

DYNAMIC MONITORING AND RAPID DIAGNOSIS OF RICE WATER STATUS BASED ON UAV REMOTE SENSING AND MACHINE LEARNING ALGORITHMS

SUIVI DYNAMIQUE ET DIAGNOSTIC RAPIDE DE L'ÉTAT HYDRIQUE DU RIZ FONDÉS SUR LA TÉLÉDÉTECTION PAR DRONE ET DES ALGORITHMES D' APPRENTISSAGE AUTOMATIQUE

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ABSTRACT

To accurately achieve dynamic monitoring and rapid diagnosis of rice water status throughout the entire growth period, this study screened the vegetation indices with the optimal correlations with soil moisture content (SMC), rice canopy leaf transpiration rate (Tr), net photosynthetic rate (Pn), and stomatal conductance (Gs) based on field-measured data, and established a qualitative index system for rice water diagnosis. Subsequently, machine learning algorithms were employed to construct and screen the optimal models for rice water monitoring and diagnosis, ultimately proposing a dynamic monitoring and rapid diagnosis method for rice water information based on unmanned aerial vehicle (UAV) remote sensing. The results indicated that all selected vegetation indices exhibited significant correlations with rice water parameters. Using vegetation indices as input variables and water parameters as dependent variables, the dynamic rice water monitoring models constructed by four machine learning algorithms—Logistic Regression (LR), Support Vector Regression (SVR), Back propagation Neural Network (BPNN), and Random Forest Regression (RFR)—all effectively realized the monitoring of rice water status. The Water Balance Index (WBI) could accurately characterize the degree of rice water deficit; when the Normalized Difference Red Edge Index (NDRE), Green Normalized Difference Vegetation Index (GNDVI), and Ratio Vegetation Index (RVI) were jointly used as input variables for the RFR model, the constructed qualitative diagnosis model for rice water deficit exhibited the optimal performance. In conclusion, the dynamic monitoring and rapid diagnosis model for rice water status established by integrating UAV remote sensing and machine learning algorithms provides important theoretical support for the efficient irrigation and drainage management of paddy fields.

Keywords: UAV Remote Sensing ; Machine Learning ; Rice Water Status ; Water Balance Index ; Efficient Irrigation and Drainage.

RÉSUMÉ

Afin d'assurer avec précision le suivi dynamique et le diagnostic rapide de l'état hydrique du riz pendant toute la période de croissance, cette étude a sélectionné, à partir de données mesurées sur le terrain, les indices de végétation présentant les corrélations optimales avec la teneur en eau du sol (SMC), le taux de transpiration foliaire du couvert de riz (Tr), le taux net de photosynthèse (Pn) et la conductance stomatique (Gs), puis a établi un système d'indices qualitatifs pour le diagnostic hydrique du riz. Des algorithmes d'apprentissage automatique ont ensuite été employés pour construire et sélectionner les modèles optimaux de suivi et de diagnostic hydriques du riz, ce qui a finalement

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conduit à proposer une méthode de suivi dynamique et de diagnostic rapide des informations hydriques du riz fondée sur la télédétection par véhicule aérien sans pilote (UAV). Les résultats ont indiqué que tous les indices de végétation sélectionnés présentaient des corrélations significatives avec les paramètres hydriques du riz. En utilisant les indices de végétation comme variables d'entrée et les paramètres hydriques comme variables dépendantes, les modèles de suivi dynamique de l'état hydrique du riz construits au moyen de quatre algorithmes d'apprentissage automatique — régression logistique (LR), régression à vecteurs de support (SVR), réseau neuronal à rétropropagation (BPNN) et régression par forêt aléatoire (RFR) — ont tous permis de suivre efficacement l'état hydrique du riz. L'indice de bilan hydrique (WBI) permettait de caractériser avec précision le degré de déficit hydrique du riz ; lorsque l'indice de différence normalisée du bord rouge (NDRE), l'indice de végétation par différence normalisée dans le vert (GNDVI) et l'indice de végétation par rapport (RVI) étaient utilisés conjointement comme variables d'entrée du modèle RFR, le modèle qualitatif de diagnostic du déficit hydrique obtenu présentait les meilleures performances. En conclusion, le modèle de suivi dynamique et de diagnostic rapide de l'état hydrique du riz établi en intégrant la télédétection par UAV et les algorithmes d'apprentissage automatique apporte un soutien théorique important à la gestion efficiente de l'irrigation et du drainage des rizières.

Mots clés : Télédétection par véhicule aérien sans pilote (UAV); Apprentissage automatique; Etat hydrique du riz; Indice de bilan hydrique; Efficacité d'irrigation et de drainage.

1. Introduction

As one of the three principal staple food crops globally, rice serves as a crucial pillar for ensuring global food security and constitutes a material foundation for achieving the Sustainable Development Goals (SDGs)(Zhao et al., 2022). It not only provides a staple food for nearly half of the world's population, but also plays an important role in ecosystems, significantly influencing water resource security and social stability(Van Nguyen and Ferrero, 2006). Rice is semi-aquatic and requires flooded cultivation, with irrigation water demand much higher than that of other crops(Fu et al., 2023; Cai et al., 2024). Under traditional paddy field management practices, irrigation methods are extensive and consume large amounts of water, resulting in low water use efficiency for rice and high pollutant output. This not only increases agricultural production costs but also exacerbates water resource waste and agricultural non-point source pollution (Yang et al., 2016; Zhu and Duan, 2004). Therefore, changing the traditional rice irrigation mode, improving water monitoring and regulation capacity during rice production, and achieving rapid and scientific diagnosis of rice water stress are inevitable choices for conserving freshwater resources and reducing agricultural non-point source pollution.

The water status of rice is mostly monitored indirectly by measuring the soil moisture in paddy fields or the depth of the water layer in the field. These monitoring methods have drawbacks such as high equipment deployment costs and difficulties in management and maintenance. In recent years, unmanned aerial vehicles (UAVs) have been increasingly applied in agricultural remote sensing as a new type of remote sensing platform. UAVs, as platforms carrying effective payloads, can rapidly and in real time acquire remote sensing data, fundamentally addressing the technical issues caused by the low temporal, spatial, and resolution aspects of satellite remote sensing technology. Some researchers have conducted preliminary explorations into monitoring rice water stress using UAV remote sensing (Lwandile et al., 2023; Bahuguna et al., 2021; Jeong et al., 2016); however, there has been relatively little research on selecting rice canopy-sensitive spectra, constructing vegetation indices sensitive to rice water status, and diagnosing the water status of rice. The quantitative relationship between UAV remote sensing information and rice water stress remains unclear, and there is a lack of reliable models for diagnosing rice water status.

This study takes rice as the research subject, obtains low-altitude remote sensing images of rice using drones equipped with multispectral sensors, and combines these with in-field observation data. Machine learning algorithms are employed to build a vegetation index-based dynamic monitoring model for rice moisture, and a qualitative diagnostic method for rice moisture based on UAV remote sensing is proposed. The research results can provide important theoretical support for efficient irrigation and drainage management in rice fields.

2. Materials and Methods

2.1 Experimental design

The experiment was conducted at the Chuzhou Comprehensive Hydrological Experimental Base of the State Key Laboratory of Hydrology, Water Resources and Hydraulic Engineering, Nanjing Hydraulic Research Institute (32°17'N, 118°12'E). The tested rice variety was Nanjing 46. The experimental period covered the rice-growing seasons from July to September in 2021 and 2022, with three fertilization gradients: N0 (no fertilizer), N1 (local farmers' customary fertilization rate), and N2 (1.5 times the local farmers' customary fertilization rate). The irrigation mode adopted was controlled irrigation (CI). During the regreening stage, a thin water layer of 5–25 mm was maintained on the field surface, while no water layer was established after irrigation during other growth stages. The irrigation control indicator was root-zone soil moisture at 60%–80% of its saturated water content (specific control indicators for each growth stage are given in Table 1).

Table 1. Control Indicators of Root Zone Soil Moisture at Different Growth Stages of Irrigated Rice

Reproductive period	Regreening stage	Tillering stage			Stem Elongation and Booting Stage		Heading and flowering stage	Milk maturity stage	Yellow ripening stage
		Early stage	Mid stage	Late stage	Early stage	Late stage			
Flooding Limit	25mm	100% θ_{s1}	100% θ_{s1}	100% θ_{s1}	100% θ_{s2}	100% θ_{s2}	100% θ_{s3}	100% θ_{s3}	Natural air drying
Minimum irrigation limit	5mm	70% θ_{s1}	65% θ_{s1}	60% θ_{s1}	70% θ_{s2}	75% θ_{s2}	80% θ_{s3}	70% θ_{s3}	
Root layer observation depth/cm	—	0-20	0-20	0-20	0-30	0-30	0-40	0-40	

Note: θ_s is the volumetric saturated water content of the soil in the root observation layer, while θ_{s1} , θ_{s2} , and θ_{s3} represent the saturated water content of the soil at root layer observation depths of 0–10, 0–30, and 0–60 cm, respectively. In the controlled irrigation treatment, irrigation is only allowed when the on-site measured soil moisture reaches the lower limit, and water is applied up to the upper limit, ensuring that there is no water layer on the field surface after irrigation.

2.2 Data Collection and Organization

A UAV (M350RTK) equipped with an onboard multispectral imager (MS600Pro) was used to measure the rice canopy spectrum. Each observation gathered spectral data across six bands at 450 nm, 550 nm, 660 nm, 680 nm, 840 nm, and 900 nm. Observations were conducted under clear weather conditions with wind force not exceeding Level 3, between 11:00 and 13:00. The data collection frequency was once every seven days, with additional measurements taken before and after irrigation.

Soil moisture content (SMC) was measured using the MiniTrase soil moisture observation system. Two monitoring points were established in each plot, with buried probes observing the soil layer at a depth of 20 cm. Each point was measured three times, and the average value was calculated to minimize errors. The timing and frequency of data collection aligned with those of the canopy spectral data collection.

Photosynthetic parameters were assessed using the LI-6800 photosynthesis analyzer. Fully expanded healthy leaves from the top of the main stems of rice in each plot were selected to measure transpiration rate (Tr), net photosynthetic rate (Pn), and stomatal conductance (Gs). Ten leaves were measured per plot, and the average was calculated to control for error. The sampling time and frequency were consistent with those for canopy spectral data collection.

Based on canopy spectral reflectance data, six water-sensitive vegetation indices for rice were calculated, with the calculation formulas provided in Table 2.

Table 2. Vegetation Indices and Their Calculation Formulas

Vegetation Index	Full name	Calculation formula	Reference
NDVI	Normalized Difference Vegetation Index	$(NIR - R)/(NIR + R)$	(Ao et al., 2023)
NDRE	Normalized Difference Red-edge Index	$(NIR - RE)/(NIR + RE)$	(Ma et al., 2022)
LCI	Leaf Chlorophyll Index	$(NIR - RE)/(NIR + R)$	(Yang et al., 2026)
GNDVI	Green Normalized Difference Vegetation Index	$(NIR - G)/(NIR + G)$	(Ao et al., 2023)
EVI	Enhanced Vegetation Index	$2.5 * (NIR - R) / (NIR + 6 * R - 7.5 * B + 1)$	(Li et al., 2015)
RVI	Ratio Vegetation Index Red-edge	NIR / R	(Ao et al., 2023)

Note: NIR represents the reflectance of the near-infrared band of the image, R represents the reflectance of the red band of the image, and G represents the reflectance of the green band of the image.

2.3 Model Construction and Validation

In reference to the method for calculating the critical nitrogen concentration dilution curve model, a critical soil moisture content curve model was constructed (Ulrich, 2003; Greenwood et al., 1990; Lemaire, 1997; Lyu et al., 2018). The specific methodology was as follows. First, the stomatal conductance of rice canopy samples and the corresponding soil moisture content at various growth stages under differing soil moisture levels were compared and analyzed.

Through analysis of variance, the samples were categorized based on whether rice growth was constrained by soil moisture. Second, a linear curve fitting was conducted between stomatal conductance and soil moisture content for rice samples whose soil moisture content did not satisfy the requirements for maximum stomatal conductance. Third, the stomatal conductance of rice samples that did meet the requirements for maximum stomatal conductance was considered as the maximum stomatal conductance. Fourth, the ordinate of the intersection point between the fitted linear curve and the vertical line corresponding to the maximum stomatal conductance was taken as the x-coordinate, which was regarded as the theoretical critical soil moisture content for that day. Using this critical soil moisture content model, a Water Balance Index (WBI) (Wu, 2022) was constructed to facilitate a qualitative assessment of the water status in rice.

$$W_c = a \cdot G_s^{-b} \quad (1)$$

$$WBI = \frac{W_i}{W_c} \quad (2)$$

Where a and b are parameters; G_s is the stomatal conductance of rice canopy leaves ($\text{mol} \cdot \text{m}^{-2} \cdot \text{s}^{-1}$), W_c is the critical soil moisture content (%), WBI is the water balance index, and W_i is the actual soil moisture content. $WBI = 1$ indicates that the water status of rice is optimal; $WBI > 1$ indicates water surplus; $WBI < 1$ indicates water deficit.

Four commonly utilized machine learning algorithms—linear regression model (LR), support vector regression (SVR), random forest regression (RFR), and back propagation neural network regression (BPNN)—were employed to develop models for monitoring and diagnosing rice moisture levels (Wang et al., 2006; Chen et al., 2004; Dong and Huang, 2013; Sheng, 2008). All models were validated through leave-one-out cross-validation. The coefficient of determination (R^2), mean relative error (MRE), root mean square error (RMSE), and normalized root mean square error (NRMSE) between the measured data and the predicted data from the models were computed to assess prediction accuracy, with the calculation formulas as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2} \quad (3)$$

$$MRE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (5)$$

$$NRMSE = \frac{RMSE}{\bar{y}} \quad (6)$$

Where $\hat{y}_i$, y_i , $\bar{y}$ denote the monitored value, measured value, and average value of rice moisture, respectively, while n represents the number of samples.

3. Results and Analysis

3.1 Vegetation Index Screening

Utilizing the experimental data from 2021 to 2022 as the dataset, a Pearson correlation analysis was performed to assess the relationship between the constructed vegetation indices and SMC, Tr, Pn, and Gs, in order to identify vegetation indices that are sensitive to rice water status. The findings indicated that all six vegetation indices demonstrated extremely significant correlations with SMC, Tr, Pn, and Gs ($p < 0.01$). Among these, the NDRE was recognized as the most sensitive index for rice water parameters, exhibiting correlation coefficients of 0.79, 0.86, 0.78, and 0.74 with SMC, Tr, Pn, and Gs, respectively. This outcome elucidates the sensitivity of various vegetation indices to rice water status, thereby providing a quantitative foundation for the subsequent selection of model input variables.

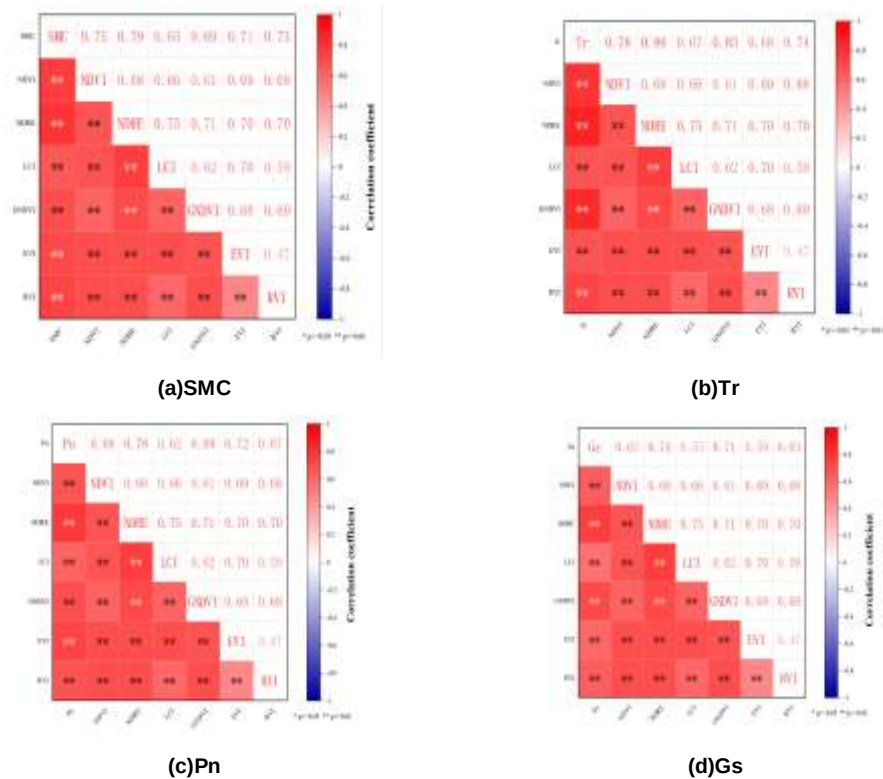


Figure. 1. Correlation Analysis between Vegetation Index and Moisture Indicator

3.2 Moisture Monitoring Model

By employing LR, SVR, RFR, and BPNN machine learning algorithms, with the three vegetation indices demonstrating the strongest correlation utilized as input variables, and SMC, Tr, Pn, and Gs designated as output variables, a monitoring model for rice water parameters was developed. The accuracy of the models was thoroughly assessed using R^2 , MRE, RMSE, and NRMSE. The results indicated that the optimal monitoring model for SMC was an SVR model incorporating NDRE, NDVI, and RVI as combined input variables ($R^2=0.65$, MRE=9.50%, RMSE=0.11, NRMSE=0.05).

The optimal monitoring model for Tr was an LR model with NDRE, GNDVI, and NDVI as combined input variables ($R^2=0.86$, MRE=12.25%, RMSE=0.00, NRMSE=0.14); the optimal monitoring model for Pn was an SVR model utilizing NDRE, EVI, and GNDVI as combined input variables ($R^2=0.78$, MRE=11.61%, RMSE=0.14, NRMSE=0.01); and the optimal monitoring model for Gs was an RFR model with NDRE as the sole input variable ($R^2=0.86$, MRE=4.03%, RMSE=0.01, NRMSE=0.15). The integration of appropriate vegetation index sets with machine learning algorithms facilitates precise quantitative characterization of rice water status, thereby providing reliable model support for the development of subsequent water diagnostic systems.

Table 3. Comparison of Rice Water Monitoring Models

Monitoring Parameters	Input variable	LR				SVR				BPNN				RFR			
		R^2	MRE	RMSE	NRMSE	R^2	MRE	RMSE	NRMSE	R^2	MRE	RMSE	NRMSE	R^2	MRE	RMSE	NRMSE
SMC	NDRE	0.62	13.70	4.69	0.13	0.66	36.35	1.14	0.03	0.71	27.02	5.78	0.19	0.66	10.30	0.93	0.02
	NDVI	0.55	13.73	5.09	0.14	0.50	24.42	0.47	0.01	0.68	15.75	6.79	0.18	0.61	7.89	3.31	0.09
	RVI	0.52	14.87	5.24	0.15	0.49	10.15	0.24	0.01	0.51	10.07	4.44	0.12	0.63	15.47	5.39	0.15
	NDRE/NDVI/RVI	0.70	11.59	4.12	0.12	0.65	9.50	0.22	0.01	0.62	15.51	5.80	0.17	0.82	5.79	2.59	0.07
Tr	NDRE	0.72	18.32	0.00	0.20	0.81	11.74	0.29	11.25	0.68	48.68	0.01	0.44	0.76	28.57	0.01	0.25
	GNDVI	0.67	18.03	0.00	0.22	0.76	18.95	0.51	22.34	0.86	22.99	0.00	0.21	0.70	20.03	0.01	0.22
	NDVI	0.60	21.69	0.01	0.24	0.77	27.71	0.50	0.02	0.76	24.59	0.00	0.20	0.61	20.63	0.01	0.22
	NDRE/GNDVI/NDVI	0.86	12.25	0.00	0.14	0.82	22.80	0.29	13.85	0.81	20.69	0.01	0.24	0.84	16.94	0.00	0.17
Pn	NDRE	0.59	8.74	6.47	0.52	0.59	16.24	0.49	0.04	0.91	93.63	4.90	0.60	0.64	40.61	7.84	0.74
	EVI	0.50	35.07	7.09	0.57	0.59	16.01	0.27	0.02	0.73	31.06	7.54	0.61	0.54	34.00	4.02	0.27
	GNDVI	0.45	37.64	7.45	0.60	0.76	26.17	0.16	0.01	0.62	57.50	12.87	2.63	0.45	36.61	9.37	0.96
	NDRE/EVI/GNDVI	0.64	23.97	6.03	10.19	0.78	11.61	0.14	0.01	0.76	51.54	6.81	0.94	0.69	34.68	8.02	0.70
Gs	NDRE	0.54	17.32	0.10	0.19	0.78	36.34	0.61	1.37	0.77	37.80	0.19	0.38	0.86	4.03	0.01	0.15
	GNDVI	0.49	17.53	0.11	0.20	0.57	20.58	0.50	0.84	0.41	18.51	0.14	0.23	0.51	36.19	0.15	0.30
	RVI	0.38	20.43	0.12	0.22	0.58	29.07	0.61	1.14	0.41	29.23	0.24	0.41	0.40	14.86	0.08	0.15
	NDRE/GNDVI/RVI	0.58	93.13	0.10	0.01	0.60	20.16	0.52	1.01	0.75	31.93	0.14	0.28	0.44	17.60	0.09	0.18

3.3 Critical Soil Moisture Curve Model

The critical soil moisture curve model calculated from the actual test data in 2021 is: $W_c = 12.895 \cdot G_s^{-0.929}$, with parameters $a=12.895$ and $b=0.929$, as shown in Figure 2. Substituting the G_s observed in the 2022 experiment into the critical moisture curve model, the simulated values of W_c were calculated. A correlation analysis was conducted between the simulated W_c values and the measured W_c values, and a 1:1 trend line was drawn to show the relationship between simulation and measurement, thereby verifying the stability of the critical soil moisture curve model, as shown in Figure 3. The results showed that the simulated and measured values had $R^2=0.95$, MRE=8.96%, RMSE=3.86, and NRMSE=0.14. The critical soil moisture curve model demonstrated stable performance and good accuracy, and can be used for qualitative diagnosis of rice water status.

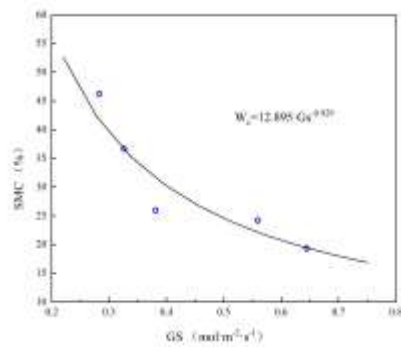


Figure 2. Critical Moisture Content Curve of Rice Samples

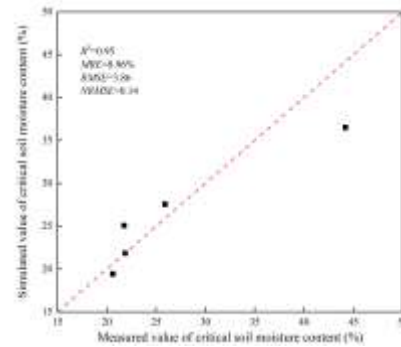


Figure 3. Comparison of simulated and measured values of critical soil moisture content

3.4 Correlation Analysis

Utilizing the experimental data from 2021 to 2022 as the dataset, a Pearson correlation analysis was performed to examine the relationship between the constructed vegetation indices and SMC, Tr, Pn, and Gs in order to identify water-sensitive vegetation indices in rice. The findings indicated that all vegetation indices exhibited a significant correlation with the WBI ($p < 0.01$). The three vegetation indices displaying the strongest correlations were the Normalized NDRE, GNDVI, and RVI, with respective correlation coefficients exceeding 0.7, specifically 0.81, 0.75, and 0.72.

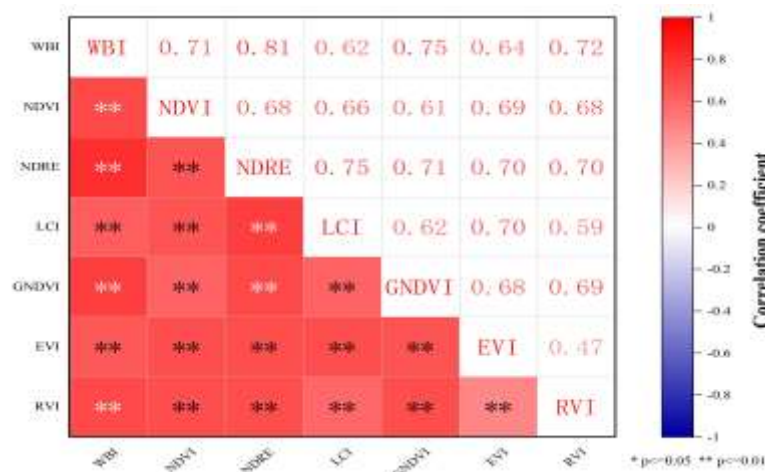


Figure 4. Correlation Analysis between Vegetation Index and WBI

3.5 Moisture Deficit Diagnosis Model

Utilizing the experimental data from 2021 to 2022 as the dataset, machine learning algorithms including LR, SVR, RFR, and BPNN were employed. The three vegetation indices that exhibited the strongest correlation were selected as input variables, while WBI served as the output variable for the construction of a qualitative diagnosis model for rice water deficit. The model's accuracy was thoroughly assessed using R^2 , MRE, RMSE, and NRMSE metrics. The findings indicated that the four machine learning algorithms—LR, SVR, BPNN, and RFR—demonstrated relatively high accuracy in predicting WBI. Furthermore, the predictive performance was enhanced when NDRE, GNDVI, and RVI were utilized concurrently as input variables. Notably, when these indices were applied as input variables to the RFR model, the prediction accuracy for WBI reached its peak, with the modeling dataset yielding $R^2 = 0.74$, MRE = 9.07%, RMSE = 0.08, and NRMSE = 0.06.

Table 4. Comparison of qualitative diagnostic models for water deficit in rice

Diagnostic Parameters	Input variable	LR				SVR				BPNN				RFR			
		R ²	MRE	RMSE	NRMSE	R ²	MRE	RMSE	NRMSE	R ²	MRE	RMSE	NRMSE	R ²	MRE	RMSE	NRMSE
WBI	NDRE	0.64	29.29	0.17	0.10	0.73	15.08	0.22	0.12	0.77	21.85	0.52	0.28	0.71	21.05	0.24	0.07
	GNDVI	0.54	35.17	0.21	0.13	0.70	87.36	0.40	0.31	0.73	24.16	0.44	0.26	0.62	28.4	0.58	0.34
	RVI	0.50	34.10	0.23	0.14	0.57	40.63	0.37	0.25	0.63	27.41	1.93	0.24	0.68	30.12	0.33	0.21
	NDRE+GNDVI+RVI	0.70	25.44	0.14	0.09	0.80	82.71	0.63	0.38	0.68	24.68	1.61	0.22	0.74	9.07	0.08	0.06

Conclusion

There exists a significant correlation between each vegetation index and the water parameters of rice. By constructing a model that utilizes vegetation indices as input variables and water parameters or WBI as dependent variables through machine learning algorithms, it becomes feasible to effectively achieve dynamic monitoring and rapid diagnosis of the water status of rice.

Variations exist among the optimal monitoring models for different moisture parameters: when NDRE, NDVI, and RVI are collectively employed as input variables in the SVR model, the monitoring performance for SMC is the most effective; when NDRE, GNDVI, and NDVI are utilized together as input variables in the LR model, the monitoring performance for Tr is superior; when NDRE, EVI, and GNDVI are jointly employed as input variables in the SVR model, the monitoring performance for Pn is optimal; when the NDRE vegetation index is utilized alone as the input variable in the RFR model, the monitoring performance for Gs is the best.

WBI can accurately characterize the degree of water deficit. When NDRE, GNDVI, and RVI are collectively used as input variables for the RFR model, the resulting qualitative diagnostic model for rice water deficit achieves optimal performance.

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