Forecasting and Analysis of Agricultural Product Logistics Demand in Tibet Based on Combination Forecasting Model

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Abstract Over the years, the logistics development in Tibet has fallen behind the transport. Since the opening of Qinghai-Tibet Railway in 2006, the opportunity for development of modern logistics has been brought to Tibet. The logistics demand analysis and forecasting is a prerequisite for regional logistics planning. By establishing indicator system for logistics demand of agricultural products, agricultural product logistics principal component regression model, gray forecasting model, BP neural network forecasting model are built. Because of the single model's limitations, quadratic-linear programming model is used to build combination forecasting model to predict the logistics demand scale of agricultural products in Tibet over the next five years. The empirical analysis results show that combination forecasting model is superior to single forecasting model, and it has higher precision, so combination forecasting model will have much wider application foreground and development potential in the field of logistics.

Key words Tibet, Agricultural logistics, Principal component regression, Neural network forecasting model, Combination forecasting model

1 Introduction

Tibet is an important passage for the western logistics, and also an important area for the development of border trade and logistics. Through the analysis of industrial structure and logistics demand, it is found that Tibet Autonomous Region has continuously adjusted and optimized the industrial structure of Tibet, so that the industrial structure and layout are upgraded. Tibet has basically formed the characteristic industrial structure system which integrates tourism, Tibetan medicine, agricultural and livestock product processing industry, folk handicrafts, characteristic plateau bio-industry, green food (drink) product processing industry, mining and building material industry. With the completion of a number of transport, energy and other major infrastructure projects, especially the Qinghai-Tibet Railway, it has a profound impact on Tibet's transportation layout. Tibet's transport pattern basically forms the three-dimensional transport network with highway as the skeleton, railway as meridian, complemented by civil aviation. In short, dramatic economic development and logistics infrastructure construction have an enormous impact on Tibet's logistics demand. Agricultural product is important strategic commodity related to people's livelihood, and the circulation industry of agricultural products is the basic industry for stabilizing the national economy. Tibet's agricultural product logistics is at the initial stage of development. Through the forecasting of agricultural product logistics demand, it is necessary to reveal changes in agricultural markets, develop scientific and rational development strategies and development plans, and provide the supporting logistics facilities, in order to provide an important basis for optimizing agricultural product logistics supply system in Tibet Autonomous Region.

2 Establishment of indicator system for agricultural product logistics demand

Population is the primary factor affecting the agricultural product logistics demand; the fundamental growth driver for logistics demand is the rapid development of the national economy, which rapidly increases the demand for goods turnover and stimulates and inhibits the development of logistics in the region, so the level of social and economic development is the major factor affecting agricultural product logistics demand; income level affects the product purchasing power, and it is a factor affecting the formation of effective demand; the level of agricultural product logistics technology directly affects the function of agricultural product logistics, and gradually becomes the determining factor restricting the development of agricultural product logistics (Han Song, 2008). The structure of consumption is determined by the level of consumption, and the structure of consumption determines the product structure, thereby affecting the quantity and quality of agricultural product logistics demand; foreign trade reflects the international logistics demand of agricultural products. According to the above analysis and related scholars' research and literature (Chen Yana and Zhao Qilan, 2005; Fan Ronghua, 2011; Lihua and Ren Zhongliang, 2011; Wei Heng, 2006; Wang Yue, 2009), we establish the indicator system for forecasting of agricultural product logistics demand, and build first level indicators from demographic factors, level of socio-economic development, income, technological advances, supply capacity, residents' consumption, and foreign trade. There are 16 secondary indicators (see Table 1).

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Table 1 The indicator system for agricultural product logistics demand in Tibet

First level indicators	Secondary indicators
Demographic factors	1 Urbanization rate (%)
	2 Population
Level of socio-economic development	3 GDP
	4 The total retail sales of social consumer goods
Income	5 The per capita disposable income of urban residents
	6 The per capita net income of farmers and herdsmen
Technological advances	7 The total power of agricultural machinery
	8 R&D investment costs
Supply capacity	9 Expenses from fiscal expenditure for agriculture, forestry and water affairs
	10 Fixed-asset investment in transport, storage and postal industry
	11 Number of rural residents engaged in transportation, storage and postal services
	12 Freight
	13 Total grain output
	14 The output value of agricultural commodities
Residents' consumption	15 The level of consumption
Foreign trade	16 Frontier import and export volume

3 Establishment of single forecasting model

3.1 Establishment of principal component regression model

Principal component regression analysis selects the following eight indicators as independent variables: X_1 urbanization rate (%); X_2 total retail sales of consumer goods (10^4 yuan); X_3 per capita disposable income of urban residents (yuan); X_4 total power of farm machinery (kW); X_5 R & D investment costs (10^4 yuan); X_6 consumption levels (yuan/person); X_7 fixed assets investment in transportation, storage and postal industry (10^4 yuan); X_8 number of rural residents engaged in transportation, storage and postal services (10^4 persons). The dependent variable Y is the total amount of agricultural product logistics in Tibet (10^4 yuan). The data for the empirical analysis are the time series data during 2000 – 2013, and the original data are from *Tibet Statistical Yearbook*, as shown in Table 2.

In this paper, we use SPSS17.0 software for principal component analysis, and select the eigenvalues greater than 1 as the standard to extract the principal component. The analysis shows that the characteristic root of the first principal component is 6.685, explaining 83.568% of the total variance, and the characteristic root of the second principal component is 1.004, explaining 12.552% of the total variance. The cumulative contribution rate of the first two principal components has reached 96.12%, indicating that the first two principal components have reflected 96.12% of information of 8 indicators, so the number of principal components is 2. The indicators with high loading on the first principal component include urbanization rate, total retail sales of consumer goods, per capita disposable income of urban residents, total power of farm machinery, consumption levels, fixed assets investment in transportation, storage and postal industry, and number of rural residents engaged in transportation, storage and postal services, indicating that the first principal component reflects the basic information of these indicators, and the first principal component is named institutional factor. The indicator with high loading on the second principal component is R & D investment cost, indicating that the second principal component basically reflects the information of R & D investment costs, and the second principal component is named technical factor. The principal component analysis of agricultural product logistics demand in Tibet extracts two principal components (F1 and F2), covering the information of all original indicators, so F1 and F2 are used as new variables to replace the original eight variables. We take the proportion of eigenvalues of two principal components to total eigenvalues of the principal components extracted as the weight, to calculate comprehensive evaluation model of principal component:

Table 2 The economic indicators for the principal component analysis of agricultural product logistics demand in Tibet

Year	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	Y
2000	19.3	425209	6448	1145276	2300	1823	233455	1.89	466296.310
2001	19.6	486482	7119	1232123	2616	1939	309574	2.04	487652.450
2002	19.8	529390	7762	1458024	6704	2725	418240	2.39	518992.820
2003	19.8	578253	8058	1812121	3603	2825	457659	2.28	553228.340
2004	19.8	631799	8200	1916271	4039	2950	564249	2.52	591295.550
2005	19.8	732328	8411	2308583	6549	3019	589262	2.98	631888.640
2006	19.8	900173	8941	2308583	9071	2990	666010	3.01	651271.400
2007	21.3	1125992	11131	3294227	4174	3215	675124	3.59	742509.620
2008	22.6	1299875	12482	3496404	5743	3504	729671	3.50	826497.830
2009	23.5	1565814	13544	3516226	5552	4027	811580	3.45	867255.290
2010	23.8	1853000	14980	4119871	4654	4513	1128472	3.69	933581.320
2011	22.7	2190000	16196	4450898	4863	4730	1445290	3.89	1022866.880
2012	22.7	2546433	18028	4994835	7992	5340	1328638	4.25	1094431.627
2013	23.7	2932151	20023	5783259	13284	6275	1604389	4.57	1175009.016

Data source: *Tibet Statistical Yearbook*.

$$F = \frac{\lambda_1}{\lambda_1 + \lambda_2} F_1 + \frac{\lambda_2}{\lambda_1 + \lambda_2} F_2$$

where λ_1 is the eigenvalue of principal component i.

The comprehensive evaluation model of principal component is as follows:

$$F = 0.89554F_1 + 0.13057F_2 = 0.2921 \times ZX_1 + 0.3266 \times ZX_2 + 0.3221 \times ZX_3 + 0.3334 \times ZX_4 + 0.2382 \times ZX_5 + 0.3421 \times ZX_6 + 0.3436 \times ZX_7 + 0.3467 \times ZX_8.$$

According to the principal component expression, we calculate the scores of F_1 and F_2 as independent variables, and the total amount of agricultural product logistics in Tibet is regarded as the dependent variable for regression analysis (Table 3).

Table 3 Tibet's agricultural product logistics amount and scores of two principal components

Y	F_1	F_2
466296.310	-3.4608	-1.0385
487652.450	-2.9540	-0.9336
518992.820	-1.7136	1.0449
553228.340	-1.6646	-0.4635
591295.550	-1.1844	-0.2003
631888.640	-0.4385	1.0275
651271.400	0.0478	2.1658
742509.620	1.3288	-0.4449
826497.830	2.2677	-0.0209
867255.290	3.1457	-0.3253
933581.320	4.6258	-0.8112
1022866.880	3.2134	0.1021
1094431.627	2.8754	0.2532
1175009.016	4.3852	0.5211

The equation of principal component after regression is as follows:

$Y = 660951.818 + 61851.390F_1 - 8747.815F_2$; $R^2 = 0.992$; $F = 472.672$; Durbin - Watson $= 1.609$.

X_1, X_2, X_3, X_4, X_5, X_6, X_7 and X_8 are substituted for F_1 and F_2, respectively, to get the regression model for agricultural product logistics demand in Tibet:

$$Y = -68157.182 + 14660.40328X_1 + 0.051231206X_2 + 8.749177199X_3 + 0.023371631X_4 - 0.061428044X_5 + 28.74308286X_6 + 0.090652478X_7 + 32761.24998X_8.$$

The eight indicators during 2000-2013 are put into the above regression equation of agricultural product logistics demand to get the forecast value during 2000 - 2013. The forecasting error is controlled in less than 5%, indicating that the model fits well.

3.2 Establishment of BP neural network forecasting model

The idea of neural network forecasting model is to use the nonlinear approximation ability to build models based on the existing data, and forecast the future trends by model. BP, an abbreviation for "backward propagation of errors", is a common method of training artificial neural networks used in conjunction with an optimization method such as gradient descent. The method calculates the gradient of a loss function with respect to all the weights in the network. The gradient is fed to the optimization method which in turn uses it to update the weights, in an attempt to minimize the loss function. It uses MSE learning approach, with good nonlinear mapping ability, curve fitting ability, learning ability and capacity of resisting disturbance.

Table 4 Statistics of neural network model for agricultural products in Tibet

Year	X_1	X_2	X_3	X_4	X_5	X_6	X_7
1990	128700	608280	582	7236	39571	221.47	735
1991	138532	644186	617	8786	45911	225.03	839
1992	152265	657121	653	10163	52423	228.53	903
1993	181563	672185	706	10451	55278	232.22	931
1994	207363	664480	817	11485	75214	236.14	1110
1995	243030	719605	878	9462	108615	239.84	1202
1996	261865	777249	975	10892	111774	243.70	1312
1997	323246	791904	1085	14169	122948	247.60	1471
1998	347198	849793	1158	15715	123332	251.54	1551
1999	376258	922138	1258	14218	153485	255.51	1669
2000	425209	962234	1331	13397	166980	259.83	1823
2001	486482	982508	1404	12663	184887	262.95	1939
2002	529390	983970	1521	12536	204237	266.88	2725
2003	578253	966001	1691	40011	235559	270.17	2825
2004	631799	959950	1861	51159	300929	273.68	2950
2005	732328	933918	2078	59904	327154	277.00	3019
2006	900173	923688	2435	77578	379614	281.00	2990
2007	1125992	938634	2788	403061	425378	284.15	3215
2008	1299875	950343	3176	628701	485152	287.08	3504
2009	1565814	905330	3532	847102	560052	290.03	4027
2010	1853000	912289	4139	891065	596053	300.21	4526
2011	2190000	937290	4904	1265282	617494	303.30	4730
2012	2546433	948963	5719	1426192	668265	307.62	5340
2013	2932151	961505	6578	1487919	708638	312.04	6275

Data source: *Tibet Statistical Yearbook*.

3.2.1 Establishment of neural network model. Based on the indicator system for forecasting of agricultural product logistics demand and the relevant literature study (Geng Yong *et al.*, 2007; Hu Xiongbin and Wang Xionghui, 2010; Hou Rui and Zhang

Bixi, 2005; Jin Qiao, 2008; Wen Peina *et al.*, 2009; Wang Xinli and Zhaokun, 2010), we consider the availability and operability of statistics in Tibet and actual characteristics of agricultural product logistics development in Tibet, and select seven indicators X_1 total retail sales of consumer goods (10^4 yuan); X_2 total grain output (t); X_3 per capita net income of farmers and herdsmen (yuan); X_4 national fiscal expenditure on agriculture (10^4 yuan); X_5 output value of agricultural commodities (10^4 yuan); X_6 population (10^4); X_7 consumption levels (yuan/person) as independent variables (see Table 4), and the amount of agricultural product logistics in Tibet (Y) as the dependent variable, to establish the neural network forecasting model. 7 economic indicators in Table 4 are regarded as the input variables (input layer) for the neural network, and the amount of agricultural product logistics as an output variable (output layer). The number of neurons in the hidden layer is calculated at 15 according to Kolmogorov Theorem.

3.2.2 Neural network training phase-determining the network structure and indicator weight. We select the values of various indicators during 1990 – 2013 in Table 4 as the samples to be input. The input sample includes 7 indicators, so the number of neurons in the input layer is 7. The amount of agricultural product logistics is as the output layer, and there is an indicator, so the number of neurons in the output layer is 1. The number of neurons in the hidden layer is 15, and the other neural network model parameters are shown in Table 5. After the initialization of weights, the BP network is trained, and the simulated error curve is shown in Fig. 1. It can be found that through five training cycles, the BP network reaches the given MSE (2.06 e – 08), the network is convergent, and the training ends. LM is employed as the training algorithm; the learning rate of training objective is 0.01; the number of training times is 5; other parameters are from MATLAB toolbox.

Table 5 BP neural network parameters for agricultural product logistics demand in Tibet

Network topology	7 – 15 – 1
Network training function	Trainlm
Transfer function in the first layer	tansig
Transfer function in the second layer	Purelin
Training period	5
Stop condition	MSE < 10 – 6

3.2.3 Neural network simulation phase. Using the output result, we fix the neural network structure of different samples and indicator weight for the simulation output of logistics demand scale to be forecasted. After training, the model performance has stabilized, and the indicator values during 2000 – 2008 are used to input into the trained neural network model, to get the predicted values of output samples of neural network forecasting model (2008 – 2013). Through error comparison (see Table 6), it indicates that the simulation effect of the model is very good, with some reference value.

Table 6 Error between actual values and predicted values during 2008 – 2013

Year	2008	2009	2010	2011	2012	2013
Actual values	826497.83	867255.29	933581.31	1022866.88	1094431.627	1175009.016
Predicted values	785229.33	811195.79	941423.353	1025024.598	1048971.327	1186040
Error	–41268.5	–56059.5	7842.043	2157.7181	–45460.3	11031.03

4 Establishment of combination forecasting model

4.1 Principle For a forecasting issue, y_t is used to represent the actual observed value ($t = 1, 2 \cdots n$, where n is the sample size). There are m kinds of forecasting methods; f_{it} is the predicted value of forecasting method i ($i = 1, 2 \cdots m$); w_i is the weight of method i in the combination forecasting model. The combination forecasting model can be expressed as:

Model 1

Objective function:

$$\min z = \sum (y_t - \sum w_i f_{it})^2 \quad (1)$$

$$s.\ t.\ \sum w_i = 1 \quad (2)$$

Predicted value is the unbiased estimate of actual value, namely $E(f_{it}) = y_t$, and $\sum w_i f_{it}$ in formula (1) is also the unbiased estimate of y_i, so formula (1) is the combination forecasting model established with the minimum bias between combination forecasting and original data as goal. The difficulty of combination forecasting lies in calculating the weight. Model 1 uses the Lagrange multiplier method, and it is easy to calculate the value of w_i, but the weights calculated based on Model 1 often contains negative weight, so there is a need to improve Model 1.

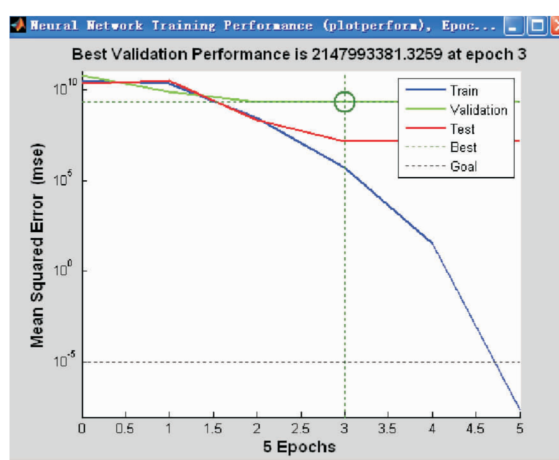

Fig. 1 Error curve

Model 2

Objective function:

$$\min z = \sum (y_t - \sum w_i f_{it})^2 \quad (3)$$

$$s.\ t.\ \sum w_i = 1 \quad (4)$$

$$w_i > 0,\ i = 1, 2 \cdots m \quad (5)$$

Through (3), we can solve the problem of negative weights in Model 1, but the weight calculation becomes more complicated in Model 2, and it is often converted to quadratic programming for solutions (Liu Xin and Xu Shiying, 2008).

4.2 Forecasting error analysis of single forecasting model for the agricultural product logistics demand in Tibet Principal component regression model:

$$Y_1 = -68157.182 + 14660.40328X_1 + 0.051231206X_2 + 8.749177199X_3 + 0.023371631X_4 - 0.061428044X_5 + 28.74308286X_6 + 0.090652478xX_7 + 32761.24998X_8;$$

Gray forecasting model: $Y_2 = [466296.31 + 5587107.748]^{e0.075259396k} - 5587107.748$;

Neural network forecasting model: see the above detailed description.

The forecasting error and results of agricultural product logistics demand scale in Tibet based on single forecasting model (principal component regression model, gray forecasting model, BP neural network model) can be shown in Table 7, 8, respectively. According to the single model forecasting results, it can be found that the variance of three single forecasting models is slightly lower than the raw data, indicating that it is stable to use these three methods for long-term forecasting. BP neural network model has the highest forecast accuracy (maximum relative error of 1.18%), followed by principal component regression model, and gray forecasting model. Fig. 2 clearly describes the single model forecasting results.

Table 7 Forecasting error of single forecasting model for the agricultural product logistics demand in Tibet

Year	Actual value	Neural network forecasting value	Error	Gray forecasting value	Error	Principal component regression forecasting value	Error
2000	466296.310	507367.440	-41071.1300	466296.31	0.000	461541.6261	4754.68
2001	487652.450	531544.340	-43891.8900	473156.99	14495.470	492779.6406	-5127.19
2002	518992.820	560644.220	-41651.4000	510140.71	8852.101	553116.5706	-34123.75
2003	553228.340	507367.440	45860.9000	553228.30	0.000	557983.0000	4754.68
2004	591295.550	531544.340	59751.2100	605791.00	14495.470	586168.4000	-5127.19
2005	631888.640	560644.220	71244.4200	640740.70	8852.101	597764.9000	-34123.75
2006	651271.400	587389.640	63881.7600	654484.50	3213.091	634683.8000	-16587.61
2007	742509.620	650743.290	91766.3300	740798.70	-1710.970	736336.0000	-6173.62
2008	826497.830	785229.330	-41268.4900	819028.30	-7469.520	825374.3000	-1123.55
2009	867255.290	811195.790	-56059.5400	829194.30	-38061.000	864797.2000	-2458.08
2010	933581.320	941423.353	7842.0429	932877.30	-704.055	917818.9000	-15762.43
2011	1022866.880	1025024.598	2157.7181	1048059.00	25191.760	1035023.0000	12156.00
2012	1094431.627	1048971.327	-45460.2900	1097748.00	3316.105	1088878.0000	-5553.73
2013	1175009.016	1186040.000	11031.0260	1177122.00	2113.367	1137948.0000	-37060.75

Table 8 Single model forecasting results

Method	Variance	Maximum relative error//%
Actual value	2.656E10	-
Neural network method	2.564E10	1.18
Gray forecasting method	2.115E10	3.05
Principal component regression method	2.549E10	1.45

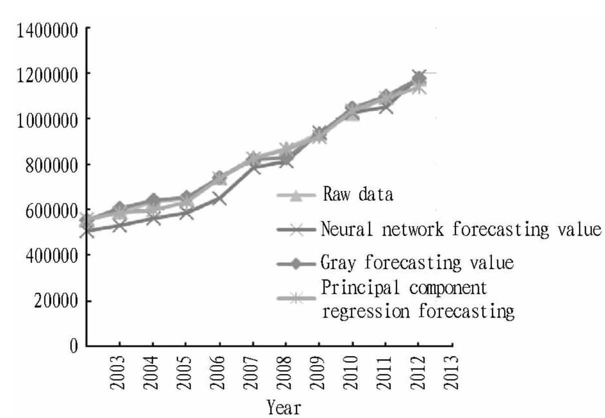

Fig. 2 The line chart of single forecasting model for Tibet's agricultural product logistics demand

4.3 Establishment of combination forecasting model According to Model 2, the combination forecasting model is transformed into quadratic linear programming model for solution and weight (see Table 9). The combination forecasting model for Tibet's agricultural product logistics demand is established as follows:

Combination forecasting model $= Y_1 \times 0.442304375 + Y_2 \times 0.584296202 - 0.026600577 \times Y_3$

where Y_1 is calculated value of principal component regression forecasting model; Y_2 is calculated value of gray forecasting model; Y_3 is calculated value of neural network forecasting model.

According to the single model forecasting values in Table 7, we use combination forecasting model to predict Tibet's agricultural product logistics demand scale during 2000 - 2013, as shown in Table 10.

Table 9 The weight of combination forecasting model

Method	Weight
Principal component regression	0.442304375
Gray forecasting	0.584296202
Neural network	-0.026600577

Table 10 Combination forecasting results of Tibet's agricultural product logistics demand scale during 2000 – 2013

Year	Actual value	Forecasting values of combination forecasting model	Relative error of forecasting results//%
2000	466296.310	463100.82	0.69
2001	487652.450	480282.98	1.51
2002	518992.820	527805.55	-1.70
2003	553228.340	557778.94	-0.80
2004	591295.550	593444.55	-0.40
2005	631888.640	635652.28	-0.60
2006	651271.840	673106.89	-3.40
2007	742509.620	750101.32	-1.00
2008	826497.830	806459.08	2.42
2009	867255.290	866564.86	0.08
2010	933581.310	949031.87	-1.70
2011	1022866.880	987072.68	3.50
2012	1094431.627	1053864.85	3.70
2013	1175009.016	1124395.92	4.30

From the forecasting results of the above single model and combination forecasting model and Fig. 3, it can be found that combination forecasting model is superior to single model in terms of the long – term forecasting stability.

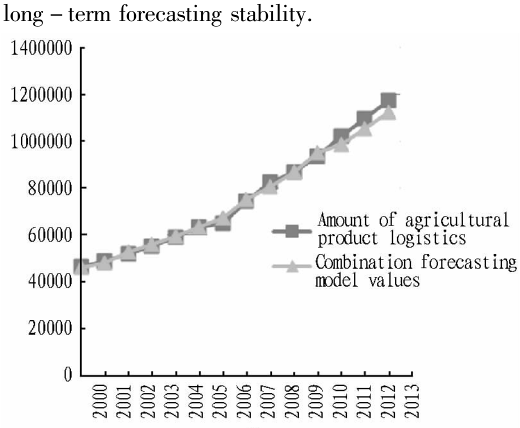

Fig. 3 Line chart of raw data of Tibet's agricultural product logistics and combination forecasting model

Based on the above forecasting results, the combination forecasting model using quadratic linear programming has high forecasting accuracy. Therefore, it is used to forecast Tibet's agricultural product logistics demand scale, as shown in Table 11.

Table 11 The combination forecasting values of Tibet's agricultural product logistics demand scale during 2014 – 2018

Year	Combination forecasting values
2014	1198840.91
2015	1277419.52
2016	1360420.64
2017	1448194.99
2018	1541137.73

5 Conclusions

The combination forecasting model results show that with the rapid development of Tibet's economy, increase of government investment, improvement of people's living standards and constant optimization of industrial structure, Tibet's agricultural product logistics demand will grow over the next five years, reaching 12.7741952 billion yuan at the end of the " Twelfth Five-Year Plan" and 15.4113773 billion yuan in 2018. The growth of agricultural product logistics demand in Tibet will certainly lead to the increase of agricultural production, promotion of agricultural product logistics services, development and application of agricultural product logistics technology. To meet the growing Tibet's agricultural product logistics demand, relevant government departments should strengthen the development strategies and development plans for Tibet's agricultural product logistics; develop modern agriculture and improve the yield and quality of agricultural products; support agricultural product logistics enterprises and improve service levels of agricultural product logistics; build agricultural product logistics park and use modern technology to enhance the level of agricultural product logistics industry and improve the supply capacity of Tibet's agricultural product logistics.

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(To page 27)

ry is a high efficient agricultural cash crop.

6.2 Blueberries are popular fruit in developed countries In the condition of increasing living demands, domestic people also have higher and higher demands for nutritional and healthy fruits. Guangdong Province is the centralized place of sales of blueberries. Every year, it needs transport from north areas. In winter, it needs import from Chile and other blueberry production countries, so the fresh blueberry demand is huge. Therefore, blueberry products have huge market potential in Guangdong Province.

6.3 Blueberry planting and production have high economic benefits in China Three years after field planting, blueberry can fruit, and in best fruiting period, the yield per 667 m^2 is about 1.0 – 1.5 tons. At the price of 60 yuan/kg, the output value per 667 m^2 is up to 30000 – 45000 yuan.

6.4 Traditional fruit structure of Guangdong Province badly needs adjustment Fruit industry of Guangdong Province has problems of few high benefit varieties, unreasonable structure, seasonal saturation and surplus, and serious plant diseases and pest insects. Developing blueberry industry in east, west and north areas of Guangdong Province is an excellent opportunity for upgrade of fruit industry for Guangdong Province. Production of blueberries can promote rapid development of fruit processing industry. However, planting area of blueberries in Guangdong Province is relatively small, fresh blueberries are in short supply and it is required to plant large amount of blueberries. Blueberry industry is a new industry and blueberry farmers lack related technologies. Therefore, it is badly necessary to establish standardized blueberry planting demonstration, popularize blueberry planting technology, set up blueberry technology training bases, and improve science and technology level of farmers' blueberry production, so as to promote rapid development of blueberry industry in Guangdong Province. At present, blueberry is already successfully cultivated in Guangdong, and about 10 varieties are suitable for planting in mountain areas of Guangdong. Compared with north blueberry planting bases, Guangdong Province has the advantage of early fruiting, so it is able to seize the market. South China is economically developed and people's living standard is high. Besides, it adjoins to Hong Kong, Macau, Taiwan and Southeast Asian countries, so it is gifted with advantages of export of fresh fruits and processed products. Blueberry as a new healthy and nutritional fruit will show its huge consumption potential.

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