remote sensing

Review

Remote Sensing Application in Chinese Medicinal Plant Identification and Acreage Estimation—A Review

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Abstract: Chinese Materia Medica Resources (CMMRs) are crucial for developing the tradition and industry of traditional Chinese medicine. Given the increasing demand for CMMRs, an accurate and effective understanding of CMMRs is urgently needed. Chinese medicinal plants (CMPs) are the most important sources of CMMRs. Traditional methods of investigating medicinal plant resources have limitations, including severe subjectivity and poor timeliness, which make it difficult to meet the demand for real-time monitoring of large-scale medicinal plant resources. In recent years, remote sensing technology has become an important means of obtaining information on medicinal plants, and the application of this technology has made up for the shortcomings of traditional methods. This paper first discusses the development of investigation methods of CMMRs; points out the importance of remote sensing technology in the application of spatial distribution and information identification and extraction of Chinese medicinal plant resources (CMPRs); analyzes the characteristics of CMPs in different planting patterns, different habitats, and different regions from the perspective of remote sensing information extraction; and explores the selection of suitable data sources, providing a reference for medicinal plant identification and information extraction. Secondly, according to the existing classification and identification methods, previous studies are summarized from the perspectives of classification scales, classification features, and classification accuracy, and the advantages and disadvantages of the commonly used remote sensing classification methods in the investigation of CMPRs are summarized and compared. Finally, the development trend of remote sensing technology in the identification and information extraction of CMPs is examined, and the key technical problems to be solved in the identification and classification of CMPs and the extraction of area information are summarized so as to provide technical support and experience references for the application of remote sensing in the investigation of CMPRs.

Keywords: Chinese medicinal plants; remote sensing; recognition extraction; classification

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Citation: Meng, J.; You, X.; Zhang, X.; Shi, T.; Zhang, L.; Chen, X.; Zhao, H.; Xu, M. Remote Sensing Application in Chinese Medicinal Plant Identification and Acreage Estimation—A Review. *Remote Sens.* **2023**, *15*, 5580. https://doi.org/10.3390/rs15235580

Academic Editors: Jochem Verrelst, Kenji Omasa, Shan Lu and Jie Wang

Received: 20 July 2023
Revised: 8 November 2023
Accepted: 27 November 2023
Published: 30 November 2023

1. Introduction

The protection and sustainable utilization of Chinese Materia Medica Resources (CMMRs) are highly valued by the government. Four national surveys of CMMRs were conducted, respectively, in the 1960s, 1970s, 1980s, and 2010s [1]. Due to the increasing demand for traditional Chinese medicine (TCM) health care services around the world, the vigorous development of TCM-related industries, the transformation of medical models, the growth of people's health needs, and the speedy development of the TCM cause and TCM-related industries led to a significant increase in the demand for CMMRs. From 2011 to 2020, the National Administration of TCM organized the fourth national survey of CMMRs; compared with the third national survey of CMMRs, great changes have broadly occurred in the CMMR industry. The type, distribution, and application of CMMRs are constantly changing in China, so it is urgent to grasp the type and distribution of CMMRs in real time accurately and quickly in order to further determine the landscape of CMMRs in China and provide a reliable scientific basis for the protection measures of CMMRs and the development policy of related industries.

The sources of CMMRs are complex and diverse, including plants, bacteria, animals, and minerals, among which Chinese medicinal plants (CMPs) are the most important type of CMMR. Traditional surveys of CMMRs have mainly focused on field surveys [2] and historical data collection, combined with subjective estimation and ground surveys, which are greatly influenced by subjective factors, complicated, and lack scientific rigor. There are also phenomena of random cutting and felling of CMPs, and scattered planting can lead to significant differences in the spatial distribution of Chinese medicinal plant resources (CMPRs). Therefore, accurate spatial distribution, information identification, and extraction of CMPRs are of great significance for their protection and utilization. At the same time, compared with agricultural and forestry resources, CMPRs have many special characteristics, such as diverse species, diverse habitats, dispersed growth distribution, and non-population-common species, which make research problems more complex [3].

Remote sensing has the advantages of large coverage, high efficiency, timeliness, and labor reduction, providing timely and accurate farmland information for the agricultural sector. Compared with traditional survey methods, it has incomparable advantages and is increasingly used in agricultural production and management. As early as the 1960s, the Remote Sensing Agricultural Applications Laboratory at Purdue University in the United States was the first to use remote sensing data for crop planting area monitoring research, successfully monitoring a single corn crop and demonstrating the feasibility of satellite remote sensing data for crop monitoring [4]. In China, in 1979, Academician Chen Shupeng began to advocate using remote sensing technology for crop yield estimation. During Chian's "Eighth Five-Year Plan" period, the remote sensing estimation of crop yield became a national science and technology task, and experimental research on remote sensing estimation of large-scale wheat, maize, and rice was conducted; as well as dynamic monitoring research on grass–cattle equilibrium in northern grasslands; monitoring and forecasting the planting area, growth, and yield of winter wheat in Hebei, Shandong, Henan, northern Anhui, Beijing, and Tianjin; rice in Hubei, Jiangsu, and Shanghai and corn in Jilin Province [5]. This indicates that remote sensing technology is continuously maturing in crop monitoring in China, and many experts and scholars have conducted research on remote sensing monitoring of medicinal plant resources, with some progress. Sun et al. [6] proposed the idea and method of applying remote sensing to the investigation of Chinese medicinal materials resources. Sun et al. [7] studied the remote sensing monitoring methods of medicinal plant resources in different ecological environments, and, respectively, expounded the monitoring methods of wild and cultivated medicinal plant resources, providing ideas and methods for remote sensing monitoring of different types of medicinal plants. Sun et al. [8] conducted the first survey and monitoring of wild *Atractylodes lancea* (Thunb.) DC. medicinal resources in China using remote sensing technology, showing the feasibility of using remote sensing technology for surveying and monitoring individual medicinal plants. With the development and progress of technology, remote sensing has been integrated with many disciplines, effectively realizing the estimation of wild CMP reserves [9], the CMP planting areas in artificial plantations, dynamic monitoring [7], etc. Remote sensing technology is indispensable in the real-time dynamic monitoring and sustainable development of CMPRs. However, due to the complexity of remote sensing data, diversity of classification methods, and sensitivity to scale, research on remote sensing identification and planting information extraction of CMPs has not been systematically sorted out, making it difficult to conduct universal research and wide-ranging applications. Figure 1 shows the trend of paper publication of remote sensing applied to CMP monitoring since 2000 (a) and keyword co-occurrence analysis.

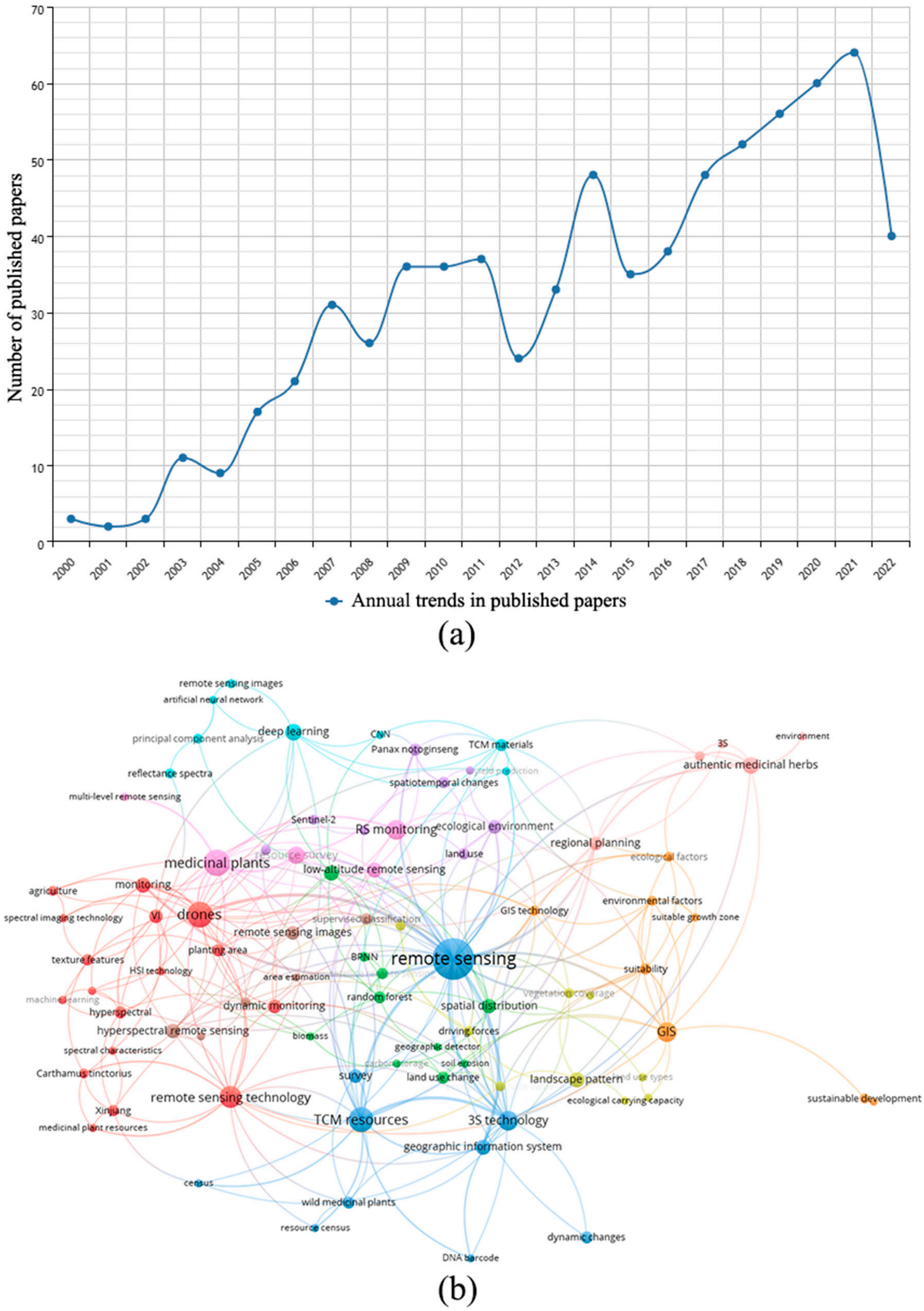

Figure 1. The trend of paper publication of remote sensing applied to CMP monitoring since 2000 (**a**) and keyword co-occurrence analysis based on VOSviewer (**b**).

Therefore, the planting patterns and habitat characteristics of CMPs are explored from the perspective of remote sensing application in this paper, providing references for data source selection, and the application of remote sensing in the identification and area extraction of CMPs is discussed. The identification and classification technology highlighted by remote sensing in the identification and area extraction of CMPs is emphasized in this paper, and the research progress of scholars is summarized and discussed, taking into account the classification scales, classification features, and classification methods. The issues and technical difficulties encountered in the research are also summarized and discussed. Then, the relevant research progress of CMP identification and information extraction is separately discussed in this paper according to different classification methods, and their advantages are compared and applicable objects described. Remote sensing data sources and classification methods can be preliminarily selected by researchers based on their own research content, methods, and objectives, combined with the types, planting patterns, and precision requirements of the CMP being studied, with reference to this paper. Finally, the key technical problems that still need to be solved in remote sensing identification and information extraction of CMPs are summarized based on previous literature reviews, and the future development direction of research is hypothesized, aiming at providing some references for further promoting remote sensing identification and information extraction research on CMPs.

2. Planting Characteristics and Applicable Satellite Remote Sensing Data for CMPs

The application of remote sensing technology in the investigation and dynamic monitoring of CMPRs is the focus of the research on the sustainable development of CMMRs, and the selection of appropriate data sources is the primary task of remote sensing monitoring of medicinal plant resources. How to select remote sensing data according to the types of CMPs to participate in the research has become a problem that many scholars need to consider first. The responses of different planting patterns and habitat characteristics to the monitoring of CMPRs should be explored in combination with actual planting characteristics, and more appropriate data sources should be selected according to the distribution and research value of medicinal plant resources in the study area. On the one hand, the accuracy of remote sensing monitoring of medicinal plant resources should be ensured; on the other hand, resource waste caused by purchasing high-resolution data sources should be avoided. Therefore, it is necessary to select appropriate data sources through research to provide reliable information for researchers of CMPRs.

2.1. Planting Patterns and Habitat Characteristics

In terms of planting patterns, CMPRs can be divided into wild and cultivated categories [10]. The former refers to non-artificially planted CMPRs distributed in a certain geographical area. There are various kinds of wild medicinal plant resources and different habitats in China. According to their living types, they can be categorized into woody plants (trees, shrubs, bamboo, vines, epiphytes, and parasitic trees), semi-woody plants (semi-shrubs and dwarf shrubs), herbaceous plants (perennial herbaceous plants, annual herbaceous plants, parasitic herbaceous plants, saprophytic herbaceous plants, and aquatic herbaceous plants), and thallophytes (mosses and lichens, algae, and fungi) [11]. Wild medicinal resources can also be further divided into abundant and rare plant species. Tree-based medicinal resources are generally densely distributed and have large scales, while shrubs are not as tall and independently distributed as trees and are more common in mountain grasslands and understories at higher elevations, making remote sensing identification and extraction of shrub-based medicinal plants more complex.

For rare medicinal plant resources, firstly, the distribution of wild rare medicinal plant resources is not concentrated in a single or dominant population but dispersed across different plant communities and geographically dispersed [7], which also creates certain difficulties in selecting remote sensing monitoring methods. Secondly, multi-spectral remote sensing data generally cannot directly obtain information on rare medicinal plant resources but can monitor vegetation cover in the medicinal plant habitat. Therefore, research on remote sensing monitoring methods for rare medicinal plant resources can be used to establish the inherent connection between the number of rare medicinal plant species and remote sensing monitoring methods to investigate the amount of rare medicinal plant resources. The selection of remote sensing images should be based on the characteristics of the rare medicinal resources themselves. When using remote sensing images for data information extraction, the spatial resolution, spectral resolution, and radiation resolution of the data should be considered from the perspective of monitoring rare medicinal plant resources.

At present, the natural quantity of rare medicinal plant resources in China is decreasing year by year [12] due to people's pursuit of wild rare medicinal plant resources in recent years and their destruction of the ecological environment system, which has led to a continuous decline in the number of rare wild medicinal plant resources. In this situation, cultivated medicinal plant resources have also received increasing attention [13]. On the one hand, cultivated medicinal plant resources can further alleviate the market demand. In this social context, remote sensing monitoring methods can effectively estimate the total amount, output, and demand of cultivated medicinal plant resources overall. Cultivated medicinal plants are mostly centrally distributed and recorded for filing, making it easier to analyze their resource distribution and information extraction than for wild medicinal plants. The investigation of cultivated medicinal plant resources, the calculation of the planting area, and the estimation of reserves can prevent the blind introduction of cultivation and provide a theoretical basis for guiding scientific and reasonable site selection for cultivation bases. Therefore, remote sensing identification and area extraction estimation of cultivated medicinal plant resources are important. More than 200 kinds of medicinal plants commonly used in China are mainly cultivated artificially. Due to the influence of growth years, planting areas, and management methods, the area and yield of medicinal plants obtained by conventional methods have a large error. Remote sensing technology has important application value and guiding significance in estimating and predicting the area and yield of cultivated medicinal plants [14]. Cultivated medicinal plants are mainly categorized based on their planting patterns: field cultivation, arable land cultivation, understory cultivation (intercropping), facility agriculture (greenhouse) cultivation, and special habitat cultivation. The research results of remote sensing in the field cultivation of CMPs can refer to the more mature remote sensing monitoring methods of some crops, and they are easier to carry out than other planting modes. Figure 2 shows classification of planting patterns of CMPs and examples of CMPs in different planting patterns.

Nowadays, in the research on remote sensing in the field of identification and classification of CMP arable-land-based cultivation and understory cultivation (intercropping), the lack of a large number of annotated data in the corresponding field and the subjectivity of manually annotated data have generally been mentioned by scholars [15]. In the case of dispersed planting of multiple kinds of traditional CMPRs within the same administrative region, if precise discrimination of the distribution area of each CMPR is required, an unmanned aerial vehicle (UAV) low-altitude remote sensing system can be used to obtain high-resolution image data of the ground, combined with texture and spectral features and ground surveys for further accurate and quantitative analysis, and secondary verification can be performed with ground sample data. Using this method, the assessment accuracy of the UAV remote sensing system in identifying, classifying, and performing area extraction for CMPRs can be confirmed to distinguish different CMPR types and distribution areas with a certain level of accuracy. Some CMPs do require intercropping with other crops to improve quality and yield. Since the spectrum characteristics of each plant and the modes of interplanting and single species are different, different classification models need to be constructed for different situations when using remote sensing image recognition to extract planting distribution areas. The typical CMP in a facility agriculture (greenhouse) model is greenhouse-cultivated ginseng, which is grown in a common warm greenhouse. The obstacle of continuous cropping of greenhouse-cultivated ginseng is an important factor restricting the planting of greenhouse-cultivated ginseng. The available ginseng resources are an important weakness that troubles the development of the ginseng industry. The dynamic monitoring of plantation distribution area and area changes using remote sensing technology is of guiding significance for the production and planning of ginseng. The roof of the ginseng shed is made of plastic film. Because of this planting mode, the garden ginseng has a particularly prominent advantage in satellite remote monitoring. Compared with the surrounding forest vegetation, the characteristics of the ginseng shed in remote sensing images are more prominent.

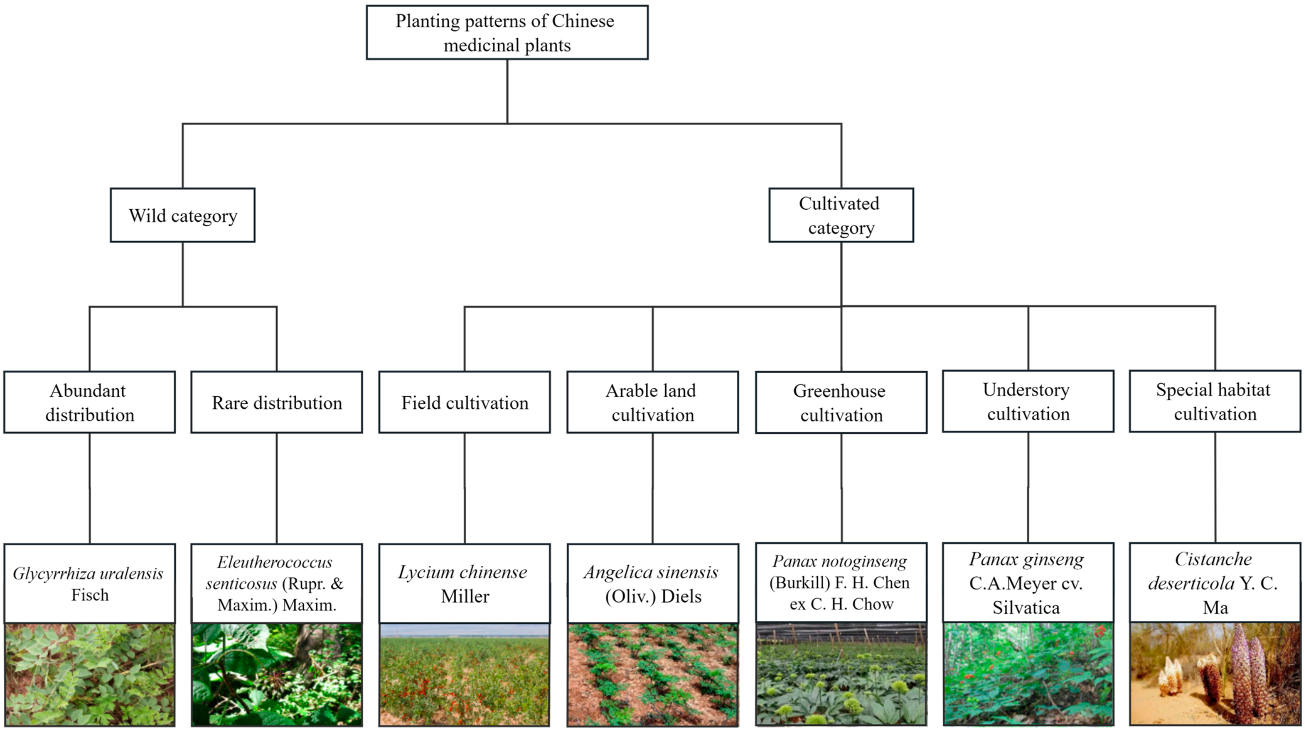

Figure 2. Classification of planting patterns of CMPs and examples of CMPs in different planting patterns.

In addition to diverse planting patterns, China has a rich and complex ecosystem, and the distribution of CMPRs varies greatly depending on the ecosystem. CMPRs have significant regional characteristics [16], and spatial characteristics and geographical environments play a decisive role in shaping the quality of CMPs, i.e., the "stress response" of medicinal plants [17]. Medicinal plants in different habitats have different spectral reflectance characteristics, which can be monitored using remote sensing techniques. In addition, some scholars use habitat factor interaction and correlation analysis with effective components of CMPs, combined with spatial overlapping analysis, to extract suitable areas for CMPs. On the basis of literature review and analysis of ecological factors such as elevation, annual precipitation and average annual temperature, Dong et al. [18] studied the distribution area of *Swertia mussotii* Franch. in Sichuan province by obtaining ecological factors, superposition analysis and GPS field verification data based on remote sensing and GIS technology. Remote sensing techniques are also involved in medicinal plants in some special habitats. Medicinal plants in certain special aquatic ecological environments can be monitored using different remote sensing methods based on their unique ecological environment information. For example, radar remote sensing can be used to estimate the resource quantity of aquatic TCM lotus, and remote sensing technology can be used to extract the special ecological environment of the parasitic plant *Cistanche deserticola* Y. C. Ma and some symbiotic plants in the desert for resource quantity estimation due to their special ecological environment types. Different types of medicinal plants have different special characteristics. Therefore, how to extract specific medicinal plant cultivation information should be analyzed according to its characteristics, and reasonable and effective remote sensing survey methods should be adopted. It is impossible to use a universal method for all cases.

2.2. Data Sources

The planting patterns and habitat characteristics of CMPs were introduced in the previous article. The selection of remote sensing data sources for monitoring CMPs should take these characteristics into account. Although the spatial resolution of early high-resolution satellites can be as high as meters, the number of bands is small, and image recognition needs to cooperate with the human eye. Chen et al. [9] used Landsat-7 ETM data from the United States, SPOT 5 data from France, and QuickBird image data from the United States to identify Jilin ginseng, mainly using manual interpretation and automatic interpretation methods. The results showed that the manual interpretation accuracy of high-resolution satellite images can reach 100%, the combination of medium-high and medium-resolution images can reach 97%, and medium-resolution satellite images can reach 90%. Although the former two have high accuracy, the cost is also high, and the manual interpretation cannot be widely promoted. Meanwhile, the workload of manual interpretation is large and time-consuming. This study explored a method for applying remote sensing technology to investigate medicinal plants. Zhang et al. [19] measured the area of wild *Glycyrrhiza uralensis* Fisch in Yanchi County, Ningxia Hui Autonomous Region, located on the Ordos Plateau, using medium-resolution ETM (15 m) satellite images combined with field data and the visual interpretation method. The comparative analysis of field verification points and image interpretation results showed that the manual interpretation accuracy of the survey sample area reached 90% when the ground resolution was 15 m, 97% when the ground resolution was 5 m, and 100% when the ground resolution was 0.61 m. This indicates that the higher the resolution of remote sensing data, the better the recognition accuracy in the survey of large area wild *G. uralensis* Fisch resources. This study discussed the influence of the spatial resolution of remote sensing data on extraction accuracy, provided a technical reference for the area estimation of large areas of wild Chinese medicinal materials, and provided a great technical scheme for wild resources investigation. Bahdu [20] studied the planting area of *Carthamus tinctorius* L. using data sources with different resolutions, such as the Worldview-2 satellite, ZY-3 satellite, and ZY-1 02C satellite, and found that high-resolution data could greatly improve the interpretation accuracy of *C. tinctorius* L., but it was difficult for automatic interpretation of *C. tinctorius* L. In order to analyze and compare which data source is more suitable for remote sensing identification of wild medicinal vegetation with more complex growth conditions, Na et al. [21,22] took wild *Apocynum venetum* L. nature reserve in Altai Alahak Township as the research object and adopted the medium-low resolution remote sensing image of domestic satellite ZY-3 and the high-resolution remote sensing image of foreign satellite Worldview-2. In this study, the same classification system was adopted for the two data sources, and the primary component analysis and texture feature were added to the traditional classification method to improve the classification accuracy. It was found that the high-resolution image of Worldview-2 was more suitable for the remote sensing identification of wild *A. venetum* L. with more complex growth conditions, while the domestic medium- and low-resolution ZY-3 was only suitable for the identification of densely distributed *A. venetum* L. and could not identify sporadic *A. venetum* L. Therefore, selecting remote sensing data sources should be based on the distribution of target objects in the specific work area. If the target objects in the study area are densely distributed and large in scale, such as artificial cultivation or single growing medicinal plant, the target objects can be identified well using remote sensing data of medium and low resolution, and there is no need to purchase high-resolution data, thus avoiding resource waste. For objects scattered and accompanied by other wild vegetation, it is considered that high-resolution satellite image data can be used to identify the objects well. Scattered wild medicinal plants are mostly planted in mountainous areas with suitable natural environmental conditions and complex terrain, and the planting plots are scattered. It is vital to provide decision support for the protection and utilization of CMMRs by studying the extraction method of the CMP planting area based on remote sensing. With the development of space remote sensing data in the direction of high spatial and temporal resolution, rich spectrum information, and wide band coverage, it has increasingly met the needs of large-scale surveys of CMMRs. Some scholars have applied Sentinel-2 [23] data and GF-6 data [24] to identify medicinal plants and achieved good results.

In addition, the unmanned aerial vehicle low-altitude remote sensing system (UAVRS) has the advantages of low cost, flexible and convenient operation and control, low-altitude flight under clouds, high timescales, etc. [14]. The spatial resolution has reached the centimeter level [25], which meets the sampling accuracy requirements, greatly reduces working time and human and material resources, and can also be used for the survey of CMMRs collected. It is especially suitable for rare medicinal plants with dispersed distribution and complex habitats. According to the characteristics of different remote sensing platforms and the distribution of medicinal plant resources, Xie [26] proposed the technical scheme of using low-altitude remote sensing such as the UAVRS to investigate medicinal plant resources, introduced the application characteristics and key technologies of unmanned aerial vehicles, and discussed the advantages and feasibility of unmanned aerial vehicles to investigate medicinal plant resources. She pointed out that the UAVRS can be used to select some representative areas based on low-resolution remote sensing images for high-resolution image supplementary acquisition, which can improve the multiple requirements of CMMR investigation. Xie [27] also conducted a survey of low-altitude remote sensing resources of endangered F. K. M. Shen in Xinjiang, and the research results clearly identified the geographical distribution area of F. K. M. Shen in Xinjiang for the first time, and the error between monitoring results and field data was only 14%. The research indicated that low-altitude remote sensing technology had the advantage of quickly obtaining the distribution status of wild F. K. M. Shen in Xinjiang and could effectively evaluate the dynamic change in wild F. K. M. Shen resources in Xinjiang. The author's research confirms that the UAVRS has a great application prospect in the investigation of CMMRs.

3. Research Status of Remote Sensing Identification of CMPs

According to different data sources and existing technical means of CMP information extraction research using satellite remote sensing technology, experts and scholars have proposed different methods of CMP identification and area information extraction, covering various sensor types, time/space/spectral resolution remote sensing data, and involving a variety of principles and technologies. The final classification effect and accuracy can be summarized by three levels of classification scales, classification features, and classification methods. Therefore, this paper summarizes and analyzes the existing research methods and progress in remote sensing in CMP identification and area information extraction from the perspective of classification scales, features, and methods. Figure 3 shows research flow chart of CMP monitoring based on remote sensing.

3.1. Classification Scales

3.1.1. Pixels

The pixel-based classification method is a classical method for remote sensing image analysis. In 2001, the Institute of Medicinal Plants, the Chinese Academy of Chinese Medical Sciences, used remote sensing technology for the first time to study the survey methodology of ginseng and other CMPRs, which created a precedent for the application of remote sensing technology in the survey of CMMRs. Sun et al. [8] used remote sensing technology for the first time to investigate the resources of the wild CMP *A. Lancea* (Thunb.) DC., they screened and classified the main influencing factors of the growth of *A. Lancea* (Thunb.) DC. According to the differences in reflectance spectral characteristics of different ground objects, the satellite remote sensing images of the Maoshan area in Jiangsu Province were interpreted, translated and inverted, and combined with field investigation data. The relationship between field data, remote sensing data, and habitat data of *A. Lancea*

(Thunb.) DC. was established, and the resources of *A. Lancea* (Thunb.) DC. in Maoshan were estimated. The results were not much different from about 10,000 plants provided by local farmers engaged in *A. Lancea* (Thunb.) DC. observation. The spatial resolution of remote sensing images will affect the extraction accuracy of vegetation information. For example, Chen et al. [9] used remote sensing data sources with different spatial resolutions to realize the investigation of ginseng resources and discussed the influence of spatial resolution of remote sensing data on extraction accuracy, which provided a useful reference for the selection of data for the investigation of medicinal species resources.

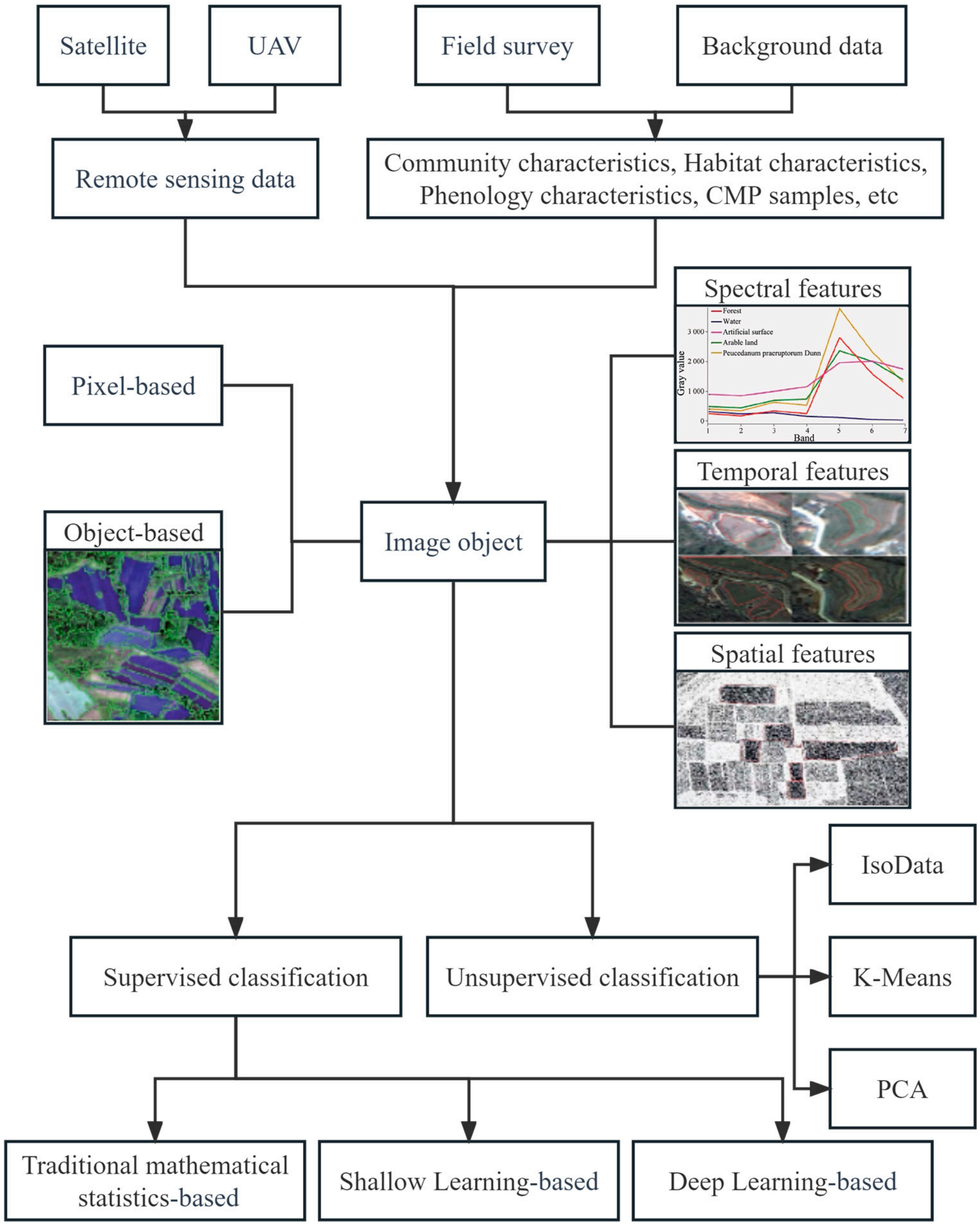

Figure 3. Research flow chart of CMP monitoring based on remote sensing.

Most remote sensing recognition of CMPs is still based on image elements, at present. The pixel-based classification method is mainly based on the spectral information characteristics of ground objects and is simple, intuitive, and easy to understand. For a large number of wild and continuously distributed medicinal plants and artificial large-scale cultivation, remote sensing data with low spatial resolution can be selected on the basis of ensuring classification accuracy, and the pixel is used as the unit for classification. This not only reduces the salt-and-pepper noise easily generated by pixel-based classification, but more importantly, the data cost is low, the steps are simple, and the time is short. However, it cannot process spatial information and is susceptible to the influence and interference of the high local heterogeneity of high-resolution images, with low classification accuracy; for the medicinal plants with complex habitats and fragmented distribution, it is difficult to obtain the ideal classification effect.

3.1.2. Objects

The traditional classification methods are difficult to apply to the CMP information extraction of high-spatial-resolution remote sensing images. Aiming at the above problems, an object-oriented remote sensing image classification method can also be used for remote sensing recognition of CMPs. An object-based CMP remote sensing image monitoring method refers to the segmentation of images into multiple homogeneous units with consistent attributes based on multi-scale segmentation technology and then the introduction of certain texture features or mathematical rules to improve the accuracy of the layout structure and distribution of medicinal plants. The key point is that the object-based classification method is not based on a single pixel but a homogeneous unit, which makes full use of the spectral statistical characteristics of the image and a series of information such as the size, shape, texture, and adjacent relationship of the ground object [28]. This method plays an important role in extracting CMP planting information and solves the problem of the fragmentation of the extraction plot of TCM. Shi et al. [15] took Fusong County, Jilin Province, as the research area and used ZY-3 satellite data as the data source to explore a method of ginseng planting area extraction based on a rule set object-based method. The research showed that, in terms of the results of multi-scale segmentation, the optimal segmentation scale of ginseng planting plots could be determined, and the fragmented and distributed ginseng planting plots could be accurately extracted based on a certain spectral feature rule set, which was beyond the reach of traditional pixel-based classification methods. Among them, the multi-scale segmentation algorithm used in this study is common in image-segmentation technology.

The object-based classification method can overcome the limitations of traditional methods and make full use of the spectral and spatial information of high-resolution images so as to extract the necessary thematic information quickly and accurately. However, the accuracy is much lower for low-resolution images, and the operation is more complicated. Compared with the classification of medicinal plants based on pixels, the object-oriented classification of medicinal plants first utilizes the different characteristics of CMPs and other vegetation and non-vegetation ground objects to establish different rules and segment the images. Therefore, the classification effect of the object-oriented classification of CMPs in complex habitats with diverse vegetation types and relatively fragmented distribution is better. And to a certain extent, the phenomenon of mismarking and missing marks is avoided. Based on the classification of objects, how to accurately and effectively classify the CMPs and other vegetation to be monitored into different objects is very important.

3.2. Categorical Features

3.2.1. Spectral Features

As the physical basis of crop remote sensing classification, spectral features result from the joint action of crop physiological and biochemical parameters and environmental factors [29]. The focus of this method is to find the “key phenological period” of different crops—that is, to find the specific period when the spectral features of the CMP to be separated have the largest difference from the background spectral features. For example, Liu et al. [30] took the medicinal plant safflower in the Changji region of Xinjiang as the research object and found that the safflower canopy and the remaining safflower canopy after picking had characteristic absorption peaks near 770 nm through the analysis of its canopy spectral features. The method proposed aimed to study the special hyperspectral features of *C. tinctorius* L. under a specific phenological stage. It provided an early theoretical basis for monitoring the growth state and physiological parameters of *C. tinctorius* L. and also laid the groundwork for the estimation of distribution area and dynamic fine monitoring of *C. tinctorius* L. in the future. Based on GF-6 remote sensing data, Li et al. [24] conducted a comparative study on the growth cycle of CMPs and winter wheat and found a special stage in the growth cycle of winter wheat. The research in this article showed that the reflectance of the spectral features of winter wheat in the grain filling period and milk maturity period in May decreased in the green band and near-red band, while the CMP showed signs of luxuriant branches and leaves in May, and the reflection of the green band and the near-red band was higher. According to the difference and magnification, the difference in spectral curve between *Angelica dahurica* (Fisch. ex Hoffm.) Benth. and Hook. f. ex Franch. and Sav., *Taraxacum mongolicum* Hand.-Mazz., *A. Lancea* (Thunb.) DC., *Saposhnikovia divaricata* (Trucz.) Schischk., and winter wheat could be distinguished, and the planting area of CMPs could be extracted. However, this study needed a parameter to distinguish whether it was a CMP or winter wheat, but this parameter depended on the empirical model and field investigation, and the selection of this parameter had a great impact on the classification results, so it needed to be carefully selected and screened. As an alternative index to study vegetation, the quantitative measurement of the vegetation index can indicate vegetation vitality, etc. [31,32]. Among them, the NDVI is the most widely used, and the NDVI is defined as the ratio of the difference between the values of the NIR band and the red band and the sum of the values of the NIR band and the red band. Zhang et al. [33] used *Paeonia lactiflora* Pall. as the data source of CMPs and analyzed the NDVI values of wild *P. lactiflora* Pall. growing points in different periods. Combined with the data of sampling points, the authors monitored the distribution area of *P. lactiflora* Pall. for multiple cycles. The result showed that the change trend of the distribution of peony resources could be retrieved and monitored based on the change in the vegetation index in different periods.

All the above studies have proved the feasibility of using spectral features for remote sensing identification and information extraction of CMPs, but the classification method based on spectral information will inevitably cause the phenomenon of "the same object with different spectrum" and "the different object with same spectrum" in the classification results [34], resulting in low classification accuracy. Because of the wide variety of CMP planting, it is often difficult to capture the image of the "best recognition period" of planting. Only relying on spectral feature classification to extract planting information of CMPs cannot achieve ideal results.

3.2.2. Temporal Features

Temporal features refer to the changing rules of vegetation in different temporal remote sensing images, which mainly reflect the physiological and biochemical differences in medicinal plants in different phenological stages. The growth and development of vegetation have phenological characteristics, and its spectral features will change with the change in seasons [35], which leads to the fact that the image classification effect of a single period is often not ideal. Therefore, the advantages of vegetation classification based on multi-temporal remote sensing images are more obvious [36]. The planting extraction method based on multi-temporal image data sources can make full use of the seasonal rhythm characteristics of medicinal plants, which has gradually become the mainstream method for remote sensing extraction of medicinal plant planting information. Liu et al. [23] studied the classification accuracy of four random forest (RF) classification methods using the multi-temporal Sentinel-2 (MSI) as the remote sensing data source, respectively, using spectral bands alone or in combination, vegetation indices (VIs), and topographic variables, and took *Zanthoxylum bungeanum* Maxim. from the Linxia Hui Autonomous Prefecture of Gansu Province as the research object. The result showed that the classification accuracy of only using spectral bands (40 input features) can reach 95.43%, and the classification accuracy can also approach 95% when only using the 15 most important features. This study demonstrated the potential of multi-temporal remote sensing data in improving the accuracy of planting area extraction of *Z. bungeanum* Maxim, which possibly also allowed for detailed remote sensing identification and classification of other special crops or tree species in other regions.

The vegetation classification method using multi-temporal information can be used in the remote sensing identification and classification extraction of CMPs. Because it follows the growth law of CMPs and conforms to the current vegetation remote sensing classification trend, the classification accuracy is greatly improved. Especially for medicinal plants grown in the field, we can start with the regional bulk crop calendar to determine the images of the different periods between the growth of medicinal plants and the crop calendar, which can be well distinguished. However, the classification method is complicated and requires time series data, and sometimes the available data cannot meet the needs.

3.2.3. Spatial Features

Rational use of the spatial features of CMPs can realize the distinction between CMPs and other non-CMPs. With the rapid development of image processing technology, spatial features have become an important means to assist spectral features and temporal features for remote sensing identification of CMPs and extracting planting information [37], especially for suppressing the phenomenon of "the same object with different spectrum". In the identification of medicinal plants and extraction of planting areas, only using the spectral information of remote sensing images cannot effectively extract the information of medicinal plants. For medicinal plants, the reflection spectrum of surrounding vegetation is similar to them, which is easily confused. If texture features can be reasonably used to find the special texture features of medicinal plants that are different from other vegetation, combined with their specific growth period, it will greatly improve the classification accuracy of remote sensing images. Jia et al. [16] took the medicinal plant Ledebouriellae Radix planted in a large area of Naiman Banner as an example, used the fused 2 m resolution Resource No. 3 (ZY-3) remote sensing image as the data source, and used the texture and spectral information of the remote sensing image to extract and understand the distribution range and planting area of Ledebouriellae Radix in Naiman Banner. The research result showed that combining spectral information and texture information could realize the discrimination of Ledebouriellae Radix. This study gradually applied spectral information and texture information to the identification of CMPs and provided a new research idea and method for the further identification and extraction of CMPs via remote sensing. Wu et al. [38] first extracted the distribution data of the *Panax notoginseng* (Burkill) F. H. Chen ex C. H. Chow planting area based on TM/OLI images using a supervised classification method. On this basis, combined with the topographic distribution characteristics of the image in the planting area of *P. notoginseng* (Burkill) F. H. Chen ex C. H. Chow, a decision tree was constructed to correct the rough extraction results of supervised classification so as to achieve the goal of rapid extraction of the distribution data of the *P. notoginseng* (Burkill) F. H. Chen ex C. H. Chow planting area and realize the rapid extraction of the spatial distribution information of the *P. notoginseng* (Burkill) F. H. Chen ex C. H. Chow planting area. The accuracy of the results was high, which could meet the requirements of research and application.

The coverage of CMPs is usually low, and the planted area of cultivated medicinal plants is relatively fragmented compared to other large crops, while wild medicinal plants may be more fragmented. Using spatial features for the remote sensing identification and distribution area extraction of medicinal plants can improve the interpretability and visualization effect of classification and can provide more comprehensive information, which is of great help to improve accuracy. However, it is usually necessary to consider the relationship between pixels and the complex influence of the surrounding environment, so its extraction and calculation are difficult and require a lot of computing resources and time.

3.3. Classification Methods

3.3.1. Supervised Classification

- Based on traditional mathematical statistics

Remote sensing image classification is divided into two categories according to whether it has prior knowledge: supervised classification and unsupervised classification [39]. Supervised classification usually selects the region of interest (ROI) of the corresponding known object from the remote sensing image in advance and uses the image features of the sample area to train the classification algorithm to complete the classification of the whole study area. At present, the supervised classification method based on traditional mathematical statistics is mainly used in the identification of cultivated medicinal plants planted in cultivated land and fields, because the identification of medicinal plants in this planting mode is relatively easy. Yi et al. [40] used the domestic Satellite Resource No. 3 (ZY-3) image to perform remote sensing identification of *Paeonia ostii* T. Hong et J. X. Zhang using the maximum likelihood method and classified and extracted the planting area of *P. ostii* T. Hong et J. X. Zhang. The overall classification accuracy was 97.81%, and the KAPPAA coefficient was 0.96. The result showed that it was feasible to estimate the *P. ostii* T. Hong et J. X. Zhang planting area based on remote sensing image classification using the maximum likelihood method. Yang et al. [41] took a ZY-3 remote sensing image as the data source and used the minimum distance method, maximum likelihood method, parallelepiped method, and Markov distance method to identify *Cynanchum otophyllum* Schneid. in Dangshan County in 2018 via remote sensing and compared and analyzed the results, providing a reference for remote sensing monitoring of the Chinese *C. otophyllum* Schneid. planting area.

The supervised classification method based on traditional mathematical statistics is suitable for situations that require interpretation, small sample data, or clear problem modeling, but it has certain requirements on the distribution and characteristics of data. Although it is often used in cultivated medicinal plants that are more easily identified, it is also very limited. If the plots are scattered, the accuracy of remote sensing image extraction is not high enough. It is easy to be restricted by the phenomena of "same thing different spectrum", "foreign body same spectrum", and "mixed pixel".

- Based on Shallow Learning

Machine learning will shift the focus of the research to how to better improve the prediction effect of the model, concerned with the problem directly related to improving the prediction effect. The non-parametric model, which tends to be automated, does not need to assume normal distribution of data and has gradually become a hot spot in the research of extracting CMP information. Dai et al. [42] used Landsat data to extract *P. notoginseng* (Burkill) F. H. Chen ex C. H. Chow planting areas in Wenshan Prefecture and Honghe Prefecture in 2010, 2012, 2014, and 2015 through a support vector machine. The classification accuracy could meet the requirements of spatial analysis and practical applications and proved the feasibility of real-time dynamic monitoring of the *P. notoginseng* (Burkill) F. H. Chen ex C. H. Chow planting area by using classification technology based on a support vector machine. As an information extraction method based on spatial data mining and knowledge discovery, a decision tree is an efficient spectral classification method. The basic idea is that the remote sensing data set is graded downward according to specific preset rules, and finally, subcategories with single or different attributes are obtained [43]. Some scholars have applied this method to the research of remote sensing identification and information extraction of CMPs. Zhu et al. [44] improved the expert decision tree model based on the domestic open-source image of GF-1 with a 16 m resolution and extracted shade image spots of *Panax notoginseng* (Burkill) F. H. Chen ex C. H. Chow using decision tree classification. In evaluating the reliability of identification and the accuracy of area extraction of *Panax notoginseng* (Burkill) F. H. Chen ex C. H. Chow, Google Images was used instead of field drawing, and visual interpretation results were used as the benchmark of spot area. The result showed that the accuracy of decision tree classification and visual interpretation is 87% and 99%, respectively, and the overall area accuracy of the results extracted using expert decision tree classification was 80%. This study showed that compared with the traditional method of artificial marking based on high-resolution commercial images and visual interpretation, the method used in the area extraction of *Panax notoginseng* (Burkill) F. H. Chen ex C. H. Chow based on a decision tree model could investigate *Panax notoginseng* (Burkill) F. H. Chen ex C. H. Chow planting resources in Wenshan at a faster speed under the condition of ensuring a certain accuracy. Traditional shallow learning is an effective, fast, and high-precision data mining method; requires a relatively small amount of data; does not require a high-quality data set; and creates a good interpretation of the model. However, it relies on artificial feature extraction, and due to the simple structure of the model, its generalization ability is limited, which reduces the classification accuracy of this method to a certain extent. The planting pattern of CMPs is closely related to the terrain, humidity, climate, soil, farming system, and other factors. Therefore, in the extraction of the planting structure of CMPs, in addition to the pixel spectral band features, other non-remote sensing information such as statistical data of CMPs, landforms, phenological characteristics, and prior knowledge of experts participate in the extraction of the planting structure of CMPs as important auxiliary information to improve the classification accuracy, but the effect of extracting complex features in the image is poor.

- Based on Deep Learning

The concept of deep learning (DL) was first proposed in 2006 [45]. Compared with traditional methods, DL algorithms can adaptively learn various features from a large number of samples and can directly input remote sensing images into the model network. At present, DL algorithms have been applied in vegetation remote sensing recognition and information extraction. However, there is little research on the application of CMPs, especially research on the fine classification of CMPs in high-resolution remote sensing images. Shi et al. [46] applied the deep convolutional neural network model to the recognition of CMPs mimicking wild planting. The method of deep learning was used to solve the problems of insufficient utilization of high-resolution image information and "salt-and-pepper noise" caused by intra-class pixel differences in traditional classification. Remote sensing data were obtained using an unmanned aerial vehicle (UAV), and the convolutional neural network was applied to the fine classification of *Lonicera japonica* Thunb. wild planting. The result showed that the overall classification accuracy of the optimized model after training could reach 97.5%, and the total accuracy of the area was 94.6%. The deep convolutional neural network based on GoogLeNet could effectively extract the information of *L. japonica* Thunb. with a broken distribution in the image and realized the fine classification of *L. japonica* Thunb. Deep learning was applied to the classification of medicinal plants from UAV high-resolution images, providing a reference for the application of a deep convolutional neural network method in the remote sensing classification of CMPs. It can be seen that deep learning algorithms have great development potential in the intelligent extraction of medicinal plant resource information in remote sensing big data.

Deep learning has the abilities of self-learning and high-speed searching for optimal solutions, and the accuracy of extracting medicinal plant types is high. However, this method needs to provide a large number of parameter training samples, the training time is long, it is difficult to provide the reasoning process and basis when classifying the types, and there are numerous deep learning models. The remote sensing recognition and classification methods of CMPRs still need further optimization.

3.3.2. Unsupervised Classification

Unsupervised classification is also known as the cluster analysis method. It can help uncover hidden structures, patterns, or relationships in the data and facilitate exploratory data analysis and insight and then complete the final classification with the classifier. Therefore, unsupervised classification can identify the distribution pattern and habitat preference of CMPs without samples. Sun et al. [47] used LANDSAT-5 TM as the data source to extract and analyze *Ginkgo biloba* L. information from multi-period TM remote sensing images using the unsupervised clustering method and obtained the spatial distribution and multi-year dynamic change in *G. biloba* L. in Pizhou City, Jiangsu Province, with the support of field investigation data. It provides an idea and method for monitoring the dynamic change in medicinal plant resources.

Since unsupervised classification does not require pre-labeled samples, it is difficult to distinguish medicinal plants from general plants, and it is more suitable for monitoring medicinal plant resources where there are basically no other similar types of vegetation in the distribution area and the species result is single, so it is rarely used in remote sensing recognition of CMPs.

4. Key Problems and Prospects

Remote sensing has made significant progress in the dynamic monitoring and identification classification of CMPRs, which provides scientific planning guidance for the sustainable development of the CMPR industry and has a good prospect in extracting the planting area of CMPRs. However, there are still some technical deficiencies that restrict the accuracy and efficiency of remote sensing extraction results. For example, cultivated medicinal plants have low vegetation coverage and are more scattered, while wild ones are more fragmented and diverse. How to accurately extract the planting area by remote sensing images will always be a problem that needs to be studied. For a long period of time in the future, the research on remote sensing identification and extraction of CMPRs should aim at reducing mixed pixels and improving extraction accuracy and should combine the characteristics of CMP types, give full play to the advantages of combined utilization of multi-source data, and carry out research on the extraction of planting information around the diversification of CMP types and the multi-scale coverage area. The research on key technologies such as data preprocessing, feature parameter extraction, and efficient classifier selection was strengthened to improve the spatial scale of the remote sensing extraction of plant CMMRs so as to meet the needs of a variety of plant CMMR investigations.

4.1. Key Problems

- There are many kinds of Chinese medicinal materials, great differences in planting patterns, and complex planting landscape patterns

There are many kinds of plant Chinese medicinal materials, and different Chinese medicinal materials have different spectral and image characteristics [48]. Due to their different characteristics, there are a variety of planting patterns. Taking field planting as an example, there are also widespread rotation, intercropping, and intercropping phenomena [49], such as bupleur–maize intercropping, rice–Coptis rice–water and drought rotation, Pinellia–maize intercropping, and so on. There were differences in spatial pattern, vertical distribution, and time variation among different planting patterns of CMPs.

At the same time, unlike the large-scale cultivation of traditional food crops, the cultivation of Chinese medicinal materials is relatively scattered, with small plots and fragmented landscapes [50]. In this case, spectral feature recognition using satellite remote sensing data is prone to mixed-pixel problems. These characteristics of CMP planting have created new requirements for remote sensing technology in terms of spatial resolution, time resolution, spectral recognition degree, recognition features, and recognition methods. It is therefore necessary to explore new remote sensing technology.

- The selection of data sources

How to make full use of multi-source data is a key issue that needs to be considered. Remote sensing identification and area extraction of CMPs involve many types, which require high spatial, temporal, and spectral resolutions of remote sensing images. How to deal with the contradictory relationship between the spectral, temporal, and spatial resolution to realize the identification of CMPRs and the accurate extraction of the planting area is a problem that needs to be considered. In addition, it has also been mentioned above that non-remote sensing data sources, such as meteorology, topography, and phenology, are often introduced into the extraction of auxiliary plant planting information of CMPs to improve the accuracy of remote sensing extraction. However, the quality of data from different sources and the difference in spatial and temporal scales will affect the accuracy of remote sensing extraction in turn. Therefore, future research needs to strengthen the research on the substitution and integration of multi-source data to achieve the "complementary advantages" between different data sources.

4.2. Prospects

- Establishment of planting pattern, habitat, and phenological characteristics database of medicinal plants

There are a variety of cultivation patterns for medicinal plants. In addition, the distribution of CMPs in different ecosystems is varied and has significant regional characteristics [51], leading to complex habitat characteristics. A sample database with reasonable classification and a sufficient quantity of information such as planting patterns, habitat characteristics, and phenological characteristics of medicinal plants should be built and applied to remote sensing recognition of medicinal plants in combination with data assimilation technology. The classification algorithm can be guided by the information in the database to improve the accuracy of the identification of medicinal plants and to understand the distribution and growth of medicinal plants more accurately. Therefore, different monitoring schemes can be developed for different models of CMPs.

(1) For CMPs planted in cultivated fields and greenhouses, the planting mode is relatively simple, and the surface distribution and spectral characteristics are obvious. Based on the appropriate adjustment of the existing remote sensing identification technology methods for crop and land-cover types, the corresponding remote sensing identification and spatial distribution mapping can be carried out. After the improvement in monitoring technology and accuracy evaluation, this kind of CMP can be demonstrated and applied in a wide range to form the spatial distribution map and area data of the corresponding CMPs. Among them, based on the accurate identification of CMPs grown in the field, it can also carry out theme monitoring and application, including growth monitoring, maturity prediction, and unit yield estimation, which can support production management situation research and judgment.

(2) For the cultivation of CMPs under forest and other field conditions, the planting mode is complex, the planting plot is broken, and the spectral characteristics are difficult to obtain due to the influence of vertical structure. At the same time, spectral and mixed pixel interference are serious due to the influence of adjacent vegetation and surrounding high vegetation. Given this situation, it is necessary to fully discover the characteristics of multi-spectral and multi-feature remote sensing technology and combine optical and microwave data, microwave data of different bands (C\X\S band), and microwave data of different polarizations (VV\VH\HH\HV) to explore the technology and method of identification and monitoring by combining multi-source remote sensing data.

(3) For the cultivation of CMPs under complex landscape patterns and CMPs under complex terrain and special habitats, the existing identification cannot be directly applied due to the complexity of their species patterns. It is necessary to carry out a targeted analysis of its spatial distribution landscape pattern and optimize the satellite remote sensing data with a corresponding resolution based on the monitoring scale. Then, the spectral and spatial characteristics were analyzed to form the recognition feature system. Finally, the application effect of different classification methods in crop recognition was discussed, and the suitable recognition method was optimized. Through the breakthrough of recognition scale, recognition feature, and recognition method, a suitable recognition technology and process were formed and applied.

- Establishment of spectral sample library of medicinal plants

Spectral data have important reference significance for remote sensing signals to identify ground objects and extract land surface information. Research on the spectral features of ground objects has attracted attention since the 1940s, and establishing a spectral database of ground objects plays an important role in quantitative remote sensing modeling, land surface parameter inversion, and environmental ecological monitoring. In recent years, various research institutions at home and abroad have built part of the ground object spectrum database [52–54], which better supports the research in ground object classification and target recognition. There is no spectral sample database for CMPs, with few sample data and scattered management. At the same time, there is a lack of a data-driven large-scale sample database covering different planting patterns and habitat characteristics, as well as multi-type sample data of CMPs such as multi-spectral, hyperspectral, and infrared [55].

Based on the spectral data of ground objects, the spectral characteristics of CMPs in visible light, near-infrared, and short-wave infrared can be studied. The spectral changes in plants under different climates, terrains, and nutrient conditions can be analyzed. The amplitude and rate of spectral variation in different growth stages of TCM plants can be analyzed, and the observation window and potential identification bands of TCM plants can be proposed. The difference in spectral characteristics between different TCM plants and between TCM plants and other plants can be analyzed, and the spectral characteristic parameters of TCM plant recognition can be established. The establishment of a CMP spectral database, the study of the relationship between CMP spectral features and remote sensing information, and the matching and recognition of non-imaging spectral data and multi-spectral imaging data can provide a theoretical basis for the remote sensing identification of CMPs and play an important role in the construction of CMP information. In particular, the main research object of species identification of wild medicinal plants should be the individual wild medicinal plants. The key technical links need to use ground-based spectrometers to measure and obtain the spectral data of medicinal plants, analyze and study them, clarify the spectral characteristics of each medicinal plant species, and establish the standard spectral characteristics database of medicinal plant species. It should be noted that in the process of establishing the database, in addition to making it have a complete analysis function, strict data specification standards should be established. The establishment of a spectral database of medicinal plants is a complex and continuous work, which requires many efforts and resources. At the same time, the spectral characteristics of different medicinal plants may vary greatly, so it is necessary to take this diversity into account and develop corresponding data collection and analysis strategies. In addition, even for the same variety, under different growth environmental conditions its spectral data are significantly different, and samples of various medicinal plants should be collected from different geographical locations to ensure that a variety of species and growth environments are covered. At the time of sample collection, data such as detailed geographic information, growth conditions, and growth stage are recorded, which will facilitate subsequent data analysis. Over time, as new data and technologies become available, spectral databases need to be constantly updated and improved.

- Fusion of multi-source and multi-temporal data

From the perspective of data source selection, the data sources applied to extract CMP information using remote sensing technology should be diversified. At present, most studies focus on the use of a single data source; however, the use of a single data source makes it difficult to meet the needs of high-precision extraction of medicinal plant information. Satellite remote sensing data are also sometimes affected by clouds, bad weather, orbital period, resolution, and other factors, resulting in data pollution, reducing remote sensing observation, and increasing the spatio-temporal discontinuity of remote sensing observation [56]. UAVRS makes up for this shortage with its flexibility, convenience, low cost of data acquisition, and the ability to fly at low altitudes under clouds [57,58]. The development of UAVRS technology has improved the accuracy and real-time performance of data collection and area extraction and expanded the application scope of medicinal plant resources research based on satellite remote sensing. It has accumulated valuable experience and provided reference value for UAVRS in the future extraction of large-area wild medicinal resources information. Microwave remote sensing has the advantages of working all day in all weather and strong penetration [59]. If it is applied to the dynamic monitoring of CMMRs, it can make the data acquisition independent of the local weather, and for some short varieties of CMPs shielded by the canopy, they can also be successfully monitored. Using multi-source and multi-temporal data fusion technology, multi-source data improve the spatial resolution of remote sensing images, and multi-temporal data improve the time resolution of remote sensing images, which is beneficial to obtain the best time phase of medicinal plant remote sensing information, better characterize the whole process of growth and development of medicinal plants, and improve the accuracy of CMP identification and information extraction.

With the development of science and technology in remote sensing data sources, the relationship between spectral resolution, spatial resolution, and temporal resolution of remote sensing data should be fully considered in view of different planting patterns and habitat characteristics of medicinal plants, combined with space remote sensing and aerial remote sensing data, as well as optical, thermal infrared, and microwave remote sensing data. Therefore, it is also necessary to strengthen the research on the scale conversion of multi-source data. It is important to improve the flexibility and accuracy of planting information extraction of plant CMMRs, meet the needs of dynamic and real-time monitoring under the broken agricultural landscape pattern, and improve the algorithm to solve or alleviate the problem of significantly reduced spatial independence of forecast data in view of the current various spatial–temporal data fusion technologies, which will reduce the spatial independence of data. Using the fused multi-source remote sensing data, the ability of feature extraction and data mining is improved so as to further improve the accuracy of medicinal plant resource information extraction. If the data of a single period do not meet the accuracy requirements for extracting information, establishing a technical system for comprehensive identification of medicinal plants with multi-source remote sensing data of the whole growth period should also be considered.

- The application of deep learning and classification automation

The continuous development of deep learning technology has also shown great potential in the automatic remote sensing monitoring and classification of CMPs. Compared with traditional methods, deep learning technology can automatically learn and extract the characteristics of medicinal plants in remote sensing monitoring and identification classification of medicinal plants, which greatly reduces the cost of manual intervention. This automatic feature extraction method can not only significantly improve the accuracy of monitoring and recognition classification but also shorten the start-up cycle and theoretical threshold. In addition, deep learning technology can deal with more complex data features and has higher flexibility and adaptability [60], as well as very good compatibility and integration capabilities. These advantages jointly promote the continuous exploration and progress of automatic monitoring, identification, and classification of medicinal plants in the field of remote sensing. Therefore, the quality and quantity of data used for deep learning model training, the appropriate network architecture, and the selection and extraction of optimal features need to be focused on. In particular, the selection of feature variables for the classification of medicinal plants has great limitations, and more attention is paid to the characteristics of medicinal plants in experimental areas, and its planting and phenological characteristics are rarely considered. It is important to make full use of the advantages of deep learning in information mining and extraction and apply it as a tool in remote sensing identification of CMP planting types and remote sensing inversion of physiological/biochemical parameters so as to improve the ability and accuracy of CMP monitoring. Evaluating the contribution rate of different features to crop classification and identification and determining the key set of identifying features for different medicinal plant types and their combinations is a concept that can be explored in future research. After improving the feature extraction method of the existing deep convolutional neural network, the method test and accuracy evaluation are carried out through the changes in samples. According to different planting patterns, differentiated target extraction schemes can be adopted:

(1) Field planting pattern: Starting with the regional bulk crop calendar, the images of the different periods of TCM growth and crop calendar were determined. The method of spectral characteristic parameter identification and classification is used to extract the target.
(2) Greenhouse planting pattern: Methods such as brightness index or building index and object form index are used to extract greenhouse information, such as the form, size, and spatial combination of the characteristics of regional traditional Chinese medicine planting greenhouses. Then combined with ground sampling survey to further confirm.
(3) Mountain planting pattern: Regional environmental information (topography, geomorphic features) was used to classify potential planting targets for medicinal plants. Based on the luminance index, morphology index, and other parameters, the "skylight" block in the forest is separated. The classification method of the vegetation characteristic index was used to distinguish medicinal plants from grassland, cultivated land, and other bare land.
(4) Underwood planting pattern: With radar and multi-spectral data, multi-source data fusion was carried out to identify and classify the medicinal plants under the forest.

5. Conclusions

This paper mainly analyzes the selection of remote sensing monitoring methods for CMPRs in different remote sensing data scales and remote sensing classification scales. It introduces the research progress of the investigation work of researchers on medicinal plant resources in China and discusses the difficulties and hot issues in the identification and classification of CMPs using remote sensing. This paper compares and analyzes the common techniques and methods of remote sensing recognition and classification at the present stage and discusses the shortcomings of related research and suggestions for improvement. In general, multi-source remote sensing technology will continue to be used in the identification and classification of medicinal plant resources, and the establishment of medicinal plant planting characteristics and a spectral database in advance can guide identification and classification and improve its accuracy. Not only that, but with the rapid development of artificial intelligence, remote sensing extraction of CMP area information has begun to develop from redundant manual interpretation to deep learning technology, which will greatly reduce the consumption of human and material resources, provide a new and fast method for the identification and extraction of planting information of CMPRs, and is expected to develop in the direction of automation. This study summarized the latest frontier results at home and abroad; based on the new needs of the development of medicinal plant resources in China, it provides a reference for improving remote sensing technology in further research on the identification and area extraction of CMPRs.

Author Contributions: Conceptualization, J.M. and X.Y.; methodology, J.M. and X.Y.; software, J.M. and X.Y.; validation, J.M. and X.Y.; formal analysis, J.M. and X.Y.; investigation, J.M. and X.Y.; resources, J.M., X.Y., X.Z., T.S., L.Z., X.C. and H.Z.; data curation, J.M. and X.Y.; writing—original draft preparation, J.M., X.Y. and M.X.; writing—review and editing, J.M., X.Y., X.Z., T.S. and X.C.; visualization, J.M. and X.Y.; supervision, J.M. and X.Y.; project administration, J.M. and X.Y.; funding acquisition, J.M., X.Z., T.S., L.Z. and X.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Scientific and Technological Innovation Project of the China Academy of Chinese Medical Sciences (No. CI2021A03902, CI2021A03901, and CICI2021B013); the Guangxi Science and Technology Development Plan (No. 2022AA01030); the National Key Research and Development Program of China (No. 2022YFD2001102).

Data Availability Statement: No new data were created for this article.

Acknowledgments: We would like to thank China Academy of Chinese Medical Sciences for providing helpful feedback on the original draft of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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