

Global Green Knowledge Flows: Analysis Based on Green Patent Network

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Abstract: Technological innovation, particularly in green technologies, is critical to addressing global sustainability challenges. Our analysis uses 6.65 million global green patents (1990-2019) to map network dynamics and directional knowledge flows. Unlike Acemoglu's findings on stable innovation networks, our analysis reveals pronounced instability in green patent networks, manifested through significant shifts in centrality patterns from end-of-pipe technologies toward preventive solutions. These structural transitions fundamentally alter knowledge flow directions, rendering standard prediction models that assume network consistency ineffective for forecasting green innovation. To address these instabilities, we developed a dynamic rolling prediction approach specifically calibrated for networks with evolving knowledge patterns. We acknowledge financial support from the National Social Science Foundation of China.

Keywords: Green Innovation; Patent Network; Knowledge Flows; Sustainable Development

1. Introduction

As global climate crises and resource limitations intensify, green technology innovation has become a critical driver for sustainable development (Khan et al. (2025); Alyahya et al. (2022); Sethi et al. (2024)), offering solutions to mitigate environmental degradation while promoting economic growth (Sharif et al. (2024); Aydin et al. (2023); Sirin (2025)). However, the conceptualization and requirements of green development continue to evolve across different time periods, reflecting advancements in technology, shifting environmental priorities, and changing societal awareness (Adams (2008); Feng et al. (2017)). While extensive research has examined how external factors like regulations and policy instruments influence green innovation (Shen et al. (2020); Zhang et al. (2020); Borsatto and Bazani (2021)), significantly less attention has been devoted to understanding how knowledge itself—its structure, flow, and accumulation—shapes the generation of new environmental technologies.

Building upon this research gap, our study investigates the knowledge-flow in green innovation. The most closely related work is by Acemoglu et al. (2016), who provides valuable insights by analyzing approximately 1.8 million U.S. patents over three decades. Their research empirically validated that innovation fundamentally represents "standing on the shoulders of giants," demonstrating that technological advancement in specific domains triggers "knowledge spillover effects" that diffuse to related fields, catalyzing further innovation. Despite these important insights into general innovation dynamics, the specific mechanisms through which internal knowledge flows shape green technology innovation remain inadequately explored, particularly given the interdisciplinary nature of environmental challenges and the dual objective of green technologies to deliver both economic value and environmental benefits (Mohammed (2021); Qamar et al. (2021)).

This perspective prompts us to contemplate more deeply: in the context of green innovation, a field of growing significance in contemporary discourse, can its development be explicated through the lens of knowledge flow and spillover? Moreover, can traditional innovation prediction models be applied to assess green innovation?

This paper makes several notable marginal contributions in addressing these questions. Firstly, it uncovers that the green patent network diverges significantly from the stability inherent in traditional patent networks. The green patent network exhibits unique dynamic characteristics of spatial and temporal variation. Unlike prior research that often overlooked the internal structure and features of green patent networks, this paper meticulously explores these aspects to gain a more profound understanding of the flow behavior of green knowledge.

Secondly, while traditional research predominantly centered on the influence of exogenous factors like policy tools (Edler and Fagerberg (2017); Borrás and Edquist (2013); Costantini et al. (2017)) and market shocks (Schilling (2015); De Dreu and van Dijk (2018); Guan et al. (2021)), on green innovation, this study unconventionally approaches

the driving mechanisms of green technology innovation by analyzing the dynamic role of green patent networks, with a focus on knowledge flows and spillover effects within patent citations. This provides a fresh and insightful vantage point for comprehending and fostering green technological innovation.

Thirdly, the proposed dynamic rolling forecasting method, developed through analysis of dynamic green innovation networks, achieves significant performance enhancements. It overcomes the limitations of traditional static models, offering a novel and effective tool for the study of unstable, especially time-varying networks. This method not only enriches the methodological toolkit for academic research but also provides crucial support for policymakers in formulating forward-looking policies.

Specifically, this paper aims to address the following two core questions:

RQ1. In what ways does the green patent network differ from the traditional patent network?

RQ2. How can the future trajectory of green technological innovation be predicted based on the characteristics of knowledge flow?

To address these questions, we construct a green innovation network for the first time by using 6.65 million global green technology patent data and their citation relationships, and portrays the knowledge flow in green innovation for the first time. Through the statistics, measurement and analysis of complex network indicators, it reveals the dynamic characteristics of the green innovation network, which is different from the stable traditional innovation network. Unlike previous studies, this paper focuses on the changing structure and characteristics of green innovation networks themselves and the sources of knowledge for innovation. On this basis, it further analyzes the impact of knowledge flows on innovation and explores the internal driving mechanisms of green technological innovation. It provides new perspectives for understanding and promoting green technological innovation.

At the same time, this paper is committed to providing solutions for the prediction of green innovation. Since the green innovation network is a time-varying network that is different from the traditional stable network, the traditional innovation prediction model based on stable networks (Acemoglu et al. (2016)) may fail. This paper originality proposes a time-varying dynamic rolling prediction method that breaks through the limitations of traditional static models and provides a new tool for studying instability, especially time-varying networks. It provides a robust methodological framework for predicting future green innovations. Our research results provide valuable insights for policymakers and businesses that aim to promote sustainable development and address global environmental challenges.

The remainder is organized as follows. Section 2 reviews the literature on definition and significance of green innovation, drivers of green innovation, predictive methods for green innovation and government decision-making based on green innovation forecasting to construct a theoretical

framework. Section 3 introduces the data and methodology used in this research, including data sources, classification criteria and comparison, and network construction. Section 4 presents the measurement results of various network metrics and reveals the unstable characteristics of green innovation networks—distinct from traditional innovation networks. It also provides empirical results and analysis comparing predictions from traditional forecasting models and the proposed dynamic rolling forecasting model, while conducting robustness tests on our dynamic rolling forecasting model using multiple patent classification criteria. Section 5 delves into a thorough discussion of the theoretical and practical insights gained from the research experiment, and discusses the possible shortcomings of this paper and future improvement directions in light of the actual situation. Finally, Section 6 provides a comprehensive summary of the entire paper, emphasizing the significance of the research.

2. Literature Review

2.1. Definition and significance of green innovation

Green innovation refers to the introduction of new or improved environmental technologies in products, processes, or services, aiming to reduce negative environmental impacts and promote sustainable development. In recent years, research on green innovation has significantly increased, and academic understanding has transcended purely technical dimensions to form a multidimensional, integrated perspective. As systematically elaborated by Hojnik and Ruzzier (2016), green innovation encompasses at least three dimensions: technological innovation, managerial innovation, and social innovation. This systematic multidimensional perspective facilitates a more comprehensive understanding of green innovation's complexity. Theoretical research on the significant importance of green innovation is abundant. From an environmental benefits perspective, green innovation serves as a direct means to address climate change and resource depletion challenges. Porter and Linde (1995) argue that green innovation reduces resource consumption and waste emissions, thereby slowing environmental degradation. From an economic perspective, the classic Porter hypothesis posits that well-designed environmental regulations (such as environmental taxes and pollution permit trading) can stimulate corporate innovation. Through technological improvements and efficiency gains, firms can offset compliance costs, ultimately enhancing their competitiveness. Rennings (2000) further notes that green innovation bolsters long-term corporate competitiveness by enhancing resource efficiency and creating green markets. From a social perspective, Dangelico and Pontrandolfo (2015) argue that proactive engagement in green innovation significantly elevates corporate brand image and reputation, effectively meets consumers' growing demand for eco-friendly products, and earns greater trust from stakeholders including investors and communities.

2.2. Drivers of green innovation

Green innovation is a complex outcome driven by multiple forces. For an enterprise, past research broadly categorizes these drivers into internal and external dimensions. Notably, digital technologies that have emerged in recent years serve as an increasingly vital enabling factor permeating these dimensions. Internal factors originate within the organization, serving as the endogenous motivation for initiating green innovation. These include the company's intrinsic environmental ethics and culture, the vision and steadfast support of senior management, and employees' environmental awareness and proactive engagement (Chen et al. (2006)). Additionally, a company's R&D investment capacity, existing technological reserves, and available surplus resources form the material foundation for pursuing green innovation. External factors encompass the institutional and market environments enterprises must navigate. Among these, policy regulations—such as environmental standards, carbon taxes, and emissions trading systems—serve as the most potent drivers. Government agencies incentivize or compel green innovation by establishing clear compliance thresholds (Jiang et al. (2018)). Simultaneously, market forces—including consumer preferences for green products, green supply chain requirements, and competitive pressures—create substantial market opportunities, exerting powerful attraction and sustained momentum for green innovation. Furthermore, the feasibility enabled by technological advancements in related fields represents an indispensable external driver of green innovation. The development of digital technologies presents new opportunities for green innovation, with research indicating that digitalization can enhance green innovation performance (Wang et al. (2024); Su et al. (2023); Liu et al. (2025)). Li et al. (2023) analyzed green innovation patent data from listed new energy vehicle companies and found that digital technologies and digital organizations can actively promote the development of green innovation networks. Enterprises can improve green innovation performance and foster green innovation collaboration by optimizing digital technologies and digital organizations.

2.3. Predictive methods for green innovation

Given the significance of green innovation, its effective prediction is crucial. Existing research proposes various forecasting methods, ranging from traditional statistical analysis to more dynamic and intelligent models: Data mining-based approaches primarily leverage big data technologies to automatically identify and extract evolutionary trends, research hotspots, and potential technological breakthroughs in green technologies from vast patent databases, academic literature, corporate annual reports, and news sources (Du et al. (2019); Wang et al. (2019); Liu et al. (2023); Tan et al. (2021); Oduro et al. (2022)). For instance, analyzing citation networks and keyword co-occurrence networks of green technology patents can predict which specialized technical fields may emerge as dominant paradigms in the future.

System dynamics-based approaches focus on the complexity and dynamism of green innovation systems. By constructing causal loop models incorporating multiple sub-systems—such as technology, market, and policy—along with their feedback loops, this approach simulates the long-term pathways and effects of green technology adoption and diffusion under different policy scenarios or market changes (Laimon et al. (2022); Rehman et al. (2017)). This method is particularly suited for evaluating the long-term, nonlinear impacts of policies.

Machine learning-based methods represent the current frontier of predictive research. Machine learning algorithms such as random forests, support vector machines, and neural networks automatically learn complex patterns from high dimensional, nonlinear historical data to generate highly accurate predictions. Liu et al. (2024) utilized a large-scale dataset of Chinese enterprises from 2010 to 2019 to identify the determinants of green innovation through machine learning algorithms, ultimately identifying the optimal model for predicting green innovation. Mao et al. (2023) employed a machine learning approach based on causal forests to address endogeneity issues, examining the impact of green innovation activities on green total factor productivity (GTFP). Han et al. (2024) employed a random forest model to explore the impact of digital transformation on green innovation, confirming that digital transformation can promote green innovation and strengthening existing arguments regarding digital transformation and green innovation.

2.4. Government decision-making based on green innovation forecasting

Research by Jiang et al. (2023) indicates a U-shaped relationship between environmental regulation and green technological innovation. As environmental administrative decentralization and regulatory decentralization intensify, environmental regulation plays a significant positive role in promoting green technological innovation. Scientific forecasting provides critical data support for governments to transition from “reactive response” to “proactive shaping” in precision environmental governance. In policy formulation pathways, predictive models can serve as “diagnostic tools,” helping governments identify key bottlenecks affecting green innovation and future areas of strength.

In the policy evaluation and optimization phase, predictive models can function as “policy simulators.” Before formal implementation, governments can use these models to simulate the environmental, economic, and innovation impacts of various policy instruments (e.g., carbon tax rates, R&D subsidy intensities, renewable energy quotas) across multiple economic-technological scenarios (Popp et al. (2010)). This forward-looking policy evaluation significantly reduces the costs of trial-and-error policy experimentation. It enables decision-makers to compare the merits of different policy options, thereby selecting and optimizing the most efficient and cost-effective policy mix. This approach ensures that public resource investments maximize the stimulation of green innovation across society.

3. Data and Methods

3.1. Data sources

Since the 1990s, international attention has been shifted widely to addressing climate change and sustainable development. We leverage Google Scholar’s global patent data to focus on green patents filed after 1990. Considering that there is a period of examination after a patent application, it is generally practice to allow a five-year review window (Acemoglu et al. (2016)). We used the data up to 2019 and selected green patents from 1990 to 2019. In addition, to reflect the innovative behavior of technology, we have excluded utility model patents and design patents. Finally, we screened out 6.65 million green invention patents filed worldwide between 1990 and 2019 according to the classification criteria in the “IPC Green Inventory” developed by the International Patent Classification (IPC) Expert Committee.

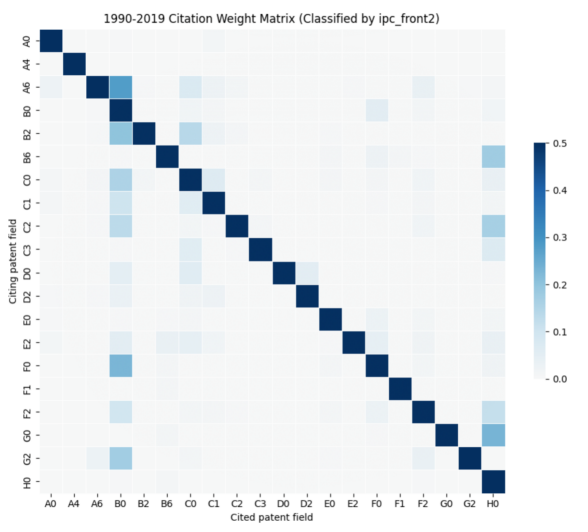
3.2. Classification criteria and network construction

We now assume that the number of inventive green patents can quantify the level of innovation in the green field, so how to reflect the knowledge spillover and flow between green technology fields?

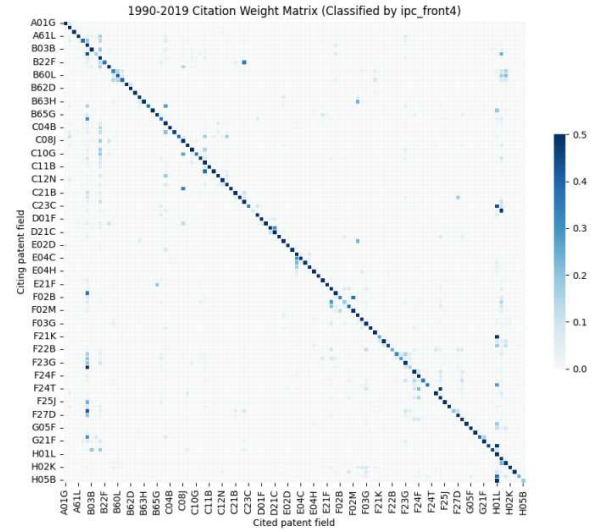
Based on the research on innovation networks by Acemoglu et al. (2016); Liu and Ma (2021), this paper uses global green patent data and citation relationships from 1990 to 2019 to calculate the citation share of each green technology field patent in the backward citations of each green technology field patent:

$$w_{ij} = \frac{cite_{ij}}{\sum_k cite_{ik}} \quad (1)$$

Among them, $cite_{ij}$ is the number of times that a patent in technical field i cites a patent in technical field j ; k is one of the technical fields cited by technical field i . In this way, the matrix Ω , consisting of w_{ij} , forms a knowledge input-output network between technical fields, i.e., a technological innovation network. Since patents themselves reflect the output of technological innovation, and backward citations of patents reflect the citations of this patent to other patents, that is, the relevant “knowledge inputs” in the process of innovation output, this technological innovation network intuitively portrays the knowledge “input-output” correlation between different technological fields in the process of green innovation, and this correlation reflects the deep spillover and flow of knowledge and technology between different fields. For each specific technology field I , we can use w_{ij} to determine the degree of dependence of the innovation process in this field I on the knowledge and technology of any field J , or the degree of importance of the knowledge and technology of any field J to the innovation output of this field I . Therefore, a suitable field division of green patents is an important prerequisite for clearly reflecting the knowledge relevance between fields. Fig 2 is a heat map of the green innovation network from 1990 to 2019 calculated for this paper. We classify the green technology



(a) Citation heat map based on the first 2 IPC numbers. The horizontal axis represents the cited category, and the color intensity indicates the weight of the citation, where the sum of each row equals 100%.



(b) Citation heat map based on the first 4 IPC numbers. The horizontal axis represents the cited category, and the color intensity indicates the weight of the citation, where the sum of each row equals 100%.

Figure 1: Citation heat map based on the top IPC numbers.

fields according to the top two IPC numbers (Fig 1a), the top four IPC numbers (Fig 1b), and the secondary classification of the "IPC Green Inventory" (Fig 2), respectively. Each cell in the figure represents the value w_{ij} , which is indicated by the color shade. The horizontal axis is the citing technology field I , and the vertical axis is the cited technology field J .

We found that, regardless of the classification method, the diagonal line of the heat map and its vicinity are the darkest in color. This shows that knowledge flow and spillover within the field and adjacent technical fields are important drivers of technological innovation in the field. From a horizontal perspective, some cited technologies are darker in most cells in their row, which shows that knowledge in these fields is more versatile and fundamental, and can provide knowledge and technical support to many other fields. From a vertical perspective, some cells in some columns are very light in color, which shows that knowledge flow and spillover between some technical fields is rare or even non-existent. Specifically, the classification using the first two digits of IPC is too rough, and after excluding special categories, the other citation relationships are not clear, which leads to the knowledge flow between fields not being obvious or being obscured by the progress of knowledge in the field. The heat map drawn using the "IPC Green Inventory" classification standard shows that after excluding intra-domain citations, other citation relationships are relatively discrete, i.e., they do not have the characteristic of being clearly distributed along the diagonal. This shows that the "IPC Green Inventory" classification method does not classify categories with high knowledge flow and rich knowledge exchange into similar categories. Therefore, using the first four digits of IPC for domain classification may be a better classification method.

In the subsequent dynamic rolling prediction analysis of green knowledge based on time-varying features, this paper also uses other classification methods to test the robustness of the model.

4. Results

4.1. The Green Innovation Network is a temporally and spatially unstable network

This research constructs a global green innovation network by drawing on 6.65 million green patent data and their citation connections spanning from 1990 to 2019. In contrast to prior research that concentrated on geographical location exchanges, this paper centers its attention on analyzing the knowledge flows among diverse green fields. We carried out a comparative analysis through the calculation of complex network indicators (Tables 1 and 2). Additionally, we utilized Python software to visualize the structure of this intricate network. Both theoretically and intuitively, this approach uncovers the remarkable spatio-temporal instability of the green innovation network structure. Specifically, (1) significant nodes exhibit temporal shifts; (2) various fields display uneven distributions within the network.

4.1.1. The nodes in the green patented network are unevenly distributed in space

Fig 3 reveals the imbalance in the spatial distribution of nodes in the green patent citation network. The green patent network is complex in composition, with significant differences in node size and distribution. In the period of 30 years, from 1990 to 2019, the three largest nodes are *C02F*, *B01D* and *H02J*, which correspond to patents related to

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1990-2019 Citation Weight Matrix (Classified by WIPO)

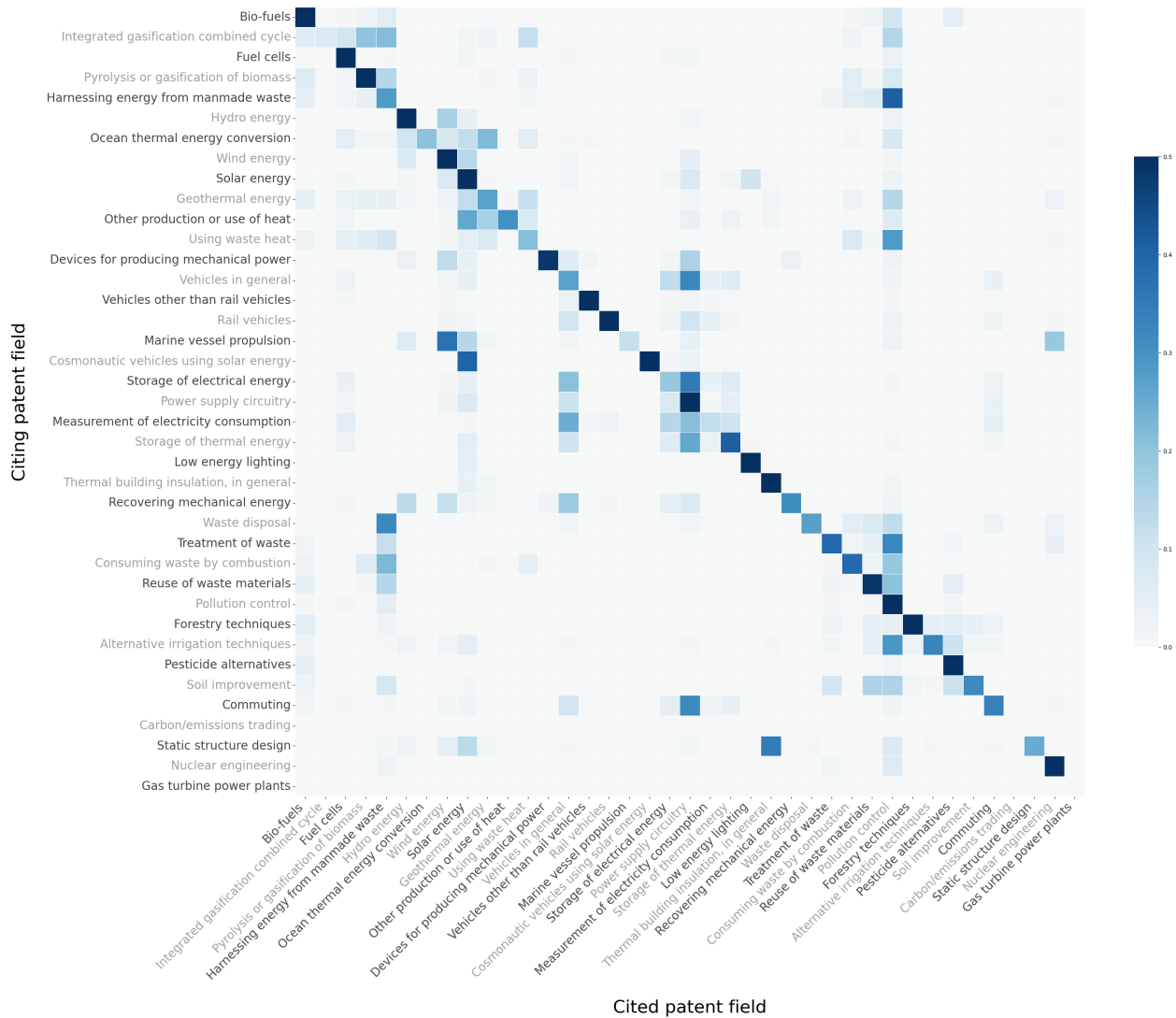


Figure 2: Citation heat map based on IPC Green Inventory classification. The horizontal axis represents the cited category, and the color intensity indicates the weight of the citation, where the sum of each row equals 100%.

Table 1

Statistical characterization of the evolution of the global green patent network, 1990-2019

Time Interval	Avg. Degree	Network Diameter	Avg. Path Length	Network Density	Global Agglomeration Factor	Avg. Efficiency	Total Nodes
1990-1999	49.7903	disconnection	disconnection	0.2023	0.4649	0.6176	124
2000-2009	73.2283	3	1.6582	0.2905	0.5424	0.6769	127
2010-2019	100.0314	3	1.5245	0.3969	0.6202	0.7378	127
1990-2019	112.0312	3	1.4801	0.4410	0.6586	0.7599	128

Total Sides	Centricity Index	SD of Degree	Gini Coeff.	Degree Distribution Entropy	Network Modularity	Max k-core	PageRank SD of Centrality
3087	1.1751	39.1612	0.4216	6.5340	0.5350	44	0.0151
4650	1.1512	48.1562	0.3668	6.6704	0.5086	60	0.0148
6352	1.0802	54.8226	0.3126	6.7600	0.5071	78	0.0143
7170	1.0396	57.0358	0.2917	6.7970	0.4990	89	0.0143

water, wastewater, sewage or sludge treatment, patents related to the separation of solid particles from liquids or gases, including filtration, centrifugal separation and membrane separation, etc., power supply and distribution devices for power systems, including circuit design, energy storage

systems (such as battery energy storage), power conversion equipment, etc. There is a huge knowledge flow between these green fields, as well as external knowledge flow. They not only constantly build and improve their own fields by referring to the knowledge of other fields, but also serve as

Table 2

Statistical description of the evolutionary characteristics of the sub-network consisting of the twenty most important nodes in the global green patent network, 1990-2019

Time Interval	Avg. Degree	Network Diameter	Avg. Path Length	Network Density	Global Agglomeration Factor	Avg. Efficiency	Total Nodes
1990-1999	32.5	2	1.0842	0.8552	0.8939	0.9578	20
2000-2009	34.6	2	1.0473	0.9105	0.9274	0.9763	20
2010-2019	37.3	2	1.0052	0.9815	0.9827	0.9973	20
1990-2019	37.6	2	1.0052	0.9894	0.9896	0.9973	20

Total Sides	Centricity Index	SD of Degree	Gini Coeff.	Degree Distribution Entropy	Network Modularity	Max k-core	PageRank SD of Centrality
325	0.3216	5.0149	0.0761	4.3026	0.5022	28	0.0343
346	0.1988	3.6523	0.0531	4.3133	0.4829	29	0.0337
373	0.0409	1.1445	0.0140	4.3212	0.4598	34	0.0361
376	0.0233	0.8000	0.0086	4.3215	0.4532	35	0.0364

an important source of knowledge for the development and reference of other green fields, and are widely used in other fields, occupying an important position in the network. The main categories with smaller nodes include *B62D*, *F24H*, *C21C*, and *H02N*, which correspond to categories related to motor vehicle steering systems (including steering mechanisms for motorcycles, trailers, etc.), fluid heaters (such as water or air heaters) that generally have heating devices, categories related to pig iron processing (such as refining and smelting of wrought iron), and categories related to non-traditional motors or generators, such as motors that utilize the piezoelectric effect, electrostriction or magnetostriction. These categories only have patent citation relationships with a limited number of other green categories, that is, there is knowledge flow with a few categories, and the flow is low, mostly one-way. This may be due to the high degree of specialization of these nodes, which makes it difficult to draw on knowledge from other fields of knowledge and further develop it. Progress can only be made through accumulation and innovation in itself. This shows that the distribution of patent citation relationships in the network system is uneven, that there is a sense of centrality in the network, and that the overall structure presents a central-peripheral structure. The field of green technology related to pollution control, biological protection and waste treatment occupies the core of the entire green patent network. This imbalance in distribution may be due to the influence of policies or certain macro factors, which have caused research to focus on some key industries; it may also be due to the influence of market demand, which has led to the emergence of “silos” with low relevance to other fields; it may also be due to the historical research foundation, with some categories having a rich historical research foundation and dedicated researchers, while some categories have just been established and lack the accumulation of knowledge in specialized fields and high-quality professional researchers. It may also be caused by the historical research foundation. Some categories have a rich historical research foundation and dedicated researchers, while some categories have just been established and lack the accumulation of knowledge in specialized fields and high-quality professional researchers.

4.1.2. The structure of the green patent network has changed significantly over time

From the perspective of knowledge sources, we calculated the proportion of green patents citing green patents from 1990 to 2019 as a percentage of all patents citing green patents worldwide. Fluctuations in this ratio reflect changes in the main sources of knowledge for green innovation: a sharp rise from 1990 to 1993, indicating that green knowledge is playing an increasingly important role in green innovation; a gradual decline from 1993 to 2006 indicates that green knowledge is becoming increasingly insufficient to support the further development of green innovation, and during this period, green knowledge from non-green fields has become increasingly important to support the further development of green innovation. During this period, extensive knowledge from non-green fields has gradually become a new trend in the development of green innovation, which may be reflected in the emergence of a large number of new green fields. The slow growth from 2006 to 2017 and the rapid growth from 2017 to 2019 indicate that after 2006, the source knowledge of green innovation gradually returned to the green field, and the driving force of knowledge from other fields on green innovation has weakened. Accordingly, we infer from the obvious changes in the sources of knowledge for green innovation that the development of green innovation has undergone a transition from vertical specialization to horizontal expansion, and the emergence of a large number of new green fields after 1993, and then a return to specialization after 2006, during the 30 years under analysis.

The degree centrality of a node in a network measures the number of direct connections that node has with other nodes, and reflects the direct influence or activity of the node in the network. In general, nodes with high centrality are key nodes for information dissemination and resource flow. To verify the inference we have mentioned, we detected the top five nodes with high centrality in the network at different time periods, and analyzed the five most critical nodes in the green patent network at different time intervals (Table 3). These five nodes to some extent reflect the most popular green innovation directions during the time period.

We find that between 1990 and 2019, water, wastewater, sewage or sludge treatment (e.g. desalination, industrial

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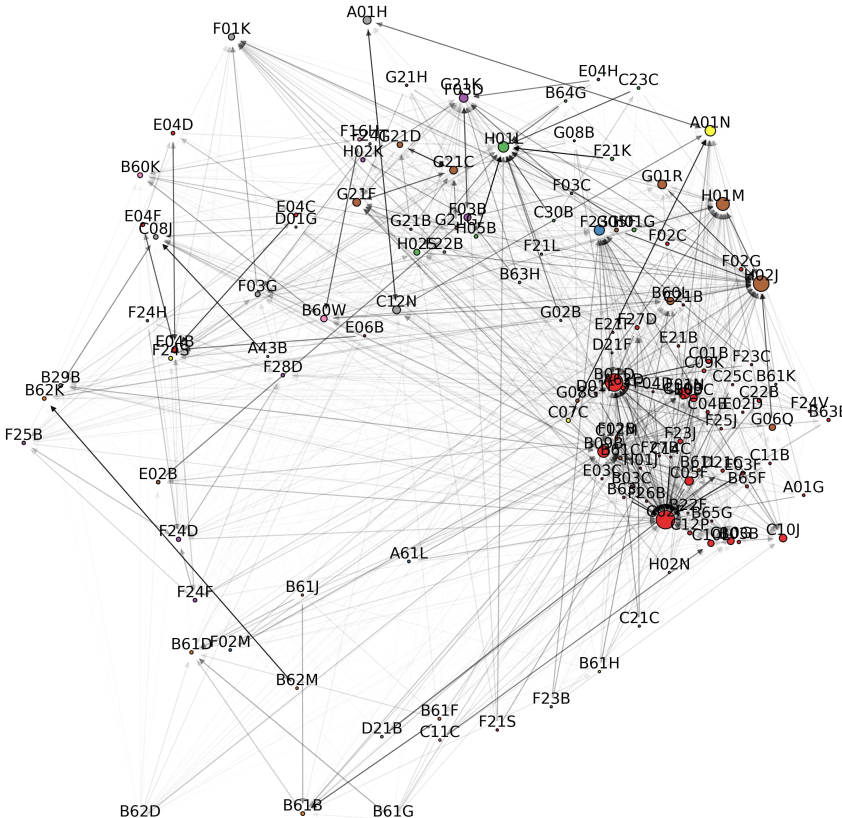


Figure 3: Green patent citation relationship network over the three decades 1990–2019, where the fields are represented by IPC numbers

Table 3
Top five nodes in terms of network neutrality centrality in different time intervals

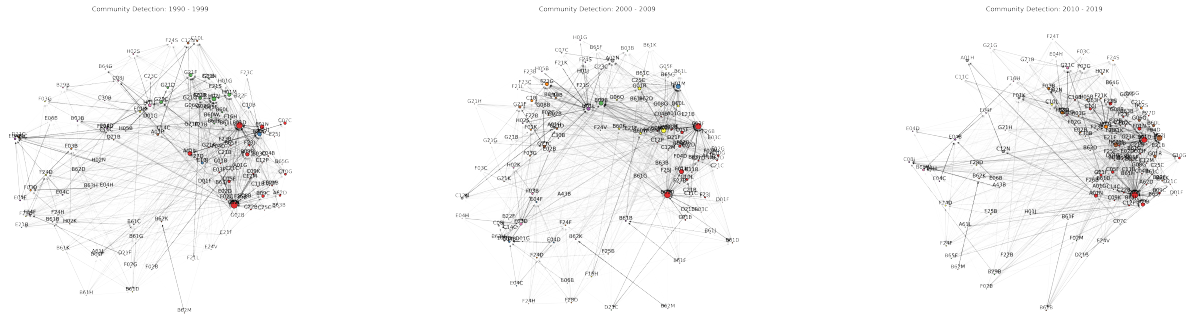
Time interval	Top five nodes (from largest to smallest)	Meaning
1990-1999	<i>C02F, B01D, F01N, F23G, A01N</i>	<i>C02F</i> : Treatment of water, wastewater, sewage or sludge; <i>B01D</i> : Separation techniques, filtration, centrifugal separation; <i>F01N</i> : Airflow silencers or exhaust devices for machines; <i>F23G</i> : Incinerators; burning of waste or low-grade fuels; <i>A01N</i> : Preservation of bodies or parts; biocides
2000-2009	<i>B01D, C02F, F01N, H02J *</i> , <i>H01M *</i>	<i>H02J</i> : Circuit installations for electricity supply; energy storage; <i>H01M</i> : Electrochemical technologies like batteries, fuel cells
2010-2019	<i>C02F, H02J, B01D, H01M, B09B *</i>	<i>B09B</i> : Treatment of solid waste, recycling, resource utilization
1990-2019	<i>C02F, B01D, H02J, H01M, F01N</i>	

Note: The superscript * indicates that it was not among the top five most important nodes in the previous network and is an emerging network center

wastewater treatment, municipal sewage treatment, etc.) and separation technology (e.g. air filtration, water purification and chemical separation, etc.) represented by *C02F* and *B01D*. The central shift from *F01N*, *F23G* and *A01N* to *H02J*, *H01M* and *B09B* reflects the transition of this technology area from traditional mechanical, combustion and chemical treatments to clean energy, energy storage and

sustainable resource management, which is also consistent with our inference.

This shift reflects the growing global emphasis on environmental protection and sustainable development. From traditional technologies such as exhaust gas treatment for internal combustion engines (*F01N*) and waste incineration (*F23G*), to innovative technologies such as electrical energy



(a) Green patent citation relationship network over the three decades 1990-1999, where the fields are represented by IPC numbers.

(b) Green patent citation relationship network over the three decades 2000-2009, where the fields are represented by IPC numbers.

(c) Green patent citation relationship network over the three decades 2010-2019, where the fields are represented by IPC numbers.

Figure 4: Green patent citation relationship network during the three decades of 1990-1999, 2000-2009, and 2010-2019, where the fields are represented by IPC numbers

storage systems (*H02J*), battery and fuel cell technologies (*H01M*), and solid waste recycling (*B09B*), technological development is moving towards greater efficiency and environmental friendliness. Meanwhile, the preservation and biocidal technologies covered by *A01N* are also developing in a more environmentally friendly and precise direction, promoting sustainable development in various fields. These shifts in technological fields are an inevitable result of the global green technology transformation towards clean energy, sustainable resource management and environmental protection technology, driven by factors such as policy, market demand and technological innovation.

In Fig 4, we have plotted a green innovation network map for each decade. By comparing and analyzing the network structure in different time intervals, we can more intuitively observe the feature that its structure changes greatly over time. In addition to the intuitive feeling, in Table 1 we list the indicators of the Green innovation network, which quantitatively interpret the time-varying characteristics of the global Green Innovation Network. We found that several key indicators of the Green Innovation Network have changed significantly over time: Network density fluctuated from 0.2023 in 1990–1999 to 0.2905 in 2000–2009, and then to 0.3969 in 2010–2019, showing a significant increase. This indicates that the connectivity at the edges of the network has significantly improved, and that green knowledge flow activities are becoming more frequent, with close knowledge exchange between green technology fields and enhanced cohesion Friedkin (1981). In addition, the global clustering coefficient increased from 0.4649 to 0.5424 and then to 0.6202, also showing a continuous increase, indicating that the degree of aggregation of the global green patent network is continuously improving, which may reflect the formation and strengthening of localized communities in the network, as shown by the closer links between specific

technology fields Berahmand et al. (2018) Saramäki et al. (2007). The network centrality index was 1.1751 in 1990-1999, declined to 1.1512 in 2000-2009, and continued to decline to 1.0802 in 2010-2019, which, although the decline is smaller, still indicates that the network has become less centralized Koschützki et al. (2005) Wang et al. (2018). This could mean that the green innovation network is no longer dominated by a few nodes, but is more decentralized. In addition, the decrease in the standard deviation of degree and Gini coefficient also indicates a more even distribution of degree among nodes. Regarding the modular structure of the network, the degree of network modularity decreases from 0.5350 to 0.5071, indicating that the modular structure of the network is gradually weakening Newman (2006). Meanwhile, the maximum k-core value increases from 44 to 78, indicating that the core area of high connectivity in the network is expanding. This may reflect the increased influence of certain key nodes in the network, and may also be related to the trend of decentralization in the network. The standard deviation of PageRank centrality decreased from 0.0151 to 0.0143, indicating a more even distribution of node importance Fortunato et al. (2008). This may mean that there is no single “super node” in the network, but rather multiple nodes sharing important roles. This may indicate that with the flow and accumulation of knowledge and the continuous enhancement of human global awareness, the development of green innovation is showing a trend of “blooming in all directions”. To better highlight the network’s features and minimize noise, we further computed the network indicators for the 20 most central nodes, as presented in Table 2.

Prediction Results

Ideally, we can use ordinary least squares (OLS) to estimate equation:

$$\ln(Patents_{J,t}) = \beta \ln(Predict_{J,t}) + \phi_J + \eta_t + \epsilon_{J,t} \quad (2)$$

where $Patents_{J,t}$ is the outcome variable of interest, representing the number of patents included in patent category J in year t , i.e., the level of green technological innovation; $Predict_{J,t}$ represents the predicted number of patents included in patent category J in year t ; ϕ_J represents the category fixed effect; η_t represents the time fixed effect; and $\epsilon_{J,t}$ represents the random error term.

For the core independent variable $Predict_{J,t}$, a static post-prediction method based on a traditional stable network was tested, and a dynamic rolling prediction method was proposed for unstable time-varying networks. The settings of the two prediction models are as follows:

4.1.3. Traditional static lag prediction model

The traditional innovation forecasting model based on knowledge flow was proposed by Acemoglu et al. (2016). The whole model assumes a stable innovation network and uses citation relationships within a fixed time window for forecasting. *CiteFlow*, however, takes advantage of the great heterogeneity in the speed of knowledge dissemination: a patent for invention of technology J usually does not receive a citation from technology I until many years after the invention. For this reason, *CiteFlow* quantifies the number of citations from technology I to J each year in a ten-year window as a proportion of the cumulative total number of patents in category J over ten years:

$$CiteFlow_{I \rightarrow J,a} = \frac{Citations_{I \rightarrow J,a}}{Patents_J} \quad (3)$$

Since the time window is 10 years and the lag a is 1 to 10 years, the predicted number of patents (innovations) in year t is the number of patents in year $t - a$ multiplied by the lag effect of 1 to 10 years, and then summed.

$$Predict_{I,t} = \sum_{K \neq I} \sum_{a=1}^{10} CiteFlow_{I \rightarrow K,a} P_{K,t-a} \quad (4)$$

4.1.4. Dynamic scrolling prediction model

In response to the temporal instability of green patent networks, we propose a dynamic rolling forecasting method that treats *CiteFlow* as a time-varying variable. This method uses rolling time windows to capture the time-varying effects of knowledge flows. This method enhances the model's ability to capture the inherent temporal dynamics of green patent networks and more accurately predict future green innovations than traditional static methods. Through rolling time windows, the method can dynamically adjust the forecasting model, thereby improving the accuracy and robustness of the forecast:

$$CiteFlow_{I \rightarrow J,a,t} = \frac{Citations_{I \rightarrow J,a,t}}{Patents_{J,t-a}} \quad (5)$$

Since *CiteFlow* is now a time-varying variable, the calculation method for the predicted value must also be

changed accordingly:

$$Predict_{I,t} = \sum_{K \neq I} \sum_{a=1}^{10} CiteFlow_{I \rightarrow K,a,t} P_{K,t-a} \quad (6)$$

According to the above two different prediction methods, this paper adopts different classification methods for prediction. If the prediction method proposed in this paper is an appropriate prediction method, then ideally, under different classification criteria, the predicted value of green patents can be predicted more accurately, that is, the future level of innovation can be further predicted based on past citation relationships and knowledge flow brought about by knowledge growth.

4.1.5. Analysis of predicted results

Based on the above data processing and model setting, the time-varying prediction strategy based on time-varying networks proposed by us has been shown to be a reasonable, effective and robust prediction method applicable to various classifications in the green patent network. The traditional static lag prediction method based on stable global technology patents is not applicable to the unstable green patent network studied in this paper.

First, we used the traditional static lag prediction method. Using global green patent data from 1990 to 2019, we classified green patents according to the two-level classification of the World Intellectual Property Organization's "IPC Green Inventory" and predicted the green innovation network. The results are shown in the last column of Table 4. We found that the correlation between the predicted value and the actual value is not significant. This may be due to the inherent instability of green innovation networks—that is, significant structural changes over time. We believe that the structural changes in green innovation networks over time may be closely related to the fact that green technological innovation is greatly affected by factors such as policies, the international environment, and climate shock events. Based on this, the static lag method, which uses a fixed ten-year reference for forecasting, is not desirable in green innovation networks, because this method is suitable for stable network structures, and the green patent network is precisely a network with obvious characteristics of change over time.

Subsequently, we used the dynamic rolling forecast model to forecast the green innovation network, and the results are shown in Table 4. We found that this forecasting method performed well in the unstable green innovation network. This indicates that the dynamic rolling forecast model can effectively capture the temporal dynamics of green knowledge flows. The predicted values of the dynamic model are significantly positively correlated with the actual values, and the R^2 values for the first four classification models all exceed 0.9. This shows that under these classification criteria, the dynamic rolling forecast model proposed in this paper can explain more than 90% of future green innovations based on the green knowledge flows of the past decade, highlighting its advantages over traditional static methods.

Table 4
Prediction results

VARIABLES	IPC2_r <i>ln(Patents_{J,t})</i>	IPC4_r <i>ln(Patents_{J,t})</i>	WIPO_Up_r <i>ln(Patents_{J,t})</i>	WIPO_sic_r <i>ln(Patents_{J,t})</i>	Patent_r <i>ln(Patents_{J,t})</i>	WIPO_sic_static <i>ln(Patents_{J,t})</i>
<i>ln(Predict_{J,t})</i>	0.0911* (0.0536)	0.287*** (0.0246)	0.398*** (0.112)	0.241*** (0.0377)	0.706*** (0.00575)	-0.291 (0.439)
Constant	8.165*** (0.115)	5.802*** (0.0466)	6.424*** (0.255)	7.353*** (0.0798)	2.864*** (0.00880)	6.750*** (0.000)
Observations	571	3,306	213	1,049	67,359	270
R-squared	0.978	0.932	0.970	0.969	0.782	0.9846

Note: Robust clustering standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We have verified the robustness of the model using different domain classification criteria, and the prediction results of these classification methods should be consistent under an ideal prediction model. The first column in Table 4 classifies according to the first two digits of the IPC number; the second column classifies according to the first four digits of the IPC number; the third column classifies according to the seven categories of the “IPC Green Inventory”; the fourth column classifies according to the second-level subcategories of the seven categories of the “IPC Green Inventory”; and the fifth column classifies according to the full IPC number, which is the most classified group. We estimate Equation (2) based on fixed categories and time fixed effects. Since the green patent network is also characterized by an uneven spatial distribution, we cluster at the category level and finally find that the dynamic rolling prediction model can effectively capture the temporal dynamics of green knowledge flows and accurately predict green innovation at different classification levels.

5. Discussion

The findings reveal that the dynamic rolling forecast method effectively captures the temporal dynamics of green knowledge flows, providing a robust tool for predicting future green innovations. These insights offer valuable guidance for policymakers, businesses, and researchers aiming to promote sustainable development and address global environmental challenges.

However, we must admit that there are still limitations to the research in this paper. First, for the identification of green patents, this paper uses the World Intellectual Property Organization’s “IPC Green Inventory” standard for classification, which ultimately resulted in 6.65 million patent samples worldwide over a period of 30 years. However, this classification standard relies on the IPC number and may not be the best way to screen green patents. In the future, we will combine machine learning-related techniques, such as LLM, to extract summary information from patents to more deeply identify green patents. Second, although the

dynamic rolling prediction model proposed in this paper can better capture the dynamics of the green innovation network than traditional models, it also has limitations. For example, the method assumes that citation relationships within a 10-year window represent the flow of knowledge between fields, which may not hold in the case of sudden technological breakthroughs or policy shifts. In the future, our research will explore more complex models that integrate exogenous factors such as policy changes and market shocks to further improve the model’s prediction accuracy in realistic complex situations.

6. Conclusion

Through an in-depth analysis of global green patent data spanning from 1990 to 2019, our research probes into the distinctiveness and dynamics of green innovation networks. Employing quantitative metrics and visual analysis, we approach this exploration from both theoretical and intuitive standpoints. The study underscores the pivotal role played by knowledge spillovers and accumulation in propelling green innovation. The results indicate that the dynamic rolling forecast method put forward in this paper is capable of effectively grasping the temporal dynamic traits of green knowledge flows. As such, it furnishes a potent instrument for predicting future green innovation. These insights offer invaluable guidance to policymakers, enterprises, and researchers who are dedicated to promoting sustainable development and grappling with global environmental challenges. Building upon prior research that has investigated the influence of exogenous factors like policies on green innovation, this paper discloses that knowledge flows serve as an endogenous driver of green technological innovation. Our study not only illuminates a novel perspective for understanding and spurring green technological innovation but also presents a trailblazing methodological framework applicable across diverse technological innovation domains. By revealing the dynamic essence of knowledge flows, our findings can assist policymakers, businesses, and research institutions in strategically allocating resources and directing

efforts towards the further innovation and development of green technologies. This, in turn, contributes to sustainable development and better enables the addressing of global environmental challenges within the context of global sustainability.

Within the framework of global sustainable development, the outcomes of our research can offer theoretical substantiation and practical direction to policymakers, enterprises, and research institutions, thereby fostering further innovation and progress within the realm of green technology. Concretely, for policymakers, this paper supplies methodological backing. It enables them to adapt incentives in accordance with technological evolution, eschew one-size-fits-all subsidy approaches, and dynamically optimize the policy milieu. Regarding enterprises, this study suggests bolstering interdisciplinary cooperation, making the most of extant technological resources, promoting the commercial implementation of green technologies, and expediting technology integration. As for research institutions, this paper advocates strengthening basic research, plugging research gaps in marginal areas, and enhancing the equilibrium of green innovation networks, thus furnishing a robust theoretical underpinning for green technological innovation. Through the promotion of green technological innovation, our research makes contributions to the attainment of the global sustainable development goals (SDGs), particularly in the aspects of combating climate change and driving high-quality economic growth. Prospective research might delve into the function of international cooperation in facilitating green knowledge flows and innovation achievements. Moreover, the incorporation of machine learning techniques has the potential to further enhance the predictive precision of the dynamic rolling forecast method and offer novel perspectives on the evolution of the green patent network.

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Data Availability

The raw global green patent datasets analyzed during the current study are not publicly available. This dataset was purchased and compiled by the research team from multiple sources and is classified as confidential research data. Public sharing is strictly prohibited due to confidentiality agreements and licensing restrictions imposed by the multiple data providers. However, to ensure research transparency and replicability, the data processing scripts, statistical codes, and formulae used to generate the charts and final conclusions in this study have been provided as supplementary materials.

Ethical Approval

This article does not contain any studies with human participants performed by any of the authors.

Informed Consent

This article does not contain any studies with human participants performed by any of the authors.