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Research Paper

Weed species discrimination based on SIMCA analysis of plant canopy spectral data

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Adoption of a site-specific weed management system (SSWMS) can contribute to sustainable agriculture. Weed classification is a crucial step in SSWMS that could lead to saving herbicides by preventing repeated chemical applications. In this study, the feasibility of visible and near infrared spectroscopy to discriminate three problematic weeds was evaluated. A greenhouse experiment was conducted to classify three common weed species: water-hemp (*Amaranthus rudis*), kochia (*Kochia scoparia*), and lamb's-quarters (*Chenopodium album*). Soft independent modelling of class analogy (SIMCA) method was used to classify these weed species based on canopy spectral reflectance. Five different pre-processing methods were evaluated to remove the irrelevant information from spectral reflectance. Analysis of data indicated that the second derivative pre-processing method applied to NIR (920–2500 nm) spectra was the best to discriminate three weed species with 100% accuracy for 63 test samples. The SIMCA model on NIR wavebands exhibited the highest discrimination power ratio. The results showed the model distance value for most developed classes in NIR range was more than three, which indicated its superior ability to discriminate weed species with low risk of misclassification. Furthermore, the discrimination power of different wavelengths obtained from the best models indicated that 640, 676, and 730 nm from the red and red-edge region, and 1078, 1435, 1490, and 1615 nm from the NIR region were the best wavelengths for weed discrimination.

1. Introduction

Weeds are the biggest threat to crop production because they cause significant yield loss in crops, limit crop rotation choices, and host insects and diseases (Cardina & Doohan, 2000; FAOSTAT, 2014; Slaughter, Giles, & Downey, 2008). Weed management is an important aspect of agricultural production as the economic cost of not managing weeds with herbicide is estimated as $21 billion approximately in the US (Yontz, 2014).

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Nomenclature

Abbreviations

BLW	Broadleaf weeds
BSBC	Best spectral band combination
CCD	Charge coupled device
InGaAs	Indium gallium arsenide
LDA	Linear discriminant analysis
MSC	Multiplicative scatter correction
NIR	Near infrared
PCA	Principal component analysis
PCs	Principal components
PLS-DA	Partial least squares discriminant analysis
SIMCA	Soft independent modelling of class analogy
SNV	Standard normal variate
SSWMS	Site-specific weed management system
UAV	Unmanned aerial vehicles
Vis/NIR	Visible and near infrared
VN	Vector normalization

Variables

A	Number of principal components in the model
a_0	The average value of the sample spectra to be corrected
a_1	The standard deviation of the sample-spectra
d_k	Discrimination power of the variable k
$d\ (r,g)$	The distance between r and g groups
E	Residual variance
e_t	The residual variance vector
F	The Fischer's F-test
L	Loadings matrix
$S^2{}_{total}$	The total residual variance
$S^2{}_u$	Residual variance for the tested sample
T	Scores matrix
$t_i l_i^T$	The ith orthogonal principal components
$\hat{t}_u$	The estimate of the scores vector
X_{cor}	Corrected spectra
$X_{i,\ fsd}$	The first-order derivative at wavelength i
X_{org}	Original sample spectra
X_{ref}	Reference spectrum
X_t	Tested spectra

Herbicide application, which is the most common weed management strategy in US agriculture, provides a convenient, economical, and effective way to control weeds. However, repeated and non-optimal use of herbicides results in herbicide resistance in weeds, excessive waste, herbicide residues in food, and environmental pollution with potential impact on human health, ecosystems, and quality and safety of agriculture products (Gil & Sinfort, 2005; Pimentel et al., 1992).

Weed distribution in fields is non-uniform (Pantazi, Moshou, & Bravo, 2016; Slaughter et al., 2008), with field borders being the most infested by weed patches. Yet, herbicides are applied uniformly across the whole field. Therefore, there is a growing need to identify and map weed distribution in the field to reduce herbicide application by applying only the best herbicide option in the areas that need application. Adoption of a sustainable weed management strategy, such as site-specific herbicide application, can improve the efficiency of herbicide application without diminishing weed control and can play an important role in reducing spraying cost and the pollution of non-target sensitive environments (Slaughter et al., 2008; Weis et al., 2008).

Weed scouting (early detection of weed) and quick target spraying (applying herbicide only on the weeds instead of soil and crop) are two critical key components of a site-specific weed management system (SSWM). Several approaches were reported for weed identification with sensing technologies, visual texture, and spectral characteristics of plants (Pantazi et al., 2016; Tian, 2002). The sensor-based systems include ultrasonic (Andújar, Weis, & Gerhards, 2012), X-ray (Haff, Slaughter, & Jackson, 2011), and optoelectronic (Andújar, Ribeiro, Fernández-Quintanilla, & Dorado, 2011; Biller, 1998) sensors, remote sensing method (Thorp & Tian, 2004), machine vision systems (Burgos-Artizzu, Ribeiro, Guijarro, & Pajares, 2011; Christensen et al., 2009; Piron, van der Heijden, & Destain, 2011; Weis & Sökefeld, 2010), and ground-level hyperspectral imaging (Hadoux, Gorretta, Roger, Bendoula, & Rabatel, 2014; Sui, Thomasson, Hanks, & Wooten, 2008; Vrindts, De Baerdemaeker, & Ramon, 2002). The ability for non-contact detection, simple measurement process, fast response, high reliability, and low power consumption make a spectral discrimination method a simple and easy application procedure that can be used in real-time application systems (Rogalski, 2003; Wang, Zhang, Dowell, & Peterson, 2001). Hyperspectral sensors can capture subtle differences in reflectance obtained from plant species (He et al., 2015).

Spectral reflectance of plant species at canopy or single leaf scale at specific stages is unique and known as the spectral signature. The spectral signature of weed species can be a useful tool for weed identification. Weeds' distinctive colours, phenological stages, and vegetation indices can enhance the differences between weed species as a distinguishing factor to classify weeds (López Granados et al., 2008). In previous studies, researchers demonstrated many spectral reflectance analysis techniques to distinguish weeds from soil background (Scotford & Miller, 2005). Spectral reflectance was successfully employed to identify weeds versus crops when there was a maximum phenological distinction between crop and weeds (López Granados et al., 2008). Identifying critical wavelengths that can effectively discriminate between crops, weeds, and soil is another step in identifying weeds from crops or bare ground (Andújar et al., 2013). Three main steps in the spectral characterization of weed species include developing spectral data pre-processing or reduction methods, building a proper classification model, and validating the best combination of pre-processing with a classification model. To discriminate between crop versus weeds, a stepwise discriminant analysis procedure identified four bands of 572.7, 676.1, 801.4, and 814.6 nm as most suitable for discrimination weeds from maize or sugar beet crop (Vrindts et al., 2002). This method discriminated sugar beet from weeds with 90% accuracy. A partial least squares discriminant analysis (PLS-DA) model was used to classify soil, wheat, broadleaf weed, and grass weed with 85% accuracy (Shapira, Herrmann, Karnieli, & Bonfil, 2013). In the other study, PLS-DA analysis of plant