other algorithms that generate FVC values using multiangular and multispectral remote-sensing data, such as SEVIRI, have adopted other methods, depending on the specific data used. The SEVIRI sensor is supported by Meteosat Second Generation (MSG) and acquires data at a fixed observation angle with respect to specific observation sites. The sunlight illumination angle varies with time. MSG has a high temporal frequency for data acquisition; therefore, a coefficient of the kernel-driven bidirectional model k0 is used as input data (Baret et al., 2007). The physical meaning of k0 is the reflectance observed by the satellite in a vertical observation at vertical solar illumination. The advantage of using k0 is that it reduces the angular effect between the sun and the satellite. The mixed pixel decomposition model is used to determine the FVC.

In terms of validation results, the FVC products of SEVIRI and MERIS sensors have good spatial consistency. However, the FVC products of the MERIS sensor systematically underestimate the FVC values (approximately 0.10–0.2) (García-Haro et al., 2008). The same problem also exists for the FVC products of the SEVIRI and VGT sensors (Validation Report of Land Surface Analysis Vegetation products, 2008, URL: http://landsaf.meteo.pt/GetDocument.do?id=301). The FVC products of VGT are higher than those of SEVIRI (by approximately 0.15); therefore, the value of the FVC products of the SEVIRI sensor lies between those of the MERIS and VGT sensors. In their validation report, Fillol et al. (2006) noted that the product

<table>
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<th>Literature</th>
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<tr>
<td>García-Haro et al., 2005</td>
<td>EUMETSAT/LSA SAF</td>
<td>SEVIRI</td>
<td>2005-now</td>
<td>Europe, Africa, South America</td>
<td><a href="http://landsaf.meteo.pt">http://landsaf.meteo.pt</a></td>
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value of VGT data was lower than that of high-resolution SPOT data, even after spatial aggregation. Thus, we can infer that the FVC products of the SEVIRI, VGT, and MERIS sensors all underestimate FVC.

13.5. CHALLENGES AND PROSPECTS FOR FVC ESTIMATION

The Earth is a planet brimming with life, where vegetation constitutes the fundamental part of the ecosystem and provides support for the survival of animal life. As a group of living organisms, vegetation has evolved over several billion years, which has given it diversified features. However, these variable features make it difficult to estimate FVC using remote-sensing technology. Data extraction would be far less complicated if all vegetation were the same. Currently, no remote-sensing method can simultaneously estimate the FVC of all vegetative species, and all remote-sensing estimation methods are limited by vegetative species, territory, solar illumination, and soil. In essence, all remote-sensing signals are radiation, and FVC is a physical parameter of a specific species of vegetation. Thus, converting between the two is crucial for estimating FVC.

Both the empirical and physical methods used in remote sensing have conversion mechanisms for estimating FVC that have advantages and disadvantages. With the empirical method, several empirical coefficients need to be determined regardless of the VI and empirical relationship used. The acquisition of these parameters is related to and restricted by land-surface conditions, vegetation types, lighting conditions, and the use of specific sensors. Application of the empirical method is usually limited by changes in these conditions. Using the radiative transfer model, physical method establishes an algorithm framework that considers more factors, thus elucidating the relationship between the optical signals and the physical vegetation parameters. The physical method is more widely applicable, at least in a theoretical sense. Because a large dataset is required and many factors such as time, space, angle, and spectral response need to be considered in the application of satellite observation data, use of the physical method may be restricted due to a lack of data. Moreover, a dilemma exists regarding model selection: if too many parameters need to be estimated in a complex model, then calculations would be difficult; if the model is simplified, then errors would inevitably occur. Thus, two problems—data and model selection—impair the applicability of the physical method.

FVC is estimated more precisely using field measurement than using the remote-sensing method on a small scale. However, due to its limitations, field measurement mainly serves as a supplementary validation method for the remote-sensing method in most applications.

FVC describes the two-dimensional distribution of vegetation, whereas LAI is a physical quantity describing the vertical distribution of vegetation. Both play an important role in quantitative land-surface analysis. With the increase in the quantity and type of remote-sensing data and the relevant field data on the global and regional scale, FVC estimation models will become more complex and comprehensive. At the same time, NDVI and other vegetation indices will continue to be applied due to their easy accessibility and will undergo constant development in the foreseeable future.

Some problems are associated with remote-sensing-based FVC estimation. For example, remote-sensing pixels have a specific spatial scale; when using remote-sensing data on a different scale to obtain FVC, the heterogeneity of pixels might bring about mismatches among the results obtained from data of different resolutions. That is, the FVC obtained from high-resolution data differs from that obtained from low-resolution data, thus causing a scale effect. In addition, current FVC estimation is based on
the response to chlorophyll content and leaf water content, which results in an FVC value representing green vegetation. Use of the NDVI of vegetation during flowering and fruiting periods would considerably affect FVC determination. Other situations, such as leaf yellowing, water content decline, and discoloration, all have some effect on remote-sensing spectral signals, thus resulting in deviations in FVC estimations. Finally, the FVC of different vegetation species in the ecosystem requires further identification and calculation, making this issue even more complex. Therefore, researchers should devote their efforts to improving remote-sensing techniques to meet the application requirements of FVC.

FVC is not the most difficult parameter to be estimated by remote-sensing techniques. At present, the precision of results obtained from remote-sensing data is approximately 80% or even higher. Progress in developing software and hardware will increase the precision and efficiency of FVC estimation even further. For field measurement, the digital photography-based extraction method is used most widely. In addition, more and newer types of platforms such as engineering vans and unmanned aircraft will become available to carry digital cameras and to ensure high-precision FVC estimation within a larger scope. VI regression, mixed pixel decomposition, and neural network methods are frequently mentioned in the literature. The neural network method has been widely applied in the algorithms used to generate products because of its capacity to integrate with the physical model, extendibility, and rapidity of calculation.

References


REFERENCES
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