Team Control Number

201988205

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2019

Shuwei Cup
Summary Sheet

Summary

Abnormal behavior of pork prices has caused widespread concern. This paper firstly analyzes the factors and volatility of pork prices, and uses statistical methods and generalized machine learning evaluation methods. Then, the AHP analysis method and TOPSIS analysis method are applied to the import model, and the breeding, production model and storage model are carried out. Mixed linear programming yielded valid conclusions.

Key word:Pork price;Factor analysis;Statistical methods;Generalized machine learning evaluation;AHP;TOPSIS;Mixed planning

Content

1 Introduction

Recently, the Chinese pork market is experiencing unprecedented shocks and challenges. The abnormal fluctuation of pork prices has occurred nationwide, causing a chain effect of price fluctuations in the pork market, catering industry and even vegetable and fruit farming in various regions.
Pork prices are of great significance in China. Many economic indicators in China, for example, in China's annual CPI (Consumer Price Index) indicators and PPI (Producer Price Index) indicators, pork prices can usually have a decisive impact, so the Chinese people usually call it "pig Phenomenon", some Chinese people even dubbed the CPI as the "China Pork Index".
Based on the above introduction, the research in this paper is meaningful, and this paper also hopes that this research can better promote the development of Chinese pork price research and modeling.

1.1 Background

Many Chinese scholars, European and American scholars as well as price appraisal agencies have conducted in-depth research on Chinese pork prices. ***Wang Yijun***[1] pointed out that the change in pork prices in China is a weather vane to analyze China's inflation situation. The main reason lies in the imbalance of China's meat production structure. Abnormal pork prices have led to a large difference between the CPI index and the pork price trend. The main cause of the abnormality is the sudden decline in stocks and the impact of African swine fever.
Han Fei[2] proposed that the fluctuation of pork price is mainly affected by five factors: trend factor, seasonal factor, monetary factor, cyclical factor and sporadic factor. The joint mechanism of these factors deserves further consideration and analysis. ***Yao Wanjun***[3] mainly made in-depth research on the industrial chain of hog prices. They believed that the low profitability of the industrial chain combined with the cobweb law of the hog market intensified the fluctuation effect of pork prices.
Yang Guiming[4] gave an economic explanation for pork price volatility, and he proposed that the pork market regulation (data surveillance) and the development of a *multi-feeding model* should be strengthened. This article is greatly inspired by this.

1.2 Work

So why is pork price so powerful? What does the fluctuation of pork prices mean? How should China's localities take a look at the current situation and look to the future pork market?
This article will try to solve each of the above questions based on mathematical modeling methods. This paper will model and solve each problem that needs to be solved according to the methods of comprehensive analysis, data preparation and analysis, and model solving. It should be noted that the analysis methods used in this paper will be interpreted to varying degrees in the paper: if it is a common method in data analysis, this article will only provide a brief explanation, and the establishment of the mathematical model will be the focus of the paper.

In order to enable the reader to better understand the meaning of the analysis or model, this article may reuse the same parameter name in different models, but it may represent different meanings. Therefore, this article does not set a separate variable interpretation item, and this will be marked separately at different stages in the future. Symbol and Assumptions will only defines some statistical symbols.

2 Problem analysis

To analyze pork prices, the first need is to obtain relevant data. Network resources are abundant, but because of the excessive indicators of price or pig feeding, this article will only select several types of data as the data base of the paper. Next, this article will give a preliminary reflection and explanation of different issues.

2.1 Data analysis

This paper first plans to analyze the macro factors of price. The data set mainly includes China's per capita income, per capita consumption, per capita consumption, and various types of meat (including pork, beef and mutton, chicken, seafood and freshwater animals from 2002 to 2018).), the value of pork imports and exports, and the PPI of pork. The reason why this article does not use pork CPI indicators is that the data is seriously incomplete, and the trend of PPI is roughly equivalent to CPI. These data are presented in a data summary table.
Note that some data is missing, so the data is first analyzed for deletion. This paper uses three different analysis methods to interpolate and observe the performance of the data.

2.1.1 Second-order difference based on least squares

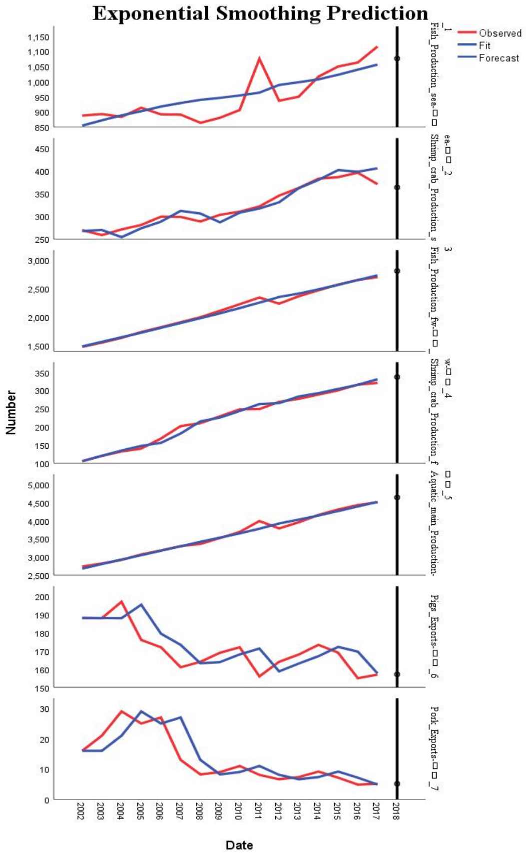
Use the second-order difference method (by MATLAB) to interpolate the data in the Missing workbook. The program code is shown in Appendix 1.

2.1.2 Grey prediction method based on least squares

The gray system is a common method for unknown structural data. Use MATLAB for gray system analysis and output stability report. The results show that the predicted results are better and intuitively superior to the second order difference. The program code is shown in Appendix 2.

2.1.3 Time series prediction

Using SPSS software for stationary time series prediction, exponential smoothing and ARIMA method prediction for smooth data. The predicted results are more satisfactory, as shown in the following figure:



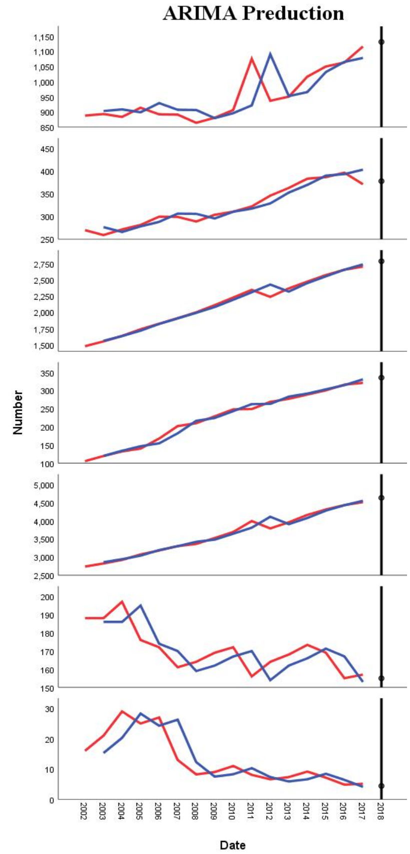


Figure 1 Interpolation of exponential smoothing

Figure 2 ARIMA method interpolation

The remaining test results can be found in Appendix 3. Based on all the above fitting conditions, this paper will select the fitting result of the ARIMA method and use the fitting data as the supporting data of the first problem.

2.2 Analysis of Question One

The analysis of the factors in the pork market involves many aspects of the market, so this paper will mainly be based on the market macro dataset, which is from the National Bureau of Statistics of China, and the record has been updated to 2018.

In general, the main factors affecting prices are the following:

- **Market Attribute (supply relationship)**

Supply is an important factor affecting prices. Under normal circumstances, the price of pork will decrease when the supply of pork increases, and the price of pork will increase when the supply of pork is insufficient. There is a negative correlation between the two. In this study, pork production, pigs, and year-end stocks were selected as supply factors to analyze pork prices.

- **Demand Attribute**

Residents' income levels are closely related to residents' ability to purchase pork. On the one hand, when residents' income is high, their ability to purchase pork is strong. When residents' income is low, their purchasing power for pork will be greatly reduced. Therefore, the income level of residents can be used as a direct signal of pork demand. On the other hand, with the improvement of people's living standards and the change of consumption concept, the consumption of beef, mutton and chicken is gradually increasing. When the price of pork is high, the price of substitutes directly affects the demand level of pork. Therefore, substitutes Price fluctuations are also particularly important for the study of pork prices. This study mainly selects beef prices and chicken prices for analysis.

- **Cost Attribute**

In the process of pork price formation, pig production costs play a particularly important role, which directly affects the price of live pigs and the total supply of pigs. These factors will eventually be transmitted to pork prices through internal mechanisms. In China's main pig-raising model, more than 90% of the pig's material cost is piglet cost and feed cost[5], resulting in piglet and feed costs becoming the most critical factors determining pig production costs. Therefore, this paper selects the price of live pigs, piglet prices and corn prices as cost factors.

- **Other Attributes**

In addition to supply and demand attributes and cost attributes, natural disasters, pig epidemics, national policies, and economic conditions are all factors that affect pork prices. Since the impact of such factors cannot be quantified, this study does not focus on these factors.

2.3 Analysis of Question Two

It is necessary to use the promotion and upgrading of farming methods to solve the increase in pork prices. On the basis of consolidating and upgrading the advantages of existing large-scale pig breeding areas, we should actively seek for the widening of pig breeding areas and the diversity and advancement of farming technology.

Due to time issues, this article will not discuss technological innovations around the world (this takes quite a while). The model points out that the combination of historical technology accumulation and different feeding patterns in different regions is a quick way to solve the current pork price.

There are large regional differences between different regions of China, so pig farming must be adapted to local conditions. To simplify the model, this paper divides China's possible aquaculture areas into northern, southern and western regions for research.

How to quantify farming in different regions? This paper will introduce the SFA (random frontier analysis) method, which is mainly aimed at quantitative comparison of breeding efficiency in northern China.

When solving the import problem, this article will conduct a comprehensive evaluation and ranking of “old partners” and some new countries. The main analytical methods used in this paper are the principal component method and the TOPSIS ideal solution method.

2.4 Analysis of Question Three

This paper mainly based on real-time data to model the allocation of sub-regions in China, and to establish distribution models and storage models for different regions (or for example, a certain region). Noting the complexity of the model, this article will be simplified in the next chapter. It is important to note that some of the results in the previous section will be comprehensively quoted in this part of the paper.

3. Symbol and Assumptions

3. 1 Symbol Description

Abbreviation	Full Name
ACF	Autocorrelation coefficient
PACF	Partial autocorrelation coefficient
ARIMA	Differential integrated moving average autoregressive model
~	Relevance
Pork_PPI_T	Pork PPI increase and decrease logic value

Table 1: Abbreviation of Relevant Terms

3.2 Fundamental assumptions

First and foremost, we make some basic assumptions and explain their rationales.

Assumption 1. *The statistics are all credible.*

All data sources in this paper are only three: China National Bureau of Statistics, China National Statistical Yearbook, China Animal Husbandry Information Network.

Assumption 2. *Modeling can be done using macro data from 2016-2018.*

The lack of macro statistics makes the data analysis of the paper may have some errors, but this is also the only choice.

Assumption 3. *In the mathematical model, the accuracy of the error is not higher than 0.00001.*

The accuracy of all mathematical models in the paper is not higher than this value, because too high precision may bring trouble to solve the data.

Assumption 4. *When setting up a scheduling model, you can ignore the smooth price changes in the market.*

This brings great convenience to our model solving, and at the same time, considering price fluctuations may further destabilize the results.

4 Analysis&Models

4.1 Analysis for Question One

4.1.1 Research on the factors of macro price fluctuation

4.1.1.1 Data observation

Based on the data set Data summary, this paper conducts multi-factor correlation analysis of macro market. The analysis objective is to correlate the influence factors or interaction factors of pork price, and then explore the multi-index representation of pork price according to the basic ideas mentioned in the previous article.

The databases include these factors:

- Supply: pork production ~ number of pigs released ~ end of year ~ (sow supply)
- Demand: Household consumption level ~ population number ~ disposable income
- Alternative: beef and mutton stock ~ beef and mutton price ~ poultry stock ~ poultry price ~ main meat aquatic products stock and price ~ vegetable price
- Cost: hog price ~ piglet price ~ corn price (pig-to-food ratio). These factors do not require further correlation analysis because they are inherent data and must be strongly correlated.

The descriptive statistical analysis results of SPSS show that the basic situation of the data set is good, a total of 17 statistics, there is no abnormal value(in Appendix 4).

Then the packet description is based on Pork_PPI_T, and the QQ diagram of the Pork_PPI in different groups is output:

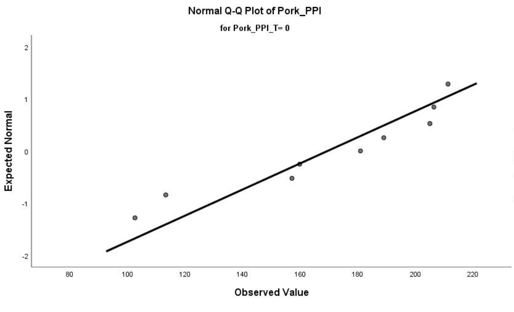


Figure 3 QQ diagram with no increase in PPI

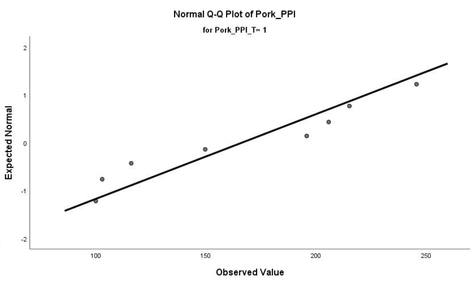


Figure 4 QQ diagram of PPI increase

The reliability of the data set was tested using the Cronbach α reliability factor, with a value of 0.818. This indicates a high reliability of the data set (0.7<=Cronbach's Alpha<0.9). At the same time, the inter-project correlation matrix indicates that, except for the "end of pigs at the end of the year" and other projects are not very high (less than 0.75), the correlation between the other projects is high, indicating the indicators collected in the table. It does have a lot to do with pork prices.

4.1.1.2 Inverse correlation method based on classification prediction

This paper proposes to use the way of predicting the importance of pork price changes, back to the importance of each indicator, and then initially explore its impact on pork prices. To avoid complexity, this article will trend the price of pork:

The log price of the first year of the pork price index is 1. If the price of the current year (since the second year) increases from the previous year, the logical value of the pork price index will be 1. Constructed a classification model that reflects changes in pork prices.

The use of integrated learning to classify and predict the change in pork prices, due to the purpose of this example, some over-fitting phenomena are allowed. The integrated learning algorithms constructed in this paper include KNN algorithm, classification tree algorithm, Bayesian network algorithm and neural network prediction method. This paper implements the above algorithm based on SPSS MODELER.

In the integrated learning of data partitioning, the accuracy of KNN algorithm is about 78.9%, and the contribution weight of indicators is not different; the comprehensive accuracy rate of C5.0 tree, CHAID tree, C&R tree and random forest simulation (boosting100) is 100%, among which The overall performance of each indicator is as follows (contribution ranking):

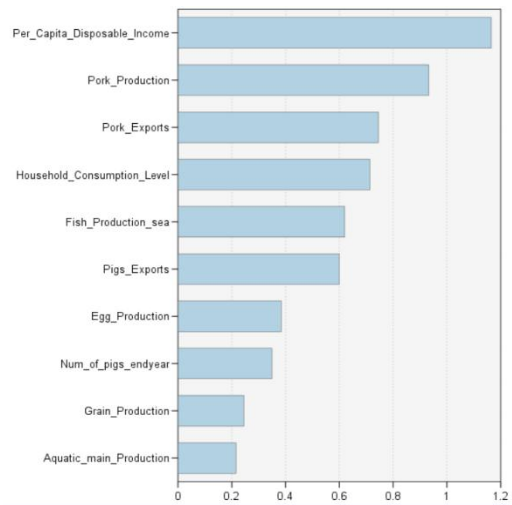


Figure 5 Integrated learning model indicator contribution

Taken together, each of the indicators we selected played a more important role in forecasting, with **pork production** having the greatest impact, followed by **beef and lamb production**, and again **pork exports, per capita consumption** and **per capita income**. The result like this figure:

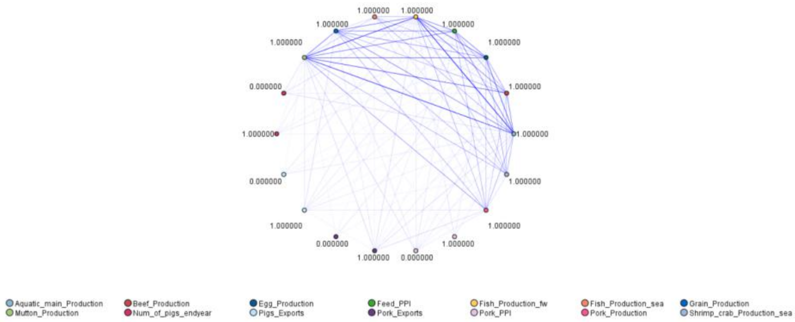


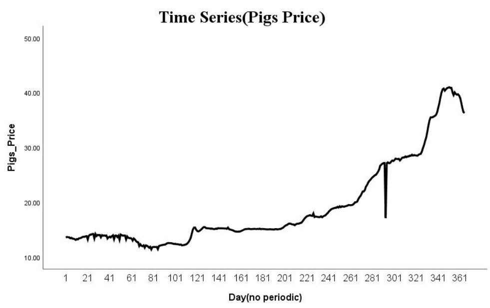
Figure 6 Network of factors

The remaining indicators have less influence, but they cannot be ignored. Details of the model can be found in Appendix 5.

This paper continues to discuss the results of the Bayesian network model and the neural network model. Since such models lack a mathematical theoretical basis, they are attached to Appendix 5 for reference.

4.1.2 Analysis of fluctuations in pork price

This article uses the pork price data from November 14, 2018 to November 14, 2019, and the monthly price data from January 2007 to November 2019 for analysis in this section. The data file is in the Data summary.



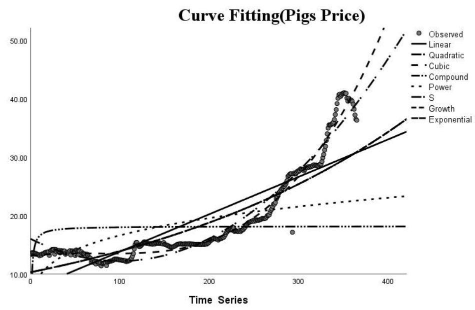
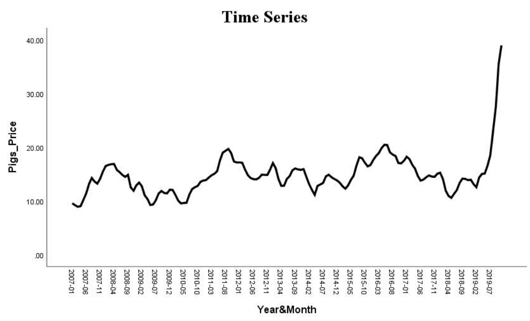


Figure 7 Date fluctuations in pork prices *Figure 8 curve fitting for Figure 7*

As can be seen from the figure, the recent pork price is obviously not in line with the fluctuation law. In the curve growth section, some nonlinear functions can be basically fitted, and in the fluctuation region, the basic fitting function used cannot be correctly estimated. The autocorrelation performance and partial autocorrelation performance of such curves tend to be unstable, so there is a greater possibility of failure of confidence determination, and it is impossible to perform exponential smoothing analysis or ARIMA analysis.

Based on this, such curves may have periodic effects or instability. To confirm what is more likely to be the cause of such anomalous curves, we analyze monthly data with a broader range of data:



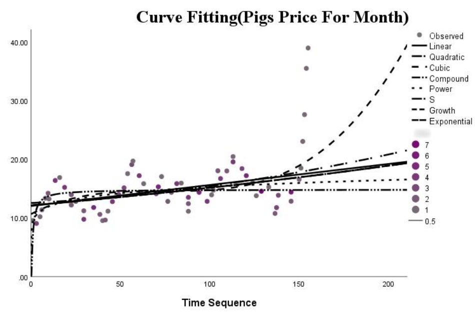
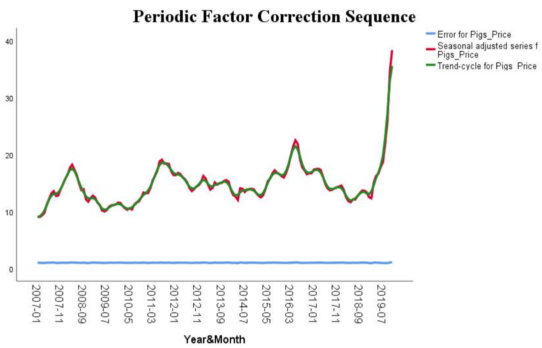


Figure 9 Month fluctuations in pork prices *Figure 10 curve fitting for Figure 9*

The results of the chart data show that from January 2007 to November 2019, there may be some cyclical fluctuations in the average pig price for each month.

According to the spectrum analysis results, the maximum frequency is about 0.032, that is, the period of the data is about 31 months. Subsequently, it is further smoothed. First, the time series is differentiated, and according to the autocorrelation rule and the maximum confidence interval rule, the first-order differential processing is performed on the data, and the data is subjected to multiplicative periodic decomposition according to the data period, and the model is corrected by using the corrected data. The results are as follows:



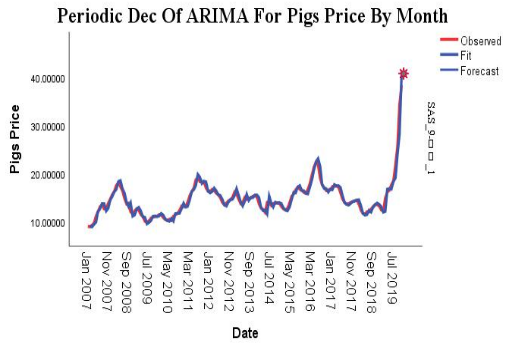
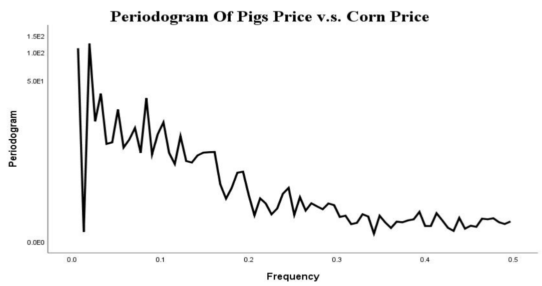


Figure 11 Month:Periodic Factor Co-Sequence1 *Figure 12 Periodic Dec of ARIMA for Pigs Price*

Finally, only the "cost" item is needed for quantitative analysis. In this paper, the "pig-to-food ratio" is reflected in the cost-benefit side, and the "pig-to-food ratio" is defined as "cost low-yield high" and vice versa.

According to the spectral analysis, it has a cycle that approximates the price of pork:



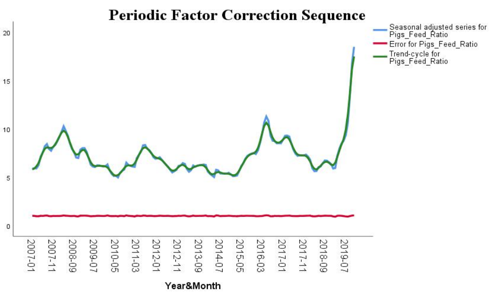


Figure 13 Periodogram of Pig food ratio *Figure 14 Month:Periodic Factor Co-Sequence2*

Is there really a strong connection between the two? Because the correlation analysis and prediction back analysis between the two are ineffective, we transform the relevance problem into a correlation problem through correlation analysis.

Since its Pearson correlation is 0.864 and the Kendall correlation is 0.522(), the correlation is significant. **Therefore, the conclusion is that there is a strong correlation between pig price and pig food ratio. This expression can be further transformed into: cost and pig price profit. There is a strong correlation between them, so the interaction between the two is also an important factor affecting the price fluctuation of pigs.**

4.2 Analysis for Question Two

4.2.1 Induction of existing pig breeding models

China's existing pig breeding models are diverse, mainly in the diversification of technology. The underlying causes are mainly geographical diversification, diversification of economic scale and diversification of market size.

- **Family farms.** Farmers with family pigs as the main body are concentrated in the poor areas and non-specialized farming areas.
- **Large-scale pig farms.** The model includes a cooperative system, which refers to the introduction of corresponding technologies, sites and management methods for self-employed or collective households to carry out centralized large-scale breeding.
- **Three-dimensional pig farm.** The model is "ecological farming", which means the use of

abundant natural resources in the local area for self-support of the biological chain. At present, the main biological chain used is the "pig-marsh-forest land or ecological field" chain to achieve sustainable development.

- **Companyized pig farms.** This model incorporates the company into the management of the above types of farms and can provide a contract-guaranteed technology-capital-management exchange system.

4.2.2 Farming modeling for regional differences

There are large regional differences between different regions of China, so pig farming must be adapted to local conditions. To simplify the model, this paper divides China's possible aquaculture areas into northern, southern and western regions for research.

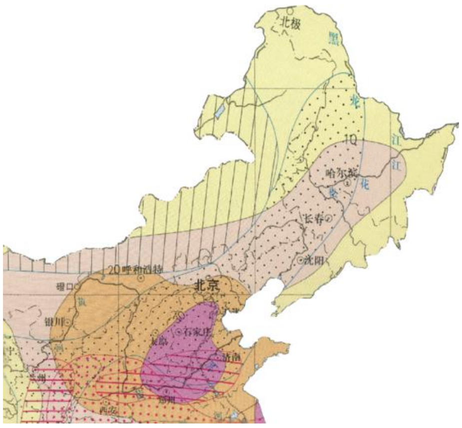
Of course, farming between different regions also has a certain similarity. We mainly study the relevant situation in the northern region, and then reuse the model to other regions depending on the difference.

❖ **Northern Region**

First, this article will exclude areas where farming is clearly impossible. This mainly includes:

- An area of extreme shortage of water resources.
- Areas that are not allowed to be farmed due to environmental pollution in the aquaculture industry.

These areas are not included in the discussion of this article.



«Figure 15 Drought conditions in northern China

The arid areas in northern China are large, with the main areas of drought occurring in the north of Henan, western Shandong and Hebei, followed by Liaoning Province, most of Jilin Province and parts of Inner Mongolia Autonomous Region.

The farming entities in the northern region are divided into two categories: individual households and large-scale farmers. This article mainly discusses the latter one.

Based on regional macro data (2015-2018) of large-scale pig breeding industry in northern China, a random frontier analysis method(SFA) was used to compare the efficiency of different regions in order to find efficient areas and set up efficiency warning zones.

The basic formula of the SFA method can be expressed as:

$$y = f(x, \beta)e^{v+u}$$

Where y represents output, x represents input, v represents a random factor affecting technical efficiency, u represents a management efficiency factor affecting production, and the remaining variables are parameters. The further model proposed by Bat tese & Coelli is expressed as:

$$\ln(y_{ij}) = \beta_0 + \sum_{n}^{\beta} \ln \beta_{(n)ij} + v_{ij} - u_{ij}$$

$$K_{ij} = e^{-u_{ij}}$$

$$u_{ij} = \beta_j u_i$$

$$\beta_j = e^{-\eta(j-T)}$$

$$\gamma = \frac{\sigma_u{}^2}{\sigma_v{}^2 + \sigma_u{}^2}$$

In the formula, i is the individual serial number, j is the period serial number, K_{ij} is the technical efficiency level of the i-th individual in the sample during the j-th period, and v_{ij} is the random factor affecting the large-scale pig breeding in the i-th province in the i-th province, u_{ij} indicates the influence The management efficiency factor of large-scale pig breeding in the first year of i province, the remaining variables are parameters to be estimated.

The logarithmic Cobb-Douglas production function can be used to generate a formula for determining the efficiency level of large-scale pig-scale aquaculture technology according to this formula[6]:

$$\ln(y_{ij}) = \beta_0 + \sum_{m=1}^{4} \beta_m \ln(L_{mij}) + v_{ij} - u_{ij}$$

In the above formula, y_{ij} represents the main product output of large-scale pig breeding in the i-th province in the i-th province. L1ij, L2ij, L3ijj, and L4i are respectively the number of large-scale pig breeding workers, labor costs, aquaculture materials and service costs in the i-th province in the i-th year. And the pig's delivery time, the rest of the variables have the same meaning.

In this paper, we use the stochastic frontier analysis software Frontier4.1 and the basic data of large-scale pig breeding in the northern provinces of 2014~2017 to measure the technical efficiency. The relevant parameters and test results are as follows(The raw data can be found in the attachment.OUT file):

parameter	**coefficient**	**Standard deviation**	**t statistic**
Β0	28.426176	15.548625	18.282116
Β1	-5.6978814	5.1864414	-1.0986109E
Β2	0.39128878	0.061504569	0.63619465
Β3	0.0074234315	0.0040324589	1.8409193
Β4	0.49351139	0.11251948	4.3860083
gamma	0.92857850	0.074139537	12.524741
mu	7.0541469	4.7874680	1.4734609
eta	0.048196134	0.046240738	1.0422873
LR test	37.612276	-	-

Table 2 SFA statistics

The basic conclusions are as follows:

- γ = 0.9286, and the LR test reached the 1% significance level, indicating that there is a significant composite structure in the error term in the model, so it is appropriate to use the SFA for technical efficiency measurement.
- The main input variables pass the significance test of 1% or 5%, which indicates that the

selection of variables is more reasonable. The number of labor, labor cost, material and service cost, and other variables of large-scale pig breeding in the northern provinces are output variables. The main product output has a significant impact.

- $\eta > 0$ indicates that the influence of time factor on β (t) will increase at a decreasing rate, indicating that the management inefficiency factor of large-scale pig breeding in provinces accelerates with time.

Through the analysis of Frontier4.1, the efficiency of large-scale pig breeding technology in the northern provinces can be obtained(in Appendix 6). All technical efficiency values are greater than 1, which means that large-scale pig breeding in the northern provinces of China is in an effective state of configuration, but needs further improvement.

Longitudinal analysis shows that the efficiency of large-scale pig breeding technology in the northern provinces of China from 2014 to 2017 is generally fluctuating, and the effects of management inefficiency and random error are weakening year by year. Horizontal analysis shows that large-scale pig breeding technology in Henan Province and Northeast China The higher efficiency value is mainly due to the vast land, adequate feed supply and sufficient energy in Henan Province and Northeast China, and the low cost of materials and services. It can better exert the promotion effect of technology on large-scale pig breeding, and its breeding is less affected by random error and management inefficiency, so they are suitable as a large-scale pig breeding site.

❖ **Other Regions**

Similar to the analysis in the northern region, the efficiency of large-scale pig breeding technology in the southern region is significantly better than that in the northern region. The efficiency values of Fujian, Hunan, Anhui, Guangdong and Jiangxi are all above 1.3, which is suitable for large-scale breeding. Further, the average number of jobs and the number of days of the column were sorted, and the results were ranked in the forefront of Fujian, Jiangxi, and Guangdong provinces. This means that the region has a clear advantage in terms of efficiency and speed of production, and it is possible to consider aquaculture migration to this area.

The western region is characterized by drought, large temperature difference and fragile environment. This paper analyzes the data of the western region by the same analysis method, and finds that the data has large random fluctuations, and the efficiency of large-scale pig breeding technology is significantly lower than that of the northern region, indicating that large-scale aquaculture migration should not be carried out in the western region.

❖ **Remote Areas**

The natural environment in remote areas is different, but for the aquaculture industry, the following dilemmas generally exist:

✧ **Market circulation and competitive pressures**

✧ **Technical block**

✧ **Small population base**

The above problems have led to a slow development of the pig breeding industry in remote areas. Considering the inconvenient transportation in this area, this paper proposes to adopt the “**regional market**” method for circulation in order to open up sales and feed back regional production. The so-called "regional market" refers to the extension of a certain area of radiation to a remote area centered on a large-scale breeding scale. In such areas, the state can control its formation into a temporary closed-loop market, allowing pork to circulate only within the radiation area. This method not only avoids the transportation difficulties of “introducing and going out” of pork, but also plays a certain protective role on the local pork market, avoiding the local pig industry to reduce the inventory due to the price competition disadvantage, and achieve the purpose of internal digestion and lower output. To alleviate market pressure.

4.2.3 Import Evaluation Model

How to stabilize pork prices in a short time, import is an effective method. China has continuously increased the circulation of meat products with foreign countries this year, and the import volume of pork is also constantly expanding. In 2018, China imported a total of 1.2 million tons of pork. The main importing countries are Germany, Spain, Canada, Brazil, the United States, the Netherlands, and Denmark. It is beneficial to meet the market demand of China and stabilize pork prices.

This section will discuss the pork import model with a view to alleviating the contradiction caused by the imbalance of pork supply and demand as soon as possible. Since the base of pork in China is too large, this section will not limit the total amount of pork imports. However, it is frustrating that the data shows that the global pork export market does not exceed 8.5 million tons, which means that the import model established in this section cannot fundamentally solve the 2019 Chinese pork shortage problem.

- **AHP evaluation method**

Use data set: import data {important country import price level, historical transaction level, intention factor, import price fluctuation risk, source distance}. We mainly use the first two data to make our judgment, because import not only needs to consider the influence of price fluctuations, but long-term cooperation is also an essential attribute. For countries that already have a partnership, commodity trade (especially sensitive goods such as pork) will be simpler and trade risks will be smaller.

Among the decision-making scores, Germany, Spain, Canada and Brazil ranked in the top four, indicating that China can promote pork imports with these countries.

- **TOPSIS evaluation method**

In fact, since the problem to be solved in this program is the shortage of pork, it is necessary to introduce a new evaluation system to allow large-scale import activities for countries that have not conducted large-scale pork imports to China.

This article will not discuss imports from China in Southeast Asia and Africa, as pigs in these regions may contain viruses in the near future.

- **Norway. Previously it was mainly seafood.**
- **Russia.**
- **Italy**
- **Australia.**
- **Argentina.**

These countries have obtained access to Chinese pork imports and should also be included in the scope of this section.

Obviously, we do not have historical imports of fresh frozen pork and pork chop in these countries, so the AHP evaluation method will be too subjective. We evaluated it using the more objective TOPSIS method. The specific indicators of the evaluation can be found in the attached: Import data file, and then using MATLAB, the result is:

Australia, Argentina, Russia, Italy, Norway
This sorting can be used to make a share allocation and prioritization of pork access in these countries.

4.3 Analysis for Question Three

4.3.1 Real-time demand for pork in different regions

Usually you can only see real-time prices, but you don't see real-time demand, you need to simulate the real-time demand.
In economics, the market's demand for commodities is divided into normal demand and generalized speculative demand. In this paper, the demand is w, w'_t represents the normal demand at time t, and w''t represents the generalized speculative demand at time t, which has:

$$\sum_t \begin{cases} w'_t = -\alpha p_t + \beta & \alpha, \beta > 0 \\ w''_t = \gamma(p_t - p_{t-1}) & \gamma > 0 \\ w_t = w'_t + w''_t \end{cases}$$

It can be seen that the establishment of a linear equation of price-demand relationship can better simulate the real-time demand of pork in different regions. At the same time, since the sample data of real-time demand is difficult to obtain, this paper uses the ARIMA model used in the first part to perform the time series fitting process on the predicted data, and sets the fitting result to approximately satisfy the ARIMA (0,0,0) model.
According to the demand data and inventory data of different provinces, in the unit of 10,000 tons, and at the same time, 10% of the inventory amount can not be listed and distributed as the warehouse quantity, and the following demand table is obtained:

area	need	area	need	area	need	area	need
Beijing	33.2986	Shanghai	46.8051	Shandong	8.4642	Sichuan	57.4404
Tianjin	18.8399	Jiangsu	78.7312	Henan	-117.0149	Guizhou	3.7442
Hebei	18.1311	Zhejiang	102.8624	Hubei	-28.3041	Yunnan	-41.796
Shanxi	17.0073	Anhui	43.2415	Hunan	-37.8697	Tibet	1.0965
Inner Mongolia	27.2072	Fujian	56.5063	Guangdong	211.4373	Shaanxi	14.3481
Liaoning	10.4735	Jiangxi	3.8764	Guangxi	7.3822	Gansu	3.0928
Jilin	-1.9742	Qinghai	3.2198	Hainan	1.6302	Ningxia	1.8186
Heilongjiang	-15.0265	Xinjiang	-8.6983	Chongqing	39.3445	total	560.1255

Table 3 area-need statistics

The following basic conditions must be met for farming:

- meeting the demand of each province.
- The neighboring provinces (geographically adjacent) can transfer production, and the provinces with other geographical relationships cannot transfer production.
- The amount of farming in each province matches the breeding efficiency.

This paper sets the planning goal as an output-efficiency summation function rather than an output summation function. This is because simply considering the output summation function may be overburdened for some provinces with lower capacity, but it is a waste of resources for provinces with high capacity and low demand.

Based on the above three principles, this paper first evaluates the overall efficiency of each province according to the SFA model used in the second part. The indicators are as follows:

area	**effect**	**area**	**effect**	**area**	**effect**	**area**	**effect**
Beijing	1.03	Shanghai	1.11	Shandong	1.13	Sichuan	1.26
Tianjin	1.09	Jiangsu	1.07	Henan	1.08	Guizhou	1.16
Hebei	1.04	Zhejiang	1.11	Hubei	1.09	Yunnan	1
Shanxi	1.06	Anhui	1.13	Hunan	1.03	Tibet	0.9
Inner Mongolia	1.08	Fujian	1.59	Guangdong	1	Shaanxi	1
Liaoning	1.1	Jiangxi	1.12	Guangxi	1.06	Gansu	1.03
Jilin	1.12	Qinghai	0.96	Hainan	1.13	Ningxia	1.01
Heilongjiang	1.02	Xinjiang	1.13	Chongqing	1.11	total	1.1

Table 4 area-effect statistics

Using the relationship between unit yield and efficiency value to fit the yield-efficiency function, select the best three relationships of the fitting program, and establish the relationship between the aquaculture quantity and the breeding efficiency:

$$p = 30.257\theta^3 - 15.619\theta^2 + 98.073$$

$$p\_t = \min \sum_i \frac{p_i}{\theta^3 + 0.52\theta^2}$$

$$For\ each\ i,\ p_i + \lambda w_{ji} \ge n_i + w_{ij}$$

$$For\ each\ i,\ w_{ij} \le p_i + S_i$$

$$Find\ the\ object: p_i\ \&\ w_{ij}$$

Where i is the provincial indicator, p_t represents the planned objective function item, pi represents the production volume required by each province, n_i represents the net demand of each region, w_{ij} represents the transfer from i province to j province, and Si represents the current inventory (This paper believes that if the province needs pork supply, it will give priority to the province. If the demand is greater than 0, the province will be 0), and the pi value and w_{ij} value of each province need to be obtained.

λ represents the transport efficiency that occurs when transporting to the province, and its mathematical relationship is defined as:

$$\lambda = 1 - \varepsilon$$

Where ε is the loss rate during transportation. We specified this as the total loss of both frozen storage and transportation, and the average value of the query was 3.98% + 0.24% = 4.22%.

Add actual conditions based on the model:

- **Any province that is out of stock must participate in production, and the output is not less than 10% of the shortage;**
- **The production capacity of any province shall not exceed 1 million tons. In particular, Beijing, Shanghai, and Tianjin shall not exceed 500,000 tons, and Tibet, Qinghai, and Ningxia shall not exceed 200,000 tons.**

The established model Lingo solution results are as follows:

area	yield	area	yield	area	yield	area	yield
Beijing	50	Shanghai	50	Shandong	0	Sichuan	0
Tianjin	2.8433	Jiangsu	100	Henan	0	Guizhou	0.5
Hebei	100	Zhejiang	100	Hubei	29.07255	Yunnan	1
Shanxi	2	Anhui	100	Hunan	1	Tibet	0.5
Inner Mongolia	3	Fujian	100	Guangdong	0.5	Shaanxi	0.5
Liaoning	1	Jiangxi	0.5	Guangxi	4	Gansu	0.5
Jilin	0	Qinghai	3.2198	Hainan	6	Ningxia	1
Heilongjiang	0	Xinjiang	0	Chongqing	0.5	total	657.6357

Table 5 area-yield statistics

4.3.2 Bulk storage model

The production volume of pork is P, P is the value given in the table; the production time is T (the unit is month), then the production efficiency is defined as:

$$\delta = \frac{P}{T}$$

Let the highest storage capacity of the region be W, the average storage capacity be WA, and the minimum storage capacity be WM, then the model is:

$$W = (\delta - v)T = (1 - \frac{v}{\delta})P$$

$$WA = \frac{W}{2}$$

$$WM = N$$

Where v represents the speed of pork demand, this paper considers it to be a constant value, and is related to per capita consumption and population; N represents the effective demand of each region, the lowest is 5% of the current inventory, otherwise the actual demand is obtained.
In addition, the market price of pork is CP, and the storage cost per unit of pork is CS. Then, based on the mass storage model of basic economic production, the average total cost can be proved as:

$$CT = (WA)(CS) + \frac{v(CP)}{P}$$

Use data set Pig farming data, taking Hebei Province as an example, using the relevant data, with a minimum of overhead (including storage overhead and purchase overhead), simulate a 12-month storage-purchase model in Lingo, and the results are as follows :

```
 D( 1)        23.09064
 D( 2)        32.91588
 D( 3)        42.74112
 D( 4)        52.31041
 D( 5)        60.62712
 D( 6)        69.71834
 D( 7)        79.39323
 D( 8)        89.50795
 D( 9)        99.95414
D( 10)        110.6501
D( 11)        121.5343
D( 12)        132.5604
```

Figure 16 Pork storage / 10,000 tons per month

```
 DP( 1)        63.30100
 DP( 2)        63.30100
 DP( 3)        63.30100
 DP( 4)        60.85876
 DP( 5)        45.86264
 DP( 6)        34.56169
 DP( 7)        26.04539
 DP( 8)        19.62758
 DP( 9)        14.79118
DP( 10)        11.14650
DP( 11)        8.399910
DP( 12)        6.330100
```

Figure 17 Pigs storage / 10,000

5 Sensitivity Analysis

The sensitivity of the model is mainly concentrated on the variables of the mathematical model, especially the storage model. We look through the feasible domain of the Lingo software plan, and the model scope is as follows:

D(1)	1689.000	5558.562	32091.00
D(2)	1689.000	3289.524	30402.00
D(3)	1689.000	1436.670	28713.00
D(4)	1689.000	487.9041	2817.791
D(5)	1689.000	961.9887	4141.437
D(6)	1689.000	3592.814	3415.603
D(7)	1689.000	19558.37	2766.811
D(8)	1689.000	7937.905	1374.459
D(9)	1689.000	5482.960	949.3816
D(10)	1689.000	4446.620	769.9381
D(11)	1689.000	3892.224	673.9436
D(12)	1689.000	3557.933	544.5437

Figure 18 Pork storage fault tolerance interval

DP(1)	675.6000	582.5373	28595.28
DP(2)	675.6000	344.7421	28595.28
DP(3)	675.6000	150.5630	28595.28
DP(4)	675.6000	51.13235	295.3045
DP(5)	675.6000	67.85156	391.8628
DP(6)	675.6000	90.03760	519.9938
DP(7)	675.6000	119.4780	690.0209
DP(8)	675.6000	158.5448	915.6432
DP(9)	675.6000	210.3856	1215.039
DP(10)	675.6000	279.1773	1612.332
DP(11)	675.6000	370.4625	2139.530
DP(12)	675.6000	INFINITY	2839.112

Figure 18 Pig storage fault tolerance interval

It can be seen that the model has a good fault tolerance.
Sensitivity issues have been considered in the rest of the models, and data perturbations have little effect on their results.

6 Strengths and Weakness

The advantage of the model is that it can comprehensively solve a problem by using statistical ideas, generalized machine learning methods and planning models. This paper still considers many disturbances under ideal conditions, making the model more explanatory.
The shortcoming of the model is that there is no further realistic verification analysis, and the data source is single and lacks the explanatory power of the data.

7 Conclusion

In this paper, the factor analysis and volatility evaluation of pork price were carried out. The AHP analysis method and TOPSIS analysis method were carried out on the imported model. The mixed linear programming of the production model and the storage model can explain the abnormal fluctuation of pork to some extent.

Appendix

1.

```
clc;
[row_data,column_data]=size(data);
for i=1:column_data
    series_naive=data(:,i);

series_analysis=series_naive(3:row_data);

x=[series_naive(2:row_data-1),series_naive(1:
row_data-2),ones(row_data-2,1)];
    result_item=x\series_analysis;

result_num=result_item(1)*series_naive(end)+
result_item(2)*series_naive(end-1)+result_it
em(3);
    disp(result_num);
    disp(result_item);
End
2.
x0=mean(data');
[row,column]=size(x0);
x1=zeros(size(x0));
n=length(x0);
```

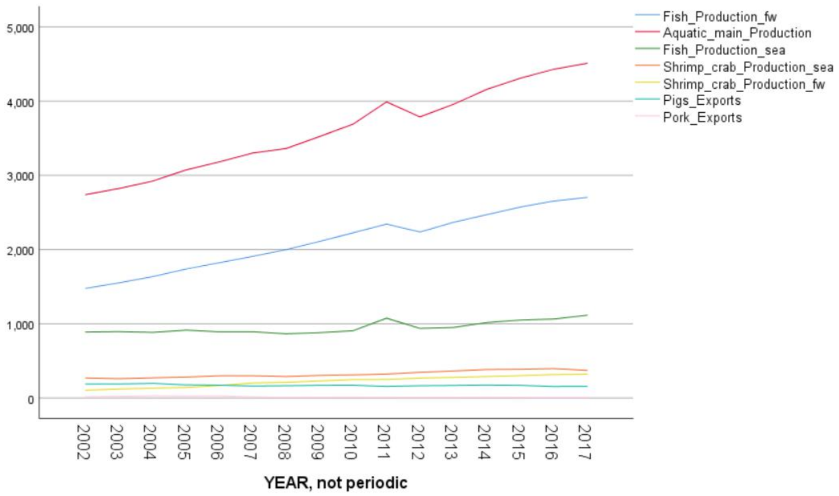
```
x1(1)=x0(1);
for i=2:n
    x1(i)=x1(i-1)+x0(i);
end
z=zeros(size(x0));
af=0.5;   for i=2:n
    z(i)=af*x1(i)+(1-af)*x1(i-1);
end
Y=zeros(n-1,1);
B=zeros(n-1,2);
for i=1:n-1
    Y(i,1)=x0(i+1);
    B(i,1)=-z(i+1);
    B(i,2)=1;
end
Para=inv(B'*B)*B'*Y;
a=Para(1);
b=Para(2);
n=1;
x1_pe=zeros(row,column+n);
x1_pe(1,1)=x1(1);
for i=1:column+n-1
```

```
    x1_pe(1,i+1)=(x0(1)-b/a)*exp(-a*i)+b/a;
end
x0_pe=zeros(size(x1_pe));
x0_pe(1,1)=x0(1);
for i=1:column+n-1
    x0_pe(1,i+1)=x1_pe(i+1)-x1_pe(i);
end
formatspec="The mean of the predicted results
is %6.4f. (by predict)\n";
fprintf(formatspec,x0_pe(1,column+n))
ev0=zeros(size(x0));
q0=zeros(size(x0));
for i=1:column
    ev0(i)=x0(i)-x0_pe(i);
    q0(i)=ev0(i)/x0(i);
end
x0_mean=mean(x0,2);
x0_s=std(x0,0,2)^2;
ev0_mean=mean(ev0,2);
ev0_s=std(ev0,0,2)^2;
C_s_prop=ev0_s/x0_s;
number_possible=0;
```

```
for i=1:column
    if abs(ev0(i))<0.6745*x0_s
        number_possible=number_possible+1;
    end
end
small_probability=number_possible/length(ev0)
;
global_control_number=0;
bad_number_relative_error=0;
for i=1:column
    str_put1='the NO.%d predict_result has the
The relative error:%6.4f.\n';
    fprintf(str_put1,i,q0(i));
    if q0(i)<0.01
        disp('Good fitting!');
    elseif q0(i)<0.05
        disp('Trusted fitting!');
    elseif q0(i)<0.2
        disp('Basic fitting.');
    else
        disp('The fitting is bad.');
```

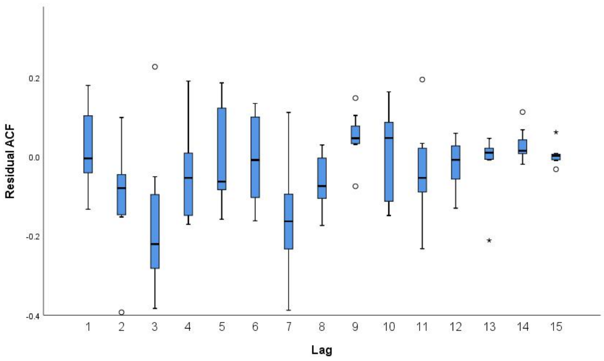
```
bad_number_relative_error=bad_number_relativ
e_error+1;
    end
end
if
(bad_number_relative_error-1)/(length(q0)-1)
<0.2
    disp('The fitting result is acceptable.');
else

global_control_number=global_control_number+
1;
End
x0_divide_columns_pe=zeros(size(data));
if chro_total_model_number==1
    x0_divide_columns_pe(1,:)=data(1,:);
    weight_coe=sum(data)/sum(sum(data));
    for i=2:column
        x0_total_pe=x0_pe(1,i)*size(data,2);

x0_divide_columns_pe(i,:)=x0_total_pe*weight
_coe;
```

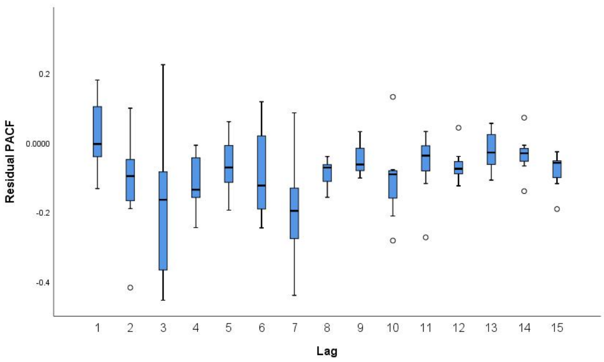
```
    end

x0_total_pe_new=x0_pe(1,column+n)*size(data,
2);

x0_divide_columns_pe_new=x0_total_pe_new*wei
ght_coe;
end
x0_divide_columns_pe_error=zeros(size(data))
;
for i=2:column

x0_divide_columns_pe_error(i,:)=x0_divide_co
lumns_pe(i,:)-data(i,:);
end
disp(x0_divide_columns_pe_new);
disp(x0_divide_columns_pe);
disp(x0_divide_columns_pe_error);
3&4.
```



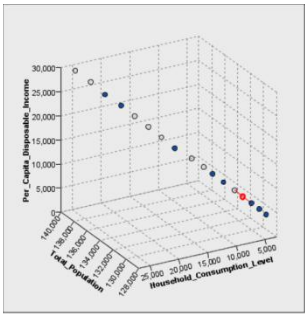
Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	.418	.372	-.028	.821	-.028	-.028	-.023	.533	.755	.821	.821
R-squared	.793	.227	.423	.986	.423	.423	.630	.902	.986	.986	.986
RMSE	30.562	28.040	4.874	75.889	4.874	4.874	8.681	14.339	52.428	75.889	75.889
MAPE	6.369	9.287	1.252	27.260	1.252	1.252	1.452	3.422	4.282	27.260	27.260
MaxAPE	22.746	37.533	5.260	107.690	5.260	5.260	5.285	10.125	11.015	107.690	107.690
MAE	20.834	18.213	3.253	46.265	3.253	3.253	6.135	10.819	40.879	46.265	46.265
MaxAE	75.555	74.125	14.000	210.831	14.000	14.000	19.386	35.159	117.603	210.831	210.831
Normalized BIC	6.213	2.212	3.341	9.005	3.341	3.341	4.601	5.499	8.265	9.005	9.005

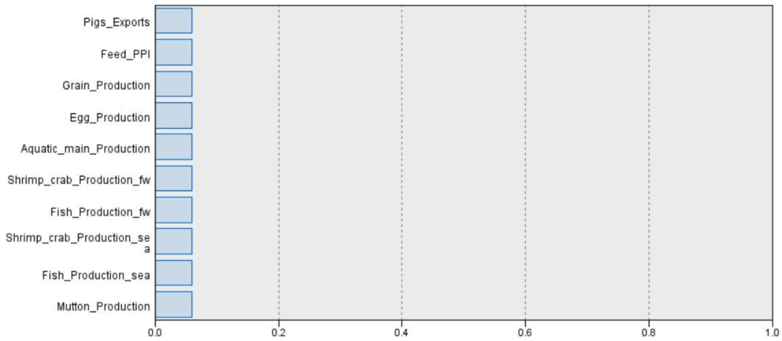


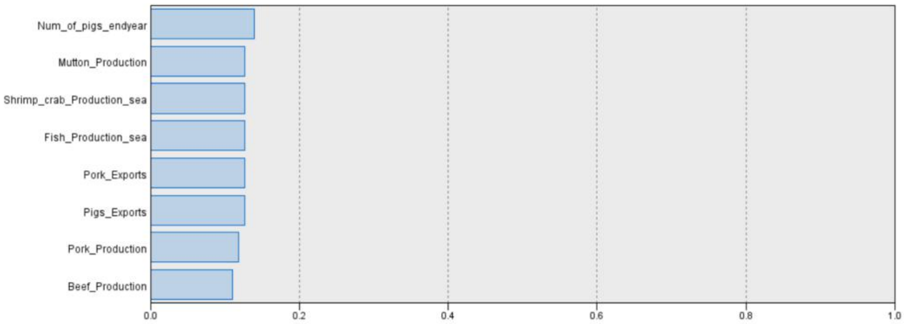


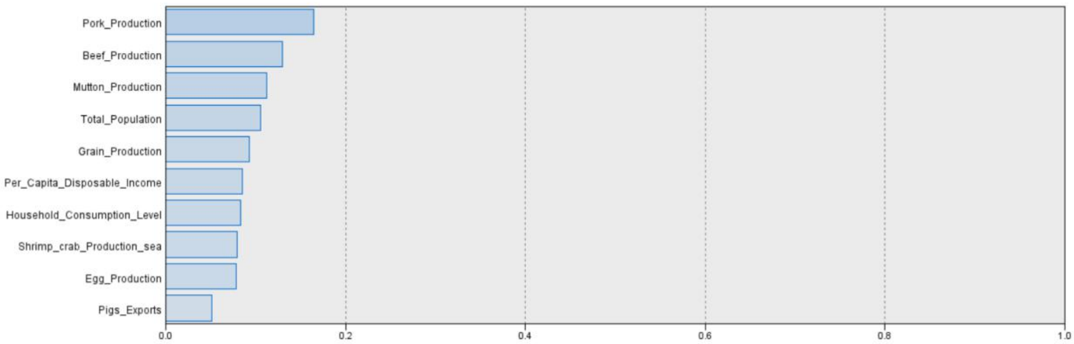
5.

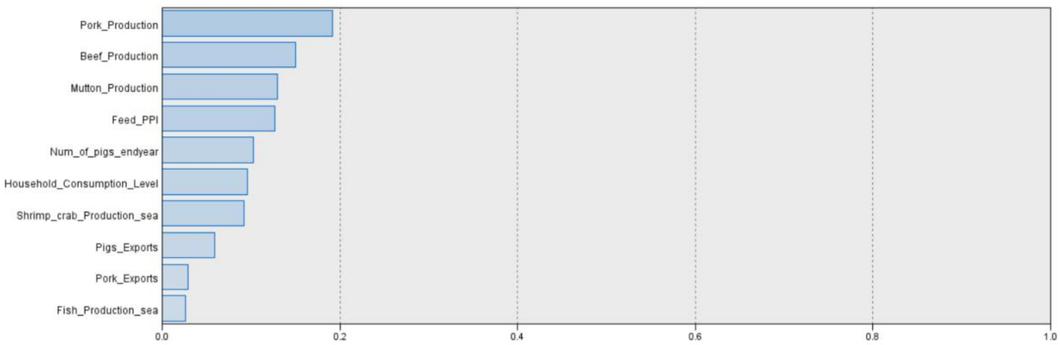

Per_Capita_Disposable_Income
Total_Population
Household_Consumption_Level

KNN


Pigs_Exports
Feed_PPI
Grain_Production
Egg_Production
Aquatic_main_Production
Shrimp_crab_Production_fw
Fish_Production_fw
Shrimp_crab_Production_sea
Fish_Production_sea
Mutton_Production
0.0
0.2
0.4
0.6
0.8
1.0


Num_of_pigs_endyear
Mutton_Production
Shrimp_crab_Production_sea
Fish_Production_sea
Pork_Exports
Pigs_Exports
Pork_Production
Beef_Production
0.0
0.2
0.4
0.6
0.8
1.0


Pork_Production
Beef_Production
Mutton_Production
Total_Population
Grain_Production
Per_Capita_Disposable_Income
Household_Consumption_Level
Shrimp_crab_Production_sea
Egg_Production
Pigs_Exports
0.0
0.2
0.4
0.6
0.8
1.0



6.

province	2014	2015	2016	2017	average
Hebei	1.1070	1.1019	1.0971	1.0926	1.0996
Shanxi	1.0190	1.0181	1.0173	1.0165	1.0177
Inner Mongolia	1.1011	1.0964	1.0918	1.0875	1.0942
Liaoning	1.0789	1.0752	1.0716	1.0683	1.0735
Jilin	1.1454	1.1386	1.1321	1.1259	1.1355
Heilongjiang	1.0644	1.0614	1.0585	1.0557	1.0600
Shandong	1.2378	1.2266	1.2159	1.2058	1.2215
Henan	1.1213	1.1156	1.1102	1.1050	1.1130
Shaanxi	1.0119	1.0113	1.0108	1.0103	1.0111
average value	1.0985	1.0939	1.0895	1.0853	1.0918

7.

```
%% TOPSIS
clc;
B=zeros(size(A));
[B_row,B_column]=size(B);
a1_max=max(A(:,1));
a1_min=min(A(:,1));
for i=1:B_row
    B(i,1)=(A(i,1)-a1_min)/(a1_max-a1_min);
```

```
end
a5_max=max(A(:,5));
a5_min=min(A(:,5));
for i=1:B_row
    B(i,5)=(A(i,5)-a5_min)/(a5_max-a5_min);
end
a3_max=max(A(:,3));
a3_min=min(A(:,3));
for i=1:B_row
    B(i,3)=(a3_max-A(i,3))/(a3_max-a3_min);
end
a4_max=max(A(:,4));
a4_min=min(A(:,4));
for i=1:B_row
    B(i,4)=(a4_max-A(i,4))/(a4_max-a4_min);
end
max_limit=0.5;
min_limit=0;
max_pro=0.3;
min_pro=0;
for i=1:B_row
    if A(i,2)>=min_pro && A(i,2)<=max_pro
```

```
        B(i,2)=1;
    elseif A(i,2)>max_pro && A(i,2)<=max_limit

B(i,2)=1-(A(i,2)-max_pro)/(max_limit-max_pro)
;
    else
        B(i,2)=0;
    end
end
for j=1:B_column
    B_column_sum_sq=0;
    for i=1:B_row

B_column_sum_sq=B_column_sum_sq+B(i,j)^2;
    end
    B_column_sum_std=sqrt(B_column_sum_sq);
    for i=1:B_row
        B(i,j)=B(i,j)/B_column_sum_std;
    end
end
w=[0.25,0.2,0.05,0.25,0.25];
B_an=B.*repmat(w,B_row,1);
```

```
Cstar=max(B_an);
Cstar(3)=min(B_an(:,3));
Cstar(4)=min(B_an(:,4));
C0=min(B_an);
C0(3)=max(B_an(:,3));
C0(4)=max(B_an(:,4));
for i=1:B_row
    Sstar(i)=norm(B_an(i,:)-Cstar);
    S0(i)=norm(B_an(i,:)-C0);
end
disp(Sstar);
disp(S0);
f=S0./(S0+Sstar);
[sort_sf,sort_ind]=sort(f,'descend');
disp(sort_ind);
disp(sort_sf);
```

reference

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