Postprint: Identification and Severity Assessment of Waterlogging Stress in Winter Wheat Based on Hyperspectral Remote Sensing

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Abstract

Frequent waterlogging stress in winter wheat not only severely compromises regional food security and ecological security, but also threatens socioeconomic stability and sustainable development. To identify waterlogging stress in winter wheat and discriminate its severity, this study established a pot experiment with waterlogging stress gradients, employing an ASD FieldSpec spectrometer and a Gaiasky-mini2 push-broom imaging spectrometer to acquire leaf- and canopy-level hyperspectral data, respectively. Integrating vegetation indices, normalized mean distance, and spectral differential difference information entropy, we monitored the occurrence of waterlogging stress and discriminated its severity in winter wheat. Experimental results demonstrated that the Simple Ratio Pigment Index (SRPI) is the optimal vegetation index for identifying waterlogging-stressed winter wheat. The red light absorption valley (RW: 640~680 nm) represents the optimal waveband for discriminating waterlogging stress severity in winter wheat. Within the RW waveband, spectral differential difference information entropy at the heading, flowering, and grain-filling stages can effectively discriminate waterlogging stress severity, with greater stress levels corresponding to larger entropy values. This study provides a novel method for waterlogging stress monitoring and exhibits promising application prospects in the precise prevention and control of waterlogging stress.

Full Text

Identification and Level Discrimination of Waterlogging Stress in Winter Wheat Using Hyperspectral Remote Sensing

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Abstract

The frequent occurrence of waterlogging stress in winter wheat not only seriously affects regional food security and ecological security, but also threatens social and economic stability and sustainable development. To identify waterlogging stress and discriminate its severity in winter wheat, this study established a waterlogging stress gradient pot experiment using winter wheat. Hyperspectral data of leaves and canopy were measured using a Gaiasky-mini2 push-broom imaging spectrometer. Combined with vegetation indices, normalized mean distance, and spectral derivative difference entropy methods, the study monitored whether winter wheat suffered from waterlogging stress and discriminated the stress level. Experimental results demonstrated that the Simple Ratio Pigment Index (SRPI) is the optimal vegetation index for identifying waterlogged winter wheat. The red light absorption valley (RW: 640–680 nm) is the optimal band for identifying waterlogging stress severity in winter wheat. Within this band, the spectral derivative difference entropy at the heading, flowering, and filling stages can discriminate waterlogging stress levels—the greater the stress level, the larger the spectral derivative difference entropy. This study provides a novel method for waterlogging stress monitoring with promising application prospects for precise prevention and control of waterlogging stress.

Keywords: hyperspectral remote sensing; waterlogging stress; vegetation index; spectral derivative difference entropy; winter wheat

1. Introduction

Agricultural production is highly dependent on climatic conditions. As one of the major natural disasters, waterlogging disasters are becoming a significant factor restricting crop growth. Waterlogging is a chronic disaster phenomenon that is difficult to monitor. Traditional monitoring methods mainly involve detecting soil moisture and water status within crops, but these suffer from high labor intensity and untimely observations. Hyperspectral remote sensing, being information-rich and non-destructive, provides a non-invasive, real-time, and reliable method for monitoring waterlogging stress. Early monitoring of waterlogging stress to provide timely information on vegetation conditions is crucial for developing precise production management plans.

Current research on hyperspectral remote sensing for monitoring crop environmental stress primarily focuses on heavy metal stress and disease stress. Liu et al. [?] diagnosed lead pollution stress levels in rice based on the fractal dimension of high-frequency spectral components, demonstrating that combining wavelet transform, fractal analysis, and fuzzy mathematics can effectively extract, measure, and model weak spectral information for monitoring heavy metal stress. Zhang et al. [?] found that the mean and standard deviation of canopy-air temperature difference distribution were good indicators for discriminating heavy metal stress levels in rice. Li et al. [?] utilized the complementary characteristics of multi-source remote sensing data, fusing hyperspectral and radar remote sensing to monitor heavy metal stress in paddy fields. Yang et al. [?] discovered that a quadratic curve model based on the 785 nm band effectively inverted the severity of sooty mold disease in tobacco leaves. Stefan et al. [?] quantified barley powdery mildew symptoms through hyperspectral imaging combined with simplex volume maximization and support vector machines, enabling accurate assessment of disease severity across all cultivars on each measurement day. Gui et al. [?] proposed a method combining convolutional neural networks and support vector machines to detect early soybean mosaic virus disease, achieving high model recognition accuracy.

Other studies have focused on discriminating freezing stress, dust stress, drought stress, and salt stress. Wang et al. [?] constructed a winter wheat freeze severity inversion model using principal component analysis, achieving highly significant results. Liang et al. [?] designed a dust stress normalized index combined with random forest classification algorithms to predict dust stress levels in wheat leaves with high accuracy. Zhang and Zhou [?] found that the green chlorophyll index, red-edge chlorophyll index, and red-edge normalized difference index were most sensitive to changes in canopy water content and mean leaf equivalent water thickness based on drought stress gradient experiments. Miguel et al. [?] established salinity effect monitoring models based on principal component analysis and an index calculating second derivative approximations in the red-edge region, finding both could effectively monitor salt stress levels, though the index-based model was simpler.

Research on crop waterlogging stress has primarily focused on detecting single waterlogging events, establishing physiological and biochemical parameter inversion models under waterlogging stress [?], and distinguishing different environmental stresses, with fewer studies on discriminating waterlogging stress severity. Xiong et al. [?] recommended using mean differences in the 670–2400 nm spectral band to reflect wheat waterlogging conditions. Xia et al. [?] combined quadratic discriminant analysis, K-nearest neighbor, and support vector machine methods, finding hyperspectral imaging feasible for detecting waterlogging stress in oilseed rape. Zhao et al. [?] detected cotton waterlogging stress based on hyperspectral images and convolutional neural networks. Gao et al. [?] established a SPAD value estimation model for waterlogged winter wheat based on correlation analysis and neural network methods using hyperspectral and digital image characteristic indices. Emengini et al. [?] found that combining hyperspectral and thermal infrared remote sensing could potentially distinguish oil pollution and waterlogging stress.

Original vegetation spectra are susceptible to noise, soil background information, and other factors during acquisition. Waterlogging stress has a weak effect on crop spectra that is difficult to detect. Spectral differentiation can reduce the influence of background information on original spectral signals, and calculating differences between different curve spectral derivatives can further reduce spectral noise effects [?]. Therefore, vegetation indices and normalized mean distance can be combined to identify waterlogged winter wheat, and spectral derivative difference entropy can be used to discriminate waterlogging stress severity.

This study focuses on the Jiangsu Province Yangzhou City region in the middle and lower reaches of the Yangtze River. Based on pot experiments, different gradient waterlogging stress treatments were applied to winter wheat at the jointing stage. Using leaf spectra and canopy hyperspectral imaging data, combined with vegetation indices, normalized mean distance, and spectral derivative difference entropy methods, this research clarifies the spectral characteristics of winter wheat leaves and canopy under waterlogging stress to identify waterlogged winter wheat and discriminate stress severity.

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2. Materials and Methods

2.1 Experimental Design

The research subjects were winter wheat varieties: Yangfumai 4 (YF4), Jimai 31 (JM31), and Jimai 38 (JM38). The experiment was conducted in a rain shelter at the Yangzhou University pot experiment station during 2018-2019. Sowing occurred on November 10, 2018, with a density of 8 holes per pot and 2 seeds per hole. At the three-leaf-one-heart stage, seedlings were thinned to 8 plants per pot, totaling 189 pots. Harvest occurred on May 28, 2019. Pots had an inner bottom diameter of 20 cm, inner top diameter of 28 cm, and height of 29 cm, with an empty pot weight of 0.54 kg. Each pot contained 10 kg of air-dried light loam soil and 5.28 g of compound fertilizer (N-P-K ratio 15%-15%-15%). After sowing, 1 kg of soil was used for covering, and 3.52 g of compound fertilizer was applied as top dressing at the jointing stage.

Waterlogging stress gradient experiments began at the winter wheat jointing stage (March 15, 2019) using the weighing method to control water. Three factors were controlled: waterlogging stress level (control CK, slight waterlogging ML, severe waterlogging SL), stress duration (5 days, 10 days, 15 days), and wheat variety (YF4, JM31, JM38). The CK treatment maintained soil relative water content at 70%-80%, ML maintained 85%-90%, and SL retained a surface water layer of approximately 1.5 cm. YF4 was a normal variety, JM31 was highly water-sensitive, and JM38 was water-insensitive. All waterlogging treatments ended on March 30, 2019, after which equal watering was controlled until harvest. The experiment comprised 21 treatment groups with 9 replicates each, totaling 189 observations.

2.2 Data Collection

Spectral data were collected every 7 days from the first waterlogging day at the jointing stage, selecting clear and windless weather between 10:00–14:00. Measurements continued until maturity, with delays on rainy days.

(1) Leaf spectral data. A portable spectroradiometer (FieldSpec3, Analytical Spectral Devices, USA) measured winter wheat leaf spectral reflectance with sampling intervals of 1.4 nm (350–1000 nm) and 2 nm (1000–2500 nm), resampled to 1 nm. A self-illuminating handheld leaf clip measured the middle portion of leaves. Each treatment measured 5 pots with 4 measurements per pot, with averages used as the leaf spectral reflectance. Standard whiteboard calibration was performed before measurement and every 30 minutes during measurement.

(2) Canopy spectral data. A Gaiasky-mini2 push-broom imaging spectrometer (Sichuan Shuanglihepu Company) measured winter wheat canopy spectral reflectance (spectral range 400–1000 nm, sampling interval 4 nm). The spectrometer was mounted on a tripod 1 m above the canopy, oriented vertically downward. Each treatment measured 5 pots, with averages used as canopy spectral reflectance. Calibration was performed using a standard whiteboard before measurement. Figure 1 [Figure 1: see original paper] shows the field data collection setup.

2.3 Methods

2.3.1 Vegetation Indices Vegetation indices integrate relevant spectral signals, enhancing vegetation information while reducing non-vegetation effects like soil background, effectively reflecting differences between vegetation and background. Each index can quantitatively indicate vegetation growth status under certain conditions. Based on previous research [?, ?], this study selected vegetation indices potentially reflecting crop water status, as shown in Table 1 .

Table 1. List of vegetation indices

Index Name	Formula
Normalized Difference Vegetation Index (NDVI) [?]	NDVI = (IR - R)/(IR + R)
Structure Insensitive Pigment Index (SIPI) [?]	SIPI = (R800 - R445)/(R800 + R680)
Normalized Difference Water Index (NDWI) [?]	NDWI = (IR - MR)/(IR + MR)
Green Normalized Difference Vegetation Index (GNDVI) [?]	GNDVI = (R750 - R550)/(R750 + R550)
Photochemical Reflectance Index (PRI) [?]	PRI = (R531 - R570)/(R531 + R570)
Simple Ratio Pigment Index (SRPI) [?]	SRPI = R430/R680

Note: Rλ is reflectance at wavelength λ; R, IR, and MR are average spectral reflectance in 645-680 nm, 757-817 nm, and 1428-1456 nm bands, respectively.

2.3.2 Normalized Mean Distance The Fisher criterion is an effective feature selection method where features with strong discriminative performance exhibit minimal within-class distance and maximal between-class distance. Relative distance between classes can measure class separability [?], with traditional distances including Euclidean, Mahalanobis, and Hamming distances [?]. This study introduced normalized mean distance to quantitatively evaluate vegetation index capability to identify waterlogged winter wheat, where larger distances indicate stronger identification ability [?]. Analyzing the relative magnitude and variation trends of optimal vegetation indices can determine whether winter wheat suffers waterlogging stress. The normalized mean distance is calculated as:

$$d_{\text{norm}} = \frac{|\mu_1 - \mu_2|}{\sigma_1 + \sigma_2}$$

where $_1$ and $_2$ are the mean vegetation index values for control and waterlogging stress treatments, respectively, and σ_1 and σ_2 are the corresponding standard deviations.

2.3.3 Spectral Derivative Difference Entropy Information entropy, introduced by Shannon [?] based on thermodynamic entropy concepts, quantifies information measurement. It can be defined as the probability of discrete random events, understood as the information amount needed to eliminate uncertainty—more information is required to eliminate uncertainty for higher entropy, and vice versa. It also measures system complexity; more complex systems with more possible states have higher entropy. This study applied information entropy to measure and evaluate waterlogging stress effects on winter wheat and resulting weak spectral distortions. Based on information entropy definition, spectral derivative difference entropy was constructed—greater stress levels produce larger spectral differences and correspondingly larger entropy values [?]. The calculation formulas are [?]:

$$E_{\text{SDD}} = -\sum_{j=1}^{p} p_{ij} \log p_{ij}$$

$$p_{ij} = \frac{(SD_{ij} - SD')^2}{\sum_{j=1}^{p} (SD_{ij} - SD')^2}$$

where i corresponds to spectra under six waterlogging stress levels; j is the number of bands within a certain range; SD is the first-derivative spectral value under waterlogging stress; and SD' is the first-derivative spectral value for normal wheat.

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3. Results and Analysis

Leaf spectral data were measured using a handheld leaf clip on the middle portion of winter wheat leaves, unaffected by background information. Canopy hyperspectral image data included both winter wheat canopy spectra and soil background information. After radiometric and geometric correction of canopy hyperspectral images, random forest algorithms were used for batch processing, with each image classified into four components: winter wheat, pot, grass, and soil. The confusion matrix yielded overall classification accuracy and kappa coefficient of 95.86% and 0.9438, respectively, indicating high accuracy. Classified winter wheat canopy spectral data were extracted for subsequent analysis.

3.1 Spectral Feature Analysis

Vegetation reflectance spectra are closely related to leaf internal structure, pigment content, and water content. Waterlogging stress induces sensitive changes in winter wheat physiological characteristics, altering leaf and canopy spectral reflectance. Waterlogging is a chronic disaster phenomenon caused by long-term soil moisture effects on vegetation growth with hysteresis, making it difficult to identify waterlogged winter wheat during the jointing stage when stress occurs. To enable early identification, spectral reflectance changes were analyzed in the first growth period after stress—comparing control and waterlogging stress (including all slight and severe waterlogging treatments) winter wheat leaf and canopy spectral reflectance at the heading stage. Averages were calculated, yielding spectral feature comparison results (Figure 2 [Figure 2: see original paper]). Control and waterlogging stress sample numbers were 60 and 360 for leaf spectral data, and 15 and 90 for canopy spectral data, respectively.

Figure 2 shows that after waterlogging stress, winter wheat spectral curves exhibited noticeable changes in the red light absorption valley (RW: 640-680 nm), red edge (RE: 670-737 nm), near-infrared (NIR: 750-900 nm), 1428-1456 nm, and 1650-1800 nm bands compared to control wheat. Under waterlogging stress, reduced absorption near the green peak (550 nm) caused an upward trend in the green peak due to pigment content effects. Decreased photosynthetic capacity under waterlogging stress reduced NDVI values, showing higher reflectance in the RW band and lower reflectance in the NIR band. In the RE band, spectra showed blue shift or movement toward shorter wavelengths due to chlorophyll and nitrogen effects [?, ?]. Waterlogging stress delayed root growth, reduced root hydraulic conductivity, caused leaf water deficit, and decreased leaf water potential, which was reflected in the 1428-1456 nm band. The 1650-1800 nm band is located in atmospheric absorption bands, making high-quality field data difficult to obtain and thus not discussed further. Canopy spectral curves showed the same trends as leaf spectra but with more pronounced differences, likely because waterlogging stress affected not only leaf physiological characteristics but also crop canopy shape and structure.

3.2 Waterlogging Stress Identification Analysis

To effectively integrate relevant spectral signals while enhancing vegetation information and reducing non-vegetation effects, six vegetation indices (NDVI, SIPI, NDWI, GNDVI, PRI, and SRPI) were selected to process winter wheat leaf spectra from the jointing stage through the entire growth period to identify waterlogged wheat. To select the optimal index for identifying waterlogging stress, normalized mean distances between control and waterlogging samples were calculated using equation (7) and compared to evaluate identification capability (Table 2).

Table 2. Normalized mean distances of PRI and SRPI

Date	PRI	SRPI
Mar 15, 2019 (pre-stress)	0.28	0.11
Mar 22, 2019	0.31	0.45
Mar 30, 2019	0.42	0.58
Apr 6, 2019	0.38	0.52
Apr 13, 2019	0.35	0.49
Apr 20, 2019	0.33	0.47
Apr 27, 2019	0.36	0.51
May 5, 2019 (maturity)	0.29	0.26

Before waterlogging stress (March 15, 2019), normalized mean distances between normal and waterlogged winter wheat were 0.11 for SRPI and 0.28 for PRI—relatively small values indicating weak separability, consistent with Figure 3 [Figure 3: see original paper]. Subsequently, except at maturity (May 5), distances for SRPI were greater than PRI for all dates. The maturity exception likely occurred because winter wheat leaves began senescing, wilting, and yellowing, introducing confounding factors. Therefore, SRPI demonstrated stronger capability than PRI to distinguish normal from waterlogged winter wheat with greater sensitivity and stability.

Figure 3 shows that throughout the growth period, NDVI and SIPI showed no consistent pattern between normal and waterlogged winter wheat, making them unsuitable for accurate identification. GNDVI and NDWI could identify waterlogged wheat after the jointing stage but showed differences even before stress, introducing systematic errors that prevented accurate early discrimination. In contrast, PRI and SRPI could identify waterlogged winter wheat throughout the entire growth period. Overall, SRPI is the optimal vegetation index for identifying waterlogged winter wheat.

3.3 Stress Level Discrimination Analysis

Differences in winter wheat leaf spectra under varying waterlogging stress levels were minor, making prediction and discrimination difficult. Therefore, this section used canopy spectral data under different stress levels. Based on previous research [?] and the above results, the following band ranges were selected for analysis: red light absorption valley (RW: 640–680 nm), red edge (RE: 670–737 nm), and near-infrared region (NIR: 750–900 nm). Spectral derivative difference entropy methods were applied to discriminate waterlogging stress levels.

Based on sections 3.1 and 3.2, winter wheat at the heading, flowering, and filling stages after waterlogging stress at jointing stage represented the optimal growth periods for identification, as jointing stage differences were not obvious (due to stress hysteresis) and maturity stage differences were confounded by leaf senescence. Canopy spectral data from these three growth periods were differentiated to obtain first-derivative spectra for control and different waterlogging stress levels. Spectral derivative differences between waterlogging stress and control groups were calculated for RW, RE, and NIR bands (Figure 4 [Figure 4: see original paper]), and spectral derivative difference entropy was computed using equations (8) and (9). Results are shown in Table 3 .

Table 3. Spectral derivative difference entropy of winter wheat in RW, RE, and NIR regions

Treatment	RW Band	RE Band	NIR Band
ML5d	0.677	0.512	0.458
ML10d	0.745	0.498	0.472
ML15d	0.823	0.521	0.465
SL5d	0.789	0.515	0.461
SL10d	0.912	0.519	0.468
SL15d	1.023	0.523	0.471

With the same soil relative water content, waterlogging stress severity increased with treatment duration; with the same treatment duration, stress severity increased with soil relative water content. Thus, stress severity followed: ML5d < ML10d < ML15d, SL5d < SL10d < SL15d; and ML5d < SL5d, ML10d < SL10d, ML15d < SL15d.

After differentiating canopy spectra, background effects on original spectral signals were reduced. Calculating spectral derivative differences under various waterlogging treatments further reduced spectral noise and enhanced spectral differences among stress levels. Figure 4 shows clear differences in spectral derivative differences among waterlogging stress levels in the RW (640–680 nm), RE (670–737 nm), and NIR (750–900 nm) bands. Information entropy was introduced to measure these differences. Table 3 shows that in the RW band, spectral derivative difference entropy increased with waterlogging stress severity, from 0.677 for ML5d to 1.023 for SL15d, following the pattern: CK < ML5d

< ML10d < SL5d < ML15d < SL10d < SL15d. In contrast, RE and NIR bands showed no consistent patterns. Therefore, spectral derivative difference entropy in the red light absorption valley (RW: 640–680 nm) can serve as an indicator for identifying waterlogging stress severity in winter wheat—greater entropy values indicate more severe waterlogging stress. Previous research indicates the RW band is more sensitive to pigment content [**?**, **?**], and spectral derivative difference entropy can reduce spectral noise and background effects.

Since winter wheat varieties showed consistent response characteristics to waterlogging stress and this study' s primary objective was to identify waterlogging stress indices and severity discrimination indicators, variety differences were not discussed.

4. Discussion

This study established a waterlogging stress gradient pot experiment to identify waterlogging stress and discriminate severity by analyzing winter wheat spectral characteristics. Combining vegetation indices, normalized mean distance, and spectral derivative difference entropy, waterlogging stress was identified and severity discriminated. Results provide theoretical significance and practical application value for precise waterlogging stress prevention and control, offering references for other environmental stress monitoring studies.

Limitations include differences between pot experiments and actual field conditions and the lack of independent experimental validation. Future research should increase both pot and field experiments, combined with cross-validation, to further verify the feasibility of this method for identifying waterlogging stress and discriminating severity.

References

[1] NGUYEN L T T, OSANAI Y, LAI K, et al. Responses of the soil microbial community to nitrogen fertilizer regimes and historical exposure to extreme weather events: Flooding or prolonged-drought[J]. Soil Biology and Biochemistry, 2018, 118: 227-236.

[2] LIU M, LIU X, CAO S, et al. Assessment of Pb-induced stress levels on rice based on fractal characteristic of spectral high-frequency components[J]. Journal of Remote Sensing, 2011, 15(4): 811-830.

[3] ZHANG B, LIU X, LIU M, et al. Thermal infrared imaging of the variability of canopy-air temperature difference distribution for heavy metal stress levels discrimination in rice[J]. Journal of Applied Remote Sensing, 2017, 11(2): ID 026036.

[4] LI X, LI L, LIU X. Collaborative inversion heavy metal stress in rice by using two-dimensional spectral feature space based on HJ-1 A HSI and radarsat-2 SAR

remote sensing data[J]. International Journal of Applied Earth Observation & Geoinformation, 2019, 78: 39-52.

[5] YANG X, LUO H, ZHAO W, et al. Study on the response model of spectral signatures of vegetation leaves on the stress level for sooty mould[J]. Spectroscopy and Spectral Analysis, 2017, 37(9): 2873-2878.

[6] STEFAN T, JAN B, ANGELINA S, et al. Quantitative assessment of disease severity and rating of barley cultivars based on hyperspectral imaging in a non-invasive, automated phenotyping platform[J]. Plant Methods, 2018, 14(1): ID 45.

[7] GUI J, FEI J, WU Z, et al. Grading method of soybean mosaic disease based on hyperspectral imaging technology[J/OL]. Information Processing in Agriculture, 2020. https://doi.org/10.1016/j.inpa.2020.10.006

[8] WANG H, WANG J, DONG Y, et al. Monitoring freeze stress levels on winter wheat from hyperspectral reflectance data using principal component analysis[J]. Spectroscopy and Spectral Analysis, 2014, 34(5): 1357-1361.

[9] LIANG L, XIANG L, QIN S, et al. Diagnosis the dust stress of wheat leaves with hyperspectral indices and random forest algorithm[C]// IEEE International Geoscience and Remote Sensing Symposium. Piscataway, New York, USA: IEEE, 2016.

[10] ZHANG F, ZHOU G. Estimation of canopy water content by means of hyperspectral indices based on drought stress gradient experiments of maize in the north plain China[J]. Remote Sensing, 2015, 7(11): 15203-15223.

[11] MIGUEL L, BELÉN D, LOURDES L, et al. Hyperspectral imaging to evaluate the effect of irrigation water salinity in lettuce[J]. Applied Sciences, 2016, 6(12): ID 412.

[12] YANG F, LI S, LIU S, et al. Research progress on hyperspectral remote sensing monitoring of crop environmental stress[J]. Journal of Agricultural Science and Technology, 2020, 22(4): 85-93.

[13] XIONG Q, WANG X, WANG Y. Spectral characteristics analysis of wheat damaged by subsurface waterlogging[J]. Spectroscopy and Spectral Analysis, 2016, 36(8): 2558-2561.

[14] XIA J, CAO H, YANG Y, et al. Detection of waterlogging stress based on hyperspectral images of oilseed rape leaves (Brassica napus L.)[J]. Computers and Electronics in Agriculture, 2019, 159: 59-68.

[15] ZHAO J, PAN F, LI Z, et al. Detection of cotton waterlogging stress based on hyperspectral images and convolutional neural network[J]. International Journal of Agricultural and Biological Engineering, 2021, 14(2): 201-208.

[16] GAO X, LI Y, LU B, et al. Estimation of SPAD value in waterlogged winter wheat based on characteristic indices of hyperspectral and digital image[J]. Chinese Journal of Applied Ecology, 2021, 32(3): 959-966.

[17] EMENGINI E, BLACKBURN A, THEOBALD J. Discrimination of plant stress caused by oil pollution and waterlogging using hyperspectral and thermal remote sensing[J]. Journal of Applied Remote Sensing, 2013, 7(4): 87-97.

[18] GUO H, YANG K, ZHANG W, et al. Spectra recognition of corn pollution degree under copper and lead ion stress[J]. Spectroscopy and Spectral Analysis, 2018, 38(1): 212-217.

[19] JIANG J, STEVEN D M, HE R, et al. Comparison and analysis of hyperspectral remote sensing identifiable models for different vegetation under waterlogging stress[J]. Spectroscopy and Spectral Analysis, 2013, 33(11): 3106-3110.

[20] SCHELL J A. Monitoring vegetation systems in the great plains with ERTS[J]. Nasa Special Publication, 1973, 351: 309.

[21] HUANG W, WANG J, LIU L, et al. Study on grain quality effecting factors and monitoring methods by using hyperspectral data in winter wheat[J]. Remote Sensing Technology and Application, 2004(3): 143-148.

[22] MCFEETERS S. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features[J]. International Journal of Remote Sensing, 1996, 17(7): 1425-1432.

[23] BARET F, GUYOT G. Potentials and limits of vegetation indices for LAI and APAR assessment[J]. Remote Sensing of Environment, 1991, 35(2-3): 161-173.

[24] GAMON J, PEÑUELAS J, FIELD C. A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency[J]. Remote Sensing of Environment, 1992, 41(1): 35-44.

[25] WANG R, SONG X, LI Z, et al. Estimation of winter wheat nitrogen nutrition index using hyperspectral remote sensing[J]. Transactions of the CSAE, 2014, 30(19): 191-198.

[26] LU J, LIU F, LUO X. Selection of image features for steganalysis based on the Fisher criterion[J]. Digital Investigation, 2014, 11(1): 57-66.

[27] WANG W. Distance metric learning: Algorithm and application[D]. Shanghai: Shanghai Jiao Tong University, 2018.

[28] TONG Q, ZHANG B, ZHENG L. Hyperspectral remote sensing: Principles, techniques, and applications[M]. Beijing: Higher Education Press, 2006.

[29] SHANNON C. The bell system technical journal[J]. Journal of the Franklin Institute, 1938, 196(4): 475-476.

[30] GUO H. Study on extraction and inversion models of weak information in maize leaf polluted under copper stress[D]. Beijing: China University of Mining & Technology (Beijing), 2019.

[31] RAMOELO A, SKIDMORE A, CHO M, et al. Regional estimation of savanna grass nitrogen using the red-edge band of the spaceborne RapidEye sensor[J]. International Journal of Applied Earth Observations & Geoinformation, 2012, 19: 151-162.

[32] RAMOELO A, DZIKITI S, VAN D, et al. Potential to monitor plant stress using remote sensing tools[J]. Journal of Arid Environments, 2015, 113: 134-144.

[33] LIU L, HUANG W, PU R, et al. Detection of internal leaf structure deterioration using a new spectral ratio index in the near-infrared shoulder region[J]. Journal of Integrative Agriculture, 2014, 13(4): 760-769.

[34] SUÁREZ L, ZARCO-TEJADA P, GONZÁLEZ-DUGO V, et al. Detecting water stress effects on fruit quality in orchards with time-series PRI airborne imagery[J]. Remote Sensing of Environment, 2010, 114(2): 286-298.

[35] CALDERÓN R, NAVAS-CORTÉS J, LUCENA C, et al. High-resolution airborne hyperspectral and thermal imagery for early detection of verticillium wilt of olive using fluorescence, temperature and narrow-band spectral indices[J]. Remote Sensing of Environment, 2013, 139: 231-245.

[36] ZHANG W, WANG X, PAN Q, et al. Hyperspectral response characteristics and chlorophyll content estimation of phyllostachys violascens leaves under drought stress[J]. Acta Ecologica Sinica, 2018, 38(18): 322-329.

[37] FU Y, FAN Y, SHENG J, et al. Study on relationship between alfalfa canopy spectral reflectance and leaf water content[J]. Spectroscopy and Spectral Analysis, 2013, 33(3): 766-769.
