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# Exploring the Technological Changes of Green Agriculture in China: Evidence from Patent Data (1998–2021)

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**Abstract:** China views the development of sustainable agriculture as a crucial aspect of agricultural development. Using green agriculture patents from 1998 to 2021, this paper analyzes the spatial and temporal distribution of patent numbers and investigates the IPC co-occurrence network. The findings are as follows. First, the number of patents for green agriculture in mainland China has increased significantly. From 2010 to 2015, the number of patents reached its highest point. Second, the spatial distribution of green agriculture patents is quite uneven, particularly in Heilongjiang province, which has the largest grain production and the lowest patent output level. Third, while the majority of IPC subclasses are well-developed, some are unevenly developed. In China, popular fields include seed breeding, planting, and organic fertilizers. This research aims to present empirical evidence for the future layout of green agriculture in China and the development of green agriculture in other developing countries.

**Keywords:** mainland China; agriculture green patents; IPC co-occurrence; SNA; coupling coordination degree



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## 1. Introduction

Since the industrial revolution, human economic activity has been characterized by the widespread use of large amounts of fossil energy (e.g., coal and oil), resulting in a significant increase in energy consumption and $CO_2$ emissions, with the result that the global greenhouse effect is increasing [1]. By the middle of the 21st century, the global population is expected to exceed 9 billion and will continue to grow [2]. Stimulated by both energy and environmental pressures and population pressure, agricultural development is an issue that every country should focus on at this stage [3]. On the one hand, agricultural production accounts for about 20% of global $CO_2$ emissions, making it the third largest contributor to climate change after the energy (35%) and industrial (21%) sectors [4]. On the other hand, agriculture is a huge carbon-neutral system [5], with significant potential to reduce $CO_2$ emissions through its role in carbon sequestration [6]. Further, green agriculture is a new mode of modern agriculture [7]. Actively developing green agriculture is of great significance to ensuring food security and promoting sustainable development in both social and economic terms [8,9]. Therefore, how to achieve green and low-carbon development of agriculture is a hot topic of concern for many scholars at present [10]. In September 2020, China set a clear target of reaching "peak carbon" by 2030 and "carbon neutrality" by 2060 [11]. At the same time, as a major agricultural country, China feeds 18% of the world's population on only 8% of the planet's arable land [9]. Studying the current status of China's agricultural green development can first provide empirical evidence for China's future technology layout. For example, technologies in soil improvement should be enhanced. Second, it can provide implications for other countries when developing green agriculture. For example, other developing countries can strengthen technologies such as seed breeding, planting, and organic fertilizers to achieve food security and low-carbon goals [12].

A review of the existing literature reveals that the vast majority of scholars agree that the support of science and technology innovation is indispensable to achieve green development in agriculture [13], but since they choose different indicators when evaluating science and technology innovation, we can divide them into two categories: The first category uses scientifically published data for research [14]. For example, Long et al. (2018) [15] compared the environmental efficiency of different regions by using the intensity of fertilizers used in the agricultural sector and found that strengthening autonomous innovation in agriculture reduced the intensity of $CO_2$ emissions. Xu et al. (2019) [16] measured the efficiency of agricultural development in 31 provinces in China from 1998 to 2016, by using agricultural carbon emissions as the non-desired output and green total factor productivity as the basis. Liu et al. (2021) [17] applied the kernel density estimation method to study the dynamic evolution of green total factor productivity in China's agriculture, using data on agricultural output values and the amount of pollution emissions, and found that green total factor productivity in China's agriculture differed significantly among provinces. Liu and Wang (2022) [18] established an evaluation system for the green brand competitiveness of agricultural products in China by using the indicator construction method, and explored the differences in green competitiveness caused by agricultural agglomeration in different regions. Chen et al. (2022) [19] used data on fertilizer intensity and farmers' economic income in each province, to construct a GAD index system to explore the spatial correlation of agricultural green development in each province in China. The second type of research was conducted using alternative methods of patent indicators [20]. For example, Ferrari et al. (2019) [21] used patent data for social network analysis to explore the impact of plant biotechnology development on the environment. Zheng et al. (2020) [22] used a social network analysis of patent data on composting technology to derive a possible trajectory for organic fertilizer development in China. Liu et al. (2021) [23] measured the level of agricultural technology innovation in China through the number of rural patents, while considering the impact of rural finance on sustainable agricultural development. Aldieri et al. (2021) [24] analyzed productivity in agriculture in the US and Europe, using patent application data and relevant environmental quality indicators. Häggmark and Elofsson (2022) [25] concluded that there are differences in the contribution of R&D efficiency to patent growth by comparing trends in patent filings in agriculture, forestry, and other sectors in the private and public sectors in six large countries, and extend the positive impact that public sector innovation plays on other sectors.

The existing research on green agricultural development has already produced a wealth of research results, but there are also certain limitations. On the one hand, there are relatively few academic results using agricultural green patent data, and most scholars base their research on macrolevel indicators to construct a comprehensive evaluation system, such as the level of agricultural economic development [26], the use of water resources by agricultural activities [9], and ecosystem maintenance [27]. There is also some literature which uses all agricultural patents for analysis [28], rather than studies conducted only on green patents, making some patent information insufficiently exposed and which is not conducive to providing academic bases for relevant departments. On the other hand, the existing studies using agricultural green patent data are mostly limited to a single part of agricultural production and cannot fully reveal the development of all agricultural green patents, nor can they uncover the core technologies in agricultural green patents. For example, Liu et al. (2022) [29] identified more detailed patent identification methods and gaps for future research, by examining the criteria for identifying and classifying slow-release and controlled-release fertilizers and the patent examination process. Hamm et al. (2020) [30] identified distributional characteristics and developmental differences in patent assignees, based on an analysis of global assignment data for pesticide and insect repellent patents. Jin et al. (2021) [31] mapped technological knowledge through the IPC co-occurrence matrix and provided technological suggestions for the future development of innovative agricultural robots. The mining of core technologies is now generally carried out by identifying the International Patent Classification (IPC) information of patents and thus building co-occurrence networks [32,33]. Based on this, in order to study the development trend of agricultural green patents in China, the direction of core technologies must be discovered, and then, applicable suggestions made for the future development. In this paper, we use the social network analysis (SNA) method to construct an IPC co-occurrence network, using agricultural green patents in mainland China from 1998 to 2021 as the research objects.

RQ1 : What is the temporal development of green patents in agriculture?
RQ2 : Is the spatial distribution of green patents in agriculture balanced?
RQ3 : What is the development of core technologies of green patents in agriculture?

The main contributions of this paper are: First, this paper focuses the research object on agricultural green patents, broadening the perspective of agricultural green development, which can provide a theoretical basis for the Chinese government to achieve agricultural emission reduction. Second, this paper constructs an IPC co-occurrence network, reveals the core technologies, and technology integration of green agriculture in China. Third, the degree of coordination in the development of core technologies is analyzed to prove whether the co-occurrence network in the earlier period will affect the later period. It can provide a basis and suggestions for the development of existing key technology areas in Chinese green agriculture. The subsequent structure of this paper is as follows: Section 2 introduces the data sources used, the methodology used, and the relevant indicator settings; Section 3 presents the main findings of this paper; and Section 4 concludes the paper and makes corresponding policy recommendations.

## 2. Data and Methods

### *2.1. Data*

This paper builds a technology network using patent IPC subclass information to expose the development of green agriculture in China and to reveal the core technologies involved. The data used in this paper are from the National Intellectual Property Administration, PRC (CNIPA), and include both granted inventions and utility model patents in mainland China. The above data were chosen because granted patents have a higher value than rejected or withdrawn patents [34], and designs are clearly not green patents [35]. The time span of the study is 1998–2021. When it comes to the statistics of the number of patents per year, the filing year is used [36,37]. The reason for using the year of application instead of the year granted is that it takes 3–5 years for a patent to go from application to being granted [34]. This has led to a sudden and significant drop in the calculation of the number of patents in recent years, affecting our discussion of the innovative capacity of Chinese green agriculture at different periods. Subsequent presentations involving time or years are counted in this paper using the application year. The study's starting point is 1998 because it is the first full year of the implementation of the "promoting agriculture through science and education" policy [38], which led to a significant increase in agricultural patents after 1998. The year 2021 is the latest full publication year of CNIPA, so this paper sets this year as the end of the study. The data selection and specific cleaning process are shown in Figure 1.

There is no official list of IPCs for agricultural green patents in China, and they are mainly defined by some scholars in the literature [39]. Therefore, based on the reliability and availability of data, this paper identifies the main IPC information based on the list of agricultural green patents listed by the World Intellectual Property Organization (WIPO) in the AGRICULTURE/FORESTRY category (https://www.wipo.int/classifications/ipc/green-inventory/home (accessed on 27 May 2022). Table 1 lists the IPC information and the industries it represents. It is important to note that the subsequent analysis in this paper is based on the IPC subclass [33].

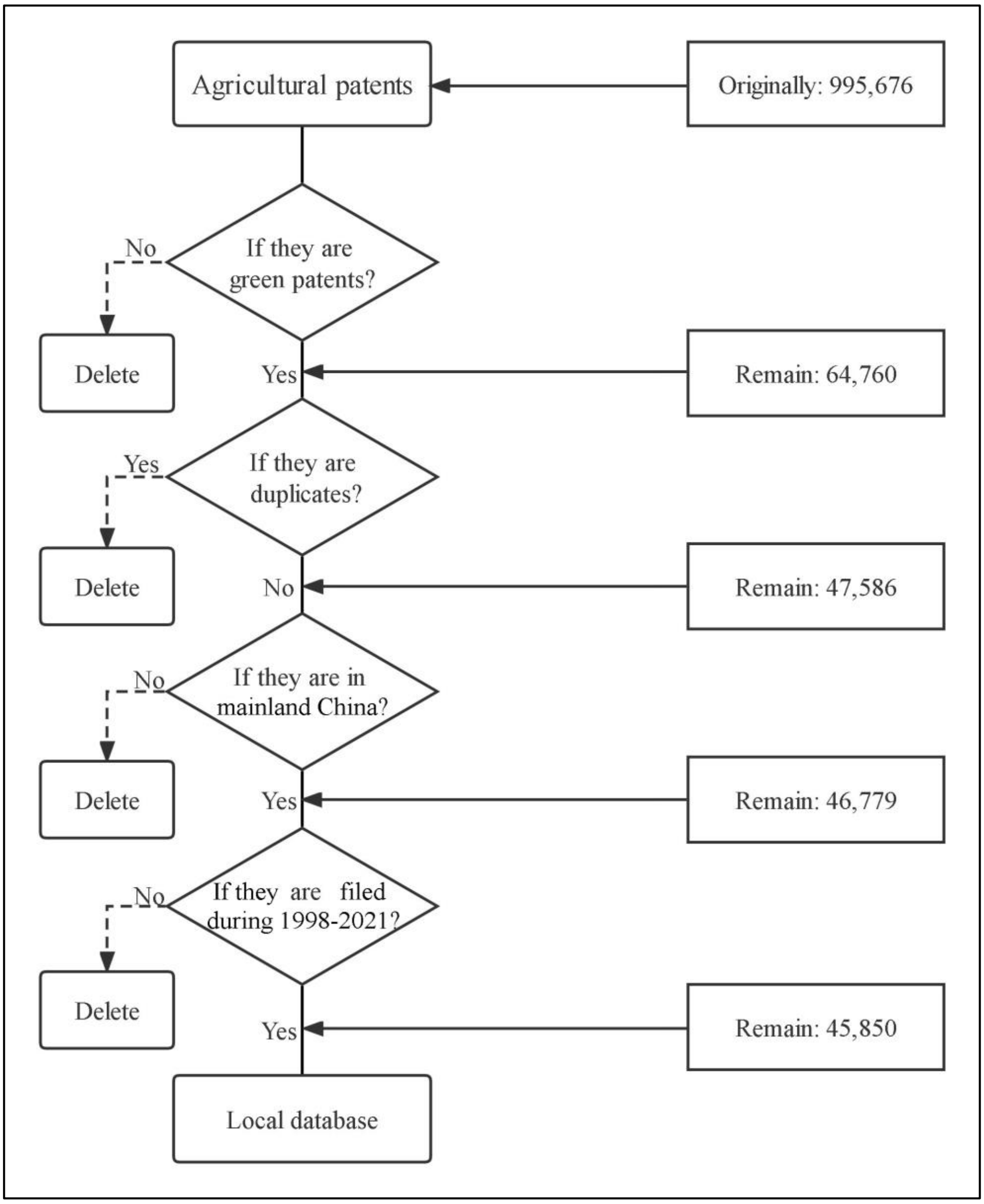


**Figure 1.** Data filtering process.

**Table 1.** The number of green agricultural patents in China (accumulated for 1998–2021).

| IPC Subclass | Descriptions | No. of Patents |
|---|---|---|
| A01G | Horticulture; cultivation of vegetables, flowers, rice, fruit, vines, hops or seaweed; forestry; watering | 21,838 |
| A01N | Biocides, e.g., as disinfectants, as pesticides, or as herbicides; pest repellants or attractants; plant growth regulators | 511 |
| C05F | Organic fertilizers not covered by subclasses C05B, C05C, e.g., fertilizers from waste or refuse | 11,296 |
| C05G | Organic fertilizers | 9635 |

**Table 1.** *Cont.*

| IPC Subclass | Descriptions | No. of Patents |
|---|---|---|
| C09K | Soil-conditioning materials or soil-stabilizing materials | 114 |
| E02D | Improving soil for agricultural purposes a01 | 2456 |

### *2.2. Methods*

First, in order to describe the size and growth of green agricultural patents in mainland China, this paper investigates the growth rate [40,41], which is calculated as shown below:

$$lny = a + bt \tag{1}$$

where $y$ is the number of patents and $t$ is the number of years. The fitted equation is first obtained by transforming the logarithm of $y$ for each year, and then the coefficient $b$ in the fitted equation is considered to be the growth rate of the number of patents obtained. For each equation, it provides an indicator $R^2$ to reflect the fit of the model. The higher the value of $R^2$, the better the model fit.

Second, this paper uses the SNA method to make the IPC co-occurrence matrix, where each node represents an IPC subclass [42,43]. As each patent contains information on at least one IPC subclass, some patents belong to multiple categories of IPC subclass at the same time. By identifying the IPC information of multiple categories, this paper counts the frequency of connections occurring between nodes and nodes as the weight of the linkage, thus constructing a patent co-occurrence network for each period. The network-level analysis metrics can reflect the structural characteristics of the network. The meanings represented by the indicators used in this paper are shown in Table 2 below.

**Table 2.** Key concepts of network indicators.

| Level | Indicators | Descriptions |
|---|---|---|
| | density | the ratio of direct connections in a network to total numbers of possible connections |
| network | average path length | the average value of the distance between any two nodes |
| | global clustering coefficient | the number of closed triplets (or 3 triangles) over the total number of triplets (both open and closed) |
| | degree centrality | the number of edges directly connected to the node |
| | betweenness centrality | the betweenness centrality for each vertex is the number of these shortest paths that pass through the vertex |
| node | constraint | measures the extent to which a node is restricted by its social network |
| | effective size | the more each node is disconnected from other primary contacts, the higher the effective size would be |
| | local clustering coefficient | a proportion of the number of links between the vertices within their neighborhoods, divided by the number of links that could possibly exist between them |

Third, the paper uses the entropy method to construct comprehensive scores for the core IPC subclass over time [44]. The social network indicators in Table 2's node section will be used to build the entropy method's indicators, which will be used to evaluate the key technologies of green agriculture patents in a comprehensive way. The specific calculation process is shown below.

The first step is indicator selection: if there are m IPCs and n indicators, the j-th indicator of the i-th IPC (i = 1, 2, ... , m; j = 1, 2, ... , n) is selected. The second step is standardizing the indicators: to solve the problems caused by the different units. The corresponding nondimensionalization is needed to convert the absolute values of the indicators into relative values, such that $q_{ij} = \left|q_{ij}\right|$, thus solving the problems caused by the different levels of the indicators between different data. As the values of positive and negative indicators represent different meanings (the higher the positive indicator value, the better, and the smaller the negative indicator value), different algorithms are needed to standardize the data for different indicators.

Positive indicators:

$$q_{ij} = \frac{q_{ij} - \min\left\{q_{1j}, \ldots, q_{mj}\right\}}{\max\left\{q_{1j}, \ldots, q_{mj}\right\} - \min\left\{q_{1j}, \ldots, q_{mj}\right\}} + 0.001 \tag{2}$$

Negative indicators:

$$q_{ij} = \frac{\max\left\{q_{1j}, \ldots, q_{mj}\right\} - q_{ij}}{\max\left\{q_{1j}, \ldots, q_{mj}\right\} - \min\left\{q_{1j}, \ldots, q_{mj}\right\}} + 0.001 \tag{3}$$

In the third step, determine the weight of the i-th IPC for the j indicator: $p_{ij} = \frac{q_{ij}}{\sum_{i=1}^{m} q_{ij}}$. In the fourth step, calculate the entropy value of the j indicator: $e_j = -k\sum_{i=1}^{m} q_{ij}\mathrm{Ln}(p_{ij})$ where $k = \ln(m)$ represents the reconciliation factor, and ensure that $0 < e_j < 1$. In the fifth step, calculate the information utility value of the j indicator: $d_j = 1 - e_j$. The larger the information utility value $d_j$, the greater the importance of the indicator. In the sixth step, the weight of the j-th indicator is calculated: $w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$. In the seventh step, calculate the composite score for the i-th IPC: $S_j = \sum_{j}^{n} w_j p_{ij}$.

Finally, this paper explores the interactions between the IPC co-occurrence matrix at different periods by using a coupling coordination model [45]. In physics, coupling refers to the phenomenon of two (or more) systems or forms of motion influencing each other through various interactions [46], and the degree of coupling is mostly used to describe the extent to which the interactions between systems or elements affect each other, determining the structure to which the system will move when it reaches a critical value. In this paper, it is used to represent the interactions between the core IPC in four periods. The specific calculation process is shown below:

$$C_i = 4 * \left\{ \frac{S_{1i}(\alpha) * S_{2i}(\beta) * S_{3i}(\chi) * S_{4i}(\delta)}{\left[S_{1i}(\alpha) + S_{2i}(\beta) + S_{3i}(\chi) + S_{4i}(\delta)\right]^4} \right\}^{\frac{1}{4}} \tag{4}$$

$$D_4 = \sqrt{C_4 * T_4} \tag{5}$$

$$T_4 = e * S_{1i}(\alpha) + f * S_{2i}(\beta) + g * S_{3i}(\chi) + l * S_{4i}(\delta) \tag{6}$$

where $D_4$ represents the CCD of the core IPC in the four periods; $T_4$ is the composite coordination indicator of the core IPC in the four periods, reflecting the degree of synergy and the development of each IPC in the four periods; and e, f, g, and l are coefficients to be determined, taking values of 0.2, 0.2, 0.2, and 0.2.

## 3. Results

In this section, the temporal distribution characteristics of the patents are first described, followed by the construction of a patent co-occurrence network. Finally, a comprehensive evaluation is given by using the entropy value method and the coupling coordination degree method.

### *3.1. Temporal Distribution of Agricultural Green Patents*

According to CNIPA data, the scale of the number of agricultural green patents in mainland China has generally achieved good growth results, but there are also relatively obvious stage differences. Figure 2 shows the trend of development in four periods. Period 1 has a high growth rate but is limited by the small size of the starting year, resulting in a relatively flat growth curve. Period 2 has the highest average growth rate and accumulates a high number of patents. Period 3 saw a peak in the number of patents, but there were also instances of negative growth. By period 4, there is a general downward trend in the number of patents, which may be due to the time delay between patent application and grant [47]. In addition, technology iteration also requires a certain amount of time for R&D reserves.

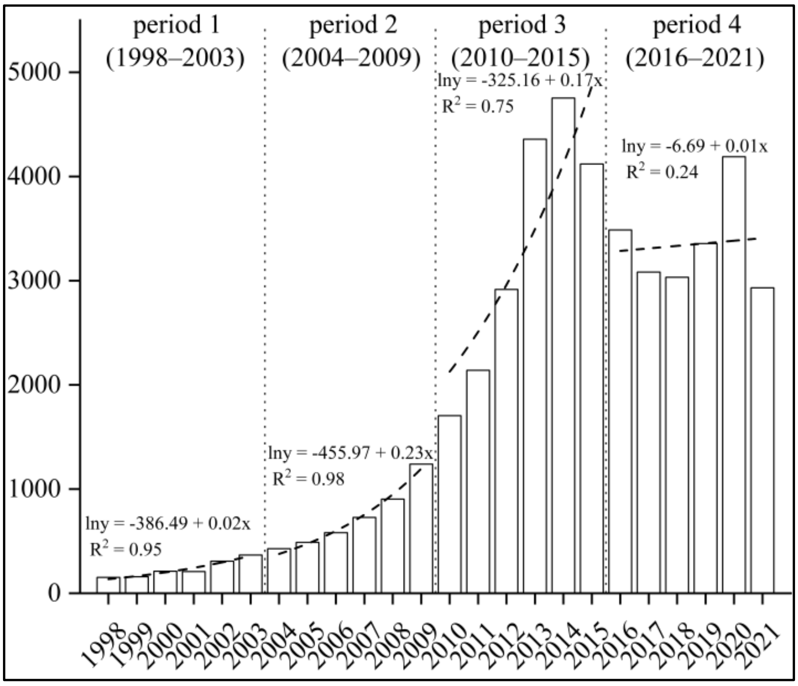


**Figure 2.** Trends in the number of patents at time latitude.

Based on the IPC classification principle, a patent may be given more than one classification number. This paper counts the number of classification numbers each patent has and calculates the percentage of different numbers to the total number of patents. Figure 3 shows the time evolution of the percentages. In general, the percentage of patents with multiple IPC subclasses is increasing, indicating that the convergence of technologies in multiple fields is the trend of patenting at this stage. Specifically, in period 1 (1998–2003), the percentage of patents with only one IPC subclass showed a clear decreasing trend, indicating that technologies in different fields had begun to combine; in period 2 (2004–2009), the percentage of patents in multiple IPC subclasses decreased as the number of patents was acquired in large numbers, probably due to the fact that the technological breakthroughs made during this period occurred mainly in a single field. This trend continued into period 3 (2010–2015), and, as can be seen from the graph, the proportion of patents with only one IPC major category gradually grew to around 55% over time. By period 4 (2016–2021), 57% of all patents have at least two IPC subclasses, indicating that over time there has been a convergence of technologies from different fields in agricultural green patents.

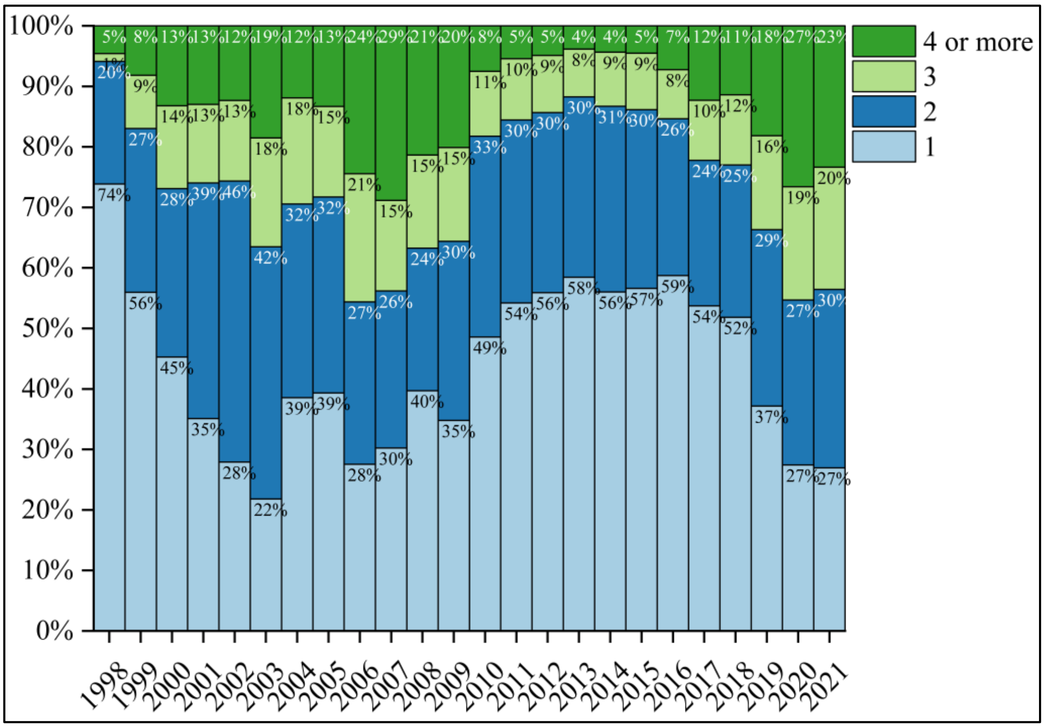


**Figure 3.** Trends in the number of IPC subclasses included in the patents.

Figure 4 illustrates the trends of five IPC subclasses that appear most frequently in the granted patents. It is found that the number of IPCs appearing in the WIPO list, such as A01G, C05F, and C05G, fluctuates considerably, representing a high degree of variability in these technology areas. However, the IPC subclasses for non-green agriculture types such as "foundations; excavations; fills; underground or submerged structures" (E02D) and "planting; seeding; fertilizing" (A01C) show a relatively stable trend. The peak for C05F occurred in period 4 (2016–2021) and remained relatively flat during period 1 (1998–2003) to period 3 (2010–2015), indicating that this category of IPC has been a relatively popular technology area and it became more popular in period 4. The number of patents of C05G shows a consistent downward trend in period 4, indicating that this type of IPC subclass is gradually fading out of the popular field.

This paper argues that the presence of multiple IPC subclasses in green agricultural patents is more indicative of technological convergence. In addition, the patentee characteristics of these patents are more indicative of instances of technological convergence. Table 3 presents the contributions of various innovation subjects to the number of patents containing multiple IPC subclasses, as well as their average growth rates for each period. Table 3 reveals that firms hold the greatest number of patents, followed by individual inventors and universities. Specifically, the leading patent owners during periods 1 and 2 were individual inventors, followed by firms and universities in roughly equal proportions. In period 3, however, firms accounted for nearly half of all patents, and universities outnumbered individual inventors. During period 4, the majority of patents originated from firms, which also experienced the highest average growth rate of the three entities. This suggests that the majority of green agriculture patents' technological convergence occurs within the innovation practices of firms. In order to promote the convergence of multiple technologies, the government should prioritize fostering an innovation-friendly environment for firms in order to increase their technology conversion rate. By the change in growth rate, it is evident that the fluctuation of firms is less pronounced than that of individuals and universities. This suggests that individual inventors and universities are less competent in their innovation of green agriculture patents, whereas corporations are more reliable. Therefore, it is necessary to enhance the innovation capacity of both individual inventors and universities.

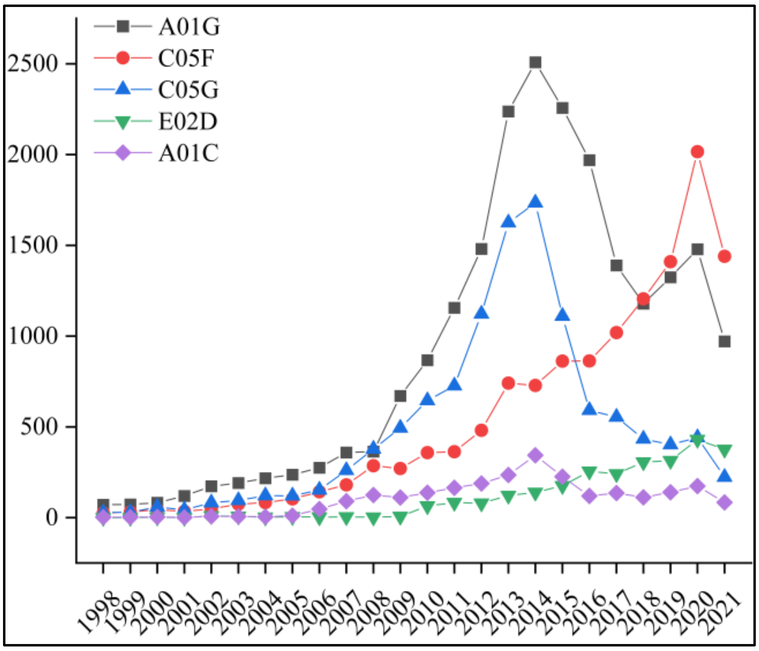


**Figure 4.** Trends of five IPC subclasses that appear most frequently.

**Table 3.** The number and average growth rate of multiple IPC subclass patents for different applicants.

| Types | Period 1 (1998–2003) | | Period 2 (2004–2009) | | Period 3 (2010–2015) | | Period 4 (2016–2021) | |
|---|---|---|---|---|---|---|---|---|
| | **No.** | **Growth Rate** | **No.** | **Growth Rate** | **No.** | **Growth Rate** | **No.** | **Growth Rate** |
| Individuals | 323 | 28% | 679 | −17.8% | 1000 | 8% | 1072 | 7% |
| Firms | 109 | 31% | 604 | 39% | 2395 | 16% | 3602 | 21% |
| Universities | 136 | 45% | 727 | 27% | 1547 | 11% | 1273 | 17% |

### *3.2. Evolution of Agricultural Green Patents in China in Spatial Distribution*

Unlike other sectors, agriculture depends to a large extent on topographical, soil, and climatic factors, as well as on socioeconomic factors such as irrigation, motorization, farming methods, and the supply and demand for agricultural products. Differences in these factors have led to heterogeneity in agricultural production in different regions [12]. At the same time, this may also lead to differences in the number of agricultural green patents in different regions, so in this section this paper explores the evolutionary process of the spatial distribution of agricultural green patents. Figure 5 shows the evolution of the number of patents granted by each province over four periods.

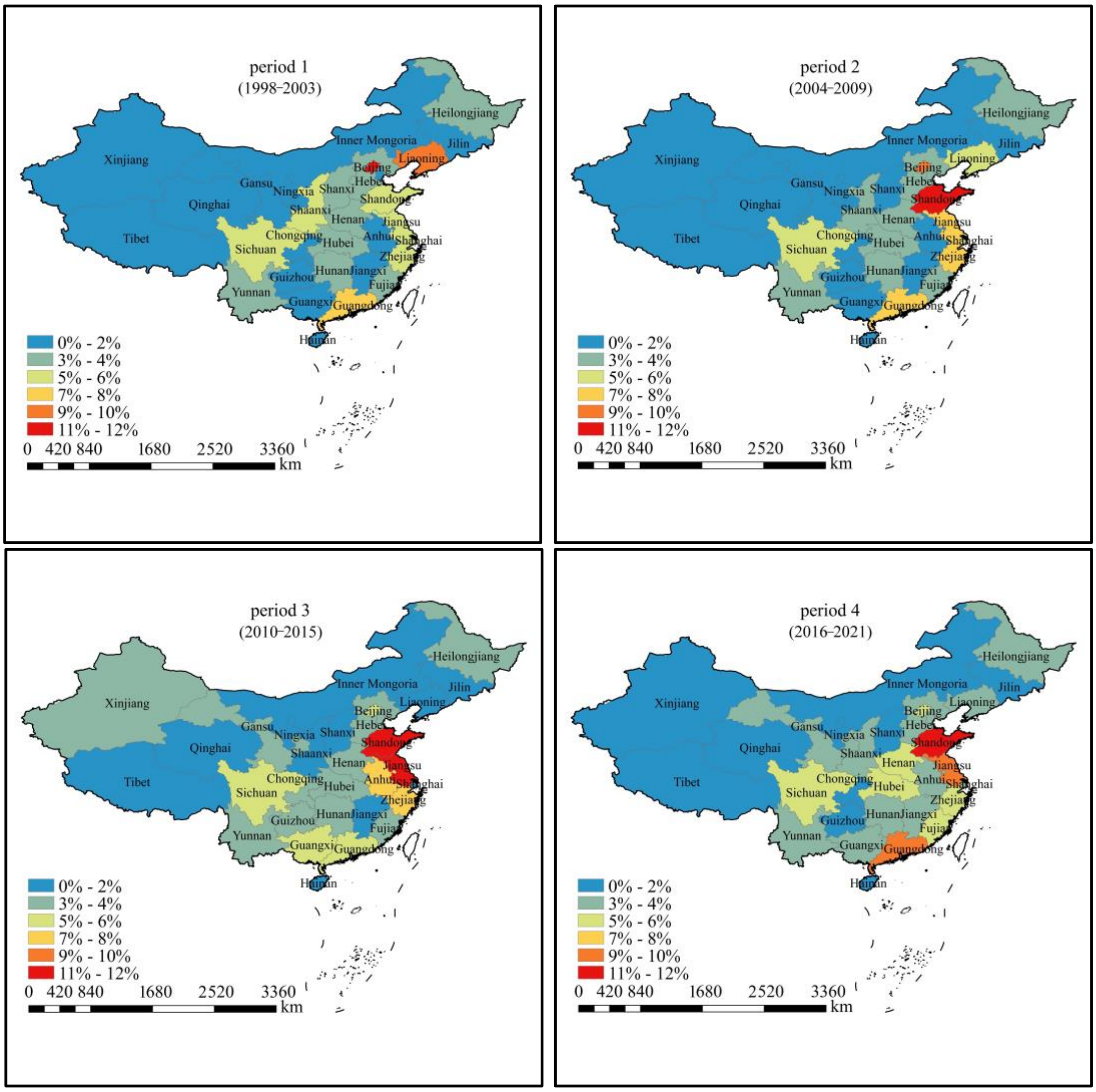


**Figure 5.** Spatial evolution of green agricultural patents in four periods.

It can be seen that there are heterogeneous differences in mainland China, showing an uneven pattern of "strong in the east and weak in the west, strong in the south and weak in the north". In other words, China's green agriculture patents are more distributed in the better-developed regions. Since innovation capacity is highly correlated with the level of economic development, which affects green development performance [48], it may lead to the uneven distribution of green agricultural patents in China. Furthermore, while regions with high levels of economic development in China tend not to rely on the primary sector as their main industry, they occupy more energy, arable land resources, and water resources [49]. Specifically, the share of northwestern China (such as Xinjiang, Gansu, Qinghai, Ningxia, and Shaanxi) is generally low. The overall share of northeastern China (such as Liaoning, Jilin, and Heilongjiang) is initially high but gradually decreasing over time. The overall share of eastern China (such as Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, and Guangdong) is gradually increasing. In addition, southwestern and central China have almost remained unchanged. The share of Gansu, Fujian, and Hubei provinces has increased over time, while the share of Anhui, Shaanxi, and Liaoning provinces has been decreasing over the previous three periods. The number of agricultural green patents in Heilongjiang province, the region with the highest grain production in China, has maintained a 3–4% share over the four periods. In contrast, Henan and Shandong provinces, which produce relatively little grain, have increased to 5% and 11%, respectively. This indicates that the development of green agriculture in Heilongjiang province has been stagnant and has not progressed as fast as the remaining two major grain-producing provinces.

### *3.3. Social Network Analysis of IPC Co-Occurrence*

In order to explore in which broad categories of IPC technology convergence is taking place, this section describes the visualization and analysis results of the IPC co-occurrence network for the four periods. Based on the need to distinguish the core technology areas for each period, each node size is ordered according to the value of weighted degree centrality, which makes the nodes in the core technology areas larger. The numerical labels on the node-to-node lines represent the frequency of intersections occurring between the categories of IPC subclass. It should be noted that in order not to create information redundancy, only points and lines with frequencies above the mean are shown in Figure 6 and are laid out based on the Fruchterman–Reingold algorithm.

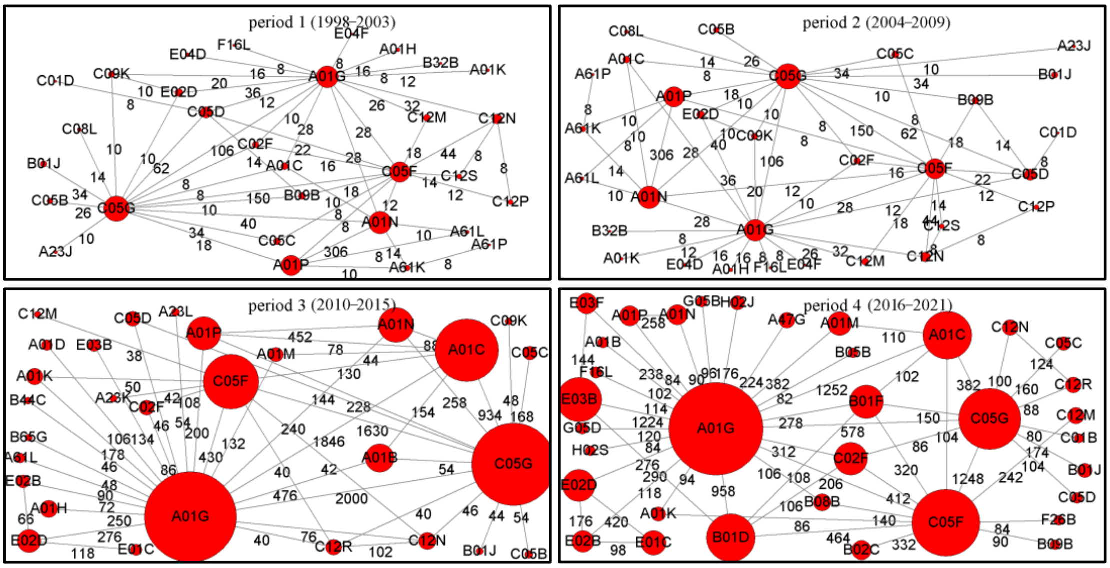


**Figure 6.** IPC code co-occurrence network visualization in four periods.

As time has progressed, the number of nodes and connections involved in the IPC co-occurrence network has grown considerably, and the frequency of each connection has also increased, suggesting that the technical areas where convergence has occurred have gradually broadened, but the most frequent co-occurrence occurred between a small number of IPCs. Specifically, the number of nodes involved in period 1 was 77, with 538 connections, of which the network cores were A01G, C05G, C05F, A01N, and A01P. The most frequent IPC co-occurrences occurred between A01N and A01P, but these two core nodes were only associated with a few edge nodes. The number of nodes remained the same in period 2, but the number of connections grew to 578. The core of the network remained the same five IPCs from the previous period, but a relatively large increase in the association of non-core nodes (such as C05D and C12N) with other nodes occurred. In period 3, the number of nodes increased to 185, the number of connections increased to 1638, and the network began to show a dual-core polycentric layout. The most frequent IPC co-occurrences occurred between C05G and A01G. In period 4, the number of nodes increased to 282, the number of connections became 3712, and the network took on a single-core polycentric structure. The most frequent IPC co-occurrences occurred between A01C and A01G. The changes in the number of cores and the main connections of the network show that the IPC co-occurrence network of agricultural green patents is becoming stable and is gradually spreading to new areas.

Table 4 below gives the evolution of the relevant metrics for the entire IPC co-occurrence network. It can be seen that the network density, the average path length, and the global clustering coefficient did not change significantly in the first two periods, while a decrease occurred in the third period. The former may be due to the fact that the number of nodes involved in the IPC co-occurrence network increased more significantly in period 3, resulting in a larger network size than in the first two periods. However, instead of all nodes expanding more evenly, the larger nodes became more massive and the smaller nodes grew less significantly in period 3, which led to the formation of several cohesive subgroups of the network instead of coalescing into blocks as before. This may make the density lower. Moreover, according to Figure 6, the overall network link frequency in the first two periods is mainly concentrated among the closed triplets, and the number of open triplets is relatively small in size. However, in period 3, the number of links in the open triplets gained a larger growth, narrowing the above-mentioned quantitative difference, and thus making the global clustering coefficient somewhat lower. In addition, in period 3, the frequency of links between large nodes achieved a larger increase compared to other small nodes, and occupied most of the total frequency, which may lead to a smaller average path length of the network. In contrast, in period 4, both the average path length and the global clustering coefficient increased significantly. The former may be due to a more pronounced increase in the frequency of small nodes compared to the previous period, while the growth of large nodes is not as pronounced, which leads to a larger path length. The latter, on the other hand, is due to a more pronounced increase in the frequency share of closed triplets in period 4 compared to period 3, as also shown in Figure 6. Therefore, the global clustering coefficient becomes larger. After four periods of development, technology convergence becomes more commonplace rather than occurring only among a few IPC subclasses.

**Table 4.** IPC co-occurrence network structural indicators.

| SNA Indicators | Period 1 (1998–2003) | Period 2 (2004–2009) | Period 3 (2010–2015) | Period 4 (2016–2021) |
|---|---|---|---|---|
| Density | 0.16 | 0.16 | 0.08 | 0.08 |
| Average path length | 2.27 | 2.27 | 2.20 | 2.25 |
| Global clustering coefficient | 0.26 | 0.26 | 0.16 | 0.22 |

Based on the decentralized and deconcentrated character of the network as a whole, and the fact that the visualization diagram can only draw node sizes based on one metric, it is not possible to comprehensively evaluate which nodes are at the heart of the network. Therefore, it is necessary to examine multiple SNA metrics together to further explore which IPCs play a more prominent role in the network and what technology domains they represent. Table 5 summarizes the ten nodes with the highest value of the indicators over time. As the number of nodes involved in the network varies in each period, with some nodes fading away and others not appearing in the early stages, the nodes selected in Table 5 below are those that existed in all four periods, but this does not mean that they were the most important IPCs in a given period. It should be noted that because Table 5 is quite voluminous, it has been treated horizontally and placed on the next page. Among the IPC subclasses listed in Table 5, those belonging to agricultural green patents are A01G, A01N, C09K, E02D, C05F, and C05G, which represent the fields presented in Table 1. Those not belonging to agricultural green patents are A01P, A01C, C12N, and B01D, which represent compounds with insect repellent or plant growth regulation activity, planting, microorganisms or enzymes, and separation, respectively. The results in Table 5 show that, in general, when degree centrality is higher, the values of betweenness centrality and constraint appear to be higher too. In all four periods, for example, A01G's degree centrality is greater than the other nodes, as are the values of betweenness centrality and constraint. It is closely followed by C05G, C05F, and E02D. From the three indicators shown in Table 5, these four nodes may be the core technologies for green agriculture in China. The metrics of the remaining nodes' value changes are more intricate, so they are not analyzed in great detail.

**Table 5.** List of top ten important agricultural green IPC subclasses.

| IPC | Period 1 (1998–2003) | | | Period 2 (2004–2009) | | | Period 3 (2010–2015) | | | Period 4 (2016–2021) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DC | BC | Con | DC | BC | Con | DC | BC | Con | DC | BC | Con |
| A01G | 98.00 | 0.57 | 0.18 | 49.00 | 0.57 | 0.18 | 146.00 | 0.69 | 0.29 | 199.00 | 0.45 | 0.13 |
| C05G | 64.00 | 0.23 | 0.23 | 32.00 | 0.23 | 0.23 | 73.00 | 0.15 | 0.43 | 108.00 | 0.15 | 0.26 |
| C05F | 58.00 | 0.15 | 0.33 | 29.00 | 0.15 | 0.34 | 58.00 | 0.11 | 0.65 | 137.00 | 0.17 | 0.21 |
| A01N | 44.00 | 0.12 | 0.58 | 22.00 | 0.12 | 0.53 | 29.00 | 0.01 | 0.56 | 36.00 | 0.01 | 0.41 |
| C09K | 28.00 | 0.04 | 0.77 | 11.00 | 0.01 | 0.50 | 20.00 | 0.01 | 0.40 | 22.00 | 0.00 | 0.42 |
| A01C | 22.00 | 0.01 | 0.53 | 8.00 | 0.00 | 0.51 | 39.00 | 0.02 | 0.72 | 68.00 | 0.02 | 0.49 |
| B01D | 12.00 | 0.00 | 0.43 | 6.00 | 0.00 | 0.43 | 14.00 | 0.00 | 0.52 | 86.00 | 0.04 | 0.42 |
| E02D | 16.00 | 0.00 | 0.67 | 5.00 | 0.00 | 0.67 | 44.00 | 0.07 | 0.41 | 90.00 | 0.14 | 0.26 |
| A01P | 28.00 | 0.04 | 0.77 | 14.00 | 0.04 | 0.77 | 25.00 | 0.01 | 0.58 | 30.00 | 0.00 | 0.43 |
| C12N | 26.00 | 0.01 | 0.49 | 13.00 | 0.01 | 0.49 | 13.00 | 0.00 | 0.51 | 15.00 | 0.00 | 0.48 |

Note: "DC" means Degree centrality, "BC" means Betweenness centrality, and "Con" means Constraint.

Furthermore, this paper uses the entropy weighting method to calculate the weights of each social network analysis indicator to evaluate the development of each node in a more complete way and to find the core technologies [50]. The specific weighting calculation results are shown in Table 6 below.

**Table 6.** Basic comprehensive evaluation index weight.

| Indicators | Information Entropy | Expected Value of Entropy | Weight Coefficient |
|---|---|---|---|
| Degree centrality | 0.91 | 0.09 | 23.75% |
| Betweenness centrality | 0.82 | 0.18 | 45.55% |
| Constraint | 0.98 | 0.02 | 6.21% |
| Effective size | 0.99 | 0.01 | 0.72% |
| Clustering coefficient | 0.91 | 0.09 | 23.77% |

After calculating the combined foundational scores for the four periods, this paper examines the dynamic development of the 10 most important IPCs in Table 5 using a coupled coordination model, with the aim of exploring whether the development of these most common IPCs over the four periods is coordinated. Does the initial co-occurrence network influence the development of the later IPC co-occurrence, and is this influence tight, resulting in positive or negative consequences? (Table 7).

**Table 7.** Coupling coordination results for top ten IPC subclasses.

| IPC | C Value | T Value | D Value | Coordination Level | Degree of Coupling Coordination |
|---|---|---|---|---|---|
| A01G | 0.85 | 0.83 | 0.84 | 9 | Good coordination |
| C05G | 0.99 | 0.56 | 0.74 | 8 | Intermediate coordination |
| C05F | 0.97 | 0.50 | 0.70 | 7 | Primary coordination |
| A01N | 0.78 | 0.24 | 0.44 | 5 | On the verge of maladjustment |
| C09K | 0.31 | 0.22 | 0.26 | 3 | Moderate maladjustment |
| A01C | 0.60 | 0.06 | 0.19 | 2 | Severe maladjustment |
| B01D | 0.89 | 0.5 | 0.72 | 7 | Primary coordination |
| E02D | 0.31 | 0.32 | 0.31 | 4 | Mild maladjustment |
| A01P | 0.68 | 0.29 | 0.47 | 5 | On the verge of maladjustment |
| C12N | 0.31 | 0.33 | 0.31 | 4 | Mild maladjustment |

This paper finds that the level of development coordination varies between categories of IPC subclass, with the average level of coordination being 5.7, somewhere between grudging coordination and the verge of maladjustment. In addition, the average C value is 0.67, indicating that the interaction between the four periods is relatively obvious. This means that although Chinese agricultural green patents are well-developed in terms of quantity, there is a lack of coordination in the integration between different technology areas. And the performance of the initial period will have a greater impact on the subsequent periods. Specifically, A01G (horticulture; cultivation of vegetables, flowers, rice, fruit, vines, hops or seaweed; forestry), C05G (mixture of fertilizers), and C05F (organic fertilizers), as IPCs within the WIPO Green List, have high C values and a high degree of coordination, showing a high level of mutually reinforcing and coordinated development. These IPCs have been popular technology convergence trends. B01D (separation) and A01P (biocidal, pest repellant, pest attractant or plant growth regulatory activity of chemical compounds or preparations), as non-WIPO Green List IPCs, have high C values and levels of coordination, showing a high degree of negative impact of the initial low level of development on subsequent periods, resulting in low levels of development in all four periods. A01C (planting; seeding; fertilization) shows a highly uncoordinated development, which suggests that its co-occurrence network is manifested in excessive pre–post differences. A01C, although poorly developed in the early periods, is becoming a popular technology in the later periods. A01N (pest repellents or inducers; plant growth regulators) has a high C value but is on the verge of uncoordinated development. This suggests that although it was more important in the network in the early stages, it still developed into a less important node in the later stages. Summing up the above results, China focuses on cultivating seeds, planting, and using environmentally friendly fertilizers to develop green agriculture, catering to economic development, while promoting biodiversity and reducing chemical pollution in agricultural production. However, some researchers have also pointed out that technologies such as soil modification and biological pest control are the critical technologies to transform agroecosystems, an area that has been increasingly underappreciated in China over time [51,52]. China needs to make up for these shortcomings to better develop green agriculture.

## 4. Conclusions

This paper examined the spatial and temporal distribution of the number and IPC co-occurrence of agricultural green patents, based on data from 1998–2021, and explored core technologies and popular convergence trends in agricultural green development. This paper obtained the following results.

First, the quantitative scale of agricultural green patents in mainland China achieved good growth results overall, with the number of patents peaking in period 3 (2010–2015). The most frequently appearing categories of the IPC subclasses are A01G (horticulture; cultivation of vegetables, flowers, rice, fruit, vines, hops or seaweed; forestry;), C05F (organic fertilizers from waste or refuse), C05G (organic fertilizers), E02D (foundations; excavations; embankments; underground or underwater structures), and A01C (planting; sowing; fertilizing). To a certain extent, this indicates that China believes these patent categories will be the main direction for the future development of green agriculture. In China, firms are the main force of innovation, and patents also show the multi-IPC classification situation. Second, there are heterogeneous differences in the spatial distribution of green agriculture patents in mainland China, showing an uneven layout of "strong in the east and weak in the west, strong in the south and weak in the north". This paper suggests that this may be due to the higher level of economic development in eastern and southern regions and their more significant demand for energy, arable land, and water resources. In addition, China, the developing country with the most patents, still has a vast imbalance in the distribution of patents in green agriculture, which raises a warning to the rest of the world. However, it remains to be seen whether this uneven distribution, which has become more substantial over time, will adversely affect the development of green agriculture in China. Due to the example that the share of green agriculture patents in Heilongjiang province, which has the highest grain production, is much smaller than that of other provinces, this paper still argues that other countries should avoid an uneven distribution similar to China when developing green agriculture.

Finally, the number of nodes and connections participating in the IPC co-occurrence network has increased significantly over time. It indicates that China's green agriculture patents are becoming increasingly diversified, incorporating more and more technologies from non-agricultural fields. However, the highest coconnections still occur between a few network cores. Different nodes show different levels of coordinated development over time. Technological directions such as cultivating seeds (A01C), growing plants (A01G), and using new fertilizers (C05F and C05G), which can cater to economic development, while promoting biodiversity and reducing chemical pollution in agricultural production, have made an outstanding achievement. However, over time, some technologies, such as soil improvement (A01N and B01D) and biological pest control (A01P), which are critical technologies for transforming agroecosystems, are receiving less attention in China, with progressively uncoordinated development. China's land resources per capita are only 1/58th of Australia's, 1/48th of Canada's, 1/15th of Russia's, 1/7th of Brazil's, and 1/5th of the US (http://www.gov.cn/test/2005-06/24/content_9234.htm (accessed on 27 May 2022)) The limited arable land has been destroyed or illegally occupied due to irrational farming or urbanization [53]. How to modify and protect the soil while maintaining stable grain production is a technology China needs to develop to achieve further green agriculture [54]. The policy insights derived from the above analysis in this paper are: First, although firms are currently the primary source of green agricultural innovation, individuals and universities contribute an equally large share of the number of patents. Based on this situation, the government should consider improving individual inventors' and universities' green innovation capacity to achieve industry–university research cooperation and balanced development. For example, the government can expand R&D expenditures, expand the number of talents brought in by universities, and promote technology exchanges and alliances between individual inventors and universities. Furthermore, firms have a more stable growth rate, proving their relatively strong innovation capability. To compensate for China's shortcomings in soil improvement and biological pest control patents, the government could consider promoting firms to develop technologies in these areas. For example, the government could set up subsidies and incentives for firms with many applications to focus more on IPC subclasses like A01N, B01D, and A01P, to reduce their R&D and promotion costs. Second, this paper argues that the uneven spatial distribution of green agricultural patents may adversely affect the development of green agriculture in China. It is because Heilongjiang province, the region with the highest grain production and fertile soil, performs poorly regarding the number of patents. However, since the current development of green agriculture patents in China is good, a more extended period is needed for observation. The analysis in this paper may be a preliminary exploration because only patent data are selected as a proxy for the innovation capacity of green agriculture. Therefore, the government should strengthen the monitoring and statistics of agricultural pollution emission, grain yield, and innovation capacity data to build a more scientific and reasonable green agriculture index system. In addition, the development of green agriculture is a systematic project, and the geological conditions and climate vary greatly across China. For provinces with a relatively large area of forest and grassland, such as in western China, the development experience of provinces with a relatively large area of plains in the east cannot be simply replicated. For example, areas such as Shandong and Henan have higher grain production and better development of green agriculture. There must be merits in developing these regions, but data support and experiments are needed to determine whether these positive practices can be effectively extended to the whole country. Therefore, it is necessary to strengthen the monitoring of essential data and ensure their timely release to measure the level of green agricultural production on time. Third, significant technology convergence still occurs in a few categories. The cultivation of plants such as vegetables, flowers, and rice (A01G), the fertilization of waste or garbage (C05F), and organic fertilizers (C05G) are the hot spots for the future of green agriculture in

China. New technological breakthroughs will likely emerge in these areas. Other developing countries can strengthen these technologies in order to achieve food security and low-carbon goals. However, more attention should also be given to crucial technologies for pollution reduction, such as biological control and soil improvement. These technologies are not well-developed in China. Therefore, the government should strengthen research in these areas for more balanced development and faster realization of green agriculture.

Although this study provides a spatial–temporal analysis of the technological convergence of green technologies in agriculture, there are certain shortcomings. As our study mainly focuses on evaluating past IPC co-occurrence developments, there are limitations in predicting future technological advances. To address this shortcoming, we will continue to deepen our research in future studies.

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