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Retraction

Retracted: Monitoring of Nitrogen Transport in Pear Trees Based on Ground Hyperspectral Remote Sensing and Digital Image Information

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] Z. Fan, D. Wang, N. Zhang, and B. Zhou, "Monitoring of Nitrogen Transport in Pear Trees Based on Ground Hyperspectral Remote Sensing and Digital Image Information," *Journal of Chemistry*, vol. 2022, Article ID 7590846, 7 pages, 2022.

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Research Article

Monitoring of Nitrogen Transport in Pear Trees Based on Ground Hyperspectral Remote Sensing and Digital Image Information

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To study nitrogen transport monitoring in pear trees based on ground-based hyperspectral remote sensing and digital image information. First, based on ground hyperspectral remote sensing and digital image information, combined with the characteristics of visible and near-infrared spectral data and digital image data, a beet nitrogen nutrition diagnosis model based on visible and near-infrared spectral and digital image information was established. The results showed that under water and nitrogen management conditions, the marked nitrogen use efficiency at soil profiles 15, 45, and 75 cm was 28.2%, 22.3%, and 16.3%, respectively. From the analysis of soil and plant nitrogen measured in this experiment, it can be seen that nitrogen nitrate fertilizer should be properly applied to pear trees in the future.

1. Introduction

Hyperspectral data acquisition is mainly completed by two sensors: a nonimaging spectrometer and an imaging spectrometer. The nonimaging spectrometer can measure the reflection spectrum of the target object in the field or indoors and generate the spectral reflectance curve. The user can directly see the spectral characteristics of the target object and process the data by the hyperspectral analysis method to achieve qualitative or quantitative monitoring [1]. An imaging spectrometer integrates spectral technology and imaging technology to achieve "Atlas integration," which can not only obtain the shape and position information of the target object in the image but also record the spectral information of the object. Each pixel point on a hyperspectral image contains a continuous reflection spectrum curve, which realizes the collection of spectral information from point to surface. It has richer spectral information and is an upgraded version of nonimaging spectrometer.

Nitrogen is the most significant nutrient element affecting crop growth and development, yield, and quality formation (Figure 1). The total nitrogen content in crops is about 0.3–5.0% of dry weight. Nitrogen participates in the composition of chlorophyll. It is not only the main component of protein, but also an important component of nucleic acid and many enzymes in plants [2]. In addition, some vitamins, some alkaloids, and some plant hormones such as auxin and cytokinin in plants contain nitrogen. In production, under nitrogen deficiency, the growth of aboveground and root systems of crops is significantly inhibited, the formation and development of reproductive organs are also limited, the plants mature in advance, and the seeds and fruits are small but not full, which significantly affects the yield and quality of crops. On the contrary, increasing the application of nitrogen fertilizer can increase crop yield and improve the quality of crop products, so the input of nitrogen fertilizer increases year by year. China is the country with the largest consumption of nitrogen fertilizer. The average annual consumption per unit of cultivated land area is three times the world average. It is expected to continue to increase in the next 10 years. With the large increase of nitrogen fertilizer applications, the nitrogen use efficiency gradually decreases. On an average, the utilization efficiency of several nitrogen fertilizers by wheat crops is 27%–34%, which is far lower than that of corn, cotton, rice, and other crops. Due to the unscientific

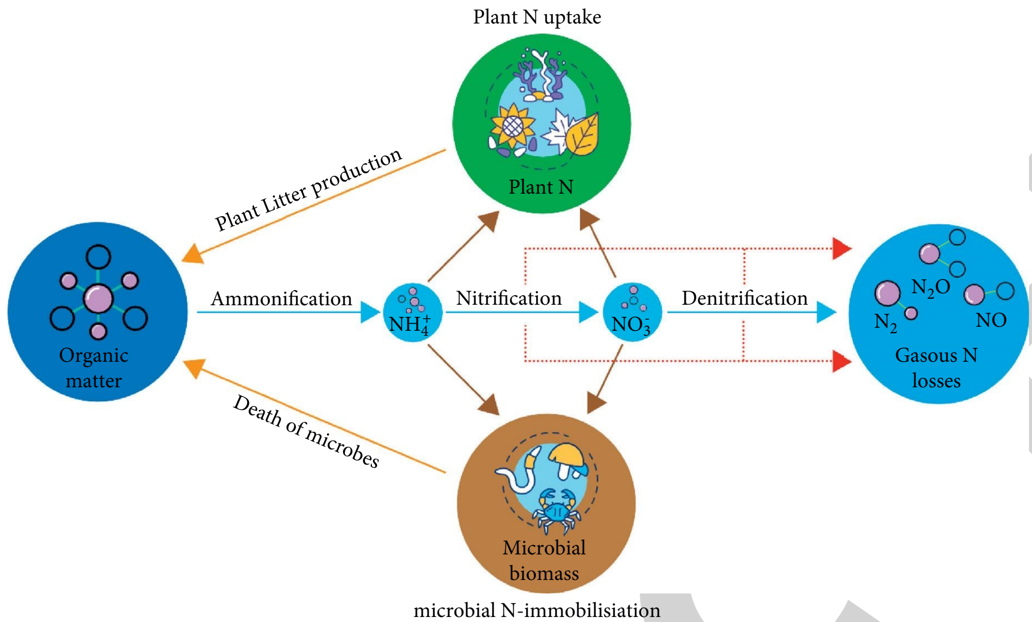

Figure 1: Nitrogen transport monitoring.

application of nitrogen fertilizer, nitrogen is often lost by leaching, denitrification, and nitrogen volatilization. The loss rate of wheat crops is 14%–55%, and that of autumn crops is 18%–55%. Most of the lost nitrogen enters groundwater and surface water, resulting in the continuous increase of nitrate nitrogen in groundwater and surface water, resulting in water eutrophication, resulting in a series of environmental problems, such as the destruction of water resources and aquatic resources, the reduction of the use value of water, the increase of the cost of water treatment, and even a threat to human health [3].

In short, nitrogen fertilizer is not only an important factor in agricultural production but also one of the most important factors polluting the environment. Rapid and effective tracking and monitoring of crop nitrogen status and determining scientific fertilization management measures are of great significance to improving nitrogen utilization efficiency, making rational use of resources, improving crop yield, improving quality, and protecting the environment. Therefore, with the deepening of people's understanding of the severity of survival security problems such as resources and the environment, how to improve nitrogen use efficiency and reduce the impact on the agricultural ecological environment is a major problem that needs to be studied and solved urgently. Precision agriculture represents the development direction of modern agriculture and is also the key field of agricultural science and technology research. Compared with traditional agriculture, precision agriculture is characterized by the exchange of high and new technology and scientific management for the maximum conservation of natural resources and the minimum pollution of the ecological environment. Its core is to properly divide the whole field into several small plots, timely obtain the information on the small plots, make decisions according to the plot in consideration of the differences in natural conditions, and accurately carry out agricultural operations in each plot, that is, carry out real-time monitoring and diagnosis of the spatial differences of soil characteristics and crop conditions, and implement regular, positioning and quantitative prescription farming on this basis, so as to fully obtain the highest benefits. Therefore, the rapid acquisition and quantitative diagnosis of crop growth information is an important key technology in today's precision agricultural technology system. At present, there is an urgent need for low-cost, high-density, high-precision, and high-reliability farmland information acquisition technology to achieve rapid, real-time, accurate, and economic access to accurate information such as crop growth and development, plant diseases and pests, water and fertilizer status, and corresponding environmental conditions [4].

Cui Y. et al. believe that nitrogen is an important nutrient element affecting the growth, development, yield, and quality of pear trees. Nitrogen is a synthetic element of protein, nucleic acid, amino acid, and other life substances, which can promote photosynthesis, improve pear quality, and increase yield [5]. Fricker et al. believe that improving the availability of nitrogen can increase ecosystem biomass at least in the short term. At present, China is the country with the largest consumption of nitrogen fertilizer in the world. Excessive application of nitrogen fertilizer will not only affect the quality and yield of pear trees but also cause a series of environmental pollution problems [6]. Therefore, Marcinkowska-Ochtyra et al. believe that the formulation of a scientific nitrogen application scheme and improvement of fertilizer utilization efficiency are not only conducive to the growth of pear trees and increase production and income, but also protect the environment, reduce pollution, and realize the common development of economic and ecological benefits [7]. Booysen et al. found that the traditional method of measuring leaf nitrogen content is time-consuming and laborious and requires destructive sampling, which makes it difficult to achieve large-area monitoring. In recent years, with the rapid development of hyperspectral remote sensing technology based on vegetation spectral characteristics, it has become possible to monitor crop nitrogen content in real-time and quickly within the region [8]. D. Kopeć et al. believe that the massive and rich spectral information carried by hyperspectral data accurately analyzes the vegetation from the macro level to the micro level of monitoring vegetation physiological parameters, which has become the development trend of modern precision agriculture. Monitoring crop growth and nutrition diagnosis by hyperspectral remote sensing will be an important basis for field management and yield and quality prediction [9]. Zhang et al. believe that due to different internal structures, natural features have different degrees of reflection, absorption, transmission, and radiation of electromagnetic waves, resulting in great differences in the reflected spectrum of electromagnetic waves between different features, which is the spectral characteristics of features. The electromagnetic wave reflection spectrum of ground objects is the manifestation of remote sensing information [10]. Liu et al. believe that both multispectral and hyperspectral can be used to estimate crop nitrogen abundance and deficiency, and the accuracy is high. The hyperspectral technology overcomes the shortcomings of discontinuous band and insufficient information in wide band, which makes the accuracy of rapid nondestructive detection of crop nitrogen content greatly improved. But at the same time, there may be a problem that massive data has not been fully utilized. It is necessary to explore more spectral analysis methods in future research to mine the effective information in hyperspectral data [11]. Luo et al. used the image of rice leaves to map the nitrogen content of a single plant, which intuitively displayed the component information distribution of a single leaf. The crop nitrogen content monitoring model based on leaf hyperspectral data has high accuracy, but the model is not unified and ignores the vertical distribution form of crop canopy, which is not suitable for other forms of the crop nitrogen prediction and has certain limitations [12]. Sun et al. believe that because the surface spectral source is mixed composite information, the canopy spectrum is mainly determined by plant biochemical components, LAI, light layer structure, soil background and other factors. People take a variety of means to process the spectrum to improve their ability to identify target information and the accuracy of the monitoring model [13].

2. Method

2.1. Image Color Feature Information Extraction. The extraction of image color features is the process of converting image data into digital data. It is the necessary data basis for the diagnosis of pear nitrogen nutrition by using pear canopy image information [14]. The processing process includes two steps: image preprocessing and color feature extraction. Image preprocessing includes image filtering and image segmentation. The extraction flow chart of image feature information is shown in Figure 2.

At present, digital image technology is widely used in crop scientific research, including crop shape information extraction, image segmentation, foreign object recognition, crop identification, nutrition diagnosis, and so on. The color value information of the image should be considered in the process of image processing [15], especially in crop nutrition diagnosis based on image color feature information.

In this study, a unified standard fixed shooting mode was adopted in the process of obtaining pear canopy images. On the one hand, the interference of random factors is inevitable, and the inherent information of pear canopy will be affected by the change of image brightness and the interference of environmental noise; On the other hand, an important step in canopy image processing is to remove irrelevant background information in the image, such as soil and shadow. [16]. Therefore, preprocessing the original image obtained in the field is a very important link in the application research of digital image technology.

By selecting an appropriate threshold limit T, the target image and the background image are divided into two different threshold intervals. When the threshold of image pixel $f(x, y) \leq T$, the point is defined as the target area point, and when the threshold $f(x, y) > T$, the point is defined as the background area point. The calculation formula can be expressed as:

$$\begin{aligned} T(x, y) &= 1, \quad f(x, y) \leq T, \\ T(x, y) &= 0, \quad f(x, y) \leq T. \end{aligned} \tag{1}$$

Among them, the set of $T(x, y) = 1$ is the target image area, and the set of $T(x, y) = 0$ is the background image area.

In this paper, the segmentation object contains green leaves, shadows, soil, withered grass, and a sun plate. The final research object is the green leaves, and the gray value difference between the leaves and the background is obvious, so the threshold segmentation method based on gray value is adopted. The image segmentation processing flow is shown in Figure 3.

Otsu method is used to calculate the segmentation threshold, which can be realized by the graythresh operation of its own function in the MATLAB software function library. Through the formula analysis of a high discrete probability density function, as shown in the following formulas:

$$p_r(r_q) = \frac{n_q}{n}, \tag{2}$$

$$q = 0, 1, 2, \ldots, L - 1, \tag{3}$$

in the formula, n is the total number of pixels in the image, n_q is the number of pixels with gray level r_q, and L is all gray levels in the image. Suppose we set a threshold value k, C_O is a group of pixels with gray level $[0, 1, \ldots, k - 1']$, and C_1 is a group of pixels with gray level $[k, k + 1, \ldots, L - 1]$. The Otsu

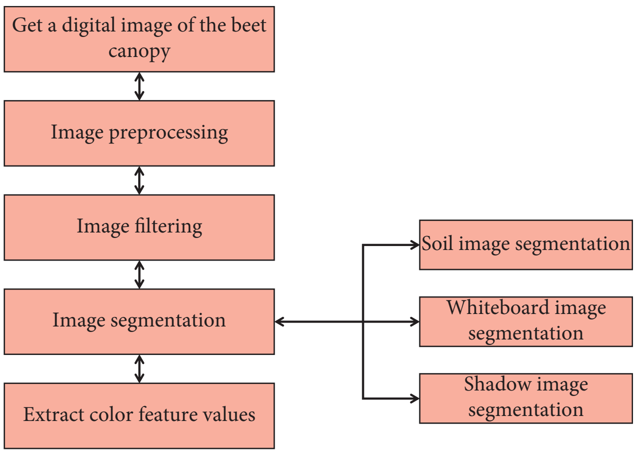

Figure 2: Flow chart of image color feature information extraction.

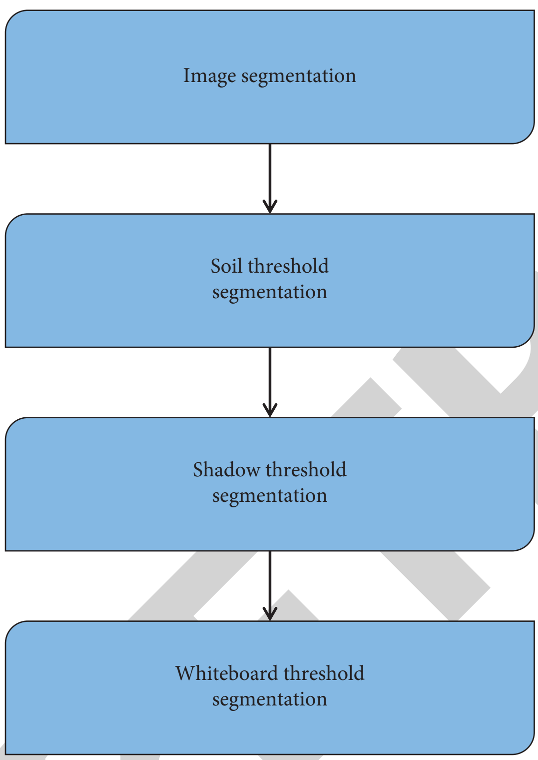

Figure 3: Flow chart of image segmentation.

method selects the closed value k of the maximum interclass variance σ_B^2, and the interclass variance formula is expressed as:

$$\sigma_B^2 = \omega_0 \left(\mu_0 - \mu_T\right) + \omega_1 \left(\mu_1 - \mu_T\right)^2. \tag{4}$$

The function graythresh finds the threshold of maximizing σ by calculating the histogram of—images. The threshold returns a normalized value between 0.0 and 1.0. The calling syntax of function graythresh is:

$$T = \text{graythresh}\left(f\right), \tag{5}$$

where f is the input image and T is the generated threshold.

2.2. Hyperspectral Vegetation Index. A vegetation index is a combination of spectral data in different bands, which can reflect crop growth and can be used to estimate a series of biophysical and biochemical parameters. It has been successfully applied to the estimation of plant nitrogen content, LAI, biomass, and chlorophyll. Vegetation index information can better reflect the plant growth status [17]. Researchers have successfully applied it to the analysis of crop nutrition status. Referring to the previous research results, this study selected some representative vegetation indexes with better application analysis results and processed the data to diagnose the nitrogen nutrition of pear trees.

In order to establish a better correlation between vegetation index and nitrogen, SPSS data analysis software is used to select modeling set data, combined with multiple stepwise regression to establish a multiple linear regression equation. The established multiple stepwise regression equation is as follows:

$$\hat{y} = -5115.844 - 765.20x_{\text{NDRE}} + 128.81x_{R-M}, \tag{6}$$

where $\hat{y}$ is the nitrogen content; x_y is the data corresponding to the selected vegetation index (λ).

The results show that the combination of multiple stepwise regression can improve the accuracy of nitrogen diagnosis the correlation has been greatly improved and the prediction accuracy of canopy nitrogen content has been greatly improved. Figure 4 shows the verification results of the vegetation index combined with SMLR on the nitrogen content of pear trees in the verification set data [18].

2.3. Migration and Residual Law of Nitrate Nitrogen in Different Soil Layers. In addition to being absorbed by crops, some soil residual nitrogen continues to remain and move in the soil. However, from the dynamics of 0–100 cm soil water during the growth period, with the passage of time, due to the influence of crop water consumption and soil surface evaporation, the overall trend of soil profile water is wavy and gradually depleted [19]. Moreover, due to the water absorption of crop roots, the water depletion of the lower layer is serious, and there is no obvious free water flow through the depth of 100 cm of the soil profile. Therefore, there will be no strong leaching of NO3-N in the crop growth season, and the marked nitrate nitrogen does not migrate out of the root zone with the water mass flow. There were significant differences in the distribution of labeled nitrogen in each layer of the profile after harvest. Both the residual nitrogen in the upper part of the soil profile and the residual nitrogen in the lower part of the soil profile moved downward under the action of soil moisture, and formed a cumulative peak at a certain position. The accumulation peaks of 15 and 45 cm labeled nitrogen of the two pear varieties appeared at 60–80 cm of the soil profile, which was directly related to the two times of irrigation in the rejuvenation period and flowering period, so that the labeled nitrate nitrogen migrated significantly with the water and mass flow [20]. There was almost no accumulation peak of labeled nitrogen in the section at 15 cm after harvest, and the % ndff value of the whole section was very low. The

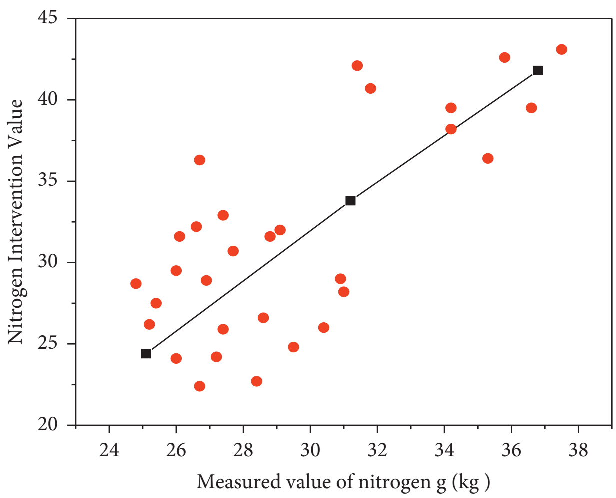

FIGURE 4: Verification results of vegetation index combined with SMLR nitrogen prediction value.

accumulation peak of 45 cm labeled nitrogen also appeared at 60–80 cm of the soil section. The CM labeled nitrogen of the two crops did not migrate significantly only diffused downward about 20 cm centered on the labeled area, and the accumulation peak appeared at 80–100 cm of the soil profile. Due to the water absorption of crop roots, the water in the lower layer moves upward, and the residual nitrogen in different marker positions moves upward. 15.45 cm labeled nitrogen moved up to the surface layer in the soil, and the upward distance was 15 cm and 45 cm, respectively. The soil marker nitrogen at the depth of 75 cm moved up to 40 cm and 35 cm. It shows that the deeper the level of residual nitrogen marker, the weaker its redistribution ability in soil and the more concentrated the residue.

3. Experimental Analysis

The experimental site is located in the digital pear garden experimental base of the 16th regiment of the first division in southern Xinjiang, which belongs to a typical temperate continental arid climate. The buried depth of groundwater is 15 m, and the precipitation is mainly distributed from July to August. During the pear test period, the precipitation from October 2017 to September 2019 was 204 mm, which was 86 mm higher than the average precipitation in previous years. The soil of the test site is alluvial tidal soil in the Piedmont Plain [21]. According to the fertility classification standard of Southern Xinjiang, the test site belongs to high fertility soil.

3.1. Experimental Scheme. The experiment was designed with multiple factors. The main treatment is the marking position, and three ^{15}N marking positions are set, that is, 45, 75, and 105 cm away from the surface. The by-treatment is crop species and varieties, namely pear trees, including 2 varieties of pear trees. There were 9 treatments in total, and each treatment was repeated 3 times. The microarea is $1\,m \times 1\,m$ and the interval between cells is 1 m to prevent mutual influence between cells. Because the crops planted in the previous seasons of the test plot are consistent with the fertilization and other factors, the test microarea is small, so the square gradient of the soil will not be considered. The field experiment arrangement adopts crop species or varieties as the district group. There are 3 ^{15}N marker positions in the district group, for a total of 9 microareas, which are randomly arranged [22]. At the same time, a $2\,m \times 2\,m$ dynamic sampling area of pear trees is set. The crop variety, sowing rate, and fertilization method are the same as those of the ^{15}N microarea, but the ^{15}N mark is not made, and it is also repeated 3 times, for a total of 9 plots.

3.2. Marking Method. ^{15}N in the treatment microarea 15 cm away from the ground surface, drill 4 holes vertically between the crop rows with a soil drill to 15 cm of the soil layer, place a PVC pipe with an inner diameter of 0.5 cm and a length of 15 cm in each hole, inject 4156 g potassium nitrate dissolved in 10 ml water into it, and then rinse the appliance with 40 ml water for 4 times. Then backfill and compact the soil in the soil drill according to the original state, and mark the injection position with a marker post. The ^{15}N marking method of the other two treatment microareas is the same except that the drilling depth is 45 and 75 cm of the soil layer, respectively [23].

The test data were statistically analyzed and analyzed for variance according to ANOVA program (LSD test $p < 0105$) in SAS software (version 6112) and *t*-test in Excel [24].

3.3. Result Analysis. With the deepening of ^{15}N marker level, the uptake of ^{15}N marker by aboveground parts of crops decreased significantly, and there were significant differences among the three marker treatments (Tables 1 and 2). It shows that pear trees have a high ability to absorb nitrate nitrogen in soil profile under the experimental conditions. Pear trees have significant differences in the total absorption of soil profiles marker ^{15}N, resulting in very significant differences in the utilization of soil marker nitrogen. The utilization rate of labeled nitrogen in different positions of the soil profile decreased significantly with the deepening of the soil profile depth. The utilization rates of labeled nitrogen at 15, 45, and 75 cm of soil profile were 28.2%, 22.3%, and 16.3%, respectively. The utilization rates of marker nitrogen of pear variety Xiaoyan 54 were 21.8%, 17.4%, and 11.5%, respectively, while those of Jing 4.1 were 21.8%, 11.6% and 7.4%. The difference of crop utilization rate of labeled nitrogen at different positions of soil profile also reached a very significant level ($p < 0.01$), but there was no interaction between crop and labeled position.

Canopy reflectance spectrum can reflect the nonpoint source information of crop population, which has good representativeness. In addition, plant hyperspectral has the characteristics of continuity and precision and has a stronger ability to detect the physical and chemical parameters of the pear canopy. On the basis of previous studies, making full use of hyperspectral parameters such as REPle, MND705, SDR/SDB, and FD742, which are sensitive to chlorophyll and biomass of different vegetation, a hyperspectral model

Table 1: ^{15}N absorption and utilization rate of aboveground parts treated with different markers.

Utilization (%)		
N	Pear	
28.2a	21.8a	21.8a
22.3b	17.4b	11.6b
16.3c	11.5c	7.4c
22.3	16.9	13.6

Table 2: Nitrogen uptake and utilization.

Tagged depth		*N* absorbed dose	
		Small weir 54	411
15	2.80a	2.18a	2.18a
45	2.23b	1.74b	1.16b
75	1.63c	1.15c	0.74c
Mean value	2.22	1.69	1.36

which can well monitor the nitrogen nutrition status of pear leaves in the later stage of jointing and filling was established. The model test results show that the model can eliminate or reduce the impact of different nitrogen levels, varieties, growth periods, and differences between different years on the model estimation, has good accuracy and universality, and has important application value in pear nitrogen monitoring and diagnosis [25]. In order to solve the shortcomings of the prediction model of protein content based on plant nitrogen nutrition and the method of inferring protein content by leaf color card, a prediction model that can really calculate protein content quickly and accurately without damage is constructed. In this study, the protein content prediction model based on plant nitrogen nutrition with a strong agronomic mechanism and the plant nitrogen nutrition monitoring model based on hyperspectral remote sensing with physical principles were linked, and the prediction model of pear grain protein content based on hyperspectral characteristic parameters was established. The prediction error was about 8%, and the results were accurate and reliable.

4. Conclusion

Based on the ground hyperspectral remote sensing and digital image information, this paper studies the nitrogen diagnosis methods of pear trees, analyzes the research progress of crop nitrogen nutrition diagnosis at home and abroad, and, combined with the characteristics of digital image data and visible near-infrared spectrum data collected in the field experiment in this study, establishes a pear nitrogen diagnosis model based on visible near-infrared spectrum and digital image information, so as to further establish a complete field pear nitrogen fertilizer recommendation system. Nitrogen is an important component of organic nitrogen-containing substances such as amino acids, proteins, nucleic acids, coenzymes, chlorophyll, hormones, vitamins, and alkaloids in plants. It is not only the structural material of cells but also the basis of material metabolism. Its content directly affects the growth and development process of fruit trees and the formation and quality of fruits. Therefore, it is of great significance to accurately grasp the nitrogen content in soil and leaves through nutritional diagnosis.

In this study, only one pear variety test sample was studied. Due to the different genetic characteristics of each pear variety, the external characteristics of different nutrient supply modes will also be different. At the same time, there are many kinds of nutrient elements that affect the growth of pear trees. The differential supply mode of these nutrient elements will also have a differential impact on the growth of pear trees, and the absorption of one nutrient element will also affect the absorption of another nutrient element. Especially for the changes of pear growth characteristics under different nutritional conditions of nitrogen, phosphorus, and potassium, it is necessary to further study and summarize diagnostic rules and quantitative experience in order to identify nutrition more accurately.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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