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Spatiotemporal Patterns and Driving Factors of Plastic Film Use in China Based on the Machine Learning Method

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Abstract. A thorough understanding of the determinants of agricultural plastic film use plays an important role in promoting sustainable agricultural development in China. From 1997 to 2022, China's use of agricultural plastic film soared, peaked, and then leveled off at a high level, indicating that agricultural output is conflicted with environmental protection The usage varied greatly from region to region, with the fact that the east and the west showed wide fluctuations, the central area remained stable at medium levels, while the northeast used the least. Influence analysis shows that agricultural machinery level and rural education investment are the strongest positive drivers, whereas total grain demand and non-agricultural industrial structure act as major inhibitors. Other factors include fiscal support, per capita GDP, and urbanization, though to a lesser extent. Overall, the study demonstrates that agricultural film usage is influenced by various forces and shows clear temporal and spatial patterns, providing quantitative evidence and policy implications for promoting sustainable agricultural practices in China.

Keywords: Plastic film, Driving factors, Spatiotemporal patterns, Machine learning

1. Introduction

Plastic pollution, one of the greatest urgent environmental problems of the 21st century, poses severe threats to ecological systems and sustainable development [1]. According to the United Nations Environment Programme, approximately 11 million tons of plastic waste end up in oceans each year, and this number is predicated to triple by 2040 without immediate interventions [2]. Plastic waste exists in various forms, among which plastic film, widely used for mulching crops in agriculture, is the major pollutant in rural areas. In China, agricultural plastic film has contributed significantly to increasing crop yields and improving water use efficiency, playing a significant role in enhancing food security. Nevertheless, excessive and improper application of plastic film has also led to severe residual pollution, causing soil degradation, carbon emissions and reduced farmland productivity [3, 4]. As is recorded in the China Rural Statistical Yearbook, 2.416 million tons of agricultural film were used in China in 2013, among which 1.375 million tons were plastic, covering 17.7641 million hectares of farmland (approximately 13.81% of the total). Against this backdrop, exploration of the spatiotemporal patterns of agricultural plastic film use in China is not only crucial for protecting arable land resources, but also essential for eco-logical civilization construction and green agricultural transformation.

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The spatiotemporal characteristics of agricultural plastic film use have been analyzed from various perspectives in previous studies, including exploration of its scale, intensity, and environmental implications across different regions of China [5-7]. Some papers have focused on the temporal trends at the national level, assessing changes in agricultural plastic film application over a span of decades [5]. Although having shed light on the overall usage patterns, such approaches often lack spatial analysis and fail to reveal provincial-level trends or dynamic changes. Other re-searchers have conducted regional comparison or statistical clustering to classify usage intensity and development patterns [8, 9]. But relying on aggregated data and static snapshots is not enough to identify dynamic changes over time and space, and limited use of visualization tools cannot show complex spatiotemporal patterns effectively. Therefore, it is necessary to adopt a more comprehensive method that is able to reflect both temporal changes and regional differences in a clear way.

In an effort to pursue environmentally sound agricultural growth in China, it is essential to explore the driving factors of agricultural plastic film use [10]. From a socio-economic perspective, some studies have pointed out that the intensity of plastic film application is significantly affected by the differences in regional agricultural structures, levels of economic development, and cropping systems [11]. For instance, plastic mulching is widely used to conserve soil moisture and increase crop yields in provinces in the arid and semi-arid northwestern regions, whereas southeastern provinces with higher rainfall tend to use less. Some scholars have explored disparities and revealed spatial patterns across the eastern, central, western, and northeastern regions, drawing the conclusion that plastic film is used on a larger scale in regions with higher levels of agricultural mechanization because machine application have significantly boosted farming efficiency. Other studies have established an index system of influencing factors and identified a certain correlation between rural residents' income levels, fiscal support for agriculture, and the use of agricultural plastic film. However, limitations remain in variable selection and the quantitative analysis of driving mechanisms. Although previous studies provide valuable insights for understanding the spatial difference in plastic film use, they mainly adopted multiple linear regression, principal component analysis and other traditional statistical methods, which struggle to address multicollinearity among variables and fail to balance variable selection and parameter estimation. For example, Lasso regression (L1 regularization) is able to remove irrelevant coefficients to optimize variable selection, but it tends to select only one variable from highly cor-related variable groups, potentially omitting important complementary factors. In contrast, ridge regression (L2 regularization) can mitigate multicollinearity but cannot eliminate redundant variables, leading to reduced model interpretability. These methodological limitations result in insufficient accuracy in identifying the driving factors of agricultural plastic film use, making it difficult to clarify the extent and di-rection of the influence of each factor.

To cope with the limitations mentioned above, this study covers 31 provinces in China as research units and establishes an analysis frame-work of spatiotemporal patterns and driving factors with panel data from 1997 to 2022. Elastic Net regression, a machine learning tool that integrates the strong pionts of L1 and L2 regularization, is employed as the core approach. While L1 regularization simplifies the model by automatically removing less important variables, L2 regularization helps revolve the problems caused by strong correlations among variables, making Elastic Net particularly suitable for studying the complex factors that affect agricultural plastic film use. In the meantime, in order to show the impact of human resources, economic development, and technology input, this study builds an index system of influencing factors in both social and

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technological aspects, including agricultural population density, farmers' education level, agricultural mechanization, and rural education investment.

The contents and contributions of this study can be classified into three parts. Firstly, this paper identified the temporal trends and regional distribution characteristics of agricultural plastic film use in China by systematically analyzing the provincial panel data from 1997 to 2022, bridging the gap of existing studies in temporal dynamic analysis. Secondly, accurate selection and quantification of influencing factors are achieved through Elastic Net regression, illuminating the impact of positive driving factors and inhibitory factors, and resolving the limitations of traditional methods in dealing with multicollinearity and variable redundancy. Finally, spatiotemporal patterns and driving factors of agricultural plastic film use are clarified, providing a scientific basis for different regions to make corresponding policies. For example, mechanized operations are proposed to coordinate with plastic film recycling in regions with high plastic film use, while technical promotion support is suggested to be provided for regions with low use, With the targeted measures adopted in different regions, sustainability of green agriculture will be more likely to be achieved.

2. Research methods

2.1. Data sources

This study covers the 31 provinces in mainland China, with areas such as Hong Kong, Macao, and Taiwan excluded owing to data limitations. The data used in this study are primarily quoted from authoritative and re-liable sources, including the China Statistical Yearbook, China Environment Statistical Yearbook, China Science and Technology Statistical Yearbook, China City Statistical Yearbook, China Population and Employment Statistical Yearbook, in addition, historical data from the official website of the National Bureau of Statistics of China. For missing values in certain provinces and years, linear interpolation was applied to ensure data continuity. Based on data spanning from 1997 to 2022, this study focuses on measuring the spatiotemporal patterns, regional differences, and dynamic evolution of agricultural plastic film in China. To better capture regional disparities, the country is categorized into four major regions: Northeast, East, Central, and West.

2.2. Elastic network regression

Elastic Net Regression shows robust performance and excels in estimating and assessing multi-dimensional issues. When dealing with-complex datasets, itis able to enhance model stability and accuracy without sacrificing simplicity and generalization. The formula is as follows.

$$\beta\left(Elastic\ network\right) = \frac{1}{2n}\sum_{m=1}^{n}\left(y_m - w^T x_m\right)^2 + \alpha\rho \| w \|_1 + \frac{\alpha(1-\rho)}{2} \| w \|_2^2 \quad (1)$$

in elastic network regression model ,where $\beta\left(Elastic\ network\right)$ denotes the estimated parameter; n is the number of samples; ym represents the observed response value for the ith sample; xm is the corresponding feature vector .w stands for weight(coefficient) vector; $\| w \|_1$ means L1 norm of w1, which promotes sparsity; $\| w \|_2^2$ means squared L2 norm of w, which promotes shrinkage; α means regularization strength parameter; ρ means mixing parameter that a controls the balance between L1 and L2 regularization, also referred to as the shrinkage parameter.

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2.3. Construction of the factors' system

This study focuses on the social and technological factors that influence the use of agricultural plastic film. Agricultural population density and the education level of agricultural workers, which are selected as indicators to measure the regional distribution of agricultural human capital (table 1). These indicators help reveal not only how many people are involved in agricultural production but also how well they are trained to use modern techniques. By integrating these social and technological dimensions, the study builds a comprehensive evaluation framework. This framework makes it possible to identify the key drivers and obstacles affecting the use of agricultural plastic film, design more targeted and practical policy actions, and provide strong evidence-based support for promoting the sustainable and high-quality transformation of agriculture.

Table 1. The Index System of Influencing Factors in Plastic Film Use.

Factors	Symbol	Meanings
Agricultural population density	PPOP	Total agricultural population/ Effective cultivated land area
Years of Education for Farmers	REC	Average education years of rural residents
Total Grain Demand	AGY	Total grain output/Agricultural totalpopulation
Urbanization Rate	URB	Urban population/Total population
Rural Disposable Income	PCDI	Disposable income of rural residents
Rural Engel Coefficient	AEC	Food consumption expenditure of rural residents/Total expenditure of rural residents
Agricultural Development Level	PGDP	Agricultural GDP/Agricultural population total
Fiscal Support for Agriculture	AFS	Expenditure on agriculture, forestry, animal husbandry and fishery/Fiscal expenditure
Rural Education Investment	AEDU	Education expenditure * (Added value of agriculture, forestry, animal husbandry and fishery/Regional added value)
Agricultural R&D Investment	ST	Expenditure on high-tech industries*(Added value of agriculture, forestry, animal husbandry and fishery/ Regional added value)
AgriculturalIndustrial Structure Upgrading	AICE	Degree of industrial structure advancement
Agricultural Market Openness	OPEN	Total import and export volume of agricultural products/ Agricultural gross output value
Agricultural Tax Burden	TAX	Agricultural tax revenue/Agricultural gross output value
Non-Agricultural Industrial Structure	AIC	1 - Agricultural output value/Output value of agriculture, forestry, animal husbandry and fishery
Agricultural Machinery Level	MA	Total power of agricultural machinery

3. Results

The annual usage of agricultural plastic film in China from 1997 to 2022 is shown in Figure 1. Overall, the usage followed a dynamic trajectory marked by an initial steep growth, a peak, and

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subsequent moderate fluctuations. To be more specific, from 1997 to 2015, fueled by the rapid expansion of agricultural output, the intensification of farming, and the large-scale adoption of plastic film mulching to raise crop yields, especially in arid and semi-arid regions, use of plastic film increased steadily from approximately 1.2 million tons, peaking at around 2.6 million tons. After 2015, the amount of plastic film applied declined slightly, as stricter environmental regulations took effect and t sustainable agricultural technologies advanced. However, the increasing demand for agricultural output, especially under the framework of China's national food security strategy, still called for large-scale usage of plastic filmin agricultural production. Recent years also witnessed intensive use of plastic film out of the continued emphasis on stable food supply, forming a persistent high-usage pattern. This trend reflects that China's agricultural sector is faced with the challenge of boosting agricultural productivity while achieving environmental sustainability. Although plastic film plays an important role in improving crop yields in the short term, its long-term environmental impacts, including soil degradation and microplastic accumulation, cannot be underestimated.

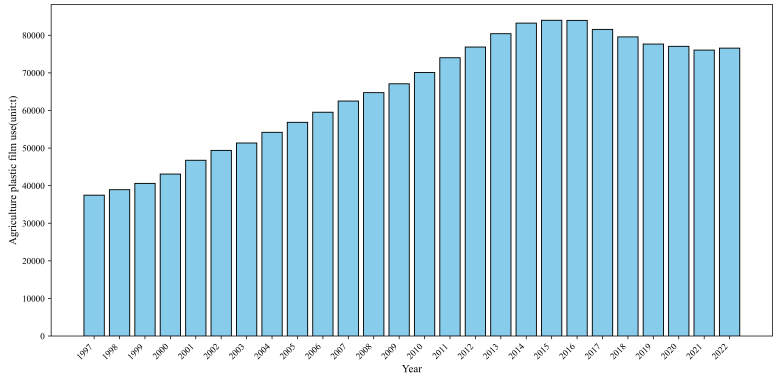

Figure 1. Usage of agricultural plastic film in China (Picture credit: Original)

Figure 2 illustrates the violin chart of usage of agricultural plastic film in China 4major regions. From the perspective of regional characteristics, the violin plot shows clear differences in the use of agricultural plastic film across China. In the eastern region, the violin shape stretches far both upward and downward, with many high-value points close to 400,000. This means the usage range is the widest and the data are highly scattered. In the central region, the violin shape is more compact, with most data concentrated in the middle range of 0-200,000. The high-value extension is not obvious, so the distribution is more focused at a medium level and less scattered than in the east. In the western region, the violin is relatively tall, with a wide usage range and many high-value points, showing greater variation in usage. In the northeast, the violin shape is the shortest and widest, with data mainly clustering between 0 and 150,000 with the fewest high-value points, meaning the usage is mostly at a low level and the variation is the smallest. In short, there are clear regional differences: the east and west show large usage ranges and strong variation, the central region is concentrated at medium levels, while the northeast is mainly at lower levels.

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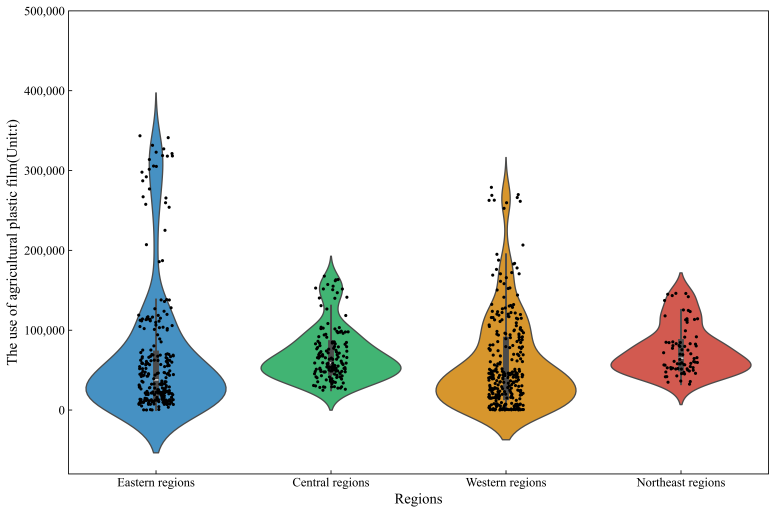

Figure 2. Violin Chart of Usage of agricultural plastic film in China Four Major Regions (Picture credit: Original)

Figure 3 shows the scatter plots of feature changes. Rural Education Investment (AEDU) rises steadily, while Agricultural Machinery Level (MA), Agricultural R&D Investment (ST), and Agricultural Tax Burden (TAX) increase mainly in the later stage. Total Grain Demand (AGY) declines quickly after an early peak, and both Rural Disposable Income (PCDI) and Agricultural Development Level (PGDP) drop sharply from high initial values. Years of Education for Farmers (REC) and Fiscal Support for Agriculture (AFS) remain stable within narrow ranges. Urbanization Rate (URB) and Agricultural Industrial Structure Upgrading (AICE) show segmented clustering, while Agricultural Population Density (PPOP), Rural Engel Coefficient (AEC), and Non-Agricultural Industrial Structure (AIC) fluctuate widely without clear trends. For Agricultural Market Openness (OPEN), most values are very low, with only a few extreme highs.

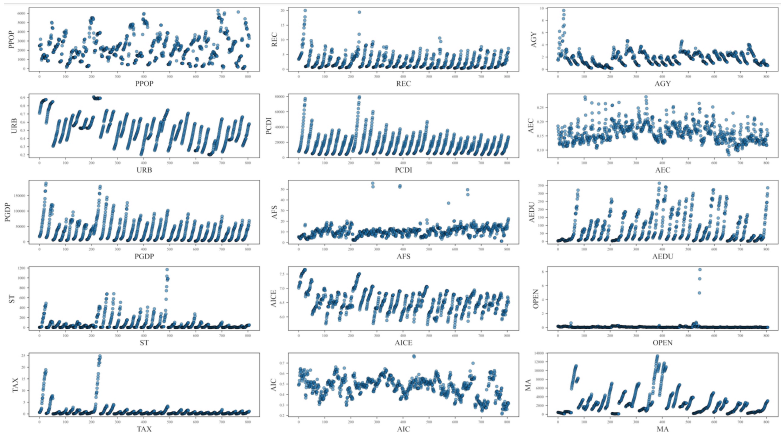

Figure 3. Scatter Plots of Factor Changes in China (Picture credit: Original)

The main criteria for variable selection are collinearity and weak correlation. When two variables have a correlation coefficient close to 1, they contain highly overlapping information, so one should be removed to avoid redundancy and overfitting. Conversely, if a variable shows correlations below 0.2 with most others, it has weak explanatory power and can also be excluded. Figure 4 presents the correlation heatmap. Specifically, strong collinearity is observed between several variables: Rural

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Disposable Income (PCDI) and Agricultural Development Level (PGDP) (0.96), Years of Education for Farmers (REC) with both PCDI and PGDP (0.88), Urbanization Rate (URB) with PCDI (0.73) and PGDP (0.79), and Agricultural Industrial Structure Upgrading (AICE) with Agricultural R&D Investment (ST) (0.83). These pairs clearly indicate information redundancy. In addition, Agricultural Market Openness (OPEN) shows correlations below 0.2 with most variables, suggesting weak ex-planatory ability. Based on these results, the variables PCDI, REC, ST, OPEN, and Non-Agricultural Industrial Structure (AIC) are excluded from further analysis.

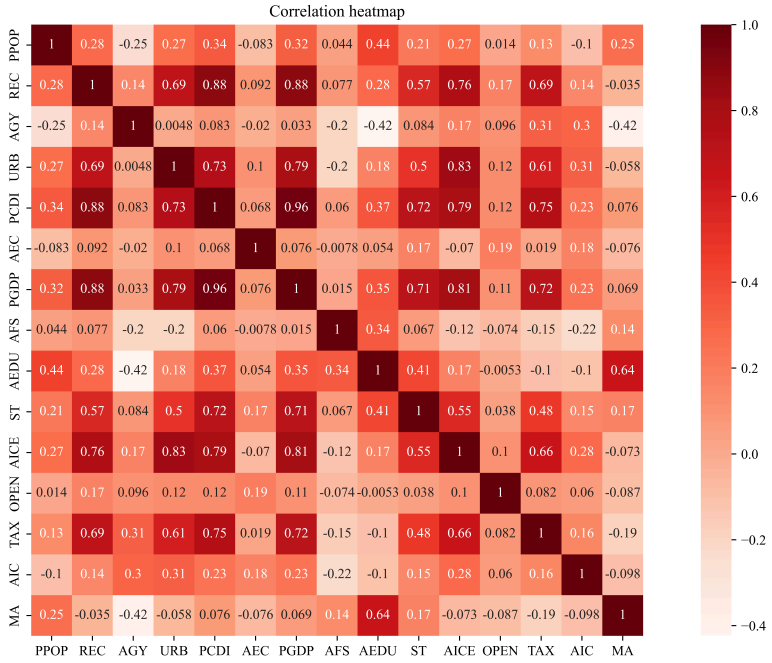

Figure 4. Correlation heatmap of explanatory variables (Picture credit: Original)

The importance ranking of factors influencing agricultural plastic film usage is illustrated in Figure 5. Agricultural Machinery Level (MA, 23,149.35) is identified as the strongest positive driver, serving as the core factor promoting film usage. The second strongest contributor is Rural Education Investment (AEDU, 10,964.65), followed by Fiscal Support for Agriculture (AFS, 2,549.63), Agricultural Development Level (PGDP, 471.39), and Urbanization Rate (URB, 162.27), all of which also exert positive effects but with gradually declining intensity. On the other hand, some factors play an inhibitory role. Total Grain Demand (AGY, -7,051.70) is the most influential negative factor, representing a strong restraining effect. It is followed by Non-Agricultural Industrial Structure (AIC, -5,618.67), Agricultural Population Density (PPOP, -2,883.44), and Agri-cultural Industrial Structure Upgrading (AICE, -2,784.39), all of which show notable inhibitory impacts. Agricultural Tax Burden (TAX, -176.66) has only a minor negative effect. Overall, the factors demonstrate a clear directional divergence and large differences in intensity, reflecting the complexity of agricultural film usage, which is shaped by the simultaneous “push-and-pull” effects of multiple drivers.

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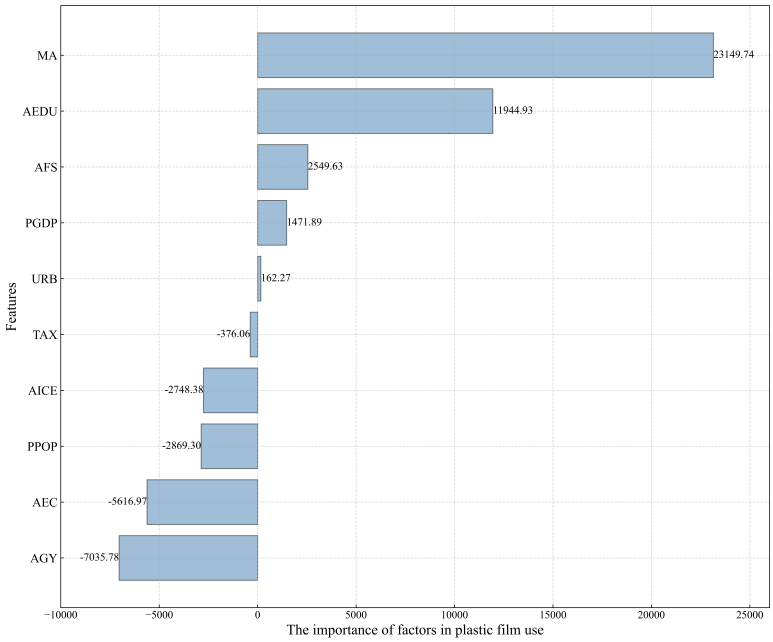

Figure 5. China's Key Influencing Factors in Plastic Film Use (Picture credit: Original)

4. Conclusion

This paper applied Elastic Net regression to identify the temporal and spatial patterns of China's agricultural plastic film usage as well as the major influencing factors, providing a clear analytical framework for understanding plastic film usage and making the optimal policy.

China's agricultural plastic film usage experienced three distinct phases over the period from 1997 to 2022: a rapid growth, a peak, and a plateau. This temporal pattern reflects the inherent tension between two core goals in China's agricultural development: the pursuit of improved agricultural productivity and the advancement of environmental sustainability, calling for a balance between production efficiency and ecological protection in the application of agricultural plastic film.

It is noteworthy that there exist huge spatial differences in the usage of agricultural plastic film. Specifically, the eastern and western regions exhibit wide usage ranges and high variability; the central region clusters at medium levels; and low usage can be found in the northeastern region. These regional differences not only reflect the diverse driving factors behind film application across areas but also highlight the necessity of formulating targeted regional policies for agricultural plastic film management rather than adopting a "one-size-fits-all" approach.

China's agricultural plastic film usage is affected by various complex factors, among which agricultural machinery level and rural education investment act as main positive drivers, while total grain demand and non-agricultural industrial structure serve as major inhibitory factors. The coexistence of strong promoting and restrictive forces indicates that agricultural film usage is shaped by a complex "push-and-pull" dynamic mechanism.

References

[1] Zhang Q.Q., Ma, Z.R., Cai, Y.Y., et al. (2021). Agricultural Plastic Pollution in China: Generation of Plastic Debris and Emission of Phthalic Acid Esters from Agricultural Films. Environmental Science & Technology, 55(18): 12459-70.

DOI: 10.54254/2755-2721/2025.LD28180

[2] Liu, E., He, W., Yan, C. (2014). 'White revolution' to 'white pollution' - Agricultural plastic film mulch in China. Environmental Research Letters, 9: 091001.
[3] Wencan, Z., Céline, L., Nils, T. (2021). A variable selection approach for highly correlated predictors in high-dimensional genomic data. Bioinformatics (Oxford, England), 37(16): 2238-2244.
[4] Mournet, M. A., Ball, I. M., Kleiman, M. E. (2025). Healthcare experiences and barriers as predictors of suicidal thoughts and behaviors among transgender adults: an elastic net regression analysis. Social Psychiatry and Psychiatric Epidemiology, 1-9.
[5] He, G., Wang, Z.H., et al., (2018). Plastic film mulching throughout the year can increase wheat yield, economic benefits, and reduce environmental risks in arid areas of the Loess Plateau. Field Crop Research. 225, 1-8.
[6] Gao, J. H., Yan, C.R., et al. (2019). The impact of plastic covering and plastic residue film on agricultural production: a meta-analysis General Theory of Science and Environment, 651: 484-492.
[7] Jia, Q. (2021). Spatiotemporal Evolution and Influencing Factors of Agricultural Environmental Efficiency in China, Discrete Dynamics in Nature and Society, (1): 3323537.
[8] Li, C., Sun, M.X., et al. (2021). Characteristics and influencing factors of plastic film pollution prevention and control in China: micro evidence from small farmers. Resources, Protection, and Recycling. 164, 105.
[9] Liu, X.Y., Xin, L.J. (2023). The spatiotemporal evolution and greenhouse gas emissions of plastic greenhouses in Chinese agriculture Environmental Science, 863: 160810.
[10] Wang, D., Chen, C. et al. (2025). Stages of Rural Transformation and Comparison between Bangladesh, China, and Pakistan: Combining Machine Learning and New Structural Economics to Promote International Agricultural Development and Policy Design. Asia Pacific Policy Research, 12 (2): 70016.
[11] Zhao, C., Wang, Y. et al. (2024). Agricultural Plastic Pollution in China: Sources, Supply Drivers, and Mitigation Strategies, Frontiers of Sustainable Development, pp. 100-102.