International Journal of Innovation in Science and Mathematics
Volume 2, Issue 1, ISSN (Online): 2347–9051

Research Jujube Pest Stress Index Leaf Pigment Hyperspectral Model Based on Wireless Sensor Networks in the Southern Region of Xinjiang

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***Abstract* – Measured southern jujube pest stress index leaf pigment, create jujube jujube leaf rust sensitive bands characteristic parameter table, analyze the spectral characteristics of the relevant characteristics and vegetation index jujube high correlation parameters. Determination of diseased leaves and growing spectrum of different pigment content. Analysis jujube leaf rust pigment content and spectral reflectance correlation study comparing jujube leaf rust pigment content and differential spectral correlation. Hyperspectral characteristic parameters to achieve the southern jujube jujube leaf rust pigments PC1/PC2 and PC1+PC2 content estimation. Using a combination of linear and polynomial fitting method to construct the canopy hyperspectral disease dates Brix content estimation model and test. The probabilistic neural network PNN and SVM classifier SVC applied to hyperspectral estimation model, comparative analysis of model accuracy. The results of the quantitative estimation of disease hyperspectral information dates pigment content in leaves of jujube growing use of high spectral monitoring and impact assessment of disease have high practical value. Classification accuracy of 98%, obtained very satisfactory recognition results.**

***Keywords* – Jujube Pests, Stress Index, Pigment Content, Estimation Model, Sensor Networks.**

I. Introduction

Located in the hinterland of southern Eurasia, rainfall, evaporation, air drying, rich in light and heat resources, based on the biological characteristics of dates, very suitable for the development of jujube industry. In recent years, with the increasing acreage in southern Xinjiang jujube, pest followed. In addition to the southern jujube pests cause yield losses, but also an important reason for the decline inherent quality of dates, there will rot, mildew and other phenomena, not only nutritious, taste mutate and produce toxic to humans, harmful substances, dates pests occur increasingly become a major factor restricting the southern jujube industry. Since the dates of leaf spectral reflectance in the visible range is mainly affected by vegetation chlorophyll in the high spectral region is mainly affected by the internal structure of the leaves, biomass, sugar, cellulose and other effects, so you can use dates canopy leaves and reflection spectra to estimate biochemical parameters, especially pigment content, analysis dates pest stress index leaf pigment content and health[1,5,8]. In this study, first create jujube jujube leaf rust sensitive bands characteristic parameter table, analyze the spectral characteristics of the relevant characteristics and vegetation index jujube high correlation parameters influencing factors for the high level of recognition than the spectral characteristic parameters for dates hazards. Second, analysis of jujube rust leaf pigment content and spectral reflectance correlation study comparing jujube leaf rust pigment content and differential correlation spectroscopy, hyperspectral characteristic parameters to achieve the southern jujube jujube leaf rust pigment content PC1/PC2 and PC1 + PC2 estimates measurements. Then uses a combination of linear and polynomial fitting method to construct the disease dates Canopy Hyperspectral Brix content model. Finally, probabilistic neural networks and support vector machine PNN SVC applied to hyperspectral estimation model, comparative analysis of model accuracy, aimed at improving the retrieval accuracy hyperspectral vegetation physiological parameters of the model[2,9].

II. Data Extraction and Create The Characteristic Parameters

View spec Program ASD companies use software and MATLAB 7.01 and statistical analysis SPSS 12.0 software processing to obtain reflectance spectra, combined with southern jujube jujube leaf rust sensitive parameters of the band created (Table I) for data analysis and the establishment of a sample library, where * denotes new create a spectral characteristic parameters[3,10].

Table I: Jujube leaf rust sensitive bands create a feature parameter

Spectral parameters	Definitions
R480	480nmreflectancevalueat a corresponding
R560	560nmreflectancevalueat a corresponding
R760*	760nmreflectancevalueat a corresponding
R850*	850nmreflectancevalueat a corresponding

FD890*	Reflectanceat890nmcorresponding toafirst order differential value
FD1860*	1860nmcorrespondingreflectanceata first-orderdifferential value
NDVI[670, 890]	（R890-R670）/（R890+R670）
NDVI[760, 789]*	（R789-R760）/（R789+R760）
NDVI[1450, 1860]*	（R1860-R1450）/（R1860+R1450）
NDVI[1870, 2170]*	（R2170-R1870）/（R2170+R1870）
DVI[480， 560]	（R560-R480）
DVI[880, 950]*	（R950-R880）
DVI[FD488, FD890]*	（FD890- FD488）
DVI[FD855, FD1860]*	（FD1860- FD855）
RVI[760, 789]*	(R789/R760)
RVI[1450, 1860]*	(R1860/R1450)
RDVI[760, 789]*	$[(R789-R760)/ (R789+R760) *(R789-R760)]^{1/2}$
RDVI[FD488, FD890]*	$[(FD890-FD488)/ (FD890+FD488) *(FD890-FD488)]^{1/2}$
RDVI[FD855, FD1860]*	$[(FD1860-FD855)/ (FD1860+FD855) *(FD1860-FD855)]^{1/2}$
SIPI	(R800-R445)/ (R800-R760)
SAVI	(R890-R670)(1+L)/ (R890+R670+L)
PRI[580,540]	(R580-R540)/ (R580+R540)
PRI[550,440]	(R550-R440)/ (R550+R440)
PRI[1450,1250]	(R1450-R1250)/ (R1450+R1250)
Lwidth	Depth675absorbhalf thewidth of thevalley depth
Dr	560 ~ 789nmbiggestfirst-orderdifferential value
Area677	480 ~ 760nmwavelengthreflectancevaluesum
REP	680 ~ 850nmmaximumwavelength corresponding toa first orderdifferential value

III. Jujube Leaf Rust Pigment and Spectral Characteristics Of Relevance

A. Jujube leaf rust pigments and spectral reflectance correlation

Jujube leaf rust pigment content associated with spectral reflectance analysis showed (Fig.1), wavelength less than 745 nm, pest jujube leaves PC1, PC2 and PC1 + PC2 content was negatively correlated with the reflectivity, especially in the 428 ~ 739nm wavelength reflectance was significantly correlated maximum point at 712 nm position; 755 ~ 865 nm, PC1, PC2 and PC1 + PC2 content and spectral reflectance was positively correlated significantly related point PC1 pigment content, the correlation coefficient maximum point at 763 nm position; wavelengths greater than 886 nm, PC1, PC2 and PC1 + PC2 content negatively correlated with reflectivity; 960 ~ 2380 nm, PC1, PC2 and PC1 + PC2 content and reflectance was significantly negatively correlated, PC1, PC2 and PC1 + PC2 content of 2252 nm, PC2 content at 1587 nm maximum correlation coefficient. Therefore, the use of reflectance southern jujube jujube leaf rust coloring pigment estimates can be found PC1, PC2 and PC1 + PC2 sensitive areas.

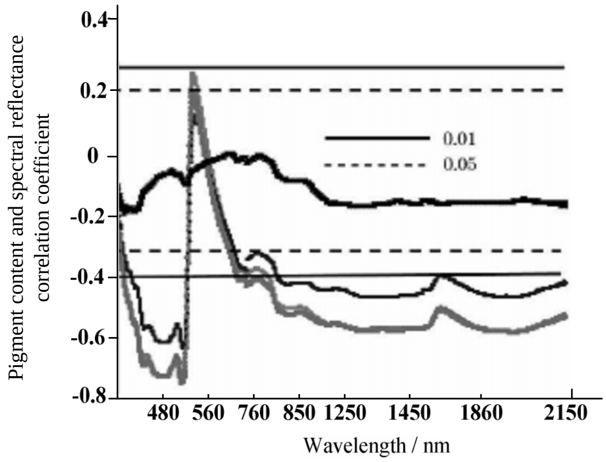

Fig.1. Jujube rust leaf pigment content and spectral reflectance correlation

B. Bay leaf rust pigment content and differential correlation spectroscopy

Correlation analysis showed (Fig. 2), pest jujube leaves PC1, PC2 and PC1 + PC2 content of their spectral reflectance first derivative in 464 ~ 486 nm, 493 ~ 629 nm, 647 ~ 688 nm, 695 ~ 706 nm, 711 ~ 762 nm, 772 ~ 983 nm, showed a significant correlation at 1103 ~ 1213 nm. At 647 ~ 681 nm and 711 ~ 762 nm two bands was a significant positive correlation, the correlation coefficients among the largest point 711 ~ 762 nm band and single band at 740 nm; rest of the band showed a significant negative correlation, the absolute value of the maximum correlation coefficient point at 489 ~ 619 nm and 563 nm single band at the absolute maximum correlation coefficient. Therefore, the use of derivative spectra for southern jujube jujube leaf rust coloring pigment estimates can be found PC1, PC2 and PC1 + PC2 sensitive areas.

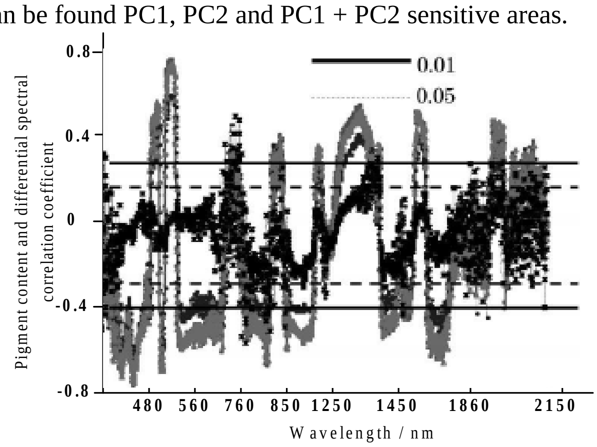

Fig.2. Bay leaf rust pigment content and differential correlation spectroscopy

C. Jujube leaf rust pigment content and spectral parameters of relevance

Table II Jujube leaf rust pigment content and spectral parameters of relevance

Parameters	Chl a	Chl b	Chl a+b	Cars
R480	-0.655	-0.557	-0.672	-0.063
R560	-0.666	-0.547	-0.648	-0.028
R760*	-0.751	-0.621	-0.741	-0.041
R850*	-0.749	-0.620	-0.739	-0.040
FD890*	-0.841	-0.658	0.821	0.061
FD1860*	-0.839	-0.657	0.822	0.060
NDVI[670, 890]	0.705	0.565	0.687	0.023
NDVI[760, 789]*	-0.797	-0.634	-0.777	-0.032
NDVI[1450, 1860]*	-0.796	-0.635	-0.777	-0.033
NDVI[1870, 2170]*	0.705	0.566	0.689	0.021
DVI[480， 560]	-0.658	-0.561	-0.668	-0.032
DVI[880, 950]*	-0.808	-0.645	-0.787	-0.036
DVI[FD488, FD890]*	-0.804	0.666	0.781	0.031
RVI[760， 789]*	-0.788	-0.643	-0.768	-0.027
RVI[1450, 1860]*	-0.786	-0.642	-0.767	-0.025
RDVI[760, 789]*	0.806	0.642	0.783	0.033
RDVI[FD488, FD890]*	0.812	0.671	0.792	0.049
RDVI[FD855, FD1860]*	0.811	0.672	0.792	0.051
SIPI	-0.597	-0.501	-0.586	
SAVI	0.711	0.563	0.689	0.034
PRI[580,540]	0.798	0.633	0.777	0.033
PRI[550,440]	0.799	0.633	0.778	0.034
PRI[1450,1250]	0.798	0.634	0.778	0.032
Lwidth	-0.707	-0.597	-0.701	0.011
Dr	0.182	0.111	0.111	-0.048
Area677	0.751	0.604	0.733	0.011

Correlation analysis showed (Table II), pest jujube leaves PC1, PC2 and PC1 + PC2 content outside except Dr other spectral characteristic parameters were significantly correlated level, NDVI [670,890], NDVI [1870,2170] *, RDVI [760,789] *, RDVI [FD488, FD890] *, RDVI [FD855, FD1860] *, SAVI, PRI [580,540], PRI [550,440], PRI [1450,1250], Dr and Area677 with PC1, PC2 and PC1 + PC2's content showed a significant positive correlation, where the correlation coefficient Area677 minimum, and RDVI [FD855, FD1860] * maximum correlation coefficient. R480, R560, R760 *, R850 *, FD890 *, FD1860 *, NDVI [760,789] *, NDVI [1450,1860] *, DVI [480,560], DVI [880,950] *, DVI [FD488 , FD890] *, RVI [760,789] *, RVI [1450,1860] *, SIPI and Lwidth with PC1, PC2 and PC1 + PC2 content showed a significant negative correlation with the absolute minimum which Lwidth correlation coefficient, and the maximum absolute value of the correlation coefficient R480. In addition, all characteristic parameters, the band combination is superior to the correlation parameters and pigment overall single band, red edge and absorption parameters; between similar spectral characteristic parameters, the new pigment spectral parameters and correlations are superior to conventional parameters. Therefore, the use of characteristic parameters to achieve high spectral southern jujube jujube leaf rust pigment PC1, PC2 and PC1 + PC2 content content estimation.

IV. Hyperspectral Estimation Models

A. Model building process

Using a combination of linear and polynomial fitting method to construct the disease dates Brixcontent Canopy Hyperspectral estimation models, mainly the following five models: a simple linear model Y=a+bx, number of model Y = a+b*ln(x),the exponential model Y = a*exp(bx),parabolic model Y=a+bx+cx^2, Cubic function Y=a+bx+cx^2+dx^3,fitting Brix value for the content of Y, x spectral variables, a, b, c, d fitting coefficients.

Supposed the dynamic and time-varying system model as follows [4,11]:

$$x_k = f_k(x_{k-1}, v_k),\ z_k = h_k(x_k, n_k) \qquad (1)$$

In (1), the subscript k denotes the time index where $K \in Z+$, x_k is a state vector at the time of k, v_k is process noise vector with independent and identical distribution, z_k is an observation vector at the time of k, and n_k is Gaussian white noises with independent and identical distribution. If the initial probability is known as:

$$p(x_0 \mid z_0) = p(x_0) \quad (2)$$

Then, the prediction state equation can be written as:

$$p(x|z_{1:k-1}) = \int p(x_k|x_{k-1})\, p(x_{k-1}|z_{1:k-1})\, dx_{k-1} \qquad (3)$$

And the updating state equation can be written as[6,12]:

$$p(x_k|z_{1:k}) = \frac{p(z_k|x_k)\, p(x_k|z_{1:k-1})}{p(z_k|z_{1:k-1})} \qquad (4)$$

Where

$$p(z_k|z_{1:k-1}) = \int p(z_k|x_k)\, p(x_k|z_{1:k-1})\, dx_k \qquad (5)$$

The above presented contents are based on the thought of Bayesian analysis.

B. Particle filter algorithm

Since the Monte Carlo method based on random sampling operation is able to turn the integral operation into summing up finite sampling points, we can turn the integral in Eq. (3) into summing up the transition probability of finite sampling points. When applying the algorithm to practice and to avoid the lack of particles, it is necessary to select the importance function and adopt a re-sampling method.

Since the probability distribution of importance function is same with $p\ (x_k|z_{1:k})$ and the probability distribution $q(x_{0:k}|z_{1:k})$ is known, it is easy to sample from the importance function. To implement the particle filter algorithm based on recursive estimation, re-sampling need the observation data before the time of k. The importance function $q(x_{0:k}|z_{1:k})$ can be represented with continued product as[7,13]:

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International Journal of Innovation in Science and Mathematics
Volume 2, Issue 1, ISSN (Online): 2347–9051

$$q(x_{0:k}|z_{1:k}) = q(x_0)\prod_{j=1}^{k} q(x_j|z_{0:j-1}, z_{1:j}) \quad (6)$$

If we assume the state conform to Markov chains and the conditions of observation variables are independent and with given state, the Recursive formula about weight value can be obtained as follows:

$$w_k = \frac{p(z_{1:k}|x_{0:k})\,p(x_{0:k})}{q(x_k|x_{0:k-1}, z_{1:k})\,q(x_{0:k-1}|z_{1:k})}$$

$$= w_{k-1}\frac{p(z_k|x_k)\,p(x_k|x_{k-1})}{q(x_k|x_{0:k-1}, z_{1:k})} \quad (7)$$

According to $p(x_{k-1}|z_{1:k})$, we can use the method of re-sampling to obtain N random sample points $\{x_{k-1}^i\}_{i=1}^N$, so that the probability can be represented as:

$$p(x_{k-1}|z_{1:k-1}) = \sum_{i=1}^{n} w_{k-1}^i \delta(x_{k-1} - x_{k-1}^i) \quad (8)$$

The updating probability can be written as:

$$p(x_k|z_{1:k}) \approx \sum_{i=1}^{N} w_k^i \delta(x_k - x_k^i) \quad (9)$$

Where

$$w_k^i = w_{k-1}^i \frac{p(z_k x_k^i)\,p(x_k^i|x_{k-1}^i)}{q(x_k^i|x_{k-1}^i, z_k)} \quad (10)$$

Sample points $\{x_k^i\}_{i=1}^N$ can be obtained through formula (1), where $\{x_{k-1}^i\}_{i=1}^N$ is a sample series at the time of $k-1$.

C. *Algorithm summary*

The main steps of particle filter algorithm can be summarized as follows:

Step1 Take n samples from $q(x_k|x_{k-1}, z_k)$ stochastically;

Step2 Calculate $p(x_k|x_{k-1})$ and $p(z_k|x_k)$ point by point;

Step3 Calculate the importance weighting coefficients of samples according to formula (8);

Step4 Normalize weighting coefficients; namely, let

$$w_k^i = \frac{w_k^i}{\sum_{i=1}^{n} w_k^i} \quad (11)$$

Step5 Estimate $p(x_k|z_{1:k})$ according to formula (9).

V. Conclusions

As shown in Table II and Table III, the coefficient of determination by the selected model are highly significant statistical tests. Criteria to determine the best model is necessary to determine the coefficients by significant statistical tests, but also the largest of its F value. Thus concluded that the best model is the content of PC1 and PC2 linear model, PC1 + PC2 content exponential model is the best model, and the best model variables R760 SAVI is logarithmic model, other variables NDVI [760,789] * , DVI [FD488, FD890] *, Dr Area677 and the best model is a linear model. Seen from Figure 3, jujube dates rust canopy spectral reflectance increases with increasing disease index in the visible range, this is because the size of the canopy spectral reflectance is determined by the concentration of chlorophyll in the visible range. Reflectance in the visible range of the absorption rate is increased to reduce the pigments, the pigment concentration. In the high spectral region is mainly affected by the internal structure of the leaves, biomass, sugar, cellulose and other factors, the incidence of dates in the high reflectance spectral region decreased, indicating that the internal structure of the vegetation has been destroyed. Therefore, you can use dates and leaf canopy reflectance spectra to estimate biochemical parameters, especially pigment content, analysis dates pest stress index leaf pigment content and health. With sicker, dates Brix content decreased. Rust date indicate not only undermine the internal organizational structure of the pigment content and dates of the blade, but also affect the quality and yield of dates.

Table III: Jujube sugar high spectral features variable linear and nonlinear regression analysis

Variable	Model	a	b	c	d	R^2	F
Rg	Linear	4.7141	-38.158			0.524	25.26
	Logarithmic	-4.4472	-2.3909			0.611	35.92
	Parabola	8.4881	-171.48	1065.62		0.682	23.63
	Cubic	9.9383	-248.32	2327.77	-6556.6	0.686	15.22
	Index	5.8368	-15.946			0.484	21.56
Rr	Linear	4.3648	-88.131			0.698	53.32
	Logarithmic	-5.1508	-1.9326			0.783	82.36
	Parabola	5.7688	-229.69	2931.36		0.776	37.61
	Cubic	8.2396	-610.13	20156.5	-231472	0.811	30.26
	Index	5.2838	-39.349			0.736	63.62
(Rg-Rr)/ (Rg+Rr)	Linear	-2.6158	10.8916			0.638	40.31
	Logarithmic	6.3336	4.9919			0.646	41.73
	Parabola	-6.7186	29.0378	-19.578		0.646	20.03
	Cubic	-6.7186	29.0378	-19.578		0.646	20.03
	Index	0.2177	5.0135			0.712	56.66
SDr/SDb	Linear	0.1392	0.2749			0.815	100.3
	Logarithmic	-2.2996	2.3003			0.775	78.72

	Parabola	0.2806	0.2416	0.0018		0.815	48.18
	Cubic	1.9716	-0.3732	0.0696	-0.0022	0.822	32.02
	Index	0.8876	0.1116			0.709	55.82

Table IV: Jujube sugar high spectral estimation model fitting and forecasting analysis

Simulation model to estimate	Fitting R^2	Forecast R^2	RMSE	Relative error
Y=2.768-1.284Ln(D480)	0.836**	0.746**	0.4382	10.23%
Y=2.768-1.284Ln(SDb)	0.782**	0.654**	0.3808	9.12%
Y=4.954*exp[-3.573*(SDnir/SDr)	0.798**	0.718**	0.3806	8.88%
Y=4.148-0.783[(SDnir-SDy)/ (SDnir+SDy)]	0.662**	0.651**	0.4122	9.64%
Y=0.323*exp[-2.798*((SDnir-SDr)/ (SDnir+SDr))]	0.811**	0.726**	0.4998	11.68%

As can be seen from Table IV and Figure 4, with a highly significant negative correlation between disease index and Brix content, fitting R^2 .R^2 high sugar content and predictive models to estimate the full spectrum of content through a very significant test 0.01 level, goodness of fit The maximum value of 0.836, the maximum relative error is 11.68%. Test results show that the use of probabilistic neural networks and support vector machine PNN SVC applied to hyperspectral estimation model, comparative analysis of model accuracy, conducted dates Brix content hyperspectral characteristic variables of linear and nonlinear regression analysis to distinguish between good and pest normal dates, classification accuracy of 98%, obtained very satisfactory recognition results.

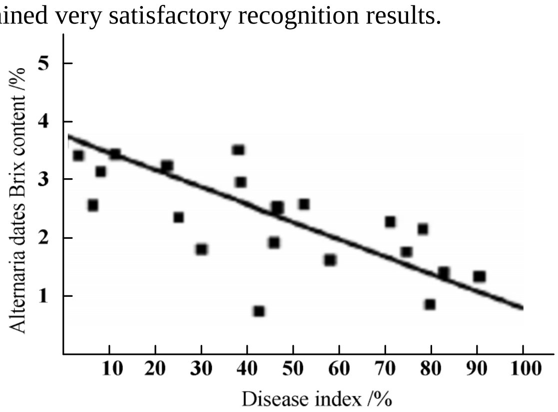

Fig.3. Relationship index and Brix levels of disease

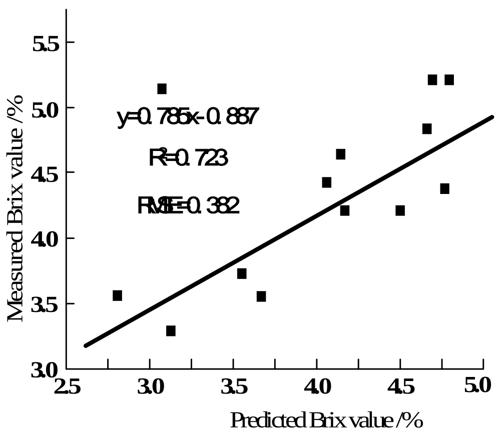

Fig.4. Comparison of measured and predicted dates of model

ACKNOWLEDGMENT

The authors wish to thank Projects supported by National Natural Science Foundation of China (No. 61162018) and the Special Fund of Henan Province basic and cutting-edge technology (No.132300410422).

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International Journal of Innovation in Science and Mathematics
Volume 2, Issue 1, ISSN (Online): 2347–9051

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