Eight Sweet Cherry Cultivars Were Evaluated Based on Principal Component Analysis

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Abstract: For comprehensive evaluation of eight varieties of sweet cherry introduced by WanZhou Chongqing, this study selected the survival rate, stem diameter, roughness in new shoots, new tip length, the density of bud, flower bud rate, leaf bud rate, density and fruit-set rate and other indicators, using principal component analysis method to evaluate the adaptability of sweet cherry in high altitude mountainous area in Wanzhou Chongqing. The results showed that Brooks was the best performer, Royamin the second, and Samitol the worst. This indicates that the use of principal component analysis to evaluate sweet cherry varieties can be used to rank the advantages and disadvantages of the experimental varieties in a concise way, and the scientific research can eliminate the differences caused by different measurement indicators due to different dimensions, which can reduce the systematic errors and improve the accuracy of the test.

1 INTRODUCTION

Sweet cherry (Prunus avium L.) is a subgenus of Plum cherry in the Rosaceae family. It is very popular among consumers because of its sweet taste and crystal red appearance. At present, sweet cherry planting in Chongqing is in a blind initial stage. Due to inappropriate selection of varieties, most production parks have the problem of only growing trees without flowering, only flowering without bearing fruit, and high fruit dropping rate despite flowering and bearing fruit. (Sun, 2016) The main way to solve these problems is to introduce sweet cherry cultivars which have less demand for low temperature according to the characteristics of short accumulation time of low temperature in Chongqing, carry out systematic variety adaptability research, and screen out high-quality sweet cherry cultivars suitable for the development of cold and cool areas at this altitude in Chongqing. Therefore, eight sweet cherry varieties, such as Brooks, Luyu, Rhoa plum, Rhoa mine, Reed, Samitol, Sandra Rose and Santina, were selected as test materials to carry out the introduction experiment in Wanzhou high altitude mountain area of Chongqing. The survival rate, stem diameter, roughness in new shoots, new tip length, the density of bud, flower bud rate, leaf bud rate, density and fruit-set rate and other indicators of introduced sweet cherry were evaluated by principal component analysis. The aim of this study is to screen out the suitable varieties for the high altitude mountainous areas of Chongqing, so as to provide a basis for the cultivation of tree species in the cold and high altitude areas of Chongqing, and help the rural revitalization industry.

2 MATERIALS AND METHODS

2.1 Research Materials

This experiment was conducted in Fengxiang village, Luotian town, Wanzhou district. The test materials included Brooks, Luyu, Rhoa plums, Rhoa min, Reed, Samitol, Sandra Rose and Santina, and the rootstock was Giesela 6, which was planted in 2019 and adopted root domain restriction cultivation. The tree was super-fine spindle shaped and carefully managed according to conventional methods.

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2.2 Research Data Acquisition

In 2022, 10 plants of each variety were randomly selected as samples and fixed at its base.

The survival rate (X1), The trunk diameter (X2), shoot coarser (X3), shoot length (X4), shoot density (X5), flower bud rate (X6), leaf bud rate (X7), flower density (X8) and fruit setting rate (X9) were statistically analyzed.

2.3 Study Data Analysis

Principal component analysis (PCA) is a multivariate statistical analysis method which extracts several independent new variables from the original variables by linear combination. In the analysis process, some principal components can be discarded, and only several principal components with large variance before and after can be taken to represent the original variables, so as to reduce the workload of index selection and calculation and avoid multiple common problems among indicators (Zhu, 2006). In this study, IBM SPSS Statistics 22 was used for the relevant operations of principal component analysis, and the calculation results were obtained and analyzed.

3 RESULTS

3.1 Standardized Processing of Data

SPSS was used to standardize and non-dimensionalize the growth trait values of 8 sweet cherry varieties, and the results are shown in Table 1.

3.2 Selection of Principal Component Factors

PCA was performed to calculate principal component eigenvalues, variance contribution rate and cumulative contribution rate of growth traits of eight sweet cherry cultivars after dimensionless standardization. As can be seen from Table 2, the eigenvalue of principal component 1 is 4.54, and the variance contribution rate is 50.44%. The eigenvalue of principal component 2 was 2.46, and the variance contribution rate was 27.39%. The cumulative variance contribution rate of principal components 1-2 was 77.83%, which met the requirements of principal component analysis, that is, the two principal components represented nine traits of eight sweet cherry varieties, so the two principal components could be selected as comprehensive evaluation indexes of sweet cherry traits.

Table 1: Normalized vectors of raw data of different indicators.

varieties	Survival rate (X1)	The trunk diameter (X2)	Shoot thickness (X3)	Shoot length (X4)	Bud density (X5)	Flower bud rate (X6)	Leaf bud percentage (X7)	Flower density (X8)	Fruit setting percentage (X9)
Brooks	0.62	-0.61	1.70	0.89	2.12	0.77	-0.94	1.31	-0.06
Rhoa min	0.04	-0.55	-0.24	0.90	0.33	1.61	-1.53	0.43	-0.67
Rhoa plums	-2.38	-0.68	-0.70	-0.37	0.29	0.68	-0.57	0.49	-0.71
Santina	0.31	0.32	0.84	0.35	0.12	-0.29	0.32	1.11	-1.16
Reed	0.62	0.01	-0.57	0.57	-0.62	-0.65	0.72	-0.19	1.09
Samitol	-0.06	-0.83	-1.54	-1.94	-1.10	-0.37	0.37	-0.67	0.64
Luyu	0.62	2.25	0.19	0.50	-.72	-1.64	1.64	-1.41	1.60
Sandra Rose	0.23	0.09	0.33	-0.89	-0.42	-0.11	-0.02	-1.07	-0.73

Table 2: Variance contribution rate of growth traits of sweet cherry by principal component analysis.

composition	The initial eigenvalue			Extract the sum of squares and loads		
	combined	Percentage of variance	The cumulative percentage	combined	Percentage of variance	The cumulative percentage
1	4.54	50.44	50.44	4.54	50.44	50.44
2	2.46	27.39	77.83	2.46	27.39	77.83
3	0.66	7.32	85.15			
4	0.60	6.61	91.76			
5	0.41	4.54	96.30			
6	0.30	3.35	99.65			
7	0.03	0.35	100.00			
8	-3.30E-16	-3.66E-15	100.00			
9	-6.98E-16	-7.75E-15	100.00			

FIG. 1 is the crushed stone diagram of the eigenvalues of different components. It can be seen that the first factor has a high eigenvalue and makes the largest contribution to the explanation of different sweet cherry characters, while the third factor has a small eigenvalue and makes negligible contribution to the explanation of different sweet cherry characters. Therefore, it is more appropriate to extract two factors.

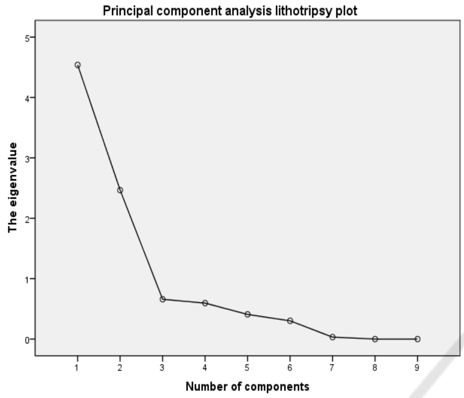

Figure 1: Lithotripsy diagram of eigenvalues of different principal components.

The principal component loading matrix reflects the relative magnitude and direction of action of each trait on the principal component load, that is, the degree of influence of the trait on the principal component (Zhang, 2018). As shown in Table 3, the first principal component mainly reflected the characteristics of flower bud percentage, leaf bud percentage, bud density, flower density, fruit setting percentage and dry diameter. The second principal component mainly reflected the survival rate, shoot thickness and shoot length.

The coefficient of each factor in the principal component expression can reflect the contribution of the factor to the principal component. In PCA, it is generally considered that the load greater than 0.3 is significant. According to the eigenvectors of the correlation matrix of sweet cherry traits in Table 3, two principal component expressions can be written:

F1=-0.07X1-0.15X2+0.09X3+0.08X4+0.18X5+0.20X6-0.21X7+0.19X8-0.17X9

F2=0.27X1+0.23X2+0.34X3+0.32X4+0.19X5-0.09X6+0.08X7+0.09X8+0.08X9

3.3 Comprehensive Evaluation of Sweet Cherry Characters

The feature vectors in Table 3 were selected, and the standardized data of traits of each variety were brought into the expression to calculate the scores in different components, and the model was established: $Z_{\text{comprehensive score}} = 50.44Z_1 + 27.39Z_2$, and the comprehensive scores of different varieties were obtained and sorted. The results are shown in Table 4.

It can be seen from Table 4 that in the first principal component (mainly reflecting flower bud rate, leaf bud rate, bud density, flower density, fruit setting rate and dry diameter characters), the order of each variety was: Brooks > Royamin > Roari > Santis > Sandera rose > Red > Samitol > Luyu; In the second principal component (survival rate of main reaction, shoot thickness and shoot length), the cultivars were ranked as: Brooks > Ruyu > Santis > Reed > Roamin > Sandra rose > Roalee > Samitol. The comprehensive scores of all traits were: Brooks > Royamin > Santis > RoyALI > Sandra ROSE > RED > LuYU > Samitol.

Table 3: Main component loading matrix and eigenvector of sweet cherry traits.

indicators	Load matrix		The feature vectors	
	Principal component 1	Principal component 2	Principal component 1	Principal component 2
Survival rate(X1)	-0.32	0.67	-0.07	0.27
The trunk diameter (X2)	-0.70	0.57	-0.15	0.23
Shoot thickness (X3)	0.39	0.83	0.09	0.34
Shoot length (X4)	0.33	0.79	0.08	0.32
Bud density (X5)	0.82	0.46	0.18	0.19
Flower bud rate (X6)	0.92	-0.23	0.20	-0.09
Leaf bud percentage (X7)	-0.93	0.18	-0.21	0.08
Flower density (X8)	0.86	0.21	0.19	0.09
Fruit setting percentage (X9)	-0.76	0.20	-0.17	0.08

Table 4: Normalizes the eigenvectors.

varieties	Principal component 1	The sorting	Principal component 2	The sorting	Principal component 3	The sorting
Brooks	1.26	1	1.24	1	97.74	1
Rhoa min	1.03	2	-0.13	5	48.25	2
Rhoa plums	0.70	3	-1.22	7	1.70	4
Santina	0.34	4	0.64	3	34.47	3
Reed	-0.66	6	0.23	4	-27.15	6
Samitol	-0.75	7	-1.50	8	-78.84	8
Luyu	-1.67	8	1.06	2	-54.99	7
Sandra Rose	-0.24	5	-0.31	6	-20.83	5

4 DISCUSSION

As a comprehensive analysis method, multivariate statistical analysis method is often used to analyze the statistical rules among the indicators when multiple objects and multiple indicators are interrelated. It is often used in crop variety resource evaluation and genetic breeding. Song X. et al (Song, 2020) used principal component analysis to screen out nitrogen efficient wheat varieties. Fu Y. et al (Fu, 2022) used principal component analysis to comprehensively evaluate excellent varieties of blueberry. He W. et al (He, 2021) used principal component analysis to comprehensively evaluate 22 potato germplasm and screened excellent germplasm resources.

In this study, the comprehensive scores of 8 sweet cherry cultivars introduced to Chongqing were obtained by principal component analysis, and the suitable sweet cherry cultivars were screened out. Principal component analysis: the first two characteristics of the principal component values greater than 1, and the cumulative contribution rate was 77.83%, the most comprehensive sweet cherry can indicators, comprehensive evaluation of 8 varieties of sweet cherry, comprehensive score results for Brooks > Royamin > Santis > RoyALI > Sandra ROSE > RED > LuYU > Samitol.

5 CONCLUSION

In this study, SPSS Statistics 22 software was used to perform standardized value and PCA on the trait data of eight sweet cherry varieties, and the principal component assignment was sorted. Brooks had the best performance, followed by Royamin and Samitol. The PCA method was used to evaluate sweet cherry varieties, and the data of different economic traits were processed dimensionless and then calculated with standardized values. The differences caused by the different dimensions of different economic traits were discarded, which could effectively reduce the systematic errors and improve the accuracy of the test.

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