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In-season Diagnosis of Winter Wheat Nitrogen Status Based on RapidSCAN Sensor using Machine Learning Coupled with Weather Data

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Abstract.

Nitrogen nutrient index (NNI) is widely used as a good indicator to evaluate the N status of crops in precision farming. However, interannual variation in weather may affect vegetation indices from sensors used to estimate NNI and reduce the accuracy of N diagnostic models. Machine learning has been applied to precision N management with unique advantages in various variables analysis and processing. The objective of this study is to improve the N status diagnostic model for winter wheat by combining remote sensing data with weather data using random forest regression. N plot experiments including five nitrogen levels (0, 120, 180, 240 and 300 kg N ha^{-1}) and four winter wheat varieties were conducted from 2016 to 2018 in Laoling

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County, Shandong Province. North China Plain in Laoling County, Shandong Province, China. The selected vegetation index in this study was normalized difference vegetation index (NDVI), normalized difference red edge (NDRE) and the corresponding nitrogen sufficiency index (NSI). The results indicated that incorporating weather data improved the performance for NNI estimation using random forest regression (R^2=0.82-0.85), compared to only using NDVI or NDRE (R^2=0.53-0.55), The Random Forest Regression Model based on NSI calculated with NDVI and NDRE and weather data obtained the best nitrogen diagnostic performance with area agreement (83%) and kappa coefficient (0.677) all N rates, varieties, stages, and years. This study is to provide a basis for precision N management and help the green and sustainable development of agriculture. More studies are needed further to evaluate it under diverse on-farm and soil and weather conditions.

Keywords.
Nitrogen nutrition index, Nitrogen diagnosis, RapidSCAN, Machine learning

INTRODUCTION

As a major grain crop in the North China Plain, the production of winter wheat is a critical issue for China's food security (Cui et al., 2018). Nitrogen (N) is one of the essential nutrients to control the growth condition of crop. Farmers applied a uniform N fertilizer based on the target yield method by their experience for smallholder farming (Zhang et al., 2016; Cui et al., 2018). However, due to the annual variation and frequent changes in climate and the uneven distribution of soil N supply capacity from field to field, winter wheat yields might vary greatly across fields (Cao et al., 2012). In order to avoid yield loss due to crop deficiency, farmers often apply very large amounts of nitrogen, especially in the early stages(Miao et al., 2011; Zhang et al., 2016). Excessive N fertilizer not only leads to low N fertilizer utilization, but also causes environmental pollution, reduces economic efficiency, and increases the risk of crop failure and disease susceptibility (Zhang et al., 2015; Zhang et al., 2021). There is an urgent need to develop a precision N management strategy that can diagnose the spatial and temporal interannual variability to meet crop nitrogen demand, increase nitrogen fertilizer use efficiency, and reduce environmental costs in the North China Plain.

In the early stage, site-specific N management was to obtain the nitrate-nitrogen content of the crop at different growth stages based on soil N_{min} tests, and to recommend N rates in combination with crop N requirement minus the soil N supply (Cui et al., 2008; Chen et al., 2011). But for a large area of fields in the North China Plain, soil N_{min} testing is time-consuming and laborious, complicated, with low economic efficiency and low operability. It is not a quite good for farmers to apply this technology to crop production. Nondestructive estimation of crop nitrogen (N) and growth status in space and time using remote sensing technology is a very promising approach in precision farming (Mulla and Miao, 2016), which has been successfully applied to wheat, rice, maize, and cotton in China. With the advancement of proximal optical sensors and low altitude remote sensing platform, significant improvements in temporal, spatial and spectral resolution were reported and enhanced crop N diagnostic potential, boosting the application of agricultural remote sensing in precision N management (Mulla and Miao, 2016; Weiss et al., 2020). Unlike normalized difference vegetation index (NDVI) that tends to saturate under high cover or N accumulation, red-edge band index, such as normalized difference vegetation index (NDRE), or more multi-band composite indices are considered to identify well the nitrogen status of crop leaves or plants (Wang et al., 2012; Cao et al., 2013).

Nitrogen nutrient index (NNI) is widely used as a good indicator to evaluate the N status of crops in precise nitrogen management strategies (Justes et al., 1994; Samborski et al., 2009). However, interannual variation in weather may affect vegetation indices from sensors used to estimate NNI and reduce the accuracy of N diagnostic models (Lu et al., 2020). Climatic conditions have a strong influence on crop growth, especially for climate-sensitive regions. In exceptional years (dry or cool weather), the performance of the model only based on vegetation index estimation may not reach the expected goals for right recommended N rate (Wang et al., 2021). Therefore, More weather information or variables needs to be considered by remote sensing N diagnostic models.

Along with the progress of computer technology, machine learning has been applied to the accurate management of N with its unique data analysis and processing in recent years (Agrimonti et al., 2020). Combining environmental and agronomic variables into crop models is the key to increase estimation accuracy and improve N diagnostic capability (Ransom et al., 2019; Saikai et al., 2020). In maize, N diagnostic models using machine learning from soil, weather and management information with active canopy sensor data have shown good performance in estimating NNI (R^2 = 0.85-0.86) and grain yield (R^2 = 0.76-0.79) (Wang et al., 2021). However, relatively few reports on the potential of rice N diagnosis in North China Plain using machine learning methods to combine remote sensing data with weather data was discussed. The objective of this study is to improve the N status diagnostic model for winter wheat by combining remote sensing data with weather data using random forest regression (one of machine learning methods).

MATERIALS AND METHODS

Study site description and experiment design

Three-year experiments were conducted from 2015 to 2018 in Laoling County, Shandong Province. North China Plain in Laoling County, Shandong Province, China. The climate is warm-temperate semi-humid continental monsoon. The accumulated rainfall and temperature during the whole winter wheat growing season (from early October to early June of the following year) was 159 mm and 1791 °C in 2015-2016, 129 mm and 2118 °C in 2016-2017 and 200 mm and 1914 °C in 2017-2018.

Two N plot experiments for each year were designed in a randomized block design including two commonly cultivated varieties with three replications. The varieties of winter wheat varied with the local varieties. In 2016, the varieties planted were Jinmai 22 (JM) and Luyuan502 (LY); in 2017, JM and Liangxing99 (LX); in 2018, JM and Shanong29 (SN). Five N rates (0, 40, 120, 180, 240 and 300 kg N ha^{-1}) were used as the treatments in each plot experiment. N fertilizer was distributed in two times splits: 40% as basal N before transplanting, 60% at Feekes 6. For all treatments, 120 kg ha^{-1} P_2O_5 was all applied before transplanting and 75 kg ha^{-1} K_2O as potassium sulfate was applied as two splits: 80% before transplanting and 20% at stem elongation stage. All field management including irrigation, weeding and pesticide applications, followed the local standard practices.

Proximal canopy sensor data collection

RapidSCAN (Holland Scientific Inc., Lincoln, Nebraska, USA) is a proximal active canopy sensor with near-infrared (NIR, 780 nm), red edge (RE, 730 nm) and red light (R, 670 nm) bands, integrating data recorder, visual operation interface, GPS, optical sensor, and battery. The sensor is height independent in the measurement range of 0.3 to 3 m. In this study, RapidSCAN is measured about 0.4-0.7 m from the rice canopy, parallel to the ground. The average of 8-10 vegetation indices readings represents each plot. Two visual vegetation indices of the sensor, NDVI ((NIR-R)/(NIR+R)) and NDRE ((NIR-RE)/(NIR+RE)) are selected for analysis.

Plant sampling and NNI caculation

Samples of winter wheat were taken immediately after the determination of proximal sensor at Feekes5, Feekes6, Feekes10.0 and Feekes10.5.2. Destructive plant samples of aboveground were collected from scanned plants by randomly clipping at each measurement date in each plot. The samples were washed, dried, crushed, and mineralized with H_2SO_4-H_2O_2. The N content of the plants was determined by Kjeldahl nitrogen determination. The critical nitrogen dilution curve for winter wheat developed by Yue et al. (2012) was used in this study as followings.

$$N_c = 41.5\ W^{-0.38} \quad (1)$$

Where N_c is the critical N concentration (g kg^{-1}) and W is the dry weight of aboveground biomass (t ha^{-1}).

The caculation for NNI was proposed by Lemaire et al. (2008)

$$NNI = N_a/N_c \quad (2)$$

Where N_a is the actual measured N concentration and N_c is determined by eq.(1).

The NNI threshold values was used to diagnose winter wheat N status directly. The NNI threshold was divided into three N nutrient status: N deficiency (NNI < 0.95), N optimal (0.95 ≤ NNI ≤ 1.05), and N surplus (> 1.05).

Selection of weather variables

The weather data was derived from the weather station of Laoling city from 2014 to 2016. Two weather factors selected in this study are as follows:

Growth degree day (GDD) refers to the number of days from planting to sensing in this study, counting only those days under active accumulated temperature (>10°C) (Raun et al., 2005).

Daily accumulative temperature (DAT) refers to the average daily effective cumulative temperature during the growth period (°C), which calculated as eq.(3)

$$\frac{\sum\left(\frac{T_{max}+T_{min}}{2}-T_{base}\right)}{n} \tag{3}$$

Where T_max、T_min and T_base refer to the maximum, minimum and base temperature of each day, and Tbase is 10 ℃.

Shannon's diversity index (SDI) refers to the distribution of rainfall in an area. The calculation eq.(4) is as follows:

$$\frac{-\sum[pi\times\ln(pi)]}{\ln(n)} \tag{4}$$

Where pi refers to the percentage of daily rainfall compared to the total rainfall and n is the number of days for a given time period.

The accumulated precipitation (APP) is calculated by the sum of daily rainfall during the growth period. The average daily sunshine hours (ASH) is obtained by average daily sunshine hours for a given period. In addition, agronomic variables on variety (VL), N basal fertilizer application (BN), and crop growing (vegetation index) were used in this study.

Two N status diagnostic strategies

Three different strategies were compared to evaluate winter wheat N diagnosis in this study.

Strategy 1: this strategy is to estimate NNI directly based on simple regression using NDVI or NDRE.

Strategy 2: Nitrogen Sufficiency Index (NSI) was calculated to decrease the confounding factors by setting up nitrogen-rich plots in adjacent fields (Lu et al., 2017). NSI calculated by NDVI (NSI_NDVI) or NDRE (NSI_NDRE) had the ability to enhance NNI estimation. This approach was to estimate NNI directly using NDVI and NDRE (NDVI&NDRE) or NSI_NDVI and NSI_NDRE (NSI_NDVI&NSI_NDRE) coupled with weather and agronomic variables through Random Forest Regression.

Statistical analysis

Vegetation index was calculated in Microsoft Excel 2016. Data collected from plot experiments were pooled and then randomly divided into a calibration dataset (75% of observations) and a validation dataset (25% of observations). Simple regressions were analyzed in SPSS 25.0 software (SPSS Inc., Chicago, IL, USA). The machine learning approach was implemented through the Python language. The program was written in PyCharm Community 2020 software and Anaconda Environment Manager and Python 3.8 environment. Random Forest regression and model evaluation were implemented by scikit-learn (sklearn) 0.23.0 in the Python language library.

The evaluation metrics for the regression models are the coefficient of determination (R^2) and the root mean square error (RMSE), and relative error (REr). In addition, the performance of the classification model is evaluated using the areal agreement and the Kappa coefficient.

Results and Discussion

Interannual variability of NNI under various varieties and N application rate

Winter wheat NNI was significantly affected by the factors of N rates, varieties and years (Fig. 1). Regardless of growth stages, as increasing N application, NNI increased significantly and tended to plateau under 240-300 kg N ha^{-1}. The NNI response to N rates varied across years and crop varieties, which might lead to differences in economical optimum N rate. Early stage (Feekes6) variation is significantly larger than late stage (Feekes10.5.2). At Feekes6 in 2016, two varieties () both showed N deficiency status across 0-300 kg N ha^{-1}, but N optimal under 200-240 kg N kg^{-1}. In addition to differences in N application, meteorological factors may be the main factor affecting the N nutrient status of the crop. Compared to 2017 and 2018, lower accumulated temperature in 2016 was found. Low temperature will affect the supply of soil nutrients and the release of N fertilizer, resulting in poor N use efficiency (NUE), which might cause nitrogen deficiency at the early stage of crop.

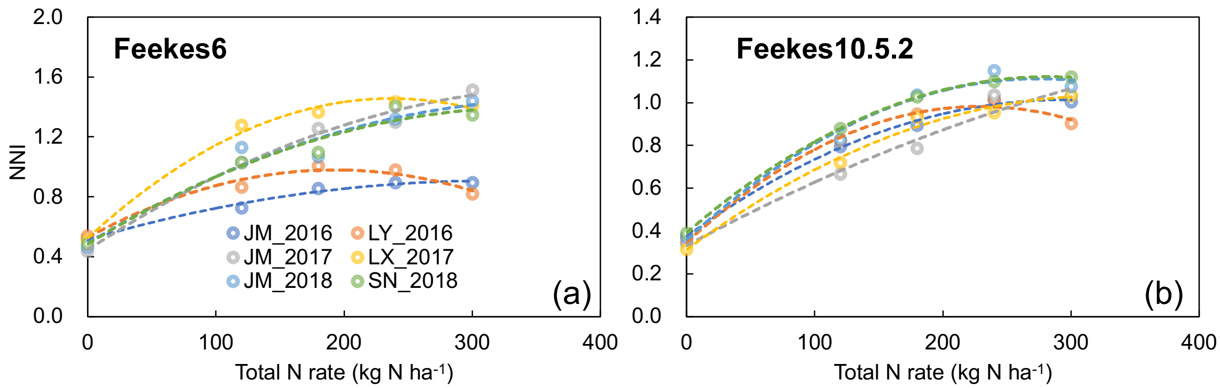

Fig 1. Variability of Nitrogen nutrient index as affected by different N rates in different years. Different color dots represent NNI in different varieties and years. The short-dotted lines indicate quadratic regression curves.

Changes in NDVI vs. NDRE among different N rates, varieties, stages, and years

RapidSCAN-based NDVI and NDRE showed similar results with NNI as affected by different n rates, varieties, stages, and years (Fig 2). At Feekes6, significantly large interannual differences in the response of N application to NDVI/NDRE were found, but similar value changes at Feekes10.5.2. Compared to NDVI, the response of NDRE to nitrogen was more similar to the performance of NNI (Fig. 1 and Fig. 2). However, vegetation indices were the lowest in 2018 from 0 to 300 kg N ha^{-1} compared to 2016 and 2017, which was different from the trend performance of NNI.

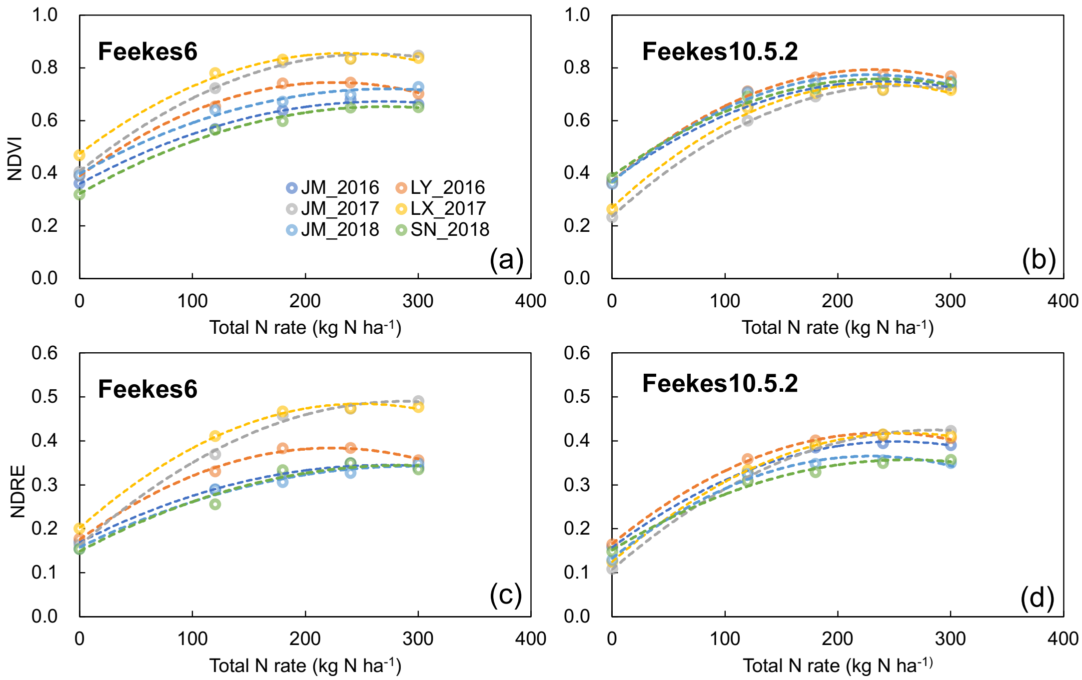

Fig 2. Changes in NDVI and NDRE as affected by different N rates in different years.
Different color dots represent NNI in different varieties and years. The short-dotted lines indicate quadratic regression curves.

Improvement of NNI estimation by NSI

The relationships between NNI and NDVI, NDRE and NSI calculated with NDVI and NDRE (NSI_NDVI; NSI_NDRE) were showed in Fig. 3. NSI_NDRE had the best correlation (R^2=0.59) with NNI. Regardless of NSI, NDRE explained 54-59% of NNI variability, which was slight better than NDVI (52-57%). The NSI approach (R^2=0.57-0.59) had a better performance of NNI estimation over original vegetation index (R^2=0.52-0.54).

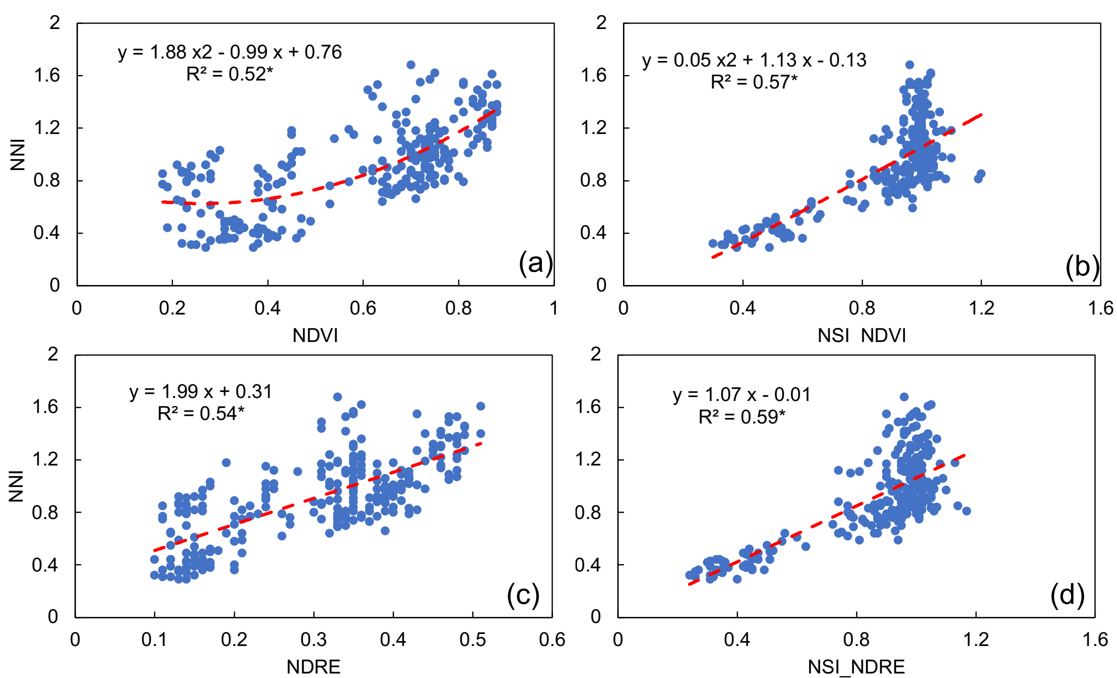

Fig 3. The relationships between NNI and NDVI (a), NSI_NDVI (b), NDRE (c), NSI_NDRE (d) across all N rates, varieties, stages, and years in calibration dataset.

Enhancement of NNI estimation coupled with weather data

Incorporating weather data improved the performance for NNI estimation using random forest regression (R^2>0.80, Fig. 4). Machine learning based on NSI_NDVI and NSI_NDRE coupled with weather variables was the best in validation, with R^2, RMSE and REr being 0.85, 0.11 and 12.4%, respectively. Similar good validation results were also found in NDVI and NDRE using random forest regression coupled with weather variables, with R^2, RMSE and REr being 0.82, 0.13 and 13.8%, respectively. The performance of NNI estimation using only vegetation indices was quite fair (R^2=0.53-0.55), and NDRE was slightly better than NDVI.

Random forest regression combined with NSI and weather variables had the best areal agreement (83%) and kappa coefficient (0.677) across all N rates, varieties, stages, and years, followed closely with original vegetation indices and weather data (areal=78%; Kappa=0.616) (Table 1). Only based on simple regression using NDRE or NDVI, the areal agreement and kappa coefficient was 55-56% and 0.269-0.288, respectively.

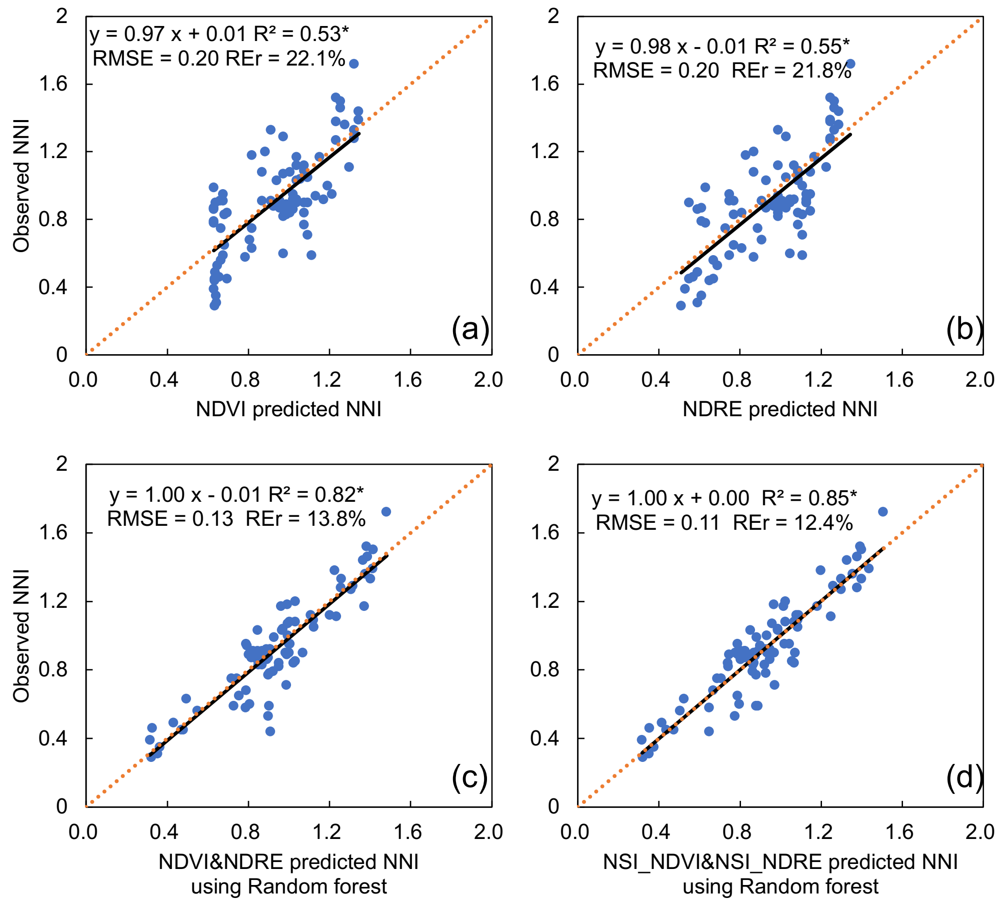

Fig 4. Validation results for predicting NNI using two N diagnostic strategies across all N rates, varieties, stages, and years.

Table 1. Areal agreement (%) and kappa statistics for different N diagnostic strategies using simple regression and andom across all N rates, varieties, stages, and years in validation dataset.

		Areal agreement	Kappa statistic
Simple regression	NDVI	55%	0.269
	NDRE	56%	0.288
Random Forest regression	NDVI&NDRE	78%	0.616
	NSI_NDVI&NSI_NDRE	83%	0.677

Conclusion

The response of NNI to N rates varies from year to year, and the similar trend was observed for NDRE or NDVI, but it is not entirely consistent. Combining proximal active canopy sensor data with weather data through machine learning methods has the potential to improve nitrogen (N) status diagnostic models for winter wheat in North China Plain. Compared to only using NDVI or NDRE (R^2=0.53-0.55), incorporating weather data improved the performance for NNI estimation using random forest regression (R^2=0.82-0.85). The Random Forest Regression Model based on NSI calculated with NDVI and NDRE and weather data obtained the best nitrogen diagnostic performance with area agreement (83%) and kappa coefficient (0.677) all N rates, varieties, stages, and years. More studies are needed further to evaluate it under diverse on-farm and soil and weather conditions.

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