Identification of corn and weeds on the leaf scale using polarization spectroscopy

Lin Fenfang[1,2], Zhang Dongyan[2,3], Wang Xiu[3], Wu Taixia[4], Chen Xinfu[5]

(1. School of Geography and Remote Sensing, Nanjing University of Information Science & Technology, Nanjing 210044, China; 2. Anhui Engineering Laboratory of Agro-Ecological Big Data, Anhui University, Hefei 230601, China; 3. Beijing Research Center for Information Technology in Agriculture, Beijing 100097, China; 4. Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing 100101, China; 5. Fujian Vocational College of Agriculture, Fuqing 350007, China)

Abstract: In order to explore the feasibility of accurate identification between crop and weed species using polarization spectroscopy, Field Imaging Spectral System (FISS) was utilized with a polaroid configuration to collect imagery data of corn and five kinds of weeds in the laboratory. Through comparisons and analysis of spectral response curves, characteristic difference and identification model accuracy between corn and weeds under four polarization angles, it was found that there was a consistency for spectral changing trends between corn and five kinds of weeds, and the spectral intensity of corn and weeds displayed highest in the no polarization status. Moreover, the selected sensitive bands under four polarization conditions to distinguish corn and weed species indicated that there were similar characteristics, as well as some differences. Finally, for overall accuracy of the identification models between corn and weeds, and the corresponding Kappa coefficients were all more than 90% . The accuracy was the highest, close to 100%, when data were measured at 0° polarization angle. Therefore, polarization technology can be used to identify corn and weeds on the leaf scale, providing an important data foundation for further application on a field scale.

Key words: FISS; polarization characteristics; identification model; corn; weed

CLC number: TP97 **Document code:** A **DOI**: 10.3788/IRLA201645.1223001

基于偏振光谱的叶片尺度下玉米与杂草识别研究

林芬芳[1,2],张东彦[2,3],王 秀[3],吴太夏[4],陈新福[5]

(1. 南京信息工程大学 地理与遥感学院, 江苏 南京 210044; 2. 安徽省农业生态大数据工程实验室 安徽大学 , 安徽 合肥 230601; 3. 北京农业信息技术研究中心, 北京 100097; 4. 中国科学院遥感与数字地球研究所, 北京 100101; 5. 福建农业职业技术学院,福建 福清 350007)

收稿日期:2016-04-17; **修订日期**:2016-05-20

基金项目:高等学校博士学科点专项科研基金新教师类(20123228120004); 公益性行业(农业)科研专项 (201303031); 国家自然科学基金(41301505, 41301471)

作者简介:林芬芳(1980-), 女,讲师,博士,主要从事农业定量遥感方面的研究。Email: linfenfang@126.com

通讯作者:张东彦(1982-), 男,副教授,博士,主要从事高光谱技术应用方面的研究。Email: hello-lion@hotmail.com

摘 要：自然界中不同种物质拥有不同的偏振特性，这些特征信号能用于检测不同的目标地物。为了探索偏振光谱技术用于精确识别作物和杂草的可行性，此研究利用配置偏振片的成像光谱仪 FISS-P 在室内采集玉米与 5 种杂草的偏振光谱影像。通过比较和分析 0°、60°、120°和无偏 4 种状态下玉米与各种杂草的光谱响应规律、光谱特征和决策识别模型精度，结果显示 4 种偏振状态下玉米和杂草的光谱变化趋势较一致，无偏状态下玉米和杂草的光谱强度最大；不同偏振状态下玉米和杂草的敏感波段既存在共性又表现出一定的差异性；4 种偏振状态下玉米杂草识别模型的总体精度和 Kappa 系数均达到 90%以上，其中，0°偏振状态下玉米和杂草识别模型的整体精度最高，接近 100%。综上，偏振光谱能够在叶片尺度较好地识别玉米和杂草，这为田间尺度进一步应用提供了扎实的数据积累。

关键词：FISS； 偏振特性； 识别模型； 玉米； 杂草

0 Introduction

Weeds are one of important environmental factors for crop growth and development, reducing the production and quality of crops. With the development of large-scale agricultural production, methods for effectively controlling weeds based on accurate weed identification have become a hot topic. Currently, there are two common methods of weed identification –machine vision and optical remote sensing[1-2]. Hyperspectral remote sensing data have been adopted for weed identification. Hyperspectral remote sensing with high spectral resolution can distinguish crop and weed species by their differences of reflected electromagnetic radiation in certain characteristic wavebands or spectral ranges[3]. Hyperspectral remote sensing data include both non-imaging and imaging data. The former identifies crop and weed species only by spectral information for the targets, while the later with high spatial resolution and high spectral resolution is a new way for detecting crop and weed species. Main process of both methods is to find different spectral signatures for crop and each weed in the visible near-infrared range as sensitive bands, and then construct a spectral index with these sensitive bands to identify them [4-5]. But the differences between spectral signatures of the crops and weeds are subtle and difficult to detect, which affects the identification accuracy[6-7]. This is because the reflection mechanisms of green plants are basically the same in the visible near-infrared bands. One of solutions is increasing information during the remote sensing process, one of which is polarization remote sensing.

Light has polarization characteristics. Thus, during reflection, scattering, transmission and emission of electromagnetic radiation of objects, the polarized properties will appear due to their own unique characteristics. This means that polarized information contains signals related to objects [8]. In addition, different substances have different polarized properties, which can make up for the shortage of traditional remote sensing and enrich radiation information of target objects. Different plants have different polarized reflection properties, which are related to the waxy coating, surface texture, surface roughness, moisture content, and physicochemical properties of leaves, as well as morphological and physiological parameters of the vegetation canopy and so on[9-11]. Raven et al. collected polarized spectra from different kinds of leaves and found that different kinds of plants have different polarized properties[12]. In addition, Vanderbilt et al. researched polarized properties of leaves belonging to various crops, finding that degrees of polarization of reflected light contain surface and internal information of leaves. This shows that polarized information can be used to identify species [13]. Sidko et al. indicated that there are differences between the polarized properties of coniferous and broad-leaved trees[14]. Zhao et al. researched polarized properties (the degree of polarization, the polarization angle, etc.) of leaves, and found the polarized reflectance of different leaves with different bands or angles of incidence with different types of lighting or different measurement conditions had general characteristics. When the polarization angle is 0°, the value of the reflectance is the maximum; when the polarization angle is 90°, the reflectance has the minimum value. The peak values has azimuth of 180° [15]. Song et al. analyzed quantitatively the polarized reflection properties of leaves from deciduous trees [16]. Zhu et al. showed the nutritional status of single leaves with polarization hyperspectra[17].

These studies explored polarized properties of leaves, which provide a new idea for the identification of different plants in agriculture. However, there are few studies that focus on identifying crops and weeds using polarization spectra and comparing polarization spectral differences between them with different polarization angles. Thus, in this paper, the polarization spectral properties of crops and five types of weeds with different measurement angles were analyzed, and the advantage of this technique used for accurate weed identification was discussed.

1 Materials and methods

1.1 Equipment

The Field Imaging Spectrometer System (FISS), including a polarizer unit (FISS-P), was used to gather the data. The FISS-P is an enclosed optomechanical subsystem that includes a CCD camera with area array detectors and a cooling device, a dispersing unit with a "prism-grating-prism" element, an objective lens and a scanning mirror[18]. The polarizer unit was mounted in front of the scanning mirror[8]. A high-contrast and high-transmission polarizer film in the visible near-infrared bands was chosen as the polarizer. The system has 344 spectral channels, and the spectral sampling interval is about 1.4 nm. Furthermore, the spectral resolution is 4-7 nm. The main technical parameters and performance of the FISS-P are shown in Wu et al[19].

1.2 Data collection

Samples were picked from the National Demonstration Base for Precision Agriculture, including corn (Zea mays *L.*), lobedleaf pharbitis (Pharbitis nil *L.* Choisy), redroot amaranth (Amaranthus retroflexus *L.*), purslane (Portulaca Oleracea *L.*), lambsquarters (Chenopodium album *L.*) and roundleaf Pharbitis (Pharbitis purpurea *L.* Voigt). Corn belongs to the family poaceae with a dark green surface and cilia on both sides. There is trichome on the reverse side of the lobedleaf pharbitis. Redroot amaranth has pubescence on both sides and the edge. Purslane has a bright smooth surface without trichome. For lambsquaters, there is no powder above the blade, and there are powder particles below the blade. Regarding the roundleaf Pharbitis, the whole plant is covered with short pubescence and backward hirsute.

The whole sample was picked before the sun went down, and was quickly transferred to the room. A certain number of fully expanded leaves of the corn and weeds plants were picked, wiped up and placed on the black fabric surface, which were used for polarization imaging. In addition, to make the radiative correction for the original DN (digital number) data, a small round whiteboard was placed in the imaging range, which was collected as the polarization image of the sample. After all the preparation work was done, the polarized hyperspectral images of the leaves were collected using the FISS-P. The polarizer was rotated, with the lens spaced at a 60° angle to obtain polarized hyperspectral images at three angles (0°, 60° and 120°). The optical axis parallel to the ground was defined as 0°, and 60° and 120° were clockwise. In addition, the spectral images of the corn and weeds without the polarizer were collected for comparison.

1.3 Research methods

1.3.1 Data preprocessing

The collected spectral images had noise. To ensure accuracy of the data analysis, the original images should be preprocessed. Data preprocessing includes denoising and data normalization. The noise is caused by the measurement environment, the equipment, illumination and other factors. The spectral images were denoised using the method of combining Minimum Noise Fraction (MNF) and wave filtering [20]. After forward MNF transformation, the main component at the front of the steep turn curve was selected and processed by the adaptive wave filtering. Then, they was inversely transformed by MNF. To compare and analyze spectral signatures of the corn and weed species with the same spectral background, the reference whiteboard was used for the normalization of the imaging data, which were achieved by the Flat Field method of ENVI software.

1.3.2 Data dimensionality reduction

The sensitive band was selected using the Segmentation Principal Component Analysis (SPCA)[21]. With this method, the original hyperspectral data was divided into several subspaces by calculating the relevant matrix, and PCA transforming was done for every subspace. Then, the contribution rates (the square of the correlation coefficient between each band and the main component) were calculated to select the best sensitive band in each subspace. Compared with PCA, SPCA retains physical properties of the corn and weeds well.

1.3.3 Identification model of decision tree

C5.0 is known one of a number of decision tree algorithms. This method was proposed by Quinlan and developed based on C4.5. Its construction method is that if the inspection is selected, which makes the measurable progress maximum, and current training samples are classified, other options will not be explored. The criterion about metrics of progress is partial; the criterion of gain selection is based on the available information about step identification from given data. In contrast with other common decision tree algorithms, C5.0 based on proportional gain proposed by introduced the concept of proportional gain when looking for the suitable classified property, which is based on information entropy and information gain.

The proportional gain criterion shows the proportion of useful information generated by classification, which is useful for classification. To ensure that the rules from the obtained decision tree model are common and to prevent overtraining, growth of the tree should be controlled which means that the tree should be pruned. Two pruning methods are adopted to construct the decision tree model in C5.0. One is pre-pruning, and the other is post-pruning. Pre-pruning prunes the tree by no longer splitting on the given node or classifying the subset of training samples; Post-pruning will prune the tree after it is fully-grown[22-23]. In addition, C5.0 has the boosting integration technology, which can generate a set of classifiers. In this paper, the samples were classified as 65% training samples and 35% inspection samples, and boosting integration of 10 classifiers and pre-pruning were adopted.

2 Results and analysis

2.1 Spectral response of the corn and weed species with different polarization patterns

Spectral characteristics of leaves are the basis for identifying plants by remote sensing. The leaf thickness, surface properties of the blade, moisture content, chlorophyll content and other pigment contents are different for different types of plants. Thus, their spectral response characteristics are different. Figure 1 shows the spectral response curves of the corn and weeds with different polarization patterns. The shape and trend of the spectral curves of the corn and weeds under four polarization patterns (polarization angle of 0°, 60°, 120° and without polarization) are similar. The curves have a peak around 550 nm, and then drop. At 700 nm, curves have a sharp rise. Then, they have a slight drop after 760 nm. As shown in Fig.1, under these three polarization patterns (polarization angle of 0°, 60°, 120°), the order of the spectral response curves of the corn is consistent with that of the weed, from top to bottom, the roundleaf pharbitis, redroot amaranthus, lobedleaf pharbitis, purslane, lambsquarters and the corn. In the visible range, especially at the point reflecting green light, curves of the corn and five types of weeds can be obviously separated, and have little overlap. However, curves of the corn and weed species have much overlap without polarization. In the near-infrared range, curves of the corn and weed species have little overlap under four polarization patterns, but the order of normalized values is different with that in the visible range, and identification levels between them are obviously different. Thus, the spectral response under polarization is different with and without polarization, which provides theoretical support to the application of the polarization spectrum for plant identification.

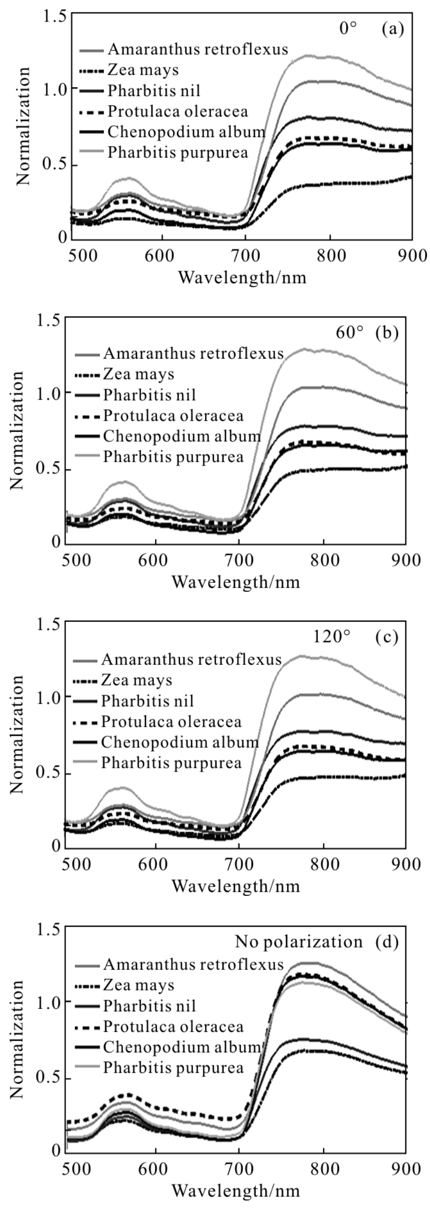


Fig.1 Spectral response curves of the corn and weeds with different polarization angles

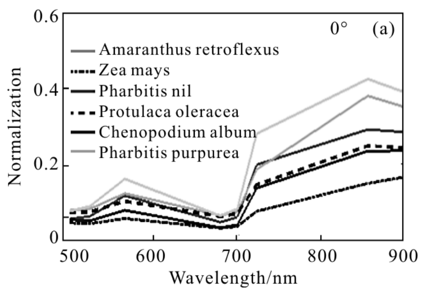
2.2 Sensitive band extraction of the corn and weeds with different polarization patterns

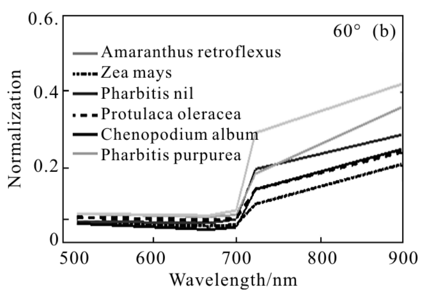
The hyperspectral data have many bands, which contain the useful information about target identification and other redundant information. The data dimensionality is reduced to solve this problem and extract the unique spectral signature of the target identification. The sensitive bands of the corn and weeds with different polarization patterns were extracted using SPCA, as shown in Tab.1. They are mainly concentrated in the visible and near infrared bands. In addition, the blue light band 495-506 nm, red light band 665-678 nm and 694-707 nm, near-infrared band 880-898 nm are sensitive bands ranges with four polarization patterns (polarization angle of 0°, 60°, 120° and without polarization). Red light band 711-721 nm is the sensitive band range with three polarization patterns (polarization angle of 0°, 60°, 120°). The 518-520 nm is the sensitive band with two polarization patterns (polarization angle of 0° and without polarization). From the difference of the sensitive bands, the green light wavelength 562 nm and the near-infrared wavelength 856 nm are the unique sensitive bands for the corn and weed species with a polarization angle of 0°; the sensitive band of green light does not appear with a polarization angle of 60°; the green light wavelength 542 nm is the unique sensitive band for the corn and weeds, with a polarization angle of 120°; the green light wavelength 620 nm and the near-infrared wavelength 833 nm are the unique sensitive bands for the corn and weeds without polarization.

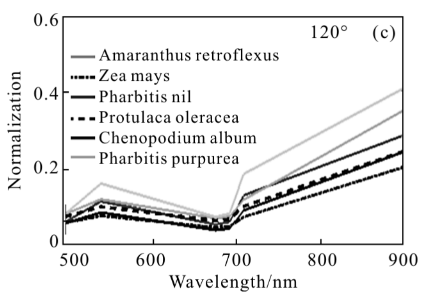
Tab.1 Sensitive band statistics of the corn and weeds with different polarization patterns (Unit:nm)

0°	60°	120°	No polarization
495	506	500	495
520	665	542	518
562	698	678	620
678	721	694	672
698	898	711	707
721	–	898	833
856	–	–	880
898	–	–	–

Figure 2 directly shows the identification levels of the corn and weed species at sensitive bands with different polarization patterns. When the polarization angle is 0°, the corn and five types of weeds can be identified at sensitive bands, especially in the green light band 562 nm, red light band 721 nm and near-infrared band. However, the purslane and lambsquarters is difficultly identified in these band. When the







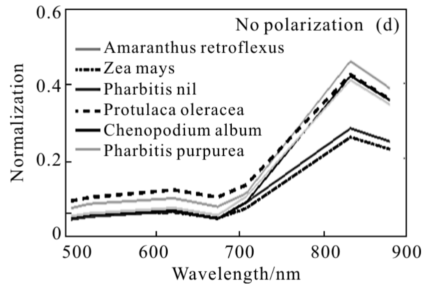


Fig.2 Spectral response curves of the corn and weeds with different polarization patterns at sensitive bands

polarization angle is 60°, the corn and other types of weed identification are difficult in the 490–699 nm band, and becomes easier after the 700 nm band, while the purslane and lambsquarters identification is still difficult. When the polarization angle is 120°, the identification of the corn and five types of weeds is similar to that having a polarization angle of 0°, while the identification level is lower. When there is no polarization, the identification level of the com and five types of weeds at sensitive bands is different from that of the other three polarization patterns; And the identification of the corn and other types of weeds is difficult in both the visible band and the near-infrared band except for purslane and redroot amaranth.

2.3 Construction of the decision identification model of the corn and weeds with different polarization patterns

Taking the extracted sensitive bands as independent variables, the decision identification model of the corn and weed species with different polarization patterns was constructed using the decision tree algorithm, which is shown in Tab.2. Total accuracy and the Kappa coefficient of the four types of models are greater than 90%. Furthermore, the model having the polarization angle of 0° is the best, and the total accuracy and the Kappa coefficient are 98.2% and 0.98, respectively. The accuracy of the decision identification model of the corn and weed species with a polarization degree of 60°, which is the simplest, is similar to that without polarization. Regarding the identification rate for single species of the plants, the user′s accuracy and the producer′s accuracy for corn and other types of weeds are similar in these four polarization patterns, and both of them are greater than 90%, except when working with purslane. This is especially true when the polarization is 0°; In this condition, the identification rates of the corn, lobedleaf pharbitis, redroot amaranth, lambsquarters and roundleaf pharbitis are greater than 96%, with the highest being near 100%.

The differences between these four types of models are as follows: for the identification rate of purslane, the user′s accuracy without polarization is the maximum, which is greater than 98%; when the polarization degree is 0°, its user′s accuracy and producer′s accuracy are 92% and 85%, respectively; when the polarization degrees are 60° or 120°, the user′s accuracy of purslane is great, while the producer´s accuracy is only 62%. The result is consistent with the spectral response rule of the corn and weed species at sensitive bands.

Tab.2 Accuracy estimation of the crop and weed species identification model with different polarization patterns

Plant species	Overall accuracy/%				Kappa coefficient				User′s accuracy/%				Producer′s accuracy/%			
	0°	60°	120°	No polarization	0°	60°	120°	No polarization	0°	60°	120°	No polarization	0°	60°	120°	No polarization
Corn	98.2	96.2	95.5	96.7	0.98	0.95	0.94	0.96	96.4	92.5	90.9	94.0	97.4	94.2	95.1	93.4
Lobedleaf pharbitis									98.5	97.5	97.9	97.3	99.4	98.8	98.2	97.6
Redroot amaranth									98.8	95.1	96.4	97.1	99.1	97.7	97.0	98.8
Purslane									91.8	88.5	83.0	97.9	84.8	63.2	62.0	85.3
Lamb-squarters									1.00	99.6	98.9	99.3	98.2	98.6	98.2	95.9
Roundleaf pharbitis									99.1	99.0	98.1	96.2	98.9	98.9	98.3	97.2

3 Discussion

Different types of plants have unique polarization properties because of different internal structures and compositions, which is the basis for spectral identifications of plants. However, the human eye or common sensors cannot capture this special information. The polarizer is added in the imaging spectrometer′s optical path to generate the linearly polarized light. Then, the spectral properties of the plants are obtained. Light intensity of plants with different polarization angles changes according to surface roughness, particle size distribution and other factors. Thus, it is the theoretical basis of using polarization properties for the corn a nd weed identification. Figure 1 and Figure 2 showed that the trend of spectral change of the corn is similar to that of weed species with four types of polarization patterns, and the spectral intensity of varieties of weeds has the maximum value without polarization. The spectral intensities of the corn and weeds have greater value under 0° polarization degree than that of the corn and weeds when the polarization degrees are 60° or 120°. These results are consistent with ones Zhao et al. found[15-18,24-25]. Since the polarizer blocks a part of the light´s intensity, the reflected light intensity with polarization patterns is relatively weak. In addition, since the corn, lobedleaf pharbitis, redroot amaranth, purslane, lambsquarters and roundleaf Pharbitis have different levels of surface roughness and vein distributions, the differences between the spectral intensities of the corn and weed species are obvious. Thus, compared with no polarization, the spectral curves of the corn and weeds have the same order in three polarization patterns (the polarization degrees of 0°, 60°and 120°).

Plants have different spectral properties at different bands. This is closely related to their structures. There are commonalities and differences between the sensitive bands of the corn and five types of weeds having different polarization patterns. The plants with four types of polarization patterns have common bands, including the blue light band 495 nm, and the red light band 678 nm and 700 nm, as well as the near-infrared band 890 nm, which are typical bands showing the chlorophyll and cell structure of leaves. The result is consistent with previous research[3-5]. Compared with no polarization pattern, the sensitive bands of the corn and weeds with three types of polarization patterns contain a red waveband, which presents the structural difference of the leaves and is one of the important characteristics for diagnosing normality and coercion in green plants. In addition, under the polarization degree of 0° and without polarization, the differences of the sensitive bands for the corn and weeds are in the green light band and in the near-infrared band. The green light band shows the type and content of pigments of leaves, which is useful for identifying plants. The result demonstrate that the model with a polarization angle of 0°is better than the decision tree models with other three polarization patterns. However, the model without polarization has the identification rate of purslane. This is because the purslane leaves developed parenchyma, which stores a large amount of water, while reflection energy without polarization contains much mixed information, including one about the moisture content of leaves.

In this paper, the polarization optics technology was introduced into the crop and weed identification, which provides a new technology for accurate weed identification. As shown by the research, the result is useful for accurate weed identification. However, because of the room measurement, limited weed species, the excavation of polarization properties, field validation and other problems, it needs further validation and research.

4 Conclusion

Compared with traditional multi-spectral remote sensing, hyperspectral remote sensing has many advantages, such as high spectral resolution and many bands. With these advantages, there are spectral properties of certain substances according to different spectral band positions and ranges, which can be used for distinguishing different substances, and achieving the goal of target identification. Polarization is information that most of substances carry during the process of reflection or total scattering. By combining it with hyperspectral remote sensing, object identification can be further improved.

In this paper, polarization images of the corn and five types of weeds with different polarization patterns were obtained using the polarization imaging spectrometer. For these data, the noise was removed using MNF, the spectral signatures was selected with SPCA, and the identification models were constructed by the decision tree algorithm C5.0. Then, we compared these models of corn and weed species identification with different polarization patterns, and analyzed their accuracy. As shown in the research, the trends of spectral changes for corn, lobedleaf pharbitis, redroot amaranth, purslane, lambsquarters, and roundleaf pharbitis are similar in the range of 490 nm to 900 nm under various polarization patterns and no polarization pattern. However, the curves order of the corn and weeds under polarization patterns is different from that without polarization. Compared with no polarization, the curves of the corn and weeds have the same order under the three polarization patterns (the polarization degree of 0°, 60°and 120°).

There are commonalities and differences between the sensitive bands of the corn and weeds having different polarization patterns. It was found that the decision identification models taking the sensitive bands as independent variables all had more than 90% of the total accuracy and Kappa coefficient. However, the total accuracy of the corn and weeds identification model under the polarization degree of 0° is the greatest, which is approximately 100%.

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