Review

A Bibliometric Analysis of the Application of Remote Sensing in Crop Spatial Patterns: Current Status, Progress and Future Directions

Pengnan Xiao [1] **, Peng Qian** [2,] ***, Jie Xu** [3] **and Mengyao Lu** [2]

[1] College of Urban and Environmental Sciences, Central China Normal University, Wuhan 430079, China; maikedang@mails.ccnu.edu.cn
[2] School of Business Administration, Zhongnan University of Economics and Law, Wuhan 430073, China; lumengyao@stu.zuel.edu.cn
[3] Faculty of Resources and Environmental Science, Hubei University, Wuhan 430062, China; 201901110800086@stu.hubu.edu.cn
[*] Correspondence: yqian@stu.zuel.edu.cn

Abstract: The crop spatial pattern (CSP) is the spatial expression of the planting structure, maturity and planting pattern of crops in a region or production unit. It reflects the situation of human agricultural production using agricultural production resources, and is very important for human survival and development. Based on 5356 publications collected from the Web of Science Core Collection[TM] (WoS), this paper's aim is to illustrate a comprehensive run-through and visualization of the subject of CSP. A time series evolution diagram of hot topics and the evolution of research hotspots are discussed in detail. Then, remote sensing monitoring methods of the crop planting area, multiple cropping, crop planting patterns and the mechanisms of crop spatial patterns are summarized, respectively. In the discussion, we focus on three important issues, namely, the remote sensing cloud platform, the changes in characteristics of the crop spatial pattern and the simulation of the crop spatial pattern. The main objective of the paper is to assist research workers interested in the area of CSP in determining potential research gaps and hotspots.

Keywords: crop spatial pattern; multiple cropping; crop planting area; crop planting patterns

1. Introduction

Agricultural land use is an activity in which human beings develop, manage and use land resources for their own survival and development needs [1]. It reflects the situation of human agricultural production using agricultural production resources within the spatial scope [2,3]. It is an important part of the land system, as well as an important piece of information to understand the types, structure and distribution characteristics of crops; it is also the basis of crop structure adjustment and optimization [4,5]. The crop spatial pattern (CSP) is the spatial expression of the planting structure, maturity and planting pattern of crops in a region or production unit, which mainly includes three aspects: the composition and layout of crops, that is, what to plant and where to plant [6,7]; multiple cropping or leisure of crops, that is, how many crops a year; and the planting mode of crops, that is, how to plant, which includes continuous cropping, rotation, intercropping and interplanting [8]. Obtaining the spatial pattern characteristics of crops and information concerning their spatiotemporal dynamic changes is the basic foundation for studying the contribution of the agroecosystem to the terrestrial carbon cycle, evaluating the impact of global change on regional agricultural production and even achieve carbon neutrality [9–11]. Therefore, it is of great theoretical and practical significance to study the spatial pattern of, and temporal and spatial dynamic changes in, crops; related directions have become the focus of scholars in the field of geography and ecology [12,13].

From the existing or ongoing research on crop spatial patterns, the methods of obtaining crop spatial pattern information mainly include summary statistics and remote sensing monitoring [14,15]. Early and traditional statistical methods obtain dynamic change information about crops in a certain administrative region through the ground collection method, and then summarize the statistics layer by layer to obtain the characteristics of the changes [16,17]. Its advantage is that it can obtain detailed information describing the quantity and rate of crop distribution change. However, due to the excessive dependence on statistical data, the research results often show a lag in time [18]. Moreover, this method consumes manpower, material and financial resources when it is used in large-scale change monitoring [6,19]. With the continuous development of space technology, remote sensing technology is widely used in Earth observation activities due to its advantages of timeliness, wide range and low cost; it provides a new scientific and technological means for the large-scale monitoring of crop spatial patterns [20,21]. The application of remote sensing technology in crop spatial pattern monitoring began at the beginning of the 20th century, and mainly focused on crop planting area monitoring. As early as the 1960s, the remote sensing Agricultural Application Laboratory of Purdue University in the United States first began to use remote sensing data to monitor crop planting areas, and successfully realized the monitoring of a single corn crop, which proved that satellite remote sensing data can be used for crop monitoring. Since the 1970s, the United States and the European Union have successively implemented the Lacie program, Agristars program and Mars program to identify crops using Landsat images and estimate the area, yield and total yield of crops [22,23]. Since then, other countries, such as China, France, Germany, the former Soviet Union, Canada, Japan, India, Argentina, Brazil, Australia and Thailand, have also carried out remote sensing monitoring research on the spatial patterns of wheat, rice, corn, soybean and other staple crops; its research content has expanded from monitoring a single crop planting area to the monitoring of multiple-cropping modes and planting modes [24–26]. The research of crop spatial patterns mainly focuses on the following aspects, including crop spatial distribution mapping [1,11,27], crop planting structure extraction [1,28,29], the multiple cropping of cultivated land [30–32] and cultivated land-use intensity [2,3,5,10,13]. The above research shows that remote sensing technology has made great progress in theory and technological methods, or in practice.

Remote sensing technology can provide scientific and accurate information for crop planting, resulting in huge economic and social benefits, which makes many scholars favor this technology and produce many classic documents. However, given the huge amount of literature, it is time-consuming to analyze the evolution path and development trend by abstracting and summarizing the problems, which has meant that few scholars have identified the development trend, hotspots and frontier in this important area of research. Therefore, with the help of bibliometric analysis, quantitative analysis of the literature is helpful for quickly extracting the frontier hotspots and identifying future research gaps. Accordingly, the aim of this paper is to solve three basic research questions in the CSP field: (1) What is the current research status of CSP? (2) What are the key authors, journals, institutions and country/region in the CSP field? (3) What are the potential research opportunities for scholars to traverse in the CSP field? In order to answer the above three questions, this paper systematically analyzes the knowledge layout and disposition of CSP by using the bibliometric method, which provides a comprehensive overview and visualization for scholars who are interested in CSP.

2. Materials and Methods

2.1. Methods and Tools

Bibliometrics is a subject that studies the distribution structure, quantitative relationship, change law and quantitative management of research information, and then discusses some structures, characteristics and laws of science and technology by using mathematical and statistical methods [33]. The literature contains a large amount of potential knowledge; bibliometrics can provide readers with a new way to understand the

world of knowledge [34]. As shown in Figure 1, the basic analysis methods include the literature publishing trend and subject categories, as well as burst analysis [35] and keyword co-occurrence network analysis [36,37].
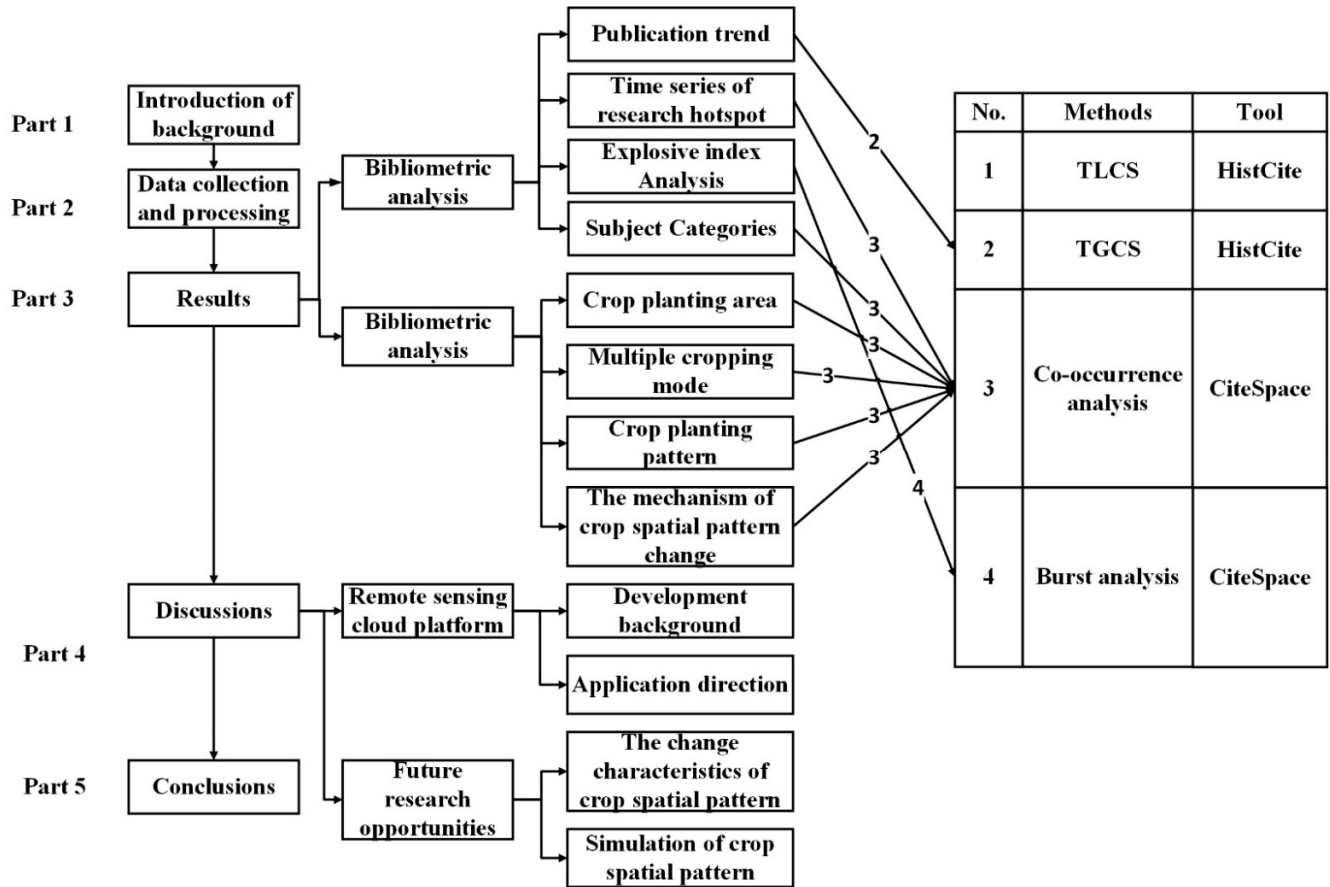

Figure 1. Workflow and methods.

HistCite[TM] is a software developed by Garfield, Paris and Stock [38], which can be used to extract field information (e.g., number of publications, authors and institution). The Total Local Citation Score (TLCS) was used to represent the total frequency of citations in the current literature list, which can also be understood as the frequency in the research field to which it belongs [39]. The Total Global Citation Score (TGCS) represents the total frequency of citations in the WoS database, and "Records" represents the number of papers published [39]. CiteSpace is a Java-based computer program developed by Chen [39], which is popularly applied in bibliometric analysis to identify and present emerging developments regarding trends and dynamics in a certain field. This paper used the bibliometric method to analyze the knowledge layout and provides a comprehensive overview for scholars, which can help them to understand the status of research and grasp potential research gaps.

2.2. Literature Search Strategy

A key component in bibliometric research is the literature data source. In this paper, after implementing the literature search strategy in Table 1, the original literature data were obtained from the Web of Science Core Collection[TM] (WoS). After removing the book chapter (11), correction (11) and letter (2), 5356 publications were selected from the Web of Science Core Collection[TM] on 5 June 2021.

Table 1. Literature search strategy.

Criteria	Details
TS	TS = ("crop spatial pattern") or TS = ("multiple cropping system" or "multiple cropping index") or TS = ("crop acreage" or "crop planting area" or "crop area") or TS = ("cropping pattern" or "crop rotation pattern" or "single cropping" or "sequential cropping" or "intercropping")
Languages	'All language'
Document types	'All document types'
Period	'2005–2020'
Database	'Web of Science Core Collection^{TM}'

3. Basic Information of Field Research

3.1. Publication Trend

The increase in the number of citations and publications in the CSP field from 2005 to 2020 is distinctly visible from Figure 2. The number of publications per year showed a growth trend ($y = 2.3309x^2 - 4.1132x + 150.28$; $R^2 = 0.9903$). When the R^2 value was equal to or close to 1, the reliability was relatively high. From 2005 to 2010, the number of citations of articles was in a state of fluctuating rise; from 2010 to 2015, it was in a high platform period; and then decreased rapidly after 2015. Since 2016, TGCS has been declining year by year, because the newly published papers have not been cited by many researchers.
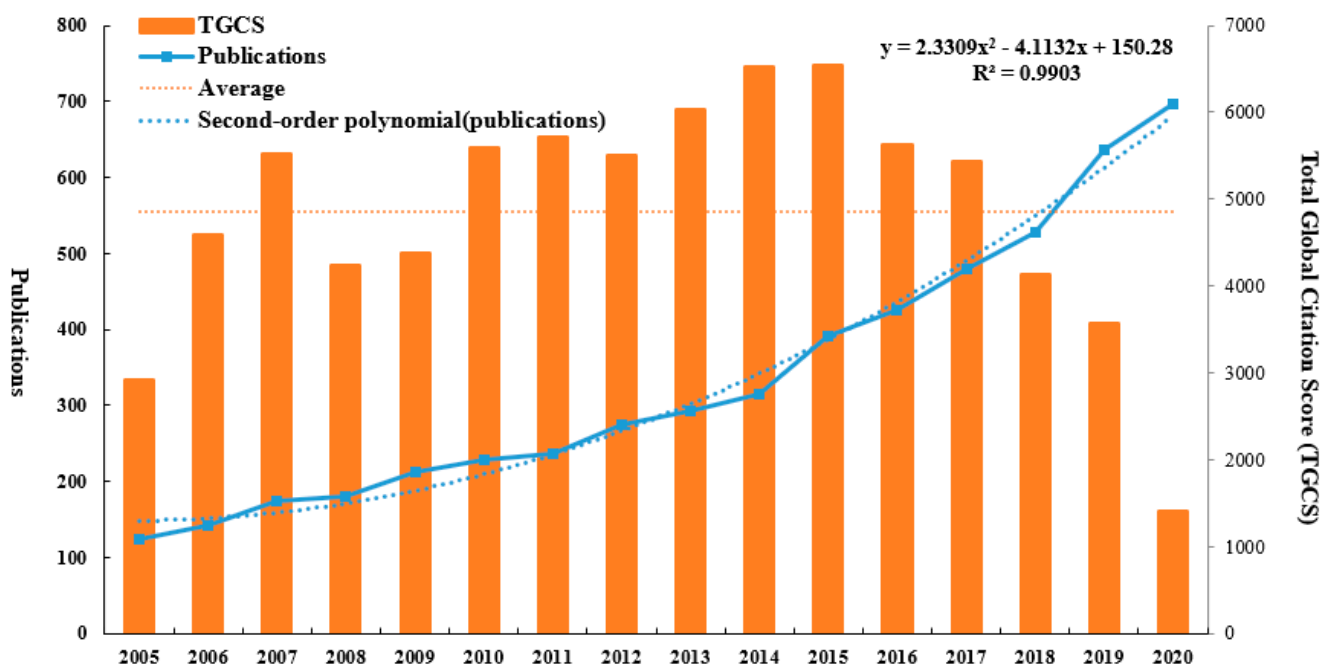
Figure 2. The publishing trend of publications and citations (2005–2020).

3.2. Subject Category

Through the co-occurrence analysis of subject categorization in CiteSpace, disciplines associated with a specific knowledge field can be found effectively and the five classes exceeding others are Agriculture, Agronomy, Agriculture (multidisciplinary), Environmental Sciences & Ecology, and Environmental Sciences. As can be seen from Figure 3, the diameter of the circle represents the proportion of classifications. The larger the circle, the higher the proportion. The lines between circles represent the relationship between categories. The thicker the lines, the closer the relationship. These results indicate that the research

domain is an interdisciplinary research field, mainly conducted from the perspective of Agriculture and Agronomy. However, it can also be combined with some other research topics with great development potential, such as Geology, Remote Sensing and Soil Science, for research.
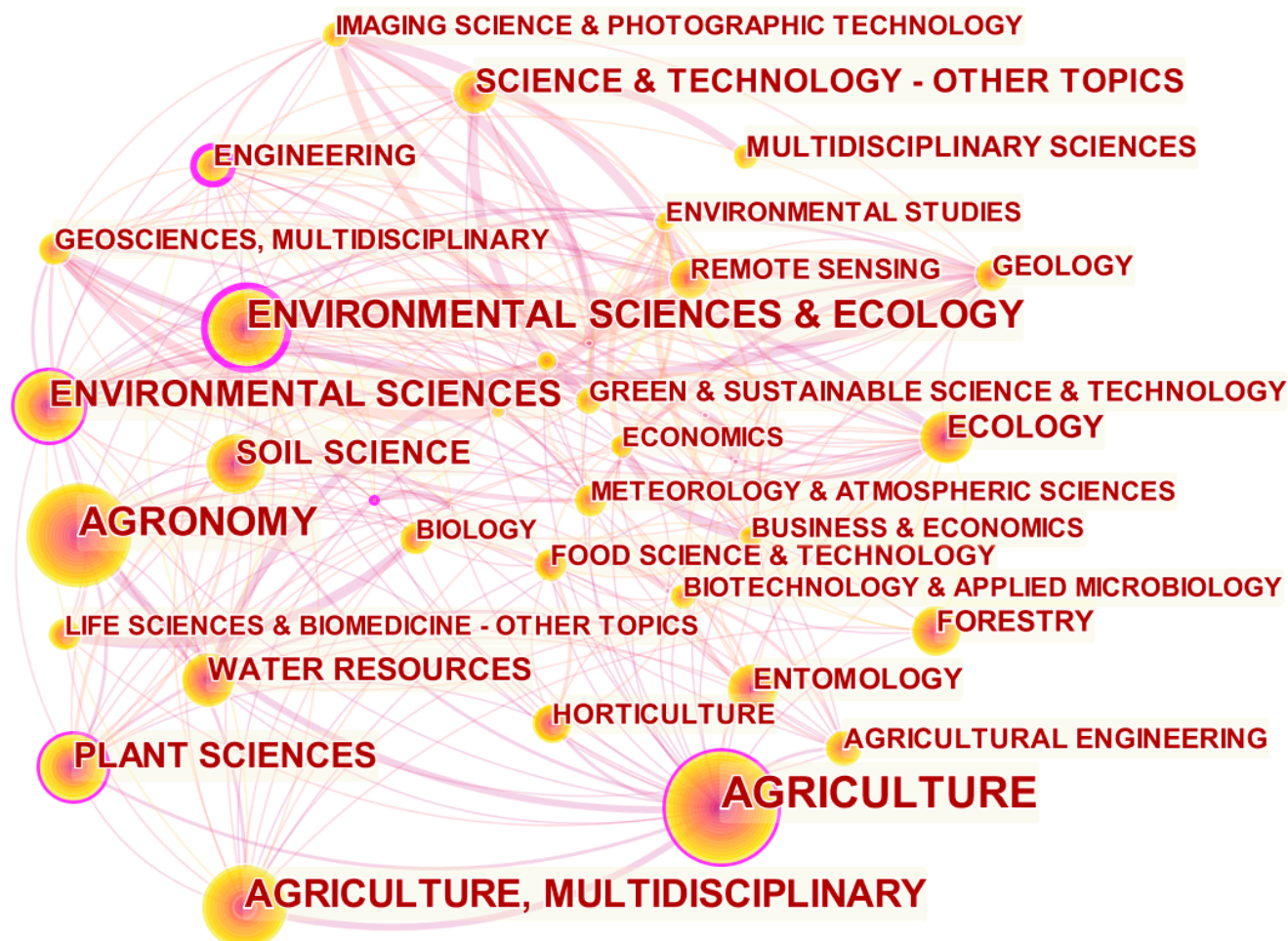
Figure 3. Subject categories of research.

3.3. Time Series Change Analysis of Hot Topics

Figure 4 is the time series evolution diagram of hot topics. From 2005 to 2020, taking each year as a period, the top 73 high-frequency keywords were merged to obtain the time series changes of 20 hot topics and the proportion of this topic in the same period. The percentage in the picture indicates the percentage of keywords with the highest probability of occurrence in the same period. As can be seen from Figure 4, (1) the topics that have received continuous attention are "cotton, rice, soybean, corn, maize, wheat, cover crop", "intercropping, intercropping system and intercrop", "yield, grain yield and crop yield", "system, cropping system, agroforestry system and farming system", etc.; (2) the themes of "agriculture, conservation agriculture, sustainable agriculture, climate-smart agriculture", "landscape, land use, land use change, land cover" and "food security, sustainability, economics" are becoming increasingly mature, and the degree of attention is decreasing steadily; (3) for "irrigation, deficit irrigation, irrigation management" and factors related to agricultural production, such as "soil, soil fertility and soil organic carbon", "nitrogen, phosphorus, fertilizer", "crop rotation, rotation" and "climate change, drought, evaporation, drought stress, water, and temperature", etc., the researchers' attention to them is relatively stable; (4) researchers focus on the use of remote sensing technology to monitor the spatial pattern of crops—for example, the research on " remote sensing, leaf area index, vegetation

index, NDVI" has increased rapidly since 2013; (5) some keywords, including "farmer, smallholder farmer, smallholder" and "Model, dynamics, Simulation, pattern, Impact", have attracted attention in recent years, which shows that farmers' planting preferences and large-scale regional simulation have become hot spots in the study of crop spatial pattern.
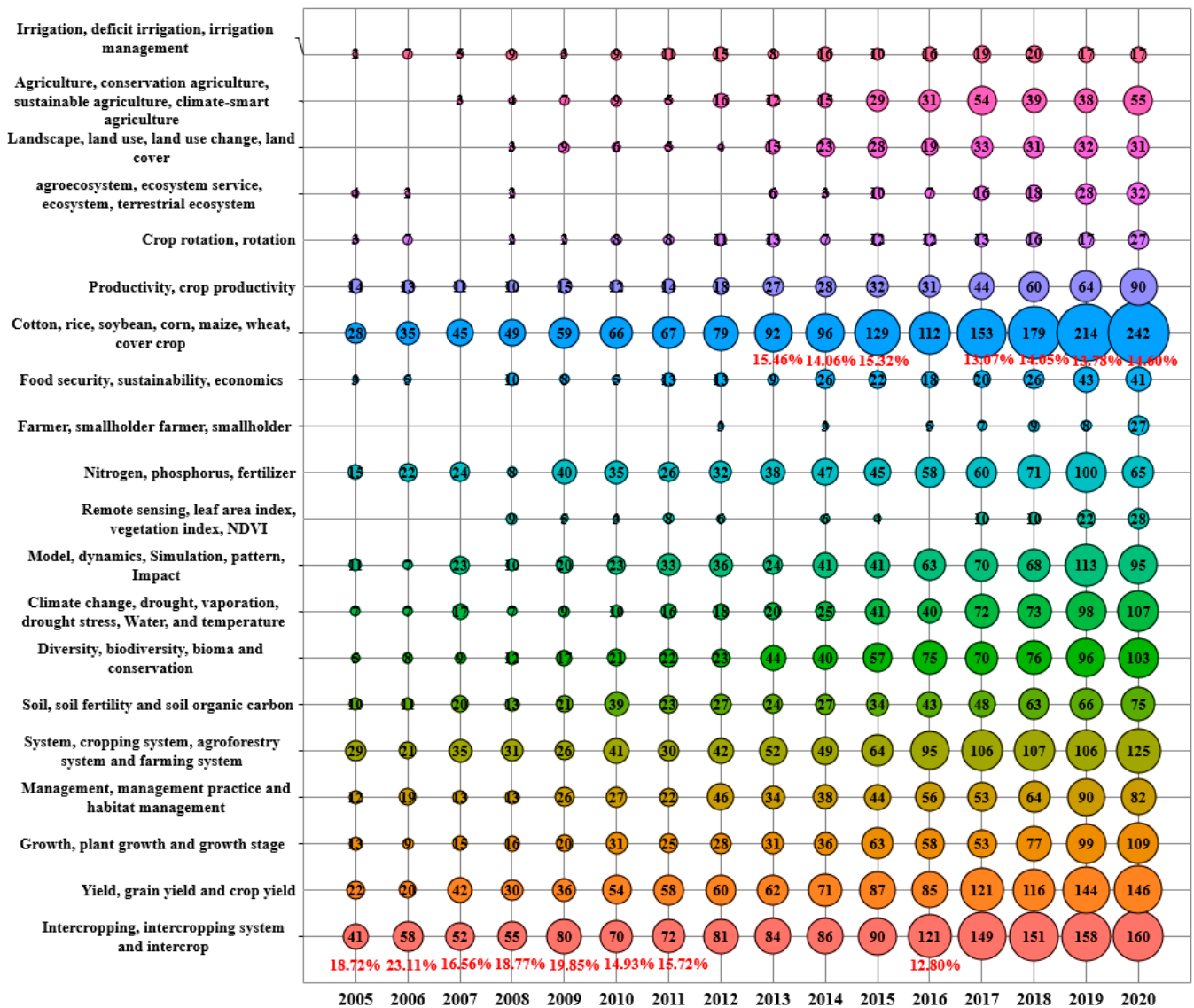
Figure 4. Temporal changes in hot topics (2005–2020).

3.4. Evolution Analysis of Research Hotspots Based on Explosive Index

By analyzing keywords with CiteSpace's burstiness detection, 185 keywords with explosive degree were obtained. After removing the keywords with a total frequency of less than 5, the results shown in Figure 5 were obtained. The keywords were sorted in the horizontal direction according to the initial year of the outbreak. The left ordinate is the word frequency of the keywords, corresponding to the height of the histogram. The height of the pointed bars in the chart corresponds to the right ordinate, indicating the length of the outbreak cycle. The diameter of the circle where the key words are located indicates the height of its burst index, which is used to identify research topics that grow significantly or decline rapidly in a short period of time [40].

Figure 5. Keywords with explosive characteristics.

Therefore, the evolution of research hotspots can be divided into three stages. In the first stage (2005–2010), there were many keywords with a high frequency, long outbreak period and high outbreak degree, which indicated that they were focused on by researchers during this period. After 2005, the keywords that appeared and quickly became research hotspots include "maize", "soybea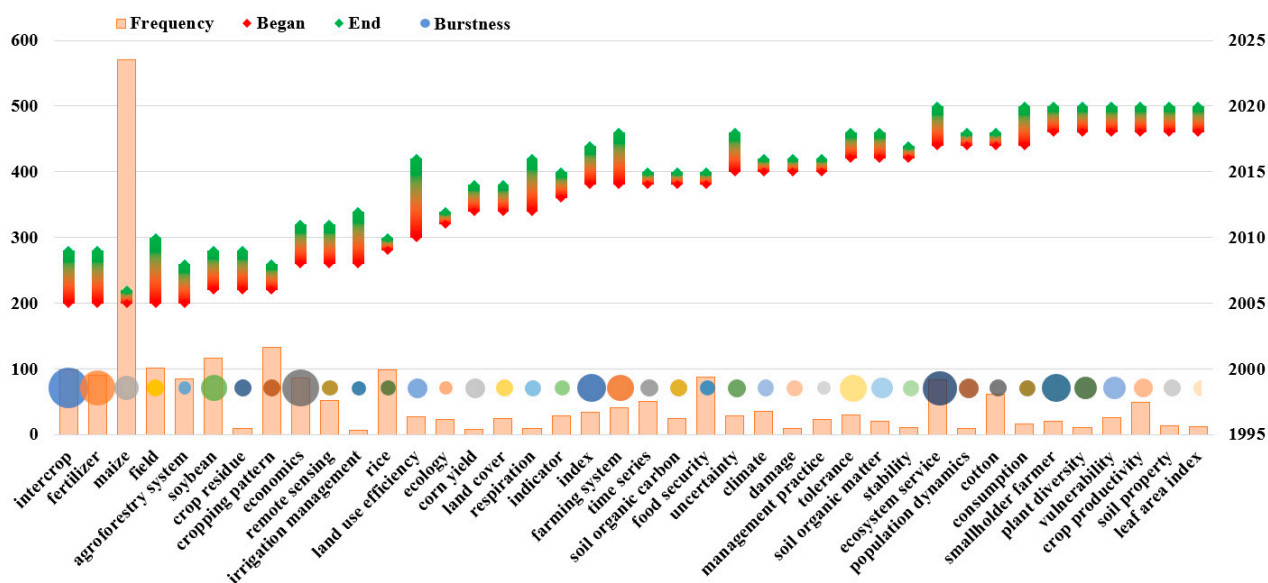n", "economics" and "agroforestry system", which indicates that those keywords attracted scholars' attention in this period. The frequency of the earlier "maize" was the highest, but the explosive index was not high, which showed that many scholars were focusing on it. In the second stage (2010–2015), some short-term but high-explosivity keywords appeared, including "ecology", "respiration", "land cover", "land use efficiency" and "rice". In addition, scholars at this stage paid special attention to the theoretical research content of land use, the relationship between cultivated land protection and urban expansion and restoration. In the third stage (from 2015 to now), the explosive words appearing in this stage include "stability", "plant diversity" and "vulnerability", which are discussed from the perspective of global change and multiple situations. In addition, some key factors, especially "population dynamics" and "soil property", will become hot topics in the near future, because they are facing many new challenges in the fields of social, ecological and economic development.

4. Remote Sensing Monitoring System of Crop Spatial Pattern

Tang and others believe that the spatial pattern of crops can be studied from four aspects: crop planting areas, multiple-cropping mode, crop planting patterns and the mechanism of crop spatial pattern change [4,6]. Therefore, the following four questions need to be answered: (1) What is the principle and implementation method of remote sensing monitoring of crop planting areas? (2) What is the principle and implementation method of remote sensing monitoring of the multiple-cropping mode? (3) What is the principle and implementation method of remote sensing monitoring of crop planting patterns? (4) What is the mechanism of crop spatial pattern change? According to the keyword word frequency analysis results obtained from the keyword co-occurrence analysis, the keywords were sorted according to their meaning, as shown in Figure 6. Four aspects are discussed in detail in this article.
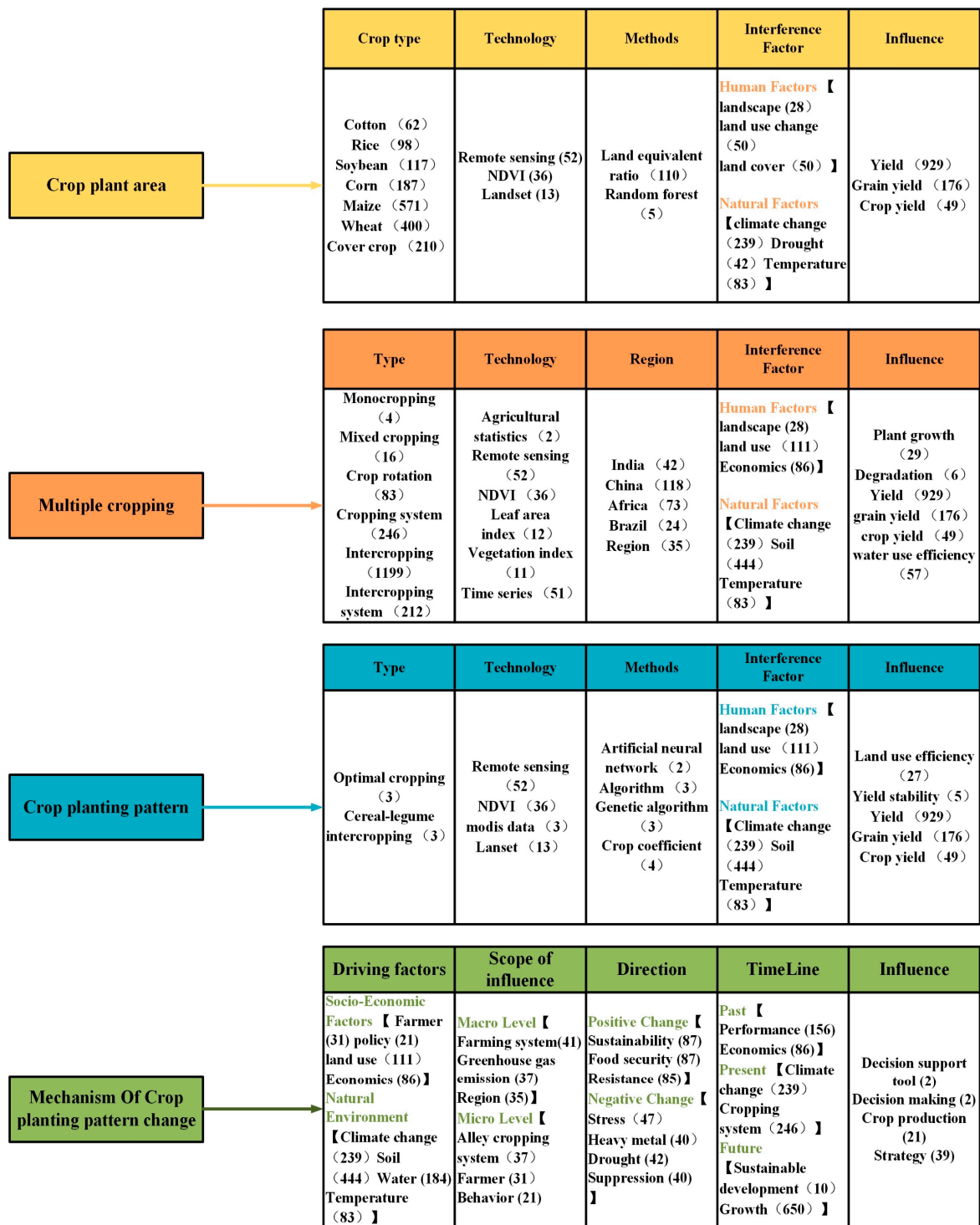
Crop type	Technology	Methods	Interference Factor	Influence
Cotton（62）Rice（98）Soybean（117）Corn（187）Maize（571）Wheat（400）Cover crop（210）	Remote sensing (52) NDVI (36) Landset (13)	Land equivalent ratio（110）Random forest（5）	Human Factors 【landscape（28）land use change（50）land cover（50）】Natural Factors 【climate change（239）Drought（42）Temperature（83）】	Yield（929）Grain yield（176）Crop yield（49）

Type	Technology	Region	Interference Factor	Influence
Monocropping（4）Mixed cropping（16）Crop rotation（83）Cropping system（246）Intercropping（1199）Intercropping system（212）	Agricultural statistics（2）Remote sensing（52）NDVI（36）Leaf area index（12）Vegetation index（11）Time series（51）	India（42）China（118）Africa（73）Brazil（24）Region（35）	Human Factors 【landscape (28) land use（111）Economics (86)】Natural Factors 【Climate change（239）Soil（444）Temperature（83）】	Plant growth（29）Degradation（6）Yield（929）grain yield（176）crop yield（49）water use efficiency（57）

Type	Technology	Methods	Interference Factor	Influence
Optimal cropping（3）Cereal-legume intercropping（3）	Remote sensing（52）NDVI（36）modis data（3）Lanset（13）	Artificial neural network（2）Algorithm（3）Genetic algorithm（3）Crop coefficient（4）	Human Factors 【landscape (28) land use（111）Economics (86)】Natural Factors 【Climate change（239）Soil（444）Temperature（83）】	Land use efficiency（27）Yield stability（5）Yield（929）Grain yield（176）Crop yield（49）

Driving factors	Scope of influence	Direction	TimeLine	Influence
Socio-Economic Factors 【Farmer (31) policy (21) land use（111）Economics (86)】Natural Environment 【Climate change（239）Soil（444）Water (184) Temperature（83）】	Macro Level 【Farming system(41) Greenhouse gas emission (37) Region (35)】Micro Level 【Alley cropping system（37）Farmer (31) Behavior (21)】	Positive Change 【Sustainability (87) Food security (87) Resistance (85)】Negative Change 【Stress（47）Heavy metal (40) Drought (42) Suppression (40)】	Past 【Performance (156) Economics (86)】Present 【Climate change（239）Cropping system（246）】Future 【Sustainable development（10）Growth（650）】	Decision support tool (2) Decision making (2) Crop production (21) Strategy (39)

Figure 6. Keyword classification map based on four key problems.

4.1. Remote Sensing Monitoring Method of Crop Planting Area

Information such as crop planting area and yield is an important basis for the formulation of food policies and economic plans, which has always been highly valued by social and government departments [41]. The remote sensing monitoring of crop planting areas is mainly based on the differences in the spectral characteristics of different crops recorded by remote sensors, and the recognition of different crop planting areas is carried out through the surface information recorded by remote sensing images. In general, as shown in Figure 7, the remote sensing monitoring methods of crop planting areas can be

divided into three categories: those based on spectral characteristics, those based on crop phenological characteristics and those based on multi-source data [6,42].
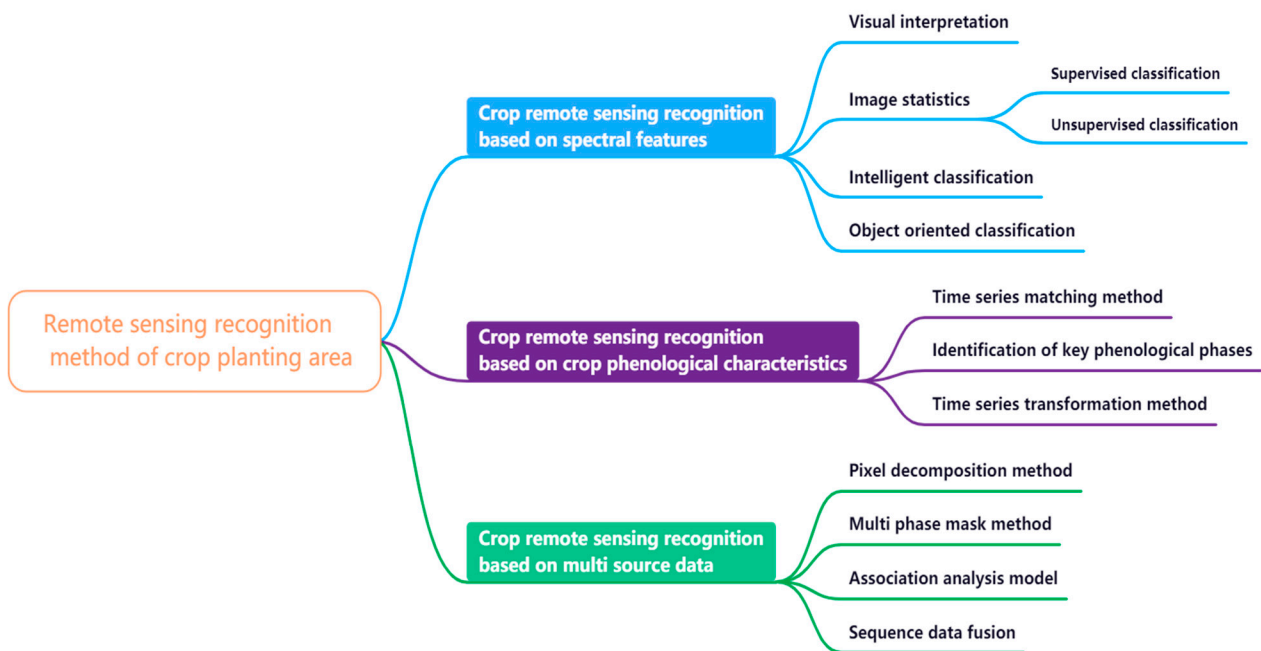
Figure 7. Remote sensing recognition method of crop planting area.

4.1.1. Crop Remote Sensing Recognition Method Based on Spectral Features

1. Visual interpretation. The early remote sensing monitoring of crop planting area is mainly based on visual interpretation, that is, relying on the spectral law, geological law and the experience of experts who have a deep understanding of the situation of the study area and the spectral characteristics of crops, inferring crop types from a series of characteristics of remote sensing images, including brightness, tone, position, time, texture and structure [6,42]. The advantage of this method is to make full use of experts' prior knowledge and comprehensive understanding of image features, as well as the advantages of the human brain, so as to avoid the possible errors caused by only using spectral analysis, and the recognition accuracy is high [43–45]. However, the disadvantages of this method are strong subjectivity, low efficiency, high cost and high requirements for time and personnel, so it is not suitable for large-scale crop remote sensing recognition [46–48].

2. Image-based statistical classification. This method includes supervised and unsupervised classification. It mainly calculates the statistical characteristics between pixels, including the mean value, variance, standard deviation and dispersion, to establish the discriminant function between crop categories, so as to realize crop type recognition [8]. Supervised classification based on statistical features is the first remote sensing classification method for crop recognition, and the remote sensing classification method has been extended to the whole world [49]. As crops also belong to vegetation and have similar spectral characteristics to other vegetation, it is often necessary to select the time phase with obvious differences between crops and other vegetation spectral characteristics [50,51]. However, in large-scale monitoring, especially in areas with complex planting conditions, the classification accuracy is still difficult to control, and classification methods using other effective identification marks are still immature [52]. Therefore, a combination of automatic classification and visual interpretation is also commonly used [41].

3. Intelligent classification algorithm. The traditional supervised and unsupervised classification is limited by human or surface environmental factors, which makes

it difficult to achieve the research purposes and requirements with classification accuracy [53]. Due to the limitation of the resolution of satellite remote sensing data, satellite image elements have the characteristics of comprehensive spectral information, which causes the computer classification to face many unclear situations [54]. There are many phenomena of the "same object with different spectrum" and "foreign object with same spectrum". According to the point independence principle of spectral characteristics of ground objects, the proportion of misclassification is very high [55]. In recent years, an intelligent classification algorithm with a high degree of automation has become one of the new hot spots. At present, the common intelligent classification methods of crop area extraction mainly include the neural network [56,57], support vector machine [58], decision tree [59] and random forest [60,61].

4. Object-oriented classification method. The object-oriented classification method has outstanding advantages in the application of high-resolution remote sensing images [62]. It not only makes full use of the spectral characteristics of the ground objects, but also considers their shape, texture and structure, so as to form a number of non-overlapping non-empty sub regions after segmentation to reduce "salt-and-pepper noise" [63]. As the objects are relatively uniform, the phenomena of "same spectra with different object" and "same object with different spectra" are solved to some extent [4,64–66].

4.1.2. Crop Remote Sensing Recognition Method Based on Crop Phenological Characteristics

Due to the characteristics of seasonal rhythm and phenological change, the time-phase change law of remote sensing data of time series can be used to recognize different crop types. The vegetation index is the most widely used parameter to describe the seasonal change characteristics of vegetation.

1. Time series matching method. High temporal resolution images can fully reflect the seasonal changes in vegetation, and the same vegetation in the same area has similar change curves, so different ground features can be identified using the change characteristics of the vegetation index time series [41]. By analyzing the matching degree between the unknown pixel spectral curve and the pure pixel spectral curve, the surface feature types are identified [67,68], including the spectral angle classification, spectral feature fitting and binary coding [69,70]. Inspired by the spectral analysis of hyperspectral remote sensing, this method has been applied to the analysis of time series data to identify crop types [71,72]. The purpose of this method is to make use of the differences in seasonal rhythm, so as to avoid the problem of similar spectral characteristics among crop types [73]. However, the spatial resolution of remote sensing data, which can form time series and is often used in large-scale research, is usually very low, so the monitoring accuracy is not high [74].

2. Dentification of key phenological periods. In general, the same crop has relatively stable growth and development characteristics in the same area [75]. The key phenological period can allow crops and other vegetation a greater degree of recognition, which can be used as an important basis to improve the accuracy of crop type recognition [76]. The purpose of this method is to analyze the characteristic value of the key phenological period of crop growth in time series data by selecting the appropriate remote sensing image and using the local crop phenology information, so as to achieve the purpose of crop extraction [77]. This method can make crop type recognition more targeted, thus avoiding the blindness of remote sensing data selection.

3. Time series transformation method. Each crop has a unique seasonal growth pattern, which makes the NDVI time series curve reflect its phenological characteristics. The change characteristics of time series data can be described quantitatively after the correlation transformation, and then the crop types can be identified [78]. The amplitude and phase angle images of each crop were extracted using the harmonic analysis of time series, and then the crops were identified using discriminant analysis [79,80]. Based on the discrete Fourier transform to detect the frequency distribution, the ex-

tracted biological features can be introduced into the classification feature space, so the separability between categories is improved [81]. The core idea of this method is to extract the time series features of crops different from other land objects using various transformation methods, and can obtain some specific details so that the results of crop classification are more accurate, but only the low-spatial resolution data can be used.

4.1.3. Crop Remote Sensing Recognition Method Based on Multi-Source Data

Due to the influence of the weather, climate and other natural conditions, it is difficult to obtain timely, full coverage of high-resolution remote sensing images [82]. The advantage of high-temporal resolution remote sensing is that it can obtain complete time series in the crop growing season, but the disadvantage is that it is limited by spatial resolution and low monitoring accuracy, especially in areas with complex planting structures [83]. Many practices have proved that the combination of spectral features and time series information can provide more accurate results in the recognition of ground objects [84]. Therefore, the main trend of crop recognition at a regional scale is to make full use of the advantages of multi-source remote sensing and combine low- and medium-spatial resolution remote sensing [85].

The crop remote sensing recognition method based on multi-information source data can make full use of the characteristics of various data, realize complementary advantages, make up for the defects of single remote sensing data and classification methods, and greatly improve the precision of crop remote sensing recognition [86]. The combination of multi-source data includes not only the combination of multi-source remote sensing images, but also the combination of remote sensing images and non-remote sensing data sources. The combination of multi-source remote sensing images can obtain more information and reduce the ambiguity of understanding.

1. Pixel decomposition method. The key point of this method is to provide endmembers from medium- and high-resolution images, and decompose pixels based on low-spatial resolution images of a single scene or multiple scenes in a key phenological period. A large number of studies at home and abroad show that the accuracy of crop recognition is high, which can basically meet actual needs [87–89]. This method considers the availability of different types of remote sensing data and makes full use of the advantages of multi-resolution remote sensing with relatively high accuracy. However, the disadvantages of this method are that it does not take advantage of the time advantage of low-spatial resolution remote sensing, the effect is more obvious when the planting structure is relatively simple, and the result is a low-spatial resolution abundance map, which can count the total planting area of crops, but the determination of sub-pixel positions cannot provide much support.

2. Correlation analysis model. The key aspect of this method is to establish a semi-quantitative or regression model with low-resolution time series or key phenological data to identify crops [90–92]. There are also studies that consider the quantitative functional relationship between the vegetation index and planting area in the key phenological period of crops [93]. The principle of this is that, when the pixel is mixed with other types of ground objects, the slope of the curve in the key period will change. The advantage of this method is that it makes full use of the advantages of multi-resolution remote sensing, highlights key phenological characteristics, makes the theory more sufficient and the accuracy higher. However, the disadvantage of this method is that the result is still an abundance map, which cannot determine the specific location of the sub-pixels and is only used to count the total planting area and the approximate planting distribution.

3. Multi-phase mask method. The key aspect of this method is to make use of the time continuity advantage of low-spatial resolution remote sensing data, distinguish crops and non-crops based on the seasonal rhythm characteristics of crops, and identify crop types based on medium- and high-resolution images with crop areas as masks [94,95].

This method takes advantage of the time advantage of low-resolution remote sensing to narrow the spatial range of crop recognition, reduce the influence of "the same object with different spectrum" and "foreign object with the same spectrum" to a certain extent, so as to improve the recognition accuracy. However, it is necessary to formulate relevant rules to ensure the mixed pixels contain crops in the mask.

4. Sequence data fusion. The key aspect of this method is the fusion of low-resolution time series data and high-resolution multispectral data, which not only improves the spatial resolution and clarity, but also the accuracy and reliability of recognition [96,97]. The advantage of this method is that it fully integrates the advantages of multi-resolution remote sensing in time and space and improves the spatial accuracy without losing the advantages of time series. However, when using single or several temporal high-resolution remote sensing images to fuse with time series low-spatial resolution remote sensing images, it is necessary to focus on the temporal differences between images of different scales, which also further verifies the applicability of this method.

4.2. Remote Sensing Monitoring of Multiple Cropping

Cultivated land is an important form of land resource utilization, and carries the basic food sources for human survival. Its change has a very important impact on food security and the stability of the ecological environment. In recent years, with the increasingly prominent distance between people and land, the promotion of urbanization and the rising price of food, food issues have gradually become a hot topic of global concern, and regional food security has also attracted a large amount of attention [30]. Multiple cropping is the most simple, direct and effective way to increase regional grain yield. The multiple cropping index is the basic index to measure the intensive utilization degree of cultivated land resources in the study of the farming system, and it is also an important technical index for the macro-evaluation of the basic situation of cultivated land resource utilization [98,99]. It refers to the times of planting crops in a year.

Generally speaking, in the case of a certain yield per unit area, the higher the multiple cropping index, the higher the degree of cultivated land utilization, and the higher the grain yield. On the contrary, the smaller the multiple cropping index, the lower the degree of cultivated land utilization and the lower the grain yield [100]. Multiple cropping can make full use of the characteristics of agricultural natural conditions in Asia, such as abundant light and heat resources, uneven spatial and temporal distribution of water conditions and small cultivated land area, and improve the utilization efficiency of land, light, heat and water resources so as to ensure the agricultural production capacity to meet the survival needs of many people.

The application of remote sensing technology in multiple cropping mode monitoring mainly uses different fitting methods to obtain the crop growth curve according to the crop seasonal activity process described by the time series vegetation index, so as to realize the effective monitoring of the multiple-cropping mode. The specific process is as follows: the vegetation index data obtained in a year that reflect the growth status of vegetation are arranged over time as the abscissa to form a time series to describe the annual change characteristics of vegetation growth; that is to say, the core idea of this method is that the time series change in the vegetation index corresponds to the seasonal activity process of vegetation growth and decline [6].

The temporal dynamic change in vegetation index can reflect the growth process of crops, including the periodic cycle of sowing, emergence, heading to maturity and harvesting. Figure 8 shows that the vegetation index curve of the first cropping system completed one cycle in a year, the second cropping system completed two cycles and the third cropping system completed three growth cycles. Therefore, based on the time series vegetation index, using various smoothing methods to fit the crop growth curve can realize the effective monitoring of the multiple-cropping mode [6].

The multiple cropping index can be divided into the potential multiple cropping index and the actual multiple cropping index. The potential multiple cropping index is the

maximum multiple cropping index, that is, the maximum multiple cropping index that can be achieved when making full use of light, heat and water resources in the region. However, due to the limitations of economic conditions, human costs, topography, technical level, crop varieties and other factors, the actual situation of the multiple cropping index in a region may not reach its maximum level, which is called the actual multiple cropping index here.
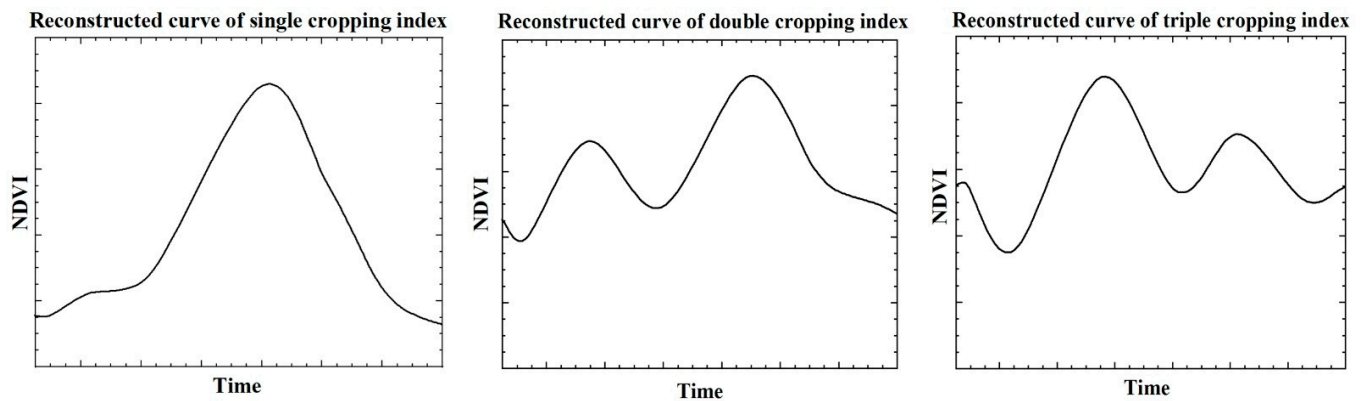
Figure 8. Concept map of multiple cropping model.

4.2.1. Research Method of Potential Multiple Cropping Index (PMCI)

1. AEZ (Agro-Ecological Zones). This method is commonly used to calculate the potential productivity of regional cultivated land in the world. Its purpose is to integrate climate, soil, topography, land use, irrigation conditions and other factors with the growth models of various crops, and finally calculate the maximum production potential of each piece of land [101,102]. The AEZ model considers the factors of crop growth more comprehensively, which has high theoretical significance and practical application value, but for small areas, the accuracy is not high.

2. Methods based on aerolithology. The core idea of this method is to divide multiple cropping potential into heat and precipitation potential, and take the smallest one as the final multiple cropping index potential. The heat and precipitation potential is divided into multiple cropping regions by the accumulated temperature of $\geq$10 °C and the average annual precipitation [103,104]. Based on the agricultural climatology model, the current development still depends on the experience stage, and the determination of the heat and precipitation threshold mostly depends on the experience value, which has some limitations.

3. Method based on an economic model. This method considers that the production of crops and the concept products in economics have some similarities; that is, under the input of some production factors, a certain output can be obtained. If light, temperature, water resources and other natural conditions are regarded as input factors, and the multiple cropping index is regarded as the output, then the potential of the multiple cropping index can be measured by using the stochastic frontier production function, which is used to measure the technical efficiency in economics [105,106]. The method based on the economic model can be used to analyze the non-benefit part of multiple cropping, but the premise of application is that multiple cropping must reach the maximum potential in some places.

4.2.2. Research Method of Actual Multiple Cropping Index (MCI)

1. Statistical method of the Statistical Yearbook. The most commonly used method is to obtain the actual multiple cropping index by dividing the sown area of crops by the cultivated area in the Statistical Yearbook. The statistical method is relatively simple in calculation. The advantage of this method is that it can quickly evaluate the change trend of the multiple cropping index on the regional scale, but the disadvantage is that

the accuracy is often restricted by the reliability and lag of statistical data, and it cannot effectively represent the local pattern change in the cultivated land multiple cropping index or accurately describe the spatial characteristics of the planting system [107,108].

$$MCI = A_h / A_c \tag{1}$$

where *MCI* is the multiple cropping index of regional cultivated land; A_h is the total harvest area of the whole year; A_c is the total area of cultivated land.

2. Peak value method. The peak value method is the most widely used method in multiple cropping monitoring due to being simple and easy to use. The core idea of the peak value method is that the peak value of the crop multiple cropping mode is consistent with that of the crop vegetation index change curve; that is, the vegetation index data of crops in one season of a year forms an obvious single-peak curve, the vegetation index of crops in two seasons of a year forms a double-peak curve and the vegetation index of crops in three seasons of a year forms a triple-peak curve. The key aspect of the peak method is to obtain the frequency and distribution of the peak. However, only calculating the peak number may cause an error in multiple cropping monitoring. As the remote sensing data are disturbed by the condition of the remote sensing sensor itself (inclination, resolution and sensor aging), cloud, atmosphere and sun height angle, the vegetation index directly obtained from the remote sensing image has a large amount of noise. This results in the irregular fluctuation of the time series vegetation index data, which is not suitable for extracting the information of the cultivated land multiple species index directly. Therefore, it is necessary to remove the noise from the time series vegetation index data and reconstruct a smooth time profile to better describe the process of cultivated land seasonal change. Common data smoothing methods are shown in Table 2. The calculation process of the multiple-cropping index is shown in Figure 9.

Table 2. Smoothing method of multiple cropping index.

| Smoothing Method	Advantages	Disadvantages
Fourier transform	1. It can not only remove the noise, but also represent the harmonic of the different vegetation growth cycle. 2. It can reflect the periodicity of the vegetation growth curve as much as possible. 3. It is realized by the software package method, and it is relatively simple to use.	1. It is sensitive to pseudo-high and pseudo-low values in NDVI data. 2. The threshold of reference setting needs experience and many experiments to obtain the best value, and the environmental and human factors have great influence.
S g filtering	1. The theory is simple and easy to implement. 2. It is not limited by the data time, space scale or sensor. 3. It can clearly describe the long-term trend of time series and local mutation information.	1. It is difficult to determine the filter coefficients and active window bandwidth. 2. S g filter reconstruction can only process the time series data with an equal interval.
Asymmetric Gaussian function fitting	It can clearly describe the long-term change trend and local mutation information of the vegetation index in time series.	1. It is difficult to find suitable peak and valley points. 2. It is not suitable for the area where the seasonal variation is not obvious.
Wavelet transform	1. Multi-resolution is the local transformation of the time and frequency domains. 2. There are many smooth wavelets to choose from.	1. Different wavelets have different experimental results, which need a large amount of data to verify. 2. It has not been used for a long time in the field of data smoothing and needs further research and exploration.
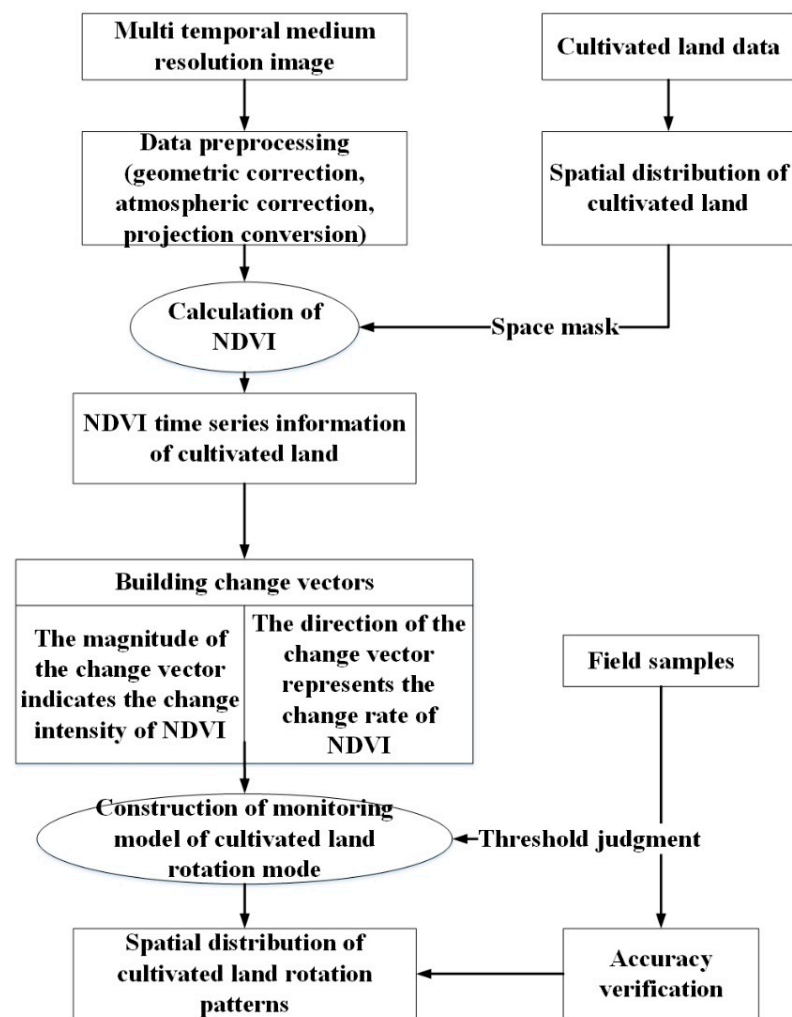
Figure 9. Calculation process of multiple cropping index.

4.3. Remote Sensing Monitoring of Crop Planting Patterns

Crop planting is a comprehensive summary of continuous cropping, rotation, intercropping and interplanting [109]. The planting mode of crops is closely related to the pattern of crop replanting. Both of them make full use of natural resources such as water, soil, light and heat to improve the utilization rate of light energy and land yield [110]. However, there are still significant differences between them. The mode of crop replanting mainly describes the amount of crop planting in a certain region or production unit in a year, while the crop planting mode explains the planting order and mode of crops under different multiple cropping patterns.

For the area with more than one year of maturity, the planting method of the same crop in the same field is continuous cropping, while the planting mode of rotating different crops in the same field in sequence is called rotation [111]. Rotation also includes single rotation, intercropping rotation and interplay rotation. Therefore, the crop planting mode is more complex and diverse, and the remote sensing monitoring of crop planting mode is a higher-level remote sensing application. The spectral and seasonal information recorded by remote sensing sensors is different for different planting methods [112].

The most commonly used remote sensing monitoring method of crop planting patterns is to use high-temporal resolution time series remote sensing data, such as NOAA/AVHRR and MODIS, to distinguish crop growth cycles according to the change law of the crop index, and to couple this information with the crop growth cycle model established by the ground survey so as to judge different crop planting patterns [113]. For the multi-mature area of single cropping rotation, the growth season of the crops in the front and back crops

does not coincide, and the time series remote sensing data reflect the complete growth season of each season. If the intercropping rotation is used, the later growth season of the former crop and the early stage of the later crop growth season overlap due to the planting or planting of the later plants, rows or borders of the crops in the later period of the previous season, so that the single rotation and interplanting rotation can be extracted by using the above characteristics. The remote sensing monitoring process of the cultivated land rotation mode is shown in Figure 10.
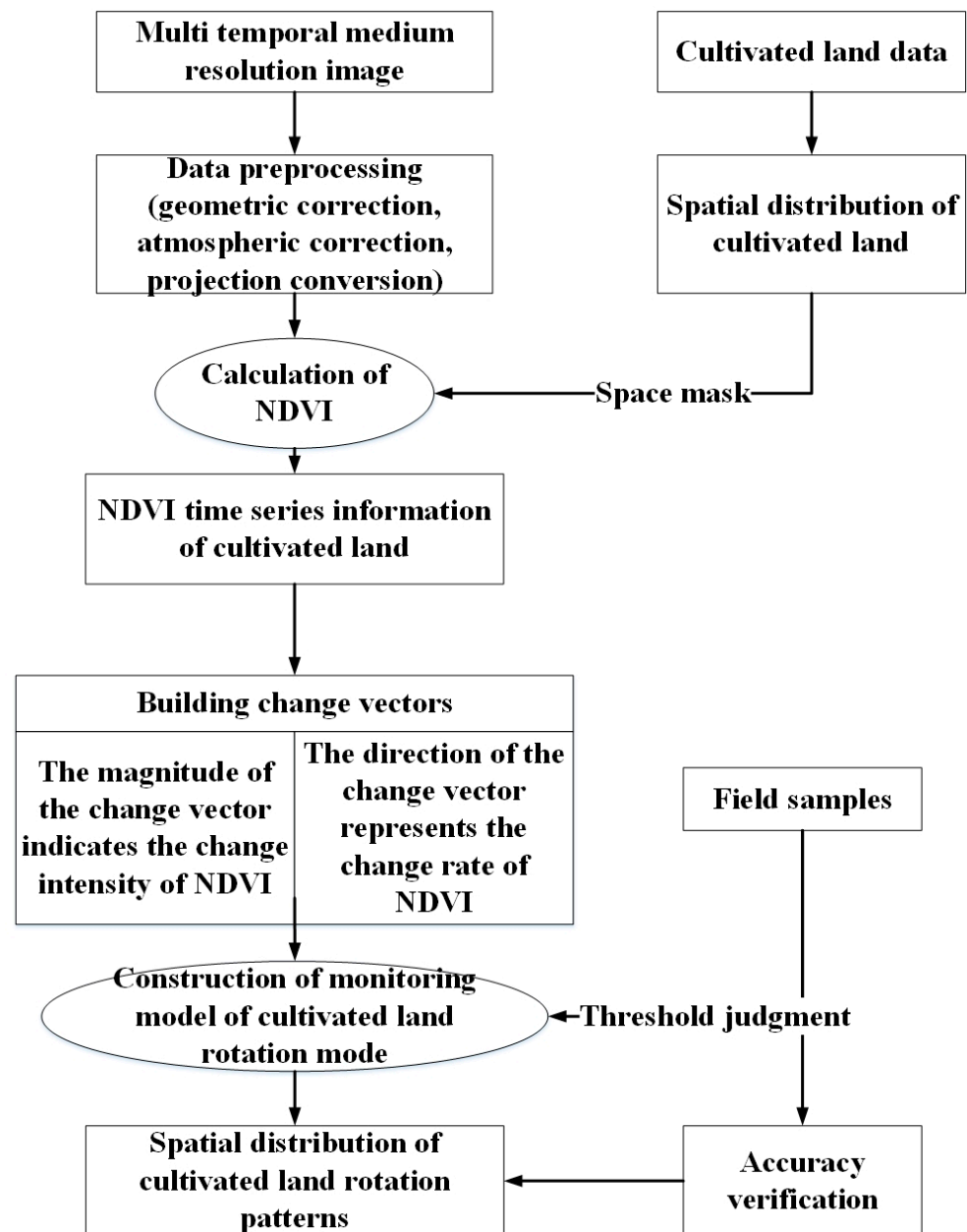

Figure 10. Remote sensing monitoring process of cultivated land rotation mode.

4.4. The Mechanism of Crop Spatial Pattern Change

The research focus on the mechanism of crop spatial pattern change is to analyze the dynamic process of crop spatial pattern change from one state to another, and analyze the internal and external reasons leading to the evolution of the crop spatial pattern, so as to determine the mechanism of different "natural-social-economic" driving factors in the evolution of the crop spatial patterns [8]. The formation of and changes in crop

spatial patterns are the products of natural factors and human activities. As a system, natural driving forces can be divided into different components, such as climate, soil and hydrology. As a system, human driving forces can be divided into population, technology, wealth, political and economic situations, and culture. Compared with the mechanisms of natural driving forces, the impact of human activities on the spatial pattern of crops is more complex.

The essence of crop spatial pattern change is the relationship between humans and the environment. The existing research on the driving mechanism of crop spatial pattern focuses on the application of a variety of system analysis and mathematical statistics methods to analyze the impact of natural ecological environment changes on crop spatial and temporal patterns. The analysis objects are usually land units with a certain area, or a certain area represented by a grid in a grid system; it is easy to establish the relationship between crop spatial pattern change and environmental factors by using geographic grid data or regional socio-economic statistics. However, the change in crop spatial patterns is affected not only by natural factors but also by social and economic factors [25,114,115]. It is difficult to fully understand the dynamic change process of the crop spatial pattern only from a certain perspective of natural driving or human driving forces. Therefore, it is necessary to integrate natural socio-economic factors and, at the same time, compare and study the dynamic characteristics of crop spatial patterns in different spatial and temporal scales, so as to truly understand the causes of their dynamic changes.

On the one hand, previous studies have only analyzed the driving mechanism of crop spatial pattern change at the macro-level, without paying attention to the decision-making behavior of farmers, which plays a key role in crop spatial pattern change [116,117]. In fact, the macro-scale spatial pattern of crops is the aggregation and synthesis of farmers' decision-making behavior and process at the micro-level; that is, the macro-scale pattern is the result of the aggregation of micro-processes [118,119]. Due to internal and external factors, different decision makers have different characteristics of adaptability to policy, sensitivity to interests, initiative, adaptability and interaction, which means that the choice or decision-making behavior regarding crops among decision makers shows significant differences, dynamics and correlations, thus leading to changes in the crop spatial pattern [120]. Therefore, in future research of crop spatial pattern change, from the perspective of the human decision-making mechanism, the analysis of crop spatial pattern change caused by the interaction between humans and the natural environment will be a development trend and an angle that warrants special attention [121].

On the other hand, the traditional research will statically analyze the relationship between the driving factors and the change results, assuming that the causal relationship between the spatiotemporal pattern change in crops and its driving factors does not change with time; that is, it posits that the driving factors determine the results of the spatial pattern change in crops [110,122,123]. This kind of research paradigm does not pay enough attention to the time mechanism, and lacks in-depth thinking on the nonlinear, multidimensional, path-dependent and feedback mechanisms of crop spatial pattern change. As shown in Figure 11, due to the multiplicity, dynamic, different time and different place correlations between humans and nature, comprehensive spatial and temporal mechanisms will be a direction of future crop spatial pattern research, so as to better describe and explain the causes, process, results and trends of crop spatial pattern change.
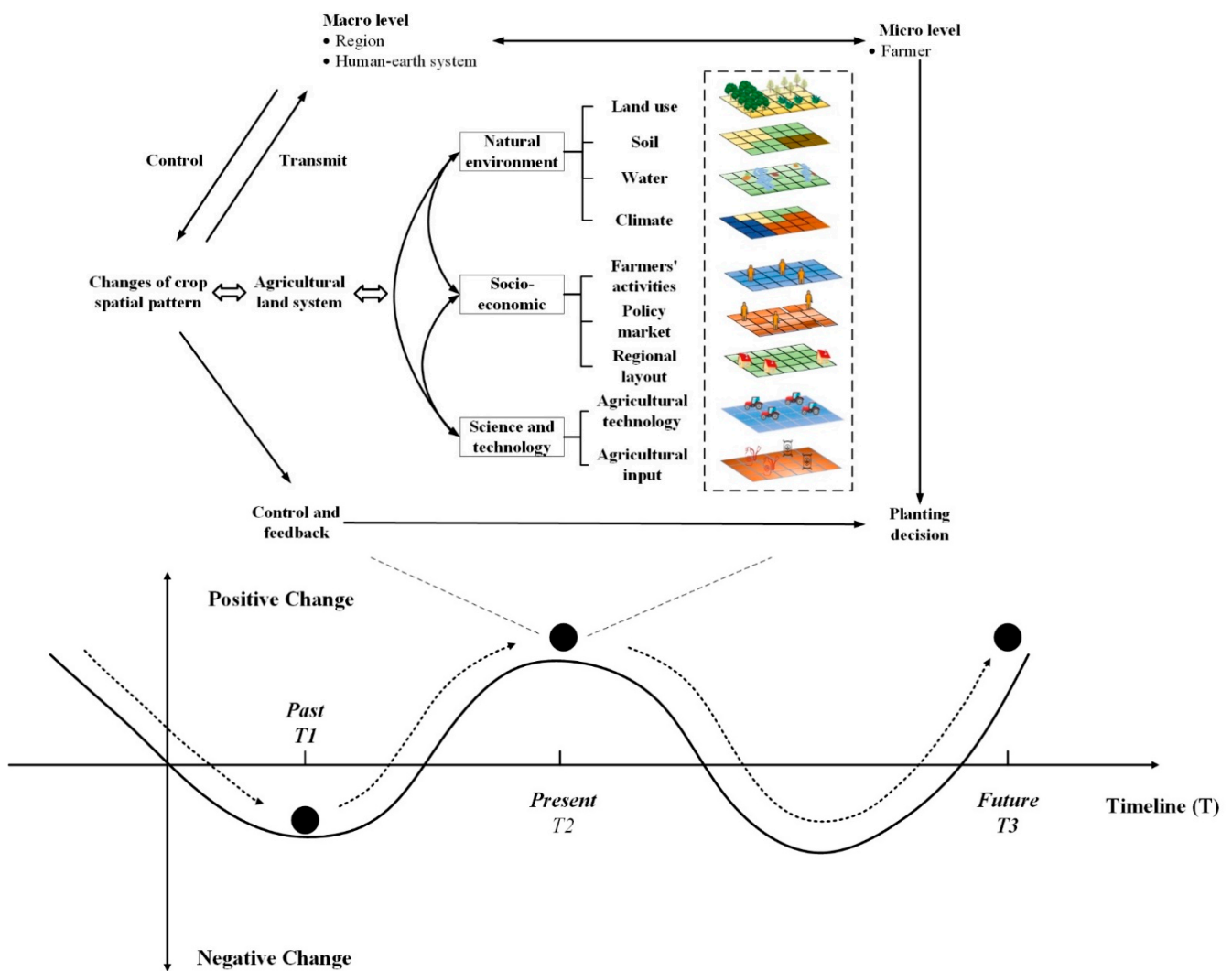
Figure 11. Mechanism chart of crop spatial pattern change.

5. Discussion

5.1. Inspiration of Remote Sensing Cloud Platform to the Research of Crop Spatial Pattern

Since the launch of the first satellite, human beings have accumulated decades of remote sensing data on a global scale [43]. With the rapid development of remote sensing technology, its spatial resolution, temporal resolution, spectral resolution and other technical indicators continue to improve, resulting in a rapid increase in various remote sensing data. At the data level, it has reflected the "5V" characteristics of large volume, variety, velocity, veracity and high value; it has entered an unprecedented era of remote sensing big data [124]. The emerging massive remote sensing data need a large amount of storage and computing resources, but the traditional desktop or server has difficulty meeting this demand. New changes urge us to seek a new scientific paradigm of "remote sensing big data", which emphasizes international cooperation, intensive data analysis, huge computing resources and high-end visualization. The development of remote sensing cloud computing technology and the emergence of platforms provide unprecedented opportunities for remote sensing big data processing and analysis, as follows: (1) there are massive data resources in the cloud, so there is no need to download them for local processing; (2) the cloud provides batch and interactive big data computing services; (3) the application programming interface (API) is provided in the cloud, so it is not necessary to install software locally for processing and analysis. This completely changes the traditional mode of remote sensing data local download, processing and analysis; further reduces

the access threshold of remote sensing data; greatly improves the operation efficiency; accelerates the iterative process of algorithm testing; and makes it possible for the rapid analysis and application of global-scale Earth system science, which is difficult to realize on a desktop or server [125]. After a period of development, many remote sensing cloud platforms have emerged, as shown in Table 3.

Table 3. Major remote sensing cloud platforms.

Platform	Country	Dataset	API	WebSite
Google earth engine (GEE)	U.S.A.	Remote sensing image, terrain data, land cover, weather, precipitation and atmospheric data, population data and some vector data	JavaScript Python	www.earthengine.google.com (5 June 2021)
NASA Earth Exchange (NEX)	U.S.A.	MODIS, Landset, VIIRS, GOES, Sentinel-2, etc.	MATLAB, IDL	www.nasa.gov/nex (5 June 2021)
Descartes Labs	U.S.A.	Remote sensing image, meteorological data, elevation, geographical location, land use data	Python	www.descarteslabs.com (5 June 2021)
AWS	Australia	Landset	C++, Go, Java, JavaScript, .NET, Node.js, PHP, Python, Ruby	www.aws.amazon.com/cn/earth (5 June 2021)
Data Cube	Germany	Landset, Sentinel, MODIS, elevation data, vegetation cover, land cover	Python	www.opendatacube.org (5 June 2021)
CODE-DE	China	Sentinel, Landset, land cover	Python	www.code-de.org (5 June 2021)
Earth Data Miner	China	Sentinel, Landset, land cover, bio ecological data, atmospheric ocean data, basic geographic data and ground observation data, stratigraphy and paleontology data, China biological species list, microbial resources data and omics data	Python	www.earthdataminer.casearth.cn (5 June 2021)
PIE-Engine	China	Landset, Sentinel	JavaScript	www.engine.piesat.cn (5 June 2021)

Being limited to the same sensor makes it impossible to provide the simultaneous interpretation of high-temporal–spatial resolution optical remote sensing data, and the classification method of different remote sensing data has also become a research hotspot. In order to integrate different Sentinel-2 and Landsat data in different temporal and spatial domains, the high-frequency observation of the provincial and even wider surface has been achieved. This gives rise to unprecedented demand for data storage and processing capacity, which can only be realized through cloud computing [4,126]. Figure 12 shows a remote sensing cloud platform framework and application direction.

Based on the cloud platform of Google Earth Engine, Tan Shen et al., used online medium-resolution optical and microwave remote sensing data, innovatively used the method of extracting features by month and histogram size and used a random forest classifier to draw a distribution map of rice planting in Hainan Province in 2016 with a 10 m resolution [127]. Carlos et al., aimed to estimate and map soybean areas in almost real time using temporal series multispectral images and vegetation indices (near-infrared and red) in the Google Earth Engine system in the state of Mato Grosso, Brazil, indicating that

the use of the MODIS images for the monitoring of soybean areas using the Google Earth Engine platform was a viable and promising automated alternative for large-scale soybean area estimates [128]. Shimpei Inoue et al., propose a novel paddy field mapping method that uses Sentinel-1 synthetic aperture radar (SAR) time series that are robust for cloud cover, supplemented by Sentinel-2 optical images that are more reliable than SAR data for extracting irrigated paddy fields [129].
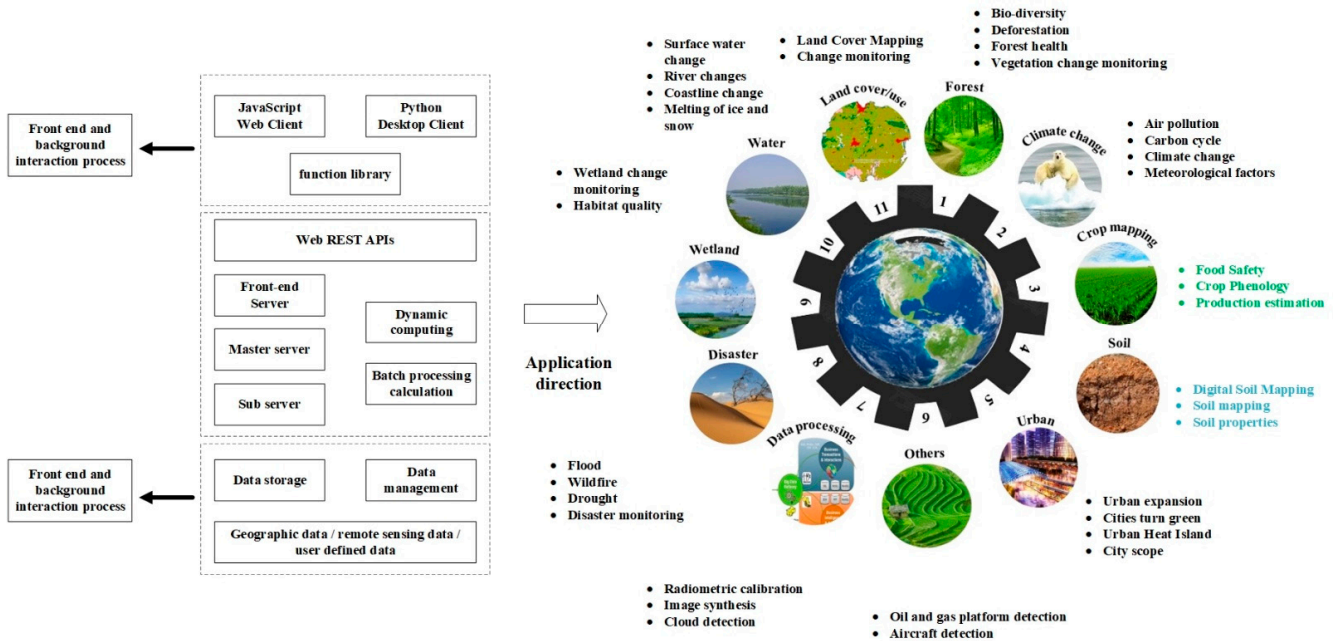

Figure 12. Remote sensing cloud platform framework and application direction.

### 5.2. Future Research Direction for Crop Spatial Pattern Change

In recent years, scholars have conducted much exploration into crop spatial pattern change, and many meaningful results have been obtained. The following aspects can be used as a reference for follow-up research.

5.2.1. The Change Characteristics of Crop Spatial Patterns

As shown in Figure 13, the spatial distribution characteristics of a single crop and the planting system characteristics of multiple crop combinations determine the spatial pattern characteristics of crops to a great extent, which can be obtained by three methods, namely data statistics, remote sensing extraction and spatial simulation [8]. The data statistics can not only obtain detailed information of the quantity and degree of the spatial pattern change in crops within the statistical unit, but also provide other information closely related to it, such as labor costs, machinery input and farmers' willingness [29,130]. However, in the monitoring of large-scale crop spatial pattern change, the use of statistical methods will consume a large amount of manpower, material and financial resources, and is also vulnerable to human factors. As statistical data can only reflect the quantity changes at the level of statistical units, it is difficult to analyze the spatial variability of crop distribution within the statistical unit.

Due to the advantages of speed and accuracy, the remote sensing methods widely used for the observation of Earth also have many problems that need further research in the extraction of crop spatial patterns, such as mixing pixels, scale conversion, "the same object with different spectrum" and "foreign object with the same spectrum" [131]. Simple remote sensing image classification methods are difficult to apply to the identification of large-scale spatial crop species, and it is difficult to obtain the characteristics of the dynamic changes in crop spatial patterns [132]. Through the formula of a series of natural factors, including climate, topography and soil, needed in the process of crop growth,

the model was constructed to simulate and analyze the spatial pattern information of crops. However, social and economic factors such as planting habits, prices of agricultural products and agricultural policies closely related to the real spatial distribution of crops are not sufficiently taken into consideration [133].
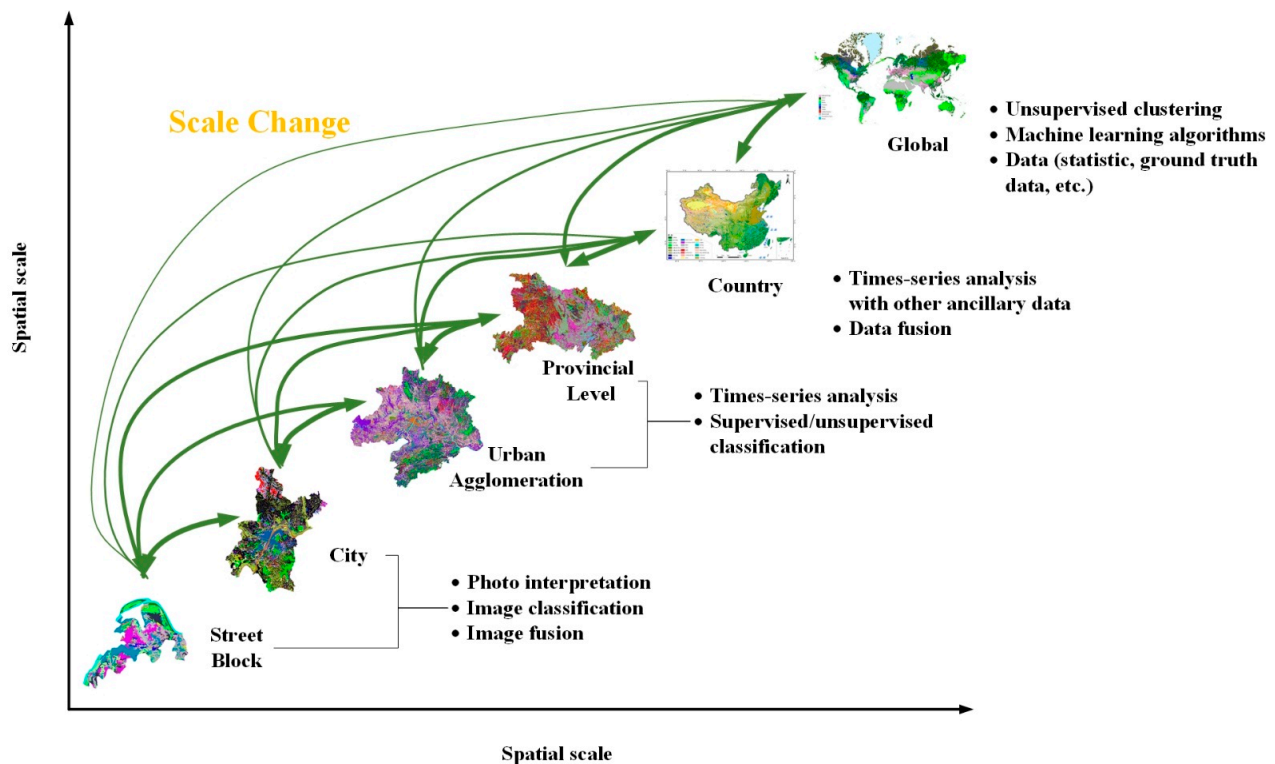
Figure 13. Data processing methods for different spatial scales.

The occurrence, function and evolution of the crop spatial pattern change process at different scales affect the actual rate and spatial distribution of crop spatial pattern change, which makes the composite method based on multi-scale and multi-information source data fusion an important research direction of crop spatial pattern dynamic change characteristics [134]. The differences in scale, accuracy and collection methods between different data sources will affect the application process of multi-source data. Therefore, the characteristics of multiple data information can be fully utilized to realize complementary advantages, make up for the defects of single remote sensing data and classification methods and improve the accuracy of information acquisition and analysis [135]. For example, the classification rules and systems adopted by different remote sensing data sets may be different, and the crop area obtained from remote sensing data may not be consistent with the number of crop areas obtained from statistical data. In the study of crop spatial distribution, data mutual verification and reducing data differences can not only help data users choose appropriate data products according to their research purposes and regions, but also provide feedback for data producers, so as to promote the improvement of the data processing algorithm and better serve future crop spatial distribution mapping.

5.2.2. Simulation of Crop Spatial Pattern

The spatial patterns of crops can reflect many service functions contained in the agricultural land system, such as the circulation of nitrogen, phosphorus and potassium nutrients, food security, farmland carbon storage and landscape service, and also reflect the situation of the human utilization of agricultural production resources in a certain space [118]. The spatial pattern of crops is an important basis for the adjustment and optimization of crop structures. Therefore, it is of great practical value and important

scientific significance to carry out research on the process and characteristics of crop spatial pattern change.

In the agricultural land system, cultivated land is the most important carrier of agricultural land use, which provides the necessary natural ecological environment for the growth, development and maturity of crops [120]. Affected by many factors, the spatial pattern of crops is changing constantly, including the land use types of cultivated land, forest land and grassland, etc., which are in the process of dynamic change, and also include the alternation or transformation of different crops in the cultivated land [136]. Therefore, the premise of the change in the spatial pattern of crops was analyzed by the simulation of the dynamic change in the spatial pattern of cultivated land, because the change in cultivated land will affect the change in the spatial pattern of crops. Based on this idea, on the basis of the CLUE-S model (conservation of land use change and its effects), this study proposes a model based on farmers' decision-making behavior. At the first level, the dynamic change process and state of cultivated land spatial patterns can be expressed by simulating the dynamic change among different land use types. At the second level, based on the output of the cultivated land spatial pattern from the first level, the change in the crop spatial–temporal pattern was simulated by expressing the effect of natural factors and socio-economic factors on farmers' land use behavior. The internal factors mainly include the age structure, population structure, education level, family income and business scale, while the external factors mainly include climate change, policy, market, economic development level, changes in regional layout, interaction among farmers and path dependence [137–139]. Internal factors are the fundamental factors (wishes and ability) that determine farmers' decision making, while external factors are the specific basis of farmers' decision making.

In a certain "natural–social–economic" environment, different crops will show different yields and prices, which will greatly affect farmers' decision making and lead to changes in crop spatial patterns [140]. In the process of building the model, the feedback and correlation between different spatial scales cannot be ignored. For example, if individual farmers all choose the same crop planting method, it may lead to the saturation or surplus of agricultural products in the regional or higher-level regional market; then, the optimal crop selection at the farmer level will no longer be the optimal choice, and its crops may change with it. In addition, crop demand on the regional scale cannot be realized due to the limitation of land resources and the unsuitable site conditions on the micro-scale, which may lead to changes in and adjustment of crop spatial patterns on the micro-scale in other regions [141]. Generally speaking, the "natural–social economy" comprehensive scenario will derive new natural environment constraints, policy management measures, etc., which will continue to affect farmers' behavior, thus forming a closed feedback mechanism within the "human–nature" system, and finally realizing the dynamic simulation process of "farmers' behavior—agricultural crop spatial–temporal pattern—natural–social comprehensive scenario—farmers' behavior" [142]. The simulation of crop spatial pattern change aimed to summarize the practical problems in the land change system into corresponding mathematical problems.

As shown in Figure 14, with the help of the computer simulation model, we could analyze the rate, quantity and spatial characteristics of crop spatial pattern change from a qualitative or quantitative point of view; explain its change process and mechanism; and explore the possible change trend under different scenarios in the future, so as to inform a realistic management decision.

Level 1: Simulation of dynamic change of cultivated land pattern

Level 2: Dynamic simulation of crop pattern considering farmers' behavior

Level 3: Temporal and spatial pattern changes of crops caused by behavioral outcomes

Land use pattern change

Woodland | Cultivated land | Grassland | Construction Land | Water | Unused land

Farmers' decision making process

Individual characteristics of farmers
- Education | Age | Income
- Scale | Technology | Capital
- Risk preference | Etc.

Farmers' utilization behavior
- Direct investment: labour, Energy, Resources
- Indirect investment: Education, Technology, Life

Socio-economic drivers
- Population change
- Policies and rules
- Industrial structure
- Technical change
- Economic development level
- Economic system
- Fiscal policy
- Etc.

Results of farmers' behavior

Farming or not
- By self
- Not by self
- Transfer (in or out)

Crop Choice
- Rice
- Wheat
- Soybean
- Maize

Intensification
- Varity
- Management

Dynamic change of crop spatial and temporal pattern

Figure 14. Simulation framework of crop spatial patterns considering individual decision behaviors of farmers.

6. Conclusions

The purpose of this paper was to introduce the progress path, research hotspots and potential research directions in the CSP field formulated on the bibliometric method. Therefore, initial data were gathered together from the Web of Science Core Collection^{TM} (WoS), and 5356 related publications were acquired following data cleaning. In addition, further courses in relation to the present status, which were inclusive of publication trends, foremost journals, top authors, top institutions and main country or region, were carried out.

On the basis of the bibliometric analysis, key results are as follows: (1) the number of publications in the CSP domain has increased gradually in the period of 2005–2020; (2) 895 journals and proceedings incorporated publications regarding CSP, in which approximately 18.66% of the publications were published in 1.12% of the journals, and the *Indian Journal of Agricultural Sciences* was ranked in top place as per the number of published articles; (3) according to Price's law, 264 authors were core authors, while 15,702 authors were involved; (4) this paper discusses the current research progress of crop spatial patterns and the advantages and disadvantages of the methods from four aspects: crop planting area monitoring, multiple cropping monitoring, crop planting modes, and the mechanism of crop spatial pattern change; (5) this paper discusses the future development direction from three aspects of the crop spatial pattern research mechanism, crop spatial pattern change characteristics, and crop space pattern simulation, so as to provide corresponding support for interested researchers.

In short, in recent years, many scholars have carried out a large amount of research on the characteristics, mechanism and simulation of crop spatial pattern change, and have made great progress in theory and practice. The relevant work has played an important role in providing decision support for government departments. It is undeniable that, in essence, the spatial pattern of crops is a complex problem of the interaction between humans and environment, and its scientific research is still facing many difficulties and challenges. For example, the automatic extraction of crop spatial pattern information from remote sensing images has been a desired goal of scholars for a long time, but the effect of the automatic extraction of remote sensing information is not satisfactory at present. Realizing the automation and refinement of crop spatial pattern extraction can greatly improve the accuracy and efficiency of crop spatial pattern monitoring, and will provide stronger support for national economic construction. To solve these complex scientific problems, it is urgent to comprehensively consider the complex relationship between humans and land from a more systematic perspective in follow-up research. Therefore, the comprehensive research based on remote sensing big data, multi-scale, multi-model and high precision will be an important direction of crop spatial pattern research in the future.

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