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Comparative Static Analysis on the Agricultural Mechanization Development Levels in China's Provincial Areas

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Abstract: The foundation of the national economy is agriculture, agricultural modernization is the symbol of national modernization and agricultural mechanization is an important symbol of agricultural modernization. In this paper, the authors conducted an analysis of the agricultural mechanization levels of 31 provincial areas in China. In order to assess the agricultural mechanization levels of the provincial areas in China as accurately as possible, the authors adopted indicators in the year 2005, the year 2010 and the year 2015, and used the comparative static analysis method to observe the dynamic changes in the data over the three years. Eight items, including total agricultural mechanization power/grain output (10 million watts/10 k tons), number of large and medium-sized tractors/grain output (pcs/10 k tons), tractor plowing area/grain output (k hectares/10 k tons), total input of agricultural mechanization business operation/grain output (million yuan/10 k tons), total income of agricultural mechanization business operation/grain output (million yuan/10 k tons), and fuel consumption for agricultural production/grain output (hundred tons/10 k tons), were used as assessment indicators. With the gray weighted cluster assessment instrument, 31 provincial areas of China were classified into five gray categories at high development level, relatively high development level, medium development level, medium to low development level and low development level. An objective, scientific and comprehensive assessment of the cluster results was conducted in an effort to better provide references for the authorities to draft relevant policies and measures.

Keywords: provincial areas; agricultural mechanization development level; gray cluster assessment; sustainable development

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1. Introduction

Currently, major methods used in analyzing the agricultural mechanization development levels in China include the comprehensive assessment method, the ambiguous comprehensive assessment method, the factor analysis method, the layer analysis method and the gray association method. The non-traditional plans can be measured by means of the comprehensive assessment method. The problematic instructor address issues are reduced, also it is connected with the program development, cost efficiency and program quality. The method of reducing a great number of variables into a smaller amount of factors is referred to as the factor analysis method. This method specifically preferred only the major component analysis. Hence, these methods identified a maximum common variance of all variables that comes under the common notch. By exploring the original causes and worldviews contributory to a situation, a collection of intelligence-making techniques is preferred, hence this technique is known as layered analysis. The ambiguous is also known as sustainable agriculture, it proposes different methods, in which the numeral description plays a major role, as it indicates sustainable agriculture to various people. Hence, this method will not belong to the subsequence of arbitrary concepts [1]. In 2022, Chen et al. conducted a case study on agricultural service systems based on the grey correlation and regression analyses [2]; in 2020, Hui et al. conducted an analysis on the agricultural machinery level through grey system theory, combining the rough sets theory and artificial neural network technology [3]. In relation databases, file mining or information detection acts as a procedure for rough set theory. Moreover, it has two important notions called reduct and core. To retain the exactness of the original set, a reduction is performed. The BP network is abbreviated as a backpropagation neural network, which is the most used neural network model. According to the error back propagation algorithm, a multi-layer feed-forward network is trained via the BP network. The R&D process is abbreviated as the research and development process, to acquire a new technology a corporation works through this process, thus the new technology contains a product, provision, or system [4]. In 2006, Bai Dongyan conducted an analysis of the agricultural mechanization development level of China with the factor analysis method [5]; in 2012, Wang Mingli conducted an analysis of the agricultural mechanization development level of Tianjin with the layer analysis method [5,6]. By exploring the original causes and worldviews contributory to a situation a collection of intelligence-making techniques is preferred, hence this technique is known as layered analysis. In 2014, Yang Chunlei and Yang Wanzhang conducted an analysis of the agricultural mechanization development level of Xinjiang by determining the weights of all the assessment indicators [7]; in 2015, Lu Bingfu, Han Weiping et al. proposed to add assessment factors and expand the assessment scope and conducted an analysis of the agricultural mechanization development level of China [6]. Regarding the function of machinery, first should come measures regarding crop growth. Hence, the quality of the crop should remain the same, this can be done with the help of the organic crop rotation technique. To increase the productivity of products on the farmland and also reduce the work of farmers, they introduced mechanized vehicles, hence this technique is termed agricultural mechanization. We can simply describe agricultural mechanizing as the reduction of manpower in the farmland by implementing machinery. This tends to reduce the timing consumption of work compared to the actual manpower; as a result of this increase in the production, distribution, and utilization, the economic level of the country increases [8]. The merits of this method are that it requires fewer workers, the health risk is reduced, and due to this, the production level is increased, which tends to increase the large-scale agro-business.

To assess the agricultural mechanization development level of the provincial areas of China as accurately as possible, the authors adopted representative indicators pertaining to the connotation of agricultural machinery modernization in response to the agricultural mechanization development level of 31 provincial areas in China (excluding Hong Kong, Macau and Taiwan) who, respectively, adopted the indicators in 2005, 2010, and 2015—the end year of the 10th, 11th, 12th years of China's Five-Year Plan (a national development plan), and used the gray cluster assessment method to observe the changing process of the data over the three years [9]. Regarding the function of machinery, first we should note measures regarding crop growth. Hence, the quality of the crop should remain the same. This can be achieved with the help of the organic crop rotation technique. The gray cluster assessment method is mainly used to assess targets that belong to different pre-set categories so that these targets will be treated differently and properly in the future. As this assessment method is easy to implement and can be easily programmed, it is widely used in increasing numbers of fields such as agriculture, district planning, economic analysis, military affairs, and engineering [10]. The basic principle of the gray cluster assessment is as follows: observe the multiple characteristics indicators of the target in a comprehensive way, obtain the cluster coefficient that belongs to each sub-gray-cluster and judge the gray cluster that the target belongs to the largest cluster coefficient.

2. Assessment Method

The gray cluster assessment instrument is the earliest developed and the most widely used technology in the gray system theory and is always a trending topic in the discussions of gray system theory. In many industrial, agricultural and practical situations, evaluation analysis comes to a deadlock with incomplete data sets and small sample capacities. The gray cluster assessment method, as a branch of the gray system theory, can demonstrate the systematic behaviors, evolution regularity efficiently and precisely when the input data are not perfect. The process of categorizing risk by the degree of harm to the grey clustering risk catalog system is known as grey clustering analysis. To evaluate risk accurately, the decisions of overseas project loans are utilized. To attain the loan plan for the clustering center decision technique, sample information set clustering analysis is utilized as an outcome which is also evaluated by the clustering risk system for executing the project implementation plan outside loans. The gray cluster assessment instrument is an instrument that clusters a few observing targets into certain definable categories with the whitening weight function. Gray weighted clustering is one of the most commonly used instruments of the gray cluster assessment instruments. To perform calculations such as addition, integral or to provide a mean of some elements with more weight, a weight function is used; hence, the expected results have influenced the same set. Therefore, the obtained result will be the average weight of the element or the average sum of the element.

Suppose that there are n cluster targets, m cluster indicators and s different clusters. According to the observing value x_{ij} (i = 1, 2, . . . , n; j = 1, 2, . . . , m) on the indicator j (j = 1, 2, . . . , m), the targets are categorized as k (k = 1, 2, . . . , s) gray clusters. Then, the gray weighted cluster assessment can be conducted according to the following steps [6]. Step 1, give the k subcategory whitening weighted function of the j indicator. Step 2, confirm the cluster weights of the indicators according to the qualitative analysis conclusions. The purpose of qualitative analysis is to build non-integer data for a chemical type, response and many others. This can be explained further by witnessing a reaction that produces fuzzy gas and the color changes. Step 3, calculate the gray weighted cluster coefficient with the results obtained in the first two steps and the sample value of the target j of the indicator k x_{ij}. Step 4, if the k cluster coefficient that the whitening weighted function corresponds with is comparatively bigger, then the target i belongs to the k (k = 1, 2, . . . , s) gray category. A node is present in graph which can be grouped together by the evaluation of degree called the cluster coefficient. The overall manifestation of the cluster in the network was designed by the global version. The embeddedness of single node is manifested by a local node.

3. The Selection of Indicators and the Determining of Whitening Weighted Function

3.1. Selection of Indicators

According to the principles that the data should be inclusive, important and readily available, we have selected eight items including total agricultural mechanization power/grain output (10 million watts/10 k tons), the number of large and medium-sized tractors/grain output (pcs/10 k tons), tractor plowing area/grain output (k hectares/10 k tons), total input of agricultural mechanization business operation/grain output (million yuan/10 k tons), the total income of agricultural mechanization business operation/grain output (million yuan/10 k tons), and fuel consumption for agricultural production/grain output (hundred tons/10 k tons) as assessment indicators, which are represented by X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, respectively [5,11]. Agricultural modernization is a process in which the agricultural sector is converted dynamically with the help of advanced knowledge. While improving the agricultural sectors, which in turn forms the base for national modernization, this process plays a vital role in farmers' lives by improving the economic growth of farmers in rural areas. We can simply describe agricultural mechanization as the reduction of manpower in farmland by implementing machinery. This tends to reduce the time consumption of work compared to using actual manpower; as a result of this increase in production, distribution, and utilization, the economic level of the country increases [12]. The specific data are provided in Tables 1–3.

Table 1. Data of 31 provincial areas in 2005.

Provincial Areas	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Beijing	3.557	8.954	1.533	2.076	1.011	1.666	13.298	13.168
Tianjin	4.450	7.491	2.736	2.105	0.929	1.411	11.971	11.142
Hebei	3.266	3.856	1.834	2.028	0.957	0.755	4.925	18.845
Shanxi	2.340	3.671	2.088	1.552	0.664	0.816	7.106	10.317
Neimenggu	1.156	4.434	2.807	2.490	0.891	0.688	3.272	4.922
Liaoning	1.099	2.463	1.706	1.059	0.212	0.305	3.936	5.078
Jilin	0.570	3.518	0.713	0.884	0.046	0.438	2.617	3.564
Heilongjiang	0.723	7.028	3.252	2.854	1.604	0.393	3.321	4.101
Shanghai	0.916	3.986	1.633	0.321	1.383	1.136	1.788	5.657
Jiangsu	1.106	1.464	1.384	0.749	1.336	0.872	4.980	3.922
Zhejiang	2.591	0.552	1.215	0.014	0.902	1.282	12.740	9.885
Anhui	1.521	1.382	1.449	0.894	1.277	0.904	5.992	4.420
Fujian	1.398	0.196	0.590	0.001	0.090	0.759	8.167	9.869
Jiangxi	1.014	0.729	1.061	0.040	0.576	0.990	4.541	5.615
Shandong	2.348	5.815	1.402	1.374	0.948	0.963	7.849	20.710
Henan	1.732	2.418	1.267	1.278	1.048	0.598	3.233	5.151
Hubei	0.945	3.518	0.926	0.107	0.646	0.668	4.488	6.322
Hunan	1.191	0.329	0.792	0.013	0.401	0.642	10.013	4.568
Guangdong	1.361	0.423	0.957	0.002	0.259	0.473	4.676	4.891
Guangxi	1.284	1.143	0.698	0.000	0.043	0.639	9.720	6.176
Hainan	1.952	3.791	1.048	0.000	0.426	1.539	7.181	9.895
Chongqing	0.664	0.009	0.334	0.003	0.025	0.308	4.112	2.854
Sichuan	0.679	0.396	0.333	0.128	0.155	0.593	4.677	3.955
Guizhou	0.878	1.207	0.210	0.005	0.047	0.232	2.692	2.789
Yunnan	1.100	2.970	0.358	0.013	0.038	0.770	4.073	3.767
Tibet	2.473	7.173	0.136	0.134	0.114	0.000	0.000	0.000
Shannxi	1.371	3.404	1.585	1.470	0.824	0.853	4.481	5.934
Gansu	1.681	2.187	1.720	1.035	0.479	0.805	6.636	9.716
Qinghai	3.408	2.895	2.706	2.579	1.083	1.516	4.719	9.125
Ningxia	1.875	4.469	1.753	1.323	0.401	0.705	7.019	6.461
Xinjiang	0.994	10.529	2.553	2.560	0.938	0.944	6.615	4.658

Source: China Agricultural Mechanization Statistics Almanac 2005.

Table 2. Data of 31 provincial areas in 2010.

Provincial Areas	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Beijing	2.386	7.175	0.846	1.876	1.150	3.240	9.931	5.982
Tianjin	3.680	8.138	2.357	2.518	1.385	2.214	12.352	10.655
Hebei	3.411	5.800	1.787	2.108	1.152	1.113	6.682	10.336
Shanxi	2.589	6.746	2.359	2.011	0.858	2.250	9.003	7.598
Neimenggu	1.406	23.821	2.865	2.807	1.194	1.385	4.822	5.721
Liaoning	1.274	8.587	1.937	1.442	0.499	1.506	5.468	4.993
Jilin	0.755	10.329	1.433	1.312	0.400	1.338	4.107	4.563
Heilongjiang	0.745	13.061	2.696	2.534	1.782	1.315	3.081	4.020
Shanghai	0.879	4.877	3.334	0.448	1.400	3.237	2.253	2.905
Jiangsu	1.217	2.989	1.712	1.007	1.481	1.213	7.011	5.706
Zhejiang	3.150	1.090	1.865	0.198	1.169	2.526	20.467	14.847

Table 2. *Cont.*

Provincial Areas	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Anhui	1.756	4.048	2.291	1.171	1.709	1.503	11.096	4.733
Fujian	1.822	0.393	1.373	0.039	0.337	1.843	14.130	7.213
Jiangxi	1.947	0.849	1.483	0.199	1.137	0.797	7.434	6.617
Shandong	2.682	9.819	1.504	1.884	1.542	1.232	10.187	11.901
Henan	1.875	5.048	1.519	1.667	1.360	1.045	4.499	6.353
Hubei	1.456	5.488	1.951	0.352	1.201	1.583	9.759	7.344
Hunan	1.634	2.977	1.644	0.069	0.945	1.463	12.422	5.510
Guangdong	1.782	1.398	2.353	0.055	0.908	1.773	8.935	11.035
Guangxi	1.960	1.535	2.210	0.131	0.654	2.507	17.227	7.838
Hainan	2.358	16.521	2.410	0.034	1.054	2.580	11.985	9.635
Chongqing	0.927	0.285	1.385	0.076	0.194	1.221	6.777	4.669
Sichuan	0.979	2.827	0.680	0.110	0.261	1.581	6.499	4.061
Guizhou	1.556	2.278	0.567	0.029	0.089	0.946	4.899	3.363
Yunnan	1.575	14.696	1.083	0.012	0.103	1.355	6.235	4.271
Tibet	4.145	27.961	1.469	1.447	1.228	3.681	1.500	17.259
Shannxi	1.717	6.937	2.152	1.641	1.178	2.239	6.610	7.163
Gansu	2.064	7.639	1.858	1.256	0.643	1.259	7.915	13.315
Qinghai	4.131	80.196	3.040	2.647	1.252	3.174	11.220	10.275
Ningxia	2.045	7.833	2.310	1.812	1.071	1.956	7.199	6.628
Xinjiang	1.088	18.519	2.973	2.811	1.328	2.921	7.451	4.991

Source: China Agricultural Mechanization Statistics Almanac 2010.

Table 3. Data of 31 provincial areas in 2015.

Provincial Areas	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Beijing	3.125	10.536	1.041	1.805	1.516	4.244	11.971	12.947
Tianjin	3.039	8.693	2.101	2.306	1.920	2.958	8.914	9.315
Hebei	3.253	7.569	1.615	1.969	1.483	2.826	6.822	9.154
Shanxi	2.609	9.448	2.130	2.082	1.438	2.098	10.409	6.999
Neimenggu	1.285	23.753	2.222	2.425	1.587	1.799	5.205	4.591
Liaoning	1.363	11.156	1.907	1.645	0.906	1.247	5.939	4.824
Jilin	0.800	13.183	1.366	1.372	0.800	1.359	4.581	4.228
Heilongjiang	0.815	14.573	2.271	2.236	1.955	1.079	3.705	3.741
Shanghai	1.051	6.424	3.189	0.568	1.376	5.726	2.587	3.123
Jiangsu	1.306	4.246	1.673	1.233	1.463	1.919	7.817	4.279
Zhejiang	3.217	1.595	1.912	0.299	1.223	2.808	21.814	16.296
Anhui	1.799	5.633	2.086	1.325	1.763	1.651	14.137	4.453
Fujian	2.070	0.529	1.577	0.207	0.587	1.044	15.402	6.182
Jiangxi	0.986	0.661	1.821	0.286	1.467	1.194	7.382	4.841
Shandong	2.780	11.000	1.303	1.834	1.540	1.352	10.329	8.476

Table 3. *Cont.*

Provincial Areas	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Henan	1.892	6.232	1.497	1.682	1.554	0.981	4.671	6.064
Hubei	1.588	5.863	2.163	0.774	1.546	1.761	9.531	5.311
Hunan	1.889	3.873	1.966	0.337	1.250	1.626	18.813	6.229
Guangdong	1.938	2.069	2.684	0.182	1.164	1.278	11.478	9.072
Guangxi	2.340	2.486	2.926	0.408	1.228	1.686	23.950	8.782
Hainan	2.812	24.404	3.088	0.045	1.776	2.939	20.246	14.262
Chongqing	1.077	0.329	1.789	0.108	0.281	0.892	8.215	4.401
Sichuan	1.208	3.663	1.336	0.212	0.573	1.534	7.137	4.088
Guizhou	2.083	3.568	1.251	0.051	0.242	1.284	5.616	3.760
Yunnan	1.713	16.058	1.423	0.059	0.210	1.110	6.506	4.517
Tibet	5.672	88.244	1.403	1.352	1.133	6.990	1.694	26.334
Shannxi	2.080	8.290	2.333	1.633	1.477	1.873	9.205	7.458
Gansu	2.174	12.321	2.081	1.312	0.823	1.932	8.676	10.930
Qinghai	4.292	15.479	3.635	2.882	2.083	1.804	9.562	11.371
Ningxia	2.182	13.178	2.418	1.839	1.487	2.029	8.078	6.049
Xinjiang	1.219	25.768	3.231	3.238	1.553	3.390	7.856	4.873

Source: China Agricultural Mechanization Statistics Almanac 2015.

Some examples of gain products are wheat, oats, millets, rice, maize etc. As of now, China is a leading country in wheat production. In 2020, China achieved 20.65% of the world's wheat production. India, Russia, the USA and Canada are the top five leading producers of wheat grain.

3.2. The Determining of Whitening Weighted Function

In the assessment of gray clusters, determining the whitening weighted functions is one of the most crucial steps and is the key to the transition from qualitative analysis to quantitative modeling. The process of resolving non-integer data regarding a chemical reaction, response and others is known as qualitative analysis. The term quantitative analysis is referred to as firm information and real integers, and the term qualitative analysis is less perceptible. There is an absence of statistical tests in qualitative analysis, but in quantitative analysis, statistical tests have been taken. The whitening weighted function of the gray clusters is used to assess the degree to which a target belongs to a certain gray cluster by means of quantitative description. The whitening weighted function can be determined from the angle of the participating cluster targets or according to all the targets of the same category amid the greater environment [13]. It must be specified that such a subjective judgment must be made based on the objective reflection of known information. In this paper, our determination of the whitening weighted function was based on participating cluster targets.

As there are 31 targets for assessment, we must classify the gray clusters into five categories, which are, respectively, gray cluster at the high development level, gray cluster at a relatively high development level, gray cluster at the medium development level, a gray cluster at medium to low development level and gray cluster at the low development level [14]. If we number the indicators and the gray clusters, we will have the j (j = 1, 2, 3, 4, 5, 6, 7, 8) indicator k (k = 1, 2, 3, 4, 5) gray cluster to represent the "k" gray cluster of the "j" indicator. Next, we will set the whitening weighted function of the "k" gray cluster of the "j" indicator [15].

The two brain-based structure is followed in the environment for supervising a person's communication illustrated by gray theory. The personalities are reflected by the induvial's compassion for castigation. In the gray system theory, commonly used whitening weighted functions include the typical whitening weighted function, the upper measure whitening weighted function, the moderate measure whitening weighted function, the lower measure whitening weighted function and the triangle whitening weighted function.

For the typical whitening weight function of the k gray cluster of the j indicator: $f_j^k\left[x_j^k(1), x_j^k(2), x_j^k(3), x_j^k(4)\right]$, the turning points are, respectively, $x_j^k(1)$, $x_j^k(2)$, $x_j^k(3)$, $x_j^k(4)$. If the whitening weight function does not have the first and the second turning points, then $f_j^k(\bullet)$ is a lower measure whitening weight function, recorded as $f_j^k\left[-, \quad -, \quad x_j^k(3), \quad x_j^k(4)\right]$; if the second and the third turning points of the whitening weight function overlap, then $f_j^k(\bullet)$ is called a moderate measure whitening weight function, recorded as $f_j^k\left[x_j^k(1), \quad x_j^k(2), \quad -, \quad x_j^k(4)\right]$; if the whitening weight function does not have the third and the fourth turning points, then $f_j^k(\bullet)$ is called an upper measure whitening weight function, recorded as $f_j^k\left[x_j^k(1), \quad x_j^k(2), \quad -, \quad -\right]$. Here, we respectively select the lower measure whitening weight function to indicate the measure of gray clusters at a low development level; the moderate measure whitening weight functions to indicate the measures of gray clusters at a relatively high development level, medium development level and medium-to-low development levels [15]; the upper measure whitening weight function to indicate the measure of gray cluster at the high development level. The whitening weighted function of each provincial area can be determined from a holistic view based on the agricultural mechanization development levels of the 31 provincial areas in the year 2005, the year 2010 and the year 2015, which can be used to indicate the turning points at which each indicator starts to belong to the gray clusters. The learning material of the holistic view should be viewed as a whole. It should not be with the addition of other parts. An example of this is that health maintenance of a whole body will cooperate with this function not by separating the mind from the body [16]. In this paper, we offered the structure map of the whitening weight function of all the indicators in 2005 (see Table 4), and others can be provided accordingly.

Table 4. The structure of the whitening weight function that each indicator corresponds with in 2005.

Gray Cluster 1	Gray Cluster 2	Gray Cluster 3	Gray Cluster 4	Gray Cluster 5
$f_1^1(2.5, 3.0, -, -)$	$f_1^2(1.5, 1.8, -, 2.5)$	$f_1^3(1.0, 1.5, -, 1.8)$	$f_1^4(0.8, 0.9, -, 1.0)$	$f_1^5(-, -, 0.7, 0.9)$
$f_2^1(7.0, 8.0, -, -)$	$f_2^2(3.5, 3.9, -, 7.0)$	$f_2^3(2.0, 2.9, -, 3.9)$	$f_2^4(0.5, 1.5, -, 2.9)$	$f_2^5(-, -, 0.3, 1.5)$
$f_3^1(2.5, 3.0, -, -)$	$f_3^2(1.5, 1.7, -, 2.5)$	$f_3^3(1.0, 1.4, -, 1.7)$	$f_3^4(0.5, 1.0, -, 1.4)$	$f_3^5(-, -, 0.3, 0.7)$
$f_4^1(2.1, 2.5, -, -)$	$f_4^2(1.2, 1.4, -, 2.1)$	$f_4^3(0.3, 1.0, -, 1.5)$	$f_4^4(0.01, 0.1, -, 0.7)$	$f_4^5(-, -, 0.001, 0.04)$
$f_5^1(1.0, 1.4, -, -)$	$f_5^2(0.9, 1.0, -, 1.2)$	$f_5^3(0.5, 0.8, -, 1.0)$	$f_5^4(0.2, 0.5, -, 0.9)$	$f_5^5(-, -, 0.04, 0.2)$
$f_6^1(1.2, 1.5, -, -)$	$f_6^2(0.9, 1.0, -, 1.2)$	$f_6^3(0.7, 0.8, -, 1.0)$	$f_6^4(0.6, 0.7, -, 0.8)$	$f_6^5(-, -, 0.3, 0.6)$
$f_7^1(8.0, 10.0, -, -)$	$f_7^2(6.6, 7.5, -, 10.0)$	$f_7^3(4.7, 6.0, -, 7.5)$	$f_7^4(4.1, 4.5, -, 5.0)$	$f_7^5(-, -, 2.5, 4.4)$
$f_8^1(10.0, 15.0, -, -)$	$f_8^2(9.0, 10.0, -, 13.0)$	$f_8^3(5.5, 6.0, -, 9.5)$	$f_8^4(4.5, 5.0, -, 6.0)$	$f_8^5(-, -, 3.0, 4.5)$

Based on this and the content in Table 2, we offered the functions of the whitening weight function of the five gray clusters that the eight indicators, respectively, belong to [17]. Here, we only use X_1, the total mechanical power/grain output (10 k million watts/10 k tons) as an example and offer the whitening weight function of the five gray clusters that it belongs to. The mechanical power includes motionless oil machines, tractors, power control and automatic syndicates. The merits of mechanical power are that it does not need any power source; it will produce the power by itself [18]. When comparing its efficiency to manpower, its performance is too high. Since it is versatile in nature, it is suited to more applications. Other equations can be obtained in a similar way [19]:

$$f_1^1(x) = \begin{cases} 0 & , \quad x < 2.5 \\ \frac{x-2.5}{3.0-2.5} & , \quad x \in [2.5, 3.0) \\ 1 & , \quad x \geq 3.0 \end{cases} \quad f_1^2(x) = \begin{cases} 0 & , \quad x \notin [1.5, 2.5] \\ \frac{x-1.5}{1.8-1.5} & , \quad x \in [1.5, 1.8) \\ \frac{2.5-x}{2.5-1.8} & , \quad x \in [1.8, 2.5) \end{cases}$$

$$f_1^3(x) = \begin{cases} 0 & , \quad x \notin [1.0, 1.8] \\ \frac{x-1.0}{1.5-1.0} & , \quad x \in [1.0, 1.5) \\ \frac{1.8-x}{1.8-1.5} & , \quad x \in [1.5, 1.8) \end{cases} \quad f_1^4(x) = \begin{cases} 0 & , \quad x \notin [0.8, 1.0] \\ \frac{x-0.8}{0.9-0.8} & , \quad x \in [0.8, 0.9) \\ \frac{1.0-x}{1.0-0.9} & , \quad x \in [0.9, 1.0) \end{cases}$$

$$f_1^5(x) = \begin{cases} 0 & , \quad x \notin [0, 0.9] \\ 1 & , \quad x \in [0, 0.7) \\ \frac{0.9-x}{0.9-0.7} & , \quad x \in [0.7, 0.9) \end{cases}$$

3.3. Determining the Weight of Each Indicator

Considering the importance of each cluster indicator in measuring the development level of agricultural mechanization in the provincial areas plays a major role in data analysis and data mining application clusters. A cluster is denoted simply by a term called grouping. Groups containing objects are supplementarily similar to each other [19]. We, respectively, give the following weights to the eight indicators of X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8:

$$\eta_1 = 0.1,\ \eta_2 = 0.15,\ \eta_3 = 0.15,\ \eta_4 = 0.15,\ \eta_5 = 0.15,\ \eta_6 = 0.1,\ \eta_7 = 0.1,\ \eta_8 = 0.1$$

4. Cluster Result and Analysis

4.1. Cluster Result

According to the whitening weight functions above, the cluster weight of each indicator and the observing value of target i on the j indicator, the gray weighted cluster coefficient is obtained [20]. Based on the content of Tables 1–3 and the steps above, we can calculate the cluster results of the gray clusters of all the provincial areas (see Table 5). The task of classifying the population or information points into a number of sets such that the information points in similar groups are additionally equivalent to other information points in similar groups is called the clustering process.

4.2. Cluster Results Analysis

It can be seen from Table 5 that provincial areas that belong to the gray cluster at high development levels include Beijing, Tianjin, Neimenggu, Heilongjiang, Qinghai, and Xinjiang in 2005. In 2010, compared with 2005, among the provincial areas of gray clusters at high development levels, Beijing dropped to the gray cluster at the medium to high development level; Heilongjiang dropped to the gray cluster at the medium development level [21]. Meanwhile, Tianjin, Neimenggu, Qinghai, Xinjiang provinces belong to the gray cluster at the high development level. In 2015, compared with 2010, provincial areas in the gray cluster at the high development level include Tianjin, Neimenggu, Qinghai, Xinjiang, Zhejiang, Hainan, and Tibet.

In this study, we adopted the grain output of each provincial area as the basic data. As Beijing and Shanghai are densely populated areas where the grain output is low while the output of economic crops such as vegetables is high, the calculation results may not represent their real development level. It has reached the level of 29.75 million tons and is composed of wheat crops, rice, pulses, cereals, etc. For non-food grain classes such as oil seeds, it reached 36.10 million tons compared with the previous year in which it reached 33.21 million tons. Due to the state government's strong support for Tibet's agricultural development in recent years, the increase rate of its total agricultural mechanical power has exceeded that of its grain output, so Tibet has risen to the gray cluster at a high development level. The situation in Heilongjiang is contrary to that in Tibet. As a major grain production area, the increase rate of its grain output far exceeds that of the total agricultural mechanical power. Some examples of gain products is wheat, oats, millets, rice, maize, etc. As of now, China is the leading country in wheat production. According to the year 2020, China has achieved 20.65% of the world's wheat production. India, Russia, the USA and Canada are the top five leading producers of wheat grain. Therefore, the calculation results of these two provincial areas may not represent their true levels either. The calculation results of other provincial areas are all within the normal scope.

Table 5. Corresponding gray cluster results of the agricultural mechanization development level of the provincial areas in the three years.

Provincial Areas	2005	2010	2015
Beijing	high	medium to high	medium
Tianjin	high	high	high
Hebei	medium to high	medium	medium to low
Shanxi	medium to high	medium to high	medium to high
Neimenggu	high	high	high
Liaoning	medium	medium	medium
Jilin	low	low	low
Heilongjiang	high	medium	low
Shanghai	medium to high	medium	medium to low
Jiangsu	medium	medium	medium
Zhejiang	low	medium to high	high
Anhui	medium	medium to low	medium to low
Fujian	low	low	low
Jiangxi	medium to low	medium to low	medium to low
Shandong	medium to high	medium to high	medium to high
Henan	medium	medium	medium
Hubei	medium to low	medium to low	medium to low
Hunan	low	low	medium to low
Guangdong	low	medium to low	medium to high
Guangxi	low	low	medium to low
Hainan	medium to high	medium to high	high
Chongqing	low	low	low
Sichuan	low	low	low
Guizhou	low	low	low
Yunnan	low	low	low
Tibet	low	medium	high
Shannxi	medium	medium	medium
Gansu	medium	medium	medium
Qinghai	high	high	high
Ningxia	medium to high	medium to high	medium to high
Xinjiang	high	high	high

From the changes in data over the three years, it can be seen that the change in Zhejiang is the most significant. Zhejiang rose from the lowly-developed gray cluster provincial area in 2005 to the gray cluster at a high development level in 2015. Through our analysis, we believe that there are the following reasons. First, Zhejiang Province has a strong economy and is highly developed in terms of the comprehensive development of agriculture, forestry, husbandry and fishery. Second, as the No.1 Document from the central government has repeatedly emphasized "speeding up agricultural modernization and speeding up agricultural mechanization", Zhejiang has been increasing resource input into the development of agricultural mechanization. Third, although there are land turnovers in Zhejiang also, as the arable land base is small, the agricultural mechanization power is increasing fast, but the grain output growth rate is slow, so Zhejiang gradually rose to the gray cluster at the high development level.

The resource input for the development of agricultural mechanization in Tianjin, Neimenggu, Qinghai, and Xinjiang has been steadily increasing, so the four provincial areas have always been in the gray cluster at the high development level. Tianjin has always been vigorously promoting the construction of facility agricultural demonstration zones and developing integration, standardization and large-scale production. The arable land area per capita in Neimenggu is 0.24 hectares, which is three times that of the national average and ranks first in China. The Hetao Plain, West Liaohe Plain and the Tumochuan Plain are not only the major grain and economic crop production base of Neimenggu but are also the key areas for national agricultural development. This can be done by increasing the capital income, as the illustration method describes; when there is demand for the material, the farmer will increase the production of their product while increasing the productivity and the enhancement of more goods to the industries. Therefore, this resolves the problem of unemployment. Agriculture and husbandry in Qinghai are advanced, the planting area of grass for herd stock is large, and the number of agricultural machines for planting and harvesting grass is big, so the mechanization level in Qinghai is high. Xinjiang is a major production base of cotton in China. Breakthroughs have been made in the mechanical picking of cotton. The sowing, planting and harvesting of cotton have basically achieved whole-process mechanization, which has enabled the cotton planting area to expand in this provincial area. The sowing process can be carried out through two methods called manual sowing and seed drill. While manual sowing is a traditional method, as of now, farmers use seed drill for sowing. Then, planting is the next important step in seed growth, and for harvesting, the farmer needs to cut the grown crop from the land and clean it for sale; modern farmers use harvesters to cut the crops whereas in earlier years they used sickles to harvest crops. Hebei Province quickly dropped from the gray cluster at a relatively high development level in 2005 to the relatively lowly-developed gray cluster in 2015. Through our analysis, we believe there are the following reasons. First, Hebei Province is an important part of the "Capital Rim Economic Circle", and its major task is to ensure the sustainable supply of agricultural products for the capital. Therefore, its input to and development of grain and economic crops must stay stable. Second, Hebei Province undertakes the important tasks of receiving the outbound transfer of factories and other industrial departments of the capital and its industrial development occupies a large share of its government resources. Compared with other provincial areas, Hebei's input in the development of agricultural mechanization is small.

Among the gray cluster at the medium development level, we would like to demonstrate the situation with Henan Province as an example. The major grain planting area is in the plains, which are good for mechanical work and the use of whole-land machines. The mechanical harvesting of wheat and corn is developing well and mechanization has basically been achieved. As the "land turnover" scale continues to increase, the grain output in Henan Province once achieved an "increase in 12 consecutive years". However, due to the problems of work precision and applicability, the mechanization level is relatively low, which hinders the improvement of the comprehensive level of agricultural mechanization. By exploring the original causes and worldviews contributory to a situation, a collection of intelligence-making techniques is preferred. Hence, this technique is known as layered analysis. Among the provincial areas in the gray cluster at the medium to low-development level, we would like to demonstrate the situation with Jiangxi as an example. The arable land area in Jiangxi is small and its agricultural mechanization foundation is weak. Although resource input in developing agricultural equipment has increased quickly, the agricultural mechanization level is still relatively low compared to developed provincial areas. The grain output has been increasing in recent years, but the total output is still at the average level. Therefore, the agricultural mechanization of Jiangxi Province has always been in the gray cluster at the medium to low-development level.

Among the lowly-developed gray cluster provincial areas, we would like to demonstrate the situation with Fujiang Province and Guizhou Province as an example. In the territory of Fujian Province, there are many mountains and a vast area of sea. Arable land resources, comparatively speaking, are lacking. Therefore, the agricultural mechanical equipment develops slowly, the grain output is low and Fujian relies on forestry and fishery as its major industries. In Guizhou Province, most of the territory is mountains and hills and the arable land area is small, which is inconvenient for the use of large agricultural machines. The major crops in Guizhou are economic crops such as tobacco and rape, and the grain output is low. Both provincial areas are deeply affected by their territorial environment and the agricultural mechanization development level is low.

Regarding the factors influencing the agricultural mechanization development level of the provincial areas in the year 2005, the year 2010 and the year 2015, we conducted a comparative static analysis. Under exogenic limitation the comparative static analysis is performed, since it has two different economic results, namely before changes to the exogenous parameter and after changes to the exogenous parameter. Furthermore, static analysis is performed by the adjustment method, which compares two equilibrium states for analysis. The provincial areas in the gray cluster at the high development level should keep up their advantages. The provincial areas in the gray clusters at the high development level should make the best of their strengths and make up for their weaknesses and strive to be included in the gray cluster at the high development level. The provincial areas in the medium and gray clusters at the medium to low-development levels should, on the precondition of maintaining agricultural development stability, make up for their shortcomings as soon as possible and strengthen resource input into areas of weakness. The provincial areas in the gray cluster at relatively low development levels, which develop slowly in the modernization of agricultural mechanization due to the limitation of multiple factors, should be used for transforming the situation, transforming their thinking, taking agriculture facilities as a primary focus and developing unique agriculture with their own characteristics to further promote their agricultural mechanization level.

5. Conclusions and Policy Recommendations

Considering the static influencing factors analysis of the agricultural mechanization development in 31 provinces of China, some results can be concluded. The critical factors that affect agricultural mechanization development are the arable planting area under mechanized processing and the management of investment in agricultural mechanization. Therefore, all provinces should maintain their current advantages, remedy their own weaknesses as soon as possible, find their characteristic agricultural development path, and promote further agricultural mechanization development.

To speed up the development of agricultural mechanization in China, we propose the following recommendations based on our findings in this study:

(1) We should transform our concepts in developing the agricultural machinery industry and enhance the awareness that agricultural mechanization is representative of agricultural modernization.
(2) The government should increase input in developing agricultural mechanization. At the current stage, the income level of farmers in China is generally low, so the government should strengthen support for the farmers by providing them with more capital investment, financial support and agricultural machinery subsidies.
(3) We should speed up the infrastructure of agricultural facilities. The inadequate construction of standardized farmland and water conservation facilities both hinder the development of agricultural mechanization. Improving the infrastructure will be

conducive to expanding the land turnover scale and developing the whole process of mechanizing agriculture [22].

(4) We should give priority to innovations in the scientific research of agricultural mechanization and boost the input in agricultural mechanization research. We should promote regional agricultural mechanization technologies and research innovation. As different regions have different climates and land features, they should coordinate with and complement each other in the R&D and manufacturing of agricultural machinery.

(5) We should innovate the environment protection design of agricultural mechanization. We should speed up the promotion of electric-power-driven agricultural machines, and develop a new type of energy-saving diesel and gasoline agricultural machines. Electric agricultural machines should be promoted in farmland irrigation, farmland development and agricultural and by-products processing so as to contribute to energy saving and emission reduction.

(6) Based on the results in this paper, the government can utilize multi-part cooperation to improve the agricultural infrastructure, including digital facility investment, integrative agricultural management and many other areas. A series of agricultural machinery management modes can be established or ameliorated through analyzing the practical feedback, internet advantage, information exchange and sharing. As a result, the macro decision of agricultural machinery management can be optimized by the research.

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