Yield Prediction of Household Garbage Based on SARIMA and Exponential Smoothing Model

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Abstract. Refuse classification is a waste treatment method, which creates reuse opportunities and enhances recyclable value for domestic waste. Prolonging the use cycle of renewable resources is one of the cores of China’s sustainable development strategy. Analyzing the total amount of household waste can obtain the characteristics of regional garbage growth so that governments can promote the garbage classification process intelligently. This article chose the household garbage monthly yield data as the time series and extracted its seasonal information. We used RStudio software to develop the multiplicative seasonal autoregressive integrated moving average (SARIMA) model with 2 Holt-Winters exponential smoothing models (additive and multiplicative) for comparison. Seasonal factor charts explain that the seasonal effect cycle of series is 1 year, and its period of increase or decrease is 6 months. SARIMA(0,1,1)(1,1,0)_{12} is the optimal model for data, which is better than Holt-Winters models. The prediction accuracy of SARIMA model is 94.31%. For the next year, the SARIMA model predictions show that the growth rate of the household garbage yield is 2.65%, which is in line with the actual situation. The results of this study are valuable for the planning of waste classification policy in recent years.

1. Introduction
Xiangzhou District, Zhuhai City, Guangdong Province, China, is the most populous area in Zhuhai, and its production of household garbage accounts for about 50% of the total of Zhuhai. Since 2020, the Zhuhai Government has deployed the waste classification strategy, and all of the household garbage is transported to the Doumen Treatment Station for harmless treatment. Meanwhile, the trial garbage classification project is set up in Meihua Street, Xiangzhou District.

Time series analysis is a statistical method to research dynamic data, it has the ability to speculate the trend development of data by analyzing its change regularity. Zisheng Yang et al.[1] used the autoregressive integrated moving average (ARIMA) model to analyze and forecast the annual total output of construction garbage in Henan Province. Chen Jiao et al.[2] used the time series decomposition method to analyze the trend, periodicity, volatility of the series and measured the influence of characteristic factors on the forecast. Yanling Lv[4] built a multiplicative SARIMA model to forecast the number of tourists in Kunming, which results were consistent with the reality, and the average error of prediction is 7.03%. Xinyi Wu et al.[5] compared the forecasting effects of the exponential smoothing model and SARIMA model on the freight volume.
of the Three Gorges Ship Lock, which indicated that constructing a seasonal time series model is helpful to reduce the forecast error caused by fluctuation factors.

This article used the household garbage monthly production data to fit the time series model, analyzed the characteristics of series deterministic factors. We built three prediction models, and selects the more accurate one to make short-term forecasts, and its result can accelerate the process of waste classification in Zhuhai.

2. Data interpretation
The household garbage monthly production data in Xiangzhou District of Zhuhai City from January 2017 to March 2021 is shown in table 1. It came from Zhuhai City Management and Comprehensive Law Enforcement Bureau. The number of samples is 51, and its unit is tons.

| Period | Jan   | Feb   | Mar   | Apr   | May   | Jun   |
|-------|-------|-------|-------|-------|-------|-------|
| 2017  | 40548.90 | 34207.31 | 42781.13 | 43250.73 | 46444.81 | 46273.60 |
| 2018  | 42867.41 | 34470.34 | 44089.28 | 42739.78 | 44878.69 | 45886.10 |
| 2019  | 48460.62 | 38729.45 | 50691.23 | 51080.01 | 53065.03 | 53118.15 |
| 2020  | 49265.24 | 29608.11 | 42413.63 | 42455.05 | 48991.49 | 46952.17 |
| 2021  | 41253.88 | 36536.77 | 43813.11 |       |       |       |

| Period | Jul    | Aug   | Sep    | Oct    | Nov    | Dec    |
|-------|--------|-------|--------|--------|--------|--------|
| 2017  | 49934.01 | 61448.72 | 50060.83 | 44831.40 | 43827.76 | 48005.34 |
| 2018  | 47024.27 | 47458.52 | 47871.50 | 44244.89 | 44070.28 | 46996.65 |
| 2019  | 58124.81 | 57500.46 | 52064.96 | 53020.38 | 49824.23 | 50723.79 |
| 2020  | 45061.53 | 46707.58 | 41553.07 | 41437.08 | 40594.84 | 41123.83 |

3. Positive analysis

3.1. Deterministic factor decomposition
In order to the deterministic characteristics of the data, we used the statistical software RStudio to program and imported the data as a time series object by the ts function of the tseries package[6]. Figure 1 shows the monthly data of household garbage production in Xiangzhou District. Observing the fluctuation law, we judged that the cycle of seasonal effect is 12 months preliminarily, and the period of progressive change is 6 months.
We built the X11 model with RStudio to monitor the seasonal fluctuations of the data. X11 model is one of the most frequently used models for deterministic factors decomposition. Let the time series is composed of four major fluctuation factors: Developmental tendency ($T$), Cyclical fluctuation ($C$), Seasonal fluctuations ($S$), and Irregular fluctuation ($I$)\cite{7}. X11 model decomposes these factors with three order moving average\cite{8}, we can formulate it as:

$$x_t = f(T_t, C_t, S_t, I_t)$$

(1)

Decomposing the series and extracting its four fluctuation factors, we got the seasonal effect $S_t$ shown in panel (a) of figure 2, and the seasonal index $S_E$ shown in panel (b) of figure 2. It confirms that the length of the seasonal effect is 12 months intuitively \cite{9}. In the seasonal period, the effect was divided into two stages. The household garbage production is on the rise from February to August each year, that is spring and summer. The peak of the seasonal index es is in August, that is, Xiangzhou District produced the most garbage in August every year. There is a declining trend from August to February of the next year, that is autumn and winter. The lowest seasonal index is in February, which shows that February is the month with the least garbage yield in a year \cite{9}.

![Figure 2. Seasonal effects and indexes of the data.](image)

3.2. Multiplicative SARIMA model

3.2.1. Stationarity test and white noise test. Because the seasonal characteristics are so obvious that the garbage yield is a non-stationary series. Then we made it stationary by the seasonal adjustments \cite{11}. We used the length of periodicity as the number of differencing passes to differ the series, which has the fixed period characteristic \cite{12}. From the cycle of seasonal effect, we set the length of periodicity as $S = 12$. Figure 3 shows the difference result of the data by the RStudio, which combined the first-order difference with the seasonal difference at period (12).
Secondly, we tested the unit root and analyzed the stationarity of the first difference sequence [13]. The results of the unit root test are exhibited in table 2. The ADF value is -6.578, and the critical value is -4.728, less than the 1% confidence level. We concluded that the sequence had no unit root after the differencing and became stationary.

Table 2. Augmented Dickey-Fuller unit root test of the first and seasonal difference sequence.

| Confidence Levels | T.Stat | P-value | ADF value |
|-------------------|--------|---------|-----------|
| 0.01              | -6.578 | 0.01    | -6.578    |
| 1%                | -4.728 |         |           |
| 5%                | -3.760 |         |           |
| 10%               | -3.325 |         |           |

We used Box.test to the difference sequence for the pure random test, its results are shown in table 3. At the condition level of 5%, when the lagged orders are 6 and 12, the values of the $\chi^2$ statistic are 16.53 and 43.27, and their P-values are far less than 0.05. Therefore, the difference sequence is non-white noise. Samples of data are independent of each other, which is not affected by pure random fluctuations [14].

Table 3. White noise test of the first and seasonal difference sequence.

| Lag | Chi-sq | P-value |
|-----|--------|---------|
| 6   | 16.53  | 0.01118 |
| 12  | 43.27  | 0.00002 |

Combining with the stationarity test result, we determined that the difference sequence is a stationary and non-white noise time series. Thereout, we can build a prediction model according to the known data.

3.2.2. Obtain the orders. For the multiplicative SARIMA($p,d,q$)($P,D,Q$)$_S$ model[15], its expression is:

$$\Phi(B)\Phi_S(B)\nabla^d\nabla_S^P x_t = \Theta(B)\Theta_S(B)\varepsilon_t$$

(2)

In order to determine the parameters $p$, $q$, $P$, and $Q$ of the model[16], we analyzed the autocorrelation of the model. The autocorrelation function (ACF) of the sequence is shown in panel (a)
of figure 4 and the partial autocorrelation function (PACF) is shown in panel (b) of figure 4. The observational lags are 36 orders in the function plot.

One seasonal cycle is 12 orders. In the ACF, the non-seasonal coefficient is first-order truncated. The seasonal coefficient decays slowly, so it is trailing. The PACF shows that the non-seasonal coefficient period is trailing. Analyzing the terms of seasonal correlation, the coefficient of 12th order is non-zero significantly, and 95% coefficients are within twice the standard deviation in the subsequent cycles. Seasonal partial autocorrelation coefficient is shown as a characteristic of 12th order truncation. So, the ACF and PACF suggest $q = 1$ and $P = 1$.

For the difference sequence, its difference order is $d = D = 1$. The non-seasonal correlation model is ARMA $(0,1)$, and the seasonal correlation model is ARMA$(1,0)$ with 12 steps. Therefore, we determined the best-fit SARIMA model is SARIMA$(0,1,1)(1,1,0)_{12}$.

![Figure 4. ACF and PACF of the first and seasonal difference sequence.](image)

3.2.3. Parameter estimation and significance test. After obtaining the order from the SARIMA model, we estimated its parameters and tested its significance and the white noise situation. The results show in table 4 (the confidence level is 5%). From the estimation, the moving-average parameter $\theta_1$ is 0.452 in the non-seasonal correlation model, and the seasonal component $\phi_{12}$ is -0.652 in the seasonal one.

Testing the significance, we knew the P-values are 0.00337 and 0.00001, which is far less than 0.05. It is indicated that the coefficients of the SARIMA model are non-zero significantly. At the same time, the Pierce-Box white noise test was used in the residual sequence. The $Q$ statistic of the test obeys the chi-square distribution, and their P-values are 0.494 and 0.700. It is indicated that the residual sequence is a white noise series, the model can be fitting well[17].

For optimization, we tried to compare the SARIMA$(0,1,1)(1,1,0)_{12}$ with some similarity models[18]. The SARIMA$(0,1,1)(1,1,0)_{12}$ model has the lowest values of AIC and BIC (table 5), so it is the best SARIMA model to forecast household garbage production in Xiangzhou District[19].

| Table 4. Parameter estimation of the SARIMA$(0,1,1)(1,1,0)_{12}$ model. |
|--------------------------|-----------------|-----------------|-----------------|
| Variable                  | Estimate        | Std.Error       | P-value         |
| $\theta_1$                | 0.452           | 0.160           | 0.00337         |
| $\phi_{12}$               | -0.652          | 0.141           | 0.00001         |
| $AIC$                     | 745.004         |                 |                 |
| $BIC$                     | 749.916         |                 |                 |
| $Q$-stat(lag=6)           | 5.394           |                 | 0.49440         |
| $Q$-stat(lag=12)          | 9.032           |                 | 0.70020         |
Substituting the parameters $\theta_1 = 0.452$, $\phi_{12} = -0.652$, $S = 12$ to the formula, we derived the expression of the SARIMA$(0,1,1)(1,1,0)_{12}$ as follows:

$$\nabla \nabla_{12} x_t = \frac{1-0.452B}{1+0.652B^{12}} \varepsilon_t$$

(3)

3.3. Holt-winters exponential smoothing model

The Holt-winters exponential smoothing model has the forecastability of periodic series, so it is typically used to study some series, which has the seasonal effect. The diffusion of the original series is difficult to observe for us (figure 1). To facilitate comparison, the Holt-winters additive and multiplicative models are fitted synchronously[20], then we estimated their parameters and smoothing coefficients, as shown in table 5.

$\alpha, \beta, \gamma$ are the smoothing coefficients of Holt-winters models (table 5). $\alpha$ is a symbol of the recent observation significance, which is estimated to be 0.473 and 0.432. The coefficients $\beta$ are 0 in both the models, which indicated that the recent observations are not affected by the trend effect basically. $\gamma$ are 0.831 and 0.858, which showed that the seasonal factors have a great significance to recent observations values[21]. The parameters $a$ of the Holt-winters models are estimated to be 45193.976 and 45576.777. $b$ are both of -199.839 in the two models. As shown in table 6, we can obtain the seasonal index $S_j$ and the exponential smoothing prediction models. The models divide into the additive model and the multiplicative model.

- The additive model expression is as follow:
  $$\hat{x}_{t+k} = 45193.976 - 199.839k + S_j$$

(4)

- The multiplicative model expression is as follow:
  $$\hat{x}_{t+k} = (45576.777 - 199.839k)S_j$$

(5)

Table 5. Parameter estimation of the exponential smoothing models.

| Estimate | Additive model | Multiplicative model |
|----------|---------------|----------------------|
| $\alpha$ | 0.473         | 0.432                |
| $\beta$  | 0.000         | 0.000                |
| $\gamma$ | 0.831         | 0.858                |
| $a$      | 45193.976     | 45576.777            |
| $b$      | -199.839      | -199.839             |

Table 6. Seasonal indexes of the exponential smoothing models.

| Seasonal index | Period | Additive model | Multiplicative model |
|----------------|--------|----------------|----------------------|
| $S_1$          | Apr 21 | -1064.178      | 0.977                |
| $S_2$          | May 21 | 2791.973       | 1.067                |
| $S_3$          | Jun 21 | 1156.301       | 1.028                |
| $S_4$          | Jul 21 | 2209.168       | 1.040                |
| $S_5$          | Aug 21 | 5705.135       | 1.106                |
| $S_6$          | Sep 21 | 2451.836       | 1.028                |
| $S_7$          | Oct 21 | 2215.657       | 1.033                |
| $S_8$          | Nov 21 | 171.027        | 0.997                |
| $S_9$          | Dec 21 | 1083.901       | 1.019                |
| $S_{10}$       | Jan 22 | 352.530        | 1.009                |
| $S_{11}$       | Feb 22 | -10026.062     | 0.774                |
| $S_{12}$       | Mar 22 | -1340.463      | 0.963                |
3.4. Evaluation

To the SARIMA model and the two models of Holt-Winters, we assumed that the actual value is $T_{in}$, the back substitution predictive value is $P_{im}$, and $i$ is used to distinguish three models. When using the exponential smoothing method, the moving average leads to reduced numbers of test values. For convenient application [21], we set the numbers of forecast periods $k$ as same as exponential smoothing model, and obtained the calculation formula of the three models forecast accuracy $R$ is as follow:

$$R_i = \left(1 - \frac{E(T/T_{in})}{k}\right) \times 100\%$$  \hspace{1cm} (6)

Where $E$ is the absolute error, $E = |P - T|$, $k$ is 39, $i$ is $\{1,2,3\}$ and $n,m$ is $\{1,2,\cdots,12\}$.

Table 7 shows the prediction accuracy of models. The prediction accuracy of models follows the order from high to low: the SARIMA(0,1,1)(1,1,0)_{12} model (94.31%), the Holt-Winters multiplicative model (93.46%), the Holt-Winters additive model (93.33%).

In conclusion, the best-fit model to predict the yield of household garbage is the multiplicative SARIMA(0,1,1)(1,1,0)_{12} model.

| Model type | Accuracy(%) |
|------------|-------------|
| SARIMA(0,1,1)(1,1,0)_{12} model | 94.31 |
| Holt-Winters additive model | 93.46 |
| Holt-Winters multiplicative model | 93.93 |

To recognize the practicality of the SARIMA(0,1,1)(1,1,0)_{12} model, we used it to backtrack the garbage production prediction of April 2020 to March 2021, then calculated its relative error and exhibited in table 8. Because the garbage production of February is the lowest (figure 2), its highly fluctuating range caused the largest relative error [23]. The average relative error of the SARIMA model is 5.39%[24]. We considered the predictive values agree well with the experimental results.

| Period | Actual (t) | Predictive value (t) | Relative Error(%) |
|--------|------------|----------------------|-------------------|
| Apr 20 | 42455.05   | 42795.21             | 0.80              |
| May 20 | 48991.49   | 44694.05             | 8.77              |
| Jun 20 | 46952.17   | 47726.06             | 1.65              |
| Jul 20 | 45061.53   | 49785.68             | 10.48             |
| Aug 20 | 46707.58   | 47261.06             | 1.18              |
| Sep 20 | 41553.07   | 45335.88             | 9.10              |
| Oct 20 | 41437.08   | 41228.94             | 0.50              |
| Nov 20 | 40594.84   | 40117.29             | 1.18              |
| Dec 20 | 41123.83   | 42600.42             | 3.59              |
| Jan 21 | 41253.88   | 42237.94             | 2.39              |
| Feb 21 | 36536.77   | 28513.96             | 21.96             |
| Mar 21 | 43813.11   | 45168.75             | 3.09              |

3.5. Prediction

We used the SARIMA(0,1,1)(1,1,0)_{12} model to predict the garbage production from April 2021 to March 2022 with the forecast function in RStudio[25], it shows in table 9.
### Table 9. Predictive values of the SARIMA model.

| Period   | Apr 21 | May 21 | Jun 21 | Jul 21 | Aug 21 | Sep 21 |
|----------|--------|--------|--------|--------|--------|--------|
| Predictive value (t) | 44693.29 | 48261.72 | 47586.9 | 50194.02 | 50359.5 | 44502.79 |

| Period   | Oct 21 | Nov 21 | Dec 21 | Jan 22 | Feb 22 | Mar 22 |
|----------|--------|--------|--------|--------|--------|--------|
| Predictive value (t) | 45604.47 | 43227.23 | 43997.9 | 43091.99 | 28632.41 | 39514.35 |

Compared with the last period, garbage production increased by 2.65% year on year, which is consistent with the slow growth of garbage production characteristics in Xiangzhou District. Figure 5 supplies the prediction results of the next period. The black dashed line is the actual value, the red line is the backtracking predictive value, the blue line is the predictive value of the next year, and the gray area is the predictive confidence interval at the 95% level. The actual value is close to the backtracking prediction value, which shows that the prediction effect of the SARIMA(0,1,1)(1,1,0)_{12} model is highly accurate.

![Figure 5. Prediction graph of the SARIMA model.](image)

### 4. Conclusion

In this paper, we used the X11 model to extract the deterministic factors for the household garbage production series and knew the length of the seasonal effect is 1 year. Besides, the highest garbage yield is in August, and the lowest is in February. The garbage yield changes progressively between February and August. With data's seasonal characteristic, we built three models: the multiplicative SARIMA model, the additive model and the multiplicative model of Holt-Winters three order exponential smoothing model in RStudio, and compared their accuracy. At last, the results consider that the SARIMA(0,1,1)(1,1,0)_{12} model is the best-fit one, and its accuracy reaches 94.31%. Based on the SARIMA model, we make the short-term prediction of garbage production in Xiangzhou District. By calculation, the growth rate is 2.65% year-on-year in the next year, and it is consistent with the actual low growth rate, which verified the practicability of the model.

In addition, the maximum waste output is in August, and the least is in February in Xiangzhou District, so we suggested that the waste treatment station should allocate sanitation workers reasonably. For example, it can increase human and material resources to solve the surge problem of garbage in summer. Its low growth rate of garbage production shows that the urban population has been controlled stably in recent years. Under the condition of sufficient resources, Zhuhai municipal government should consider optimizing the talent absorption policy, stimulating the immigration of foreign population, and improving the urban economic level. In this paper, the SARIMA model is used for the short-term garbage production prediction. The study can provide the reference basis to plan garbage classification for the government in Xiangzhou District. The follow-up study should combine with the data obtained from the waste classification test area to analyze. Meanwhile, focus on the record of the type and...
structure of waste output, design the treatment method to maximize the benefit, and improve the efficiency of classified treatment.

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References
[1] Zisheng Yang, Guanyu Huang, Yaqiong Lu, Guanglin Sun. (2017) Research on Construction Waste Output Estimation Based on ARIMA Model. Journal of Zhongyuan University of Technology, 28(01): 55-59.
[2] Chen Jiao, Yanran Huang, Qinfeng Zhao, Anli Leng. (2021) Application of time series decomposition model to the prediction of the number of diabetics in Shandong Province. ZHONGGUO NONGCUN WEISHENG SHIYE GUANLI, 41(02): 93-97.
[3] Dariusz Grzesica. (2017) The Decomposition Issue of a Time Series in the Forecasting Process. International conference KNOWLEDGE-BASED ORGANIZATION, 23(3): 43-47.
[4] Yanling Lv. (2021) Forecast of Monthly Tourist Numbers in Kunming Based on the Multiplicative Seasonal Model. Operations Research and Fuzziology, 11(01): 113-121.
[5] Yixing Wu, Hang Nan, Fucun Shi, Qian Wang. (2021) Wang. Research on Cargo Volume Forecast of Three Gorges Shiplock Based on Exponential Smoothing Model. China Water Transport, 21(05): 13-15.
[6] Xiaohong Jiang, Huimin Cao. (2019) E-commerce Sales Forecast Based on ARIMA Model and R Language Implementation. Logistics Management, 42(04): 52-56+69.
[7] Jiandong Wang, Jieyu Chen, Malin Song. (2019) Factor decomposition and prediction of solar energy consumption in the United States. Journal of Cleaner Production, 234: 1210-1220.
[8] Jie Zhang, Jiaming Zhu. (2020) Predict the total amount of garbage based on multiple regression and cubic exponential smoothing method. Journal of Qiliu University of Technology, 34(4): 69-74.
[9] Hopali, Egemen, Çakmak, (2020) Aslıhan. Prediction of Daily CO2 Emissions of a Factory Using ARIMA and Holt-Winters Seasonal Methods. International Journal of Information, Business and Management, (12): 51-62.
[10] Jingwen Liu, Yuanyuan Luo, Xiaosong Li. (2010) APPLICATION OF X-11-ARIMA MODEL IN SEASONAL FLUCTUATIONS ANALYSIS AND SHORT-TERM forecast OF SCARLET FEVER. Modern Preventive Medicine, 37(20): 3816-3818.
[11] Xianfei You. (2020) Application of x11-arima model in prediction of HFMD incidence in China. Industrial & Science Tribune, 19(07): 64-66.
[12] Xin Du, Dajiang Li, Kai Liu, Nian Li. (2019) Number Prediction of Consultations in a Hospital based on SARIMA Model. Chinese Medical Record, 20(05): 45-49.
[13] Patterson K. (2011) Unit Root Tests in Time Series: Key Concepts and Problems. Palgrave Macmillan UK.
[14] Zeng Li, Clifford Lam, Jianfeng Yao, Qiwei Yao. (2019) On testing for high-dimensional white noise. The Annals of Statistics, 47(6): 3382-3412.
[15] Zhihang Peng, Changjun Bao, Yang Zhao, Honggang Yi. (2008) ARIMA Product Season Model and its Applicationon Forecasting in Incidence of Infectious Disease. Application of Statistics and Management, (02): 362-368.
[16] Suhartono. (2011) Time Series Forecasting by using Seasonal Autoregressive Integrated Moving Average: Subset, Multiplicative or Additive Model. Journal of Mathematics and Statistics, 7(1): 20-27.
[17] Xiaoni Yang, Kaixuan Zhang, Honggang Yang, Yuan Yu. (2020) Multiple Regression and ARIMA Model Prediction on the Yield of MSW in Xi’an. Environmental Sanitation Engineering, 28(02): 37-41.

[18] Aryee G, Essuman R, Djabbletey R, Owusu-Darkwa, E. (2019) Comparing the forecasting performance of sarima and holt-winters Methods of Births at a Tertiary Healthcare Facility in Ghana. Journal of Biostatistics and Epidemiology, 5(1): 18-27.

[19] Nili S, Khanjani N, Jahani Y. (2021) The effect of climate variables on the incidence of cutaneous leishmaniasis in Isfahan, Central Iran. International Journal of Biometeorology, 1-11.

[20] Wenze Wu, YuMu Lu. (2018) Research on financial revenue forecast based on Holt-Winter methods. Journal of Hubei Normal University (Natural Science), 38(2): 28-31.

[21] Bing Li, Chong Li, Yidi Wu, Yingqi Zhang, Ya Wen. (2019) Application of Holt-Winters Model in the Demand Forecast of Watt-hourMeter. Hebei Electric Power, (5): 7-9.

[22] Yan Wang. Time Series Analysis with R (2nd Edition). China Renmin University Press, 2020.

[23] Xinmin Wang, Jianwu Qi. (2017) The Application of ARIMA Model and Exponential Smoothing in Forecasting GDP of Tianshui. Journal of Lanzhou University of Arts and Science (Social Science Edition), 33(02): 54-58.

[24] Fei Xiao. (2021) Prediction of Newly-Increased Employment in Urban Areas of Guizhou Province Based on Seasonal Effect ARIMA. Statistical and Application, 10(01): 162-172.

[25] Long Zhang. (2021) Application of SARIMA Model in Prediction of Brucellosis in Xinjiang. Advances in Applied Mathematics, 10(4): 1233-1242.