



SPECTRAL CURVES FOR IDENTIFICATION OF WEEDS IN WHEAT CROP

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ABSTRACT

The principal weeds in wheat cultivation are black oats and ryegrass and their control is generally performed without considering the spatial variability of the density of weed infestation. One way to identify weed species is by analyzing spectral curves of the targets. The objective of this work was to evaluate the spectral curves of wheat, black oats and ryegrass to identify which wavelengths are able to distinguish these species. The experiment was set using the species: black oats, ryegrass and wheat. Each species was sown in individual experimental plots in a completely randomized design with nine replications. HandHeld 2, ASD[®] spectroradiometer with 325-1075 nm spectral range was used to perform readings at full bloom stage. Then, the reflectance spectral data were grouped into eight spectral bands: violet, blue, green, yellow, orange, red, red edge and near infrared. Descriptive statistics of reflectance of the targets as well as analysis of variance ($p < 0.05$) and test of Tukey for comparison of the means ($p < 0.01$) were performed using the reflectance measurement of each spectral band. The results showed that the yellow and orange spectral bands obtained higher capacities of differentiation of the species under study. It can be concluded that the analysis of spectral curves of target of black oat and ryegrass weeds and wheat crop makes it possible to differentiate species in full bloom stage.

Palavras-chave:

bandas espectrais
comprimentos de onda
reflectância

CURVAS ESPECTRAIS PARA IDENTIFICAÇÃO DE PLANTAS DANINHAS NA CULTURA DO TRIGO

RESUMO

As principais plantas daninhas no cultivo de trigo são a aveia preta e o azevém e seu controle de forma geral são realizados sem levar em consideração a variabilidade espacial da densidade de infestação das plantas daninhas. Uma forma de identificar as espécies infestantes é através da análise de curvas espectrais dos alvos. O trabalho tem como objetivo avaliar as curvas espectrais de trigo, aveia preta e azevém para identificar quais comprimentos de onda são capazes de distinguir essas espécies. O experimento foi implantado utilizando as espécies: aveia preta, azevém e trigo. Cada espécie foi semeada em parcelas experimentais individuais, em delineamento inteiramente casualizado, com 9 repetições. Foi utilizado espectrorradiômetro HandHeld 2, ASD[®] com faixa espectral de 325-1075 nm para realizar as leituras no estágio de florescimento pleno. Posteriormente os dados espectrais de reflectância foram agrupados em 8 bandas espectrais: violeta, azul, verde, amarelo, laranja, vermelho, red edge e infravermelho próximo. Foi realizada a estatística descritiva da reflectância dos alvos bem como a análise de variância ($p < 0,05$) e teste de comparação de médias Tukey ($p < 0,01$) utilizando a medida da reflectância de cada banda espectral. Os resultados demonstraram que as bandas espectrais de amarelo e laranja obtiveram maiores capacidades de diferenciação das espécies de estudo. Pode-se concluir que a análise de curvas espectrais de alvos da planta daninha aveia preta e azevém e a cultura do trigo possibilita diferenciar espécies em florescimento pleno.

INTRODUCTION

Weeds usually occupy agricultural systems spontaneously, ultimately interfering with the yield of crops of interest as they compete directly for natural resources, and indirectly by releasing allelopathic substances and impairing harvesting. Species such as black oats (*Avena strigosa* (Schreb)) and ryegrass (*Lolium multiflorum* (Lam.)), which are cultivated in several regions of Brazil, are considered weeds particularly in wheat (*Triticum aestivum* (L.)) crops (LAMEGO *et al.*, 2013).

The chemical method is commonly used in weed control with the use of herbicides. Post-emergence herbicide applications are carried out in total area in most cases, not considering the variability of weeds in agricultural areas.

The over-application of herbicides on areas without weed infestations results in environmental pollution and chemical residues (DASS *et al.*, 2017). Another reason for decreasing the amount of herbicides applied in the crops is the prevention of the rise in cases of weed resistance to the mechanisms of action of the herbicide (HEAP, 2019).

Studies that use sensors to identify weeds in agricultural crops have been intensified in the last years. Targeted weed control can provide a reduction in the use of herbicide (PEÑA *et al.*, 2013; HUANG *et al.*, 2018).

However, in order to conduct weed control in a direct way, its identification is necessary. Successful identification of one weed species compared to another depends on the presence or absence of minimal but measurable differences between species (FEILHAUER *et al.*, 2017). Optical characteristics of the plant, such as contents of pigment, water and dry matter, play a role in how the plant will reflect light and can be manipulated

to discriminate species.

Hyperspectral sensors have a spectral resolution of less than 20 nanometers. They usually characterize the electromagnetic spectrum within the 400-2500 nm range, which encompasses the visible, near and mid infrared areas (MIRIK *et al.*, 2013), which allows the generation of curves of spectral targets (LOUARGANT *et al.*, 2018). In this sense, the objective of this work was to evaluate the spectral curves of wheat, black oats and ryegrass and to identify the most efficient wavelengths in distinguishing these species.

MATERIAL AND METHODS

The experiment was conducted in Santa Maria, state of Rio Grande do Sul in an area owned by the Federal University of Santa Maria (UFSM), within the geographic coordinates 29.7180° S, 53.7375° W and average altitude of 110 m. The climate in the area is classified as Cfa with hot summer (ALVARES *et al.*, 2013). Paleudalf soil prevails in the area under study (EMBRAPA, 2013).

The area in question had been managed under no-tillage system for over six years under the rotation of summer soybean and corn crops and winter crops of black oat and wheat. In relation to the management of the area, desiccation was performed using glyphosate herbicide at a dose of 2,160 g·ha⁻¹ of a.e. (acid equivalent). For application, it was used a CO₂ pressurized backpack sprayer with fan-type tips that provided an application volume of 150 L · ha⁻¹.

The experiment had nine plots for each species, totaling 27 experimental units. Plot dimensions were 5 x 3 m, totaling 15 m², in a completely randomized design (Figure 1).

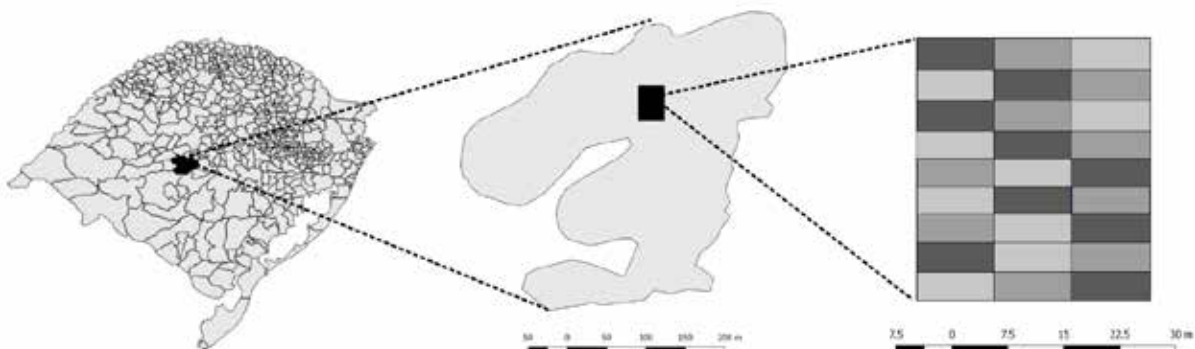


Figure 1. Location and layout of the experiment and experimental units.

The wheat, black oat and ryegrass species were manually sown on June 3, 2017, in a 0.5-m row spacing, with a population of 250,000 plants ha⁻¹. Fertilization was performed in topdressing with application of 200 kg ha⁻¹ of the formula 10-20-20 immediately after sowing. Nitrogen fertilization was also performed in topdressing using 100 kg ha⁻¹, using urea 30 days after the emergence of culture.

The spectral curves were mapped using the HandHeld 2, ASD[®] spectrum radiometer equipment, with wavelengths of 325-1075 nm. This sensor is classified as passive in reference to the source of power for the measurements, with a spectral resolution of 1nm. The wavelength range used for the analysis was 380-900 nm due to the noise at the extremes.

Reading was performed using Spectroradiometer when the crops were in full bloom. First, the equipment was calibrated in white plate so evaluation could be started. Reading of the target species in each plot were carried out. Measurements were made with the sensor in the zenith position in relation to the target, in a target-sensor distance of 0.5 m. The readings were taken when the day was completely clear, with no clouds, around 12h00 p.m. (UTC-3). For each plot, three readings were taken which were subsamples of the 9 plots of each species, totaling 27 readings for each species. Data were extracted from the equipment and previously

analyzed using View Spec Pro software version 6.0, ASD[®].

Spectral data were set at the following band wavelengths: violet (380-450 nm), blue (451-495 nm), green (496-570 nm), yellow (571-590 nm), orange (591-620 nm), red (621-700 nm), red edge (700-750 nm) and near infrared (NIR) (751-900 nm).

Descriptive statistics of reflectance of the target as well as analysis of variance ($p < 0.05$) and the test of Tukey for comparison of the means ($p < 0.01$) were performed using the reflectance measurement of each spectral curve. Graphs were also made to demonstrate the variation of the data observed through quartiles, boxplot. Statistical analyses were performed using R software (R CORE TEAM, 2018).

RESULTS AND DISCUSSION

The readings provided support to generate the spectral curves, which related the wavelengths with their respective reflectances for each target where for certain wavelengths there are larger amplitudes of reflectance differences for the species under study (Figure 2).

Plant reflectance is ruled by the concentration and distribution of biochemical compounds, internal tissue structure, as well as the properties of the leaf surface (GAO *et al.*, 2018). Therefore, differences in pigment concentration, inner structure, leaf

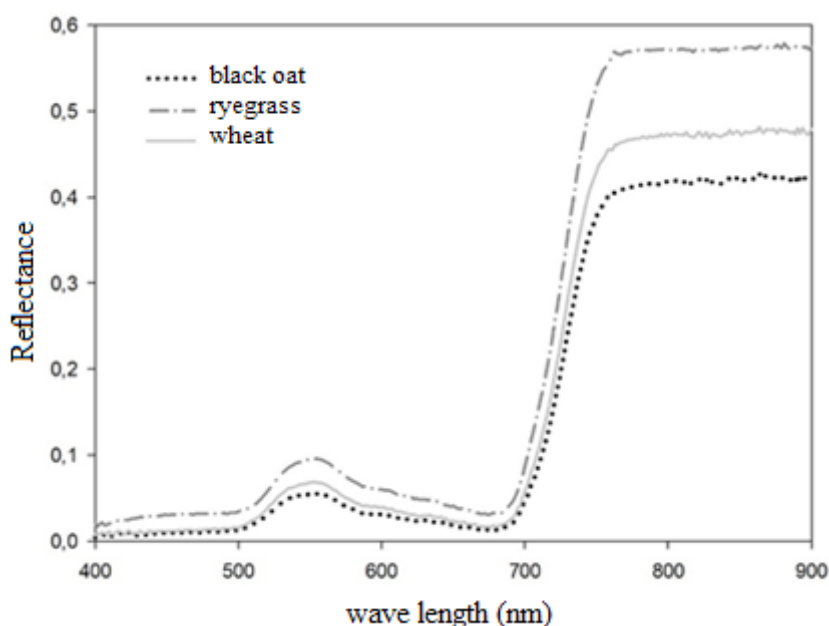


Figure 2. Spectral curves for black oat, ryegrass and wheat at full bloom. n= 27.

shape, among others that interfere with the optical properties allow the differentiation of plant species (LIPPERT *et al.*, 2015; FEILHAUER *et al.*, 2017).

The spectral curves of each species were grouped into the spectral bands for analysis. The descriptive analysis of the spectral bands for each species is shown in Table 1.

The more specific analysis of the spectral bands allows observing the difference in the reflectance they have for each band. It is also possible to

observe that some bands have larger reflectance variations in target readings. The violet band achieved a greater variation of the data obtaining coefficient of variation (CV) of 22.9, 28.0 and 26%.

Table 2 shows the test of Tukey for comparison of the means ($p < 0.01$) showing the yellow (571-590 nm) and orange (591-620 nm) spectral bands with the highest statistical distinctions for the three species, therefore, those are the bands with the best efficiency for their distinctions.

Table 1. Descriptive statistics of spectral band reflectance for the three species under study.

Band \ Species	Black Oat							
	Violet	Bluel	Green	Yellow	Orange	Red	Red Edge	NIR
Mean	0.030	0.046	0.082	0.092	0.088	0.085	0.280	0.453
Median	0.028	0.046	0.083	0.097	0.096	0.093	0.282	0.442
Minimum	0.022	0.030	0.058	0.063	0.059	0.053	0.225	0.393
Maximum	0.045	0.058	0.104	0.112	0.103	0.103	0.331	0.523
SD*	0.007	0.007	0.012	0.015	0.016	0.018	0.027	0.042
CV** (%)	22.9	16.0	15.1	16.8	18.7	21.7	9.6	9.2
Band \ Species	Ryegrass							
	Violet	Bluel	Green	Yellow	Orange	Red	Red Edge	NIR
Mean	0.012	0.016	0.039	0.037	0.029	0.022	0.184	0.332
Median	0.011	0.015	0.036	0.033	0.026	0.020	0.181	0.331
Minimum	0.008	0.012	0.031	0.029	0.024	0.017	0.146	0.265
Maximum	0.017	0.020	0.048	0.046	0.036	0.027	0.220	0.394
SD	0.003	0.003	0.007	0.007	0.005	0.004	0.029	0.051
CV (%)	28.0	20.4	17.5	17.8	17.3	18.9	15.7	15.3
Band \ Species	Wheat							
	Violet	Bluel	Green	Yellow	Orange	Red	Red Edge	NIR
Mean	0.019	0.026	0.067	0.064	0.051	0.035	0.305	0.557
Median	0.020	0.027	0.067	0.062	0.050	0.034	0.320	0.608
Minimum	0.013	0.019	0.057	0.056	0.046	0.031	0.240	0.411
Maximum	0.026	0.033	0.083	0.078	0.061	0.041	0.366	0.668
SD	0.005	0.005	0.008	0.006	0.004	0.003	0.048	0.107
CV (%)	26.0	20.1	12.2	10.0	8.9	8.921	15.8	19.3

*SD= Standard deviation. **CV= coefficient of variation. n=27.

Sensing has been evaluated for distinction of species or group of weed species based on the assumption that each species has certain characteristics that can be used to differentiate it from another, which are usually leaf shape, size and reflectance. Several authors have shown that cultivated plants and crops can be discriminated by using their spectral signature (HUANG *et al.*, 2016; HERRMANN *et al.*, 2013; SHAPIRA *et al.*, 2013).

For an efficient species distinction, it is

necessary that the values of the reflectance of the targets do not match the reflectance of the other species. It can be seen in the graphs below the variation of the reflectance readings for the yellow (Figure 3) and the orange spectral bands (Figure 4). It is observed that the reflectance variation of the three species in the yellow and orange bands do not intersect values, therefore, they are potential bands for differentiation of these species.

The reflectance of the yellow and orange spectral bands is influenced by the type of pigment,

Table 2. Results of the mean comparison analysis for the average reflectance of the bands in the three species under study.

Band Specie	Violet	Bluel	Green	Yellow	Orange	Red	Red Edge	NIR
Black Oat	0.030 a*	0.045 a	0.081 a	0.091 a	0.088 a	0.084 a	0.280 a	0.452 ab
Ryegrass	0.011 b	0.015 b	0.038 b	0.036 c	0.029 c	0.021 b	0.183 b	0.331 b
Wheat	0.018 b	0.025 b	0.067 a	0.006 b	0.050 b	0.034 b	0.305 a	0.556 a

* Different letters in the same column represent significant statistical difference. Tukey 1%.

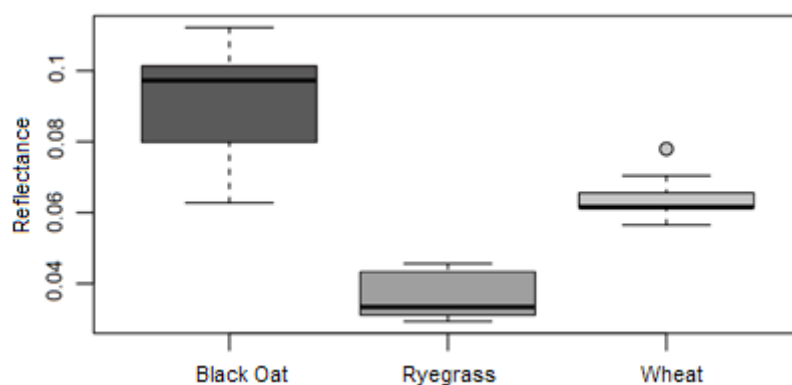


Figure 3. Variation of the reflectance of the targets in the yellow band. n= 27.

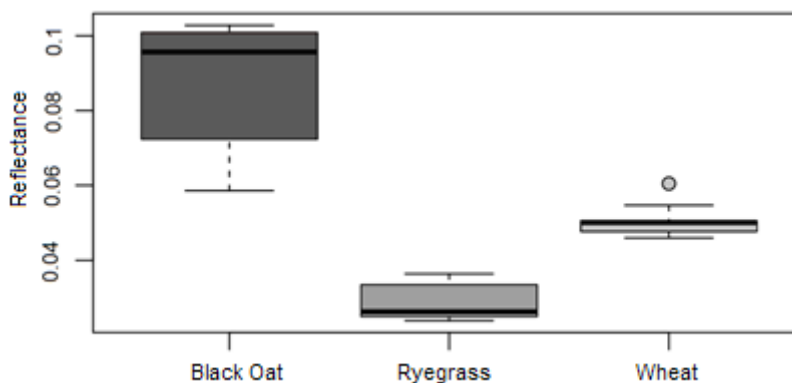


Figure 4. Variation of the reflectance of the targets in the orange band. n= 27.

as well as the amount of the pigment in the leaves (SHAPIRA *et al.*, 2013), which may vary from species to species as well as the development stage of the species.

Several studies using multispectral and hyperspectral sensors have been performed (PEÑA *et al.*, 2013; TORRES-SÁNCHEZ *et al.*, 2013; LÓPEZ-GRANADOS *et al.*, 2016; PEÑA *et al.*, 2015; LÓPEZ-GRANADOS *et al.*, 2016; PÉREZ-ORTIZ *et al.*, 2016) to improve weed control in agricultural systems.

Remarkably, extensive studies are needed to define spectral bands in order to compose bases for site-specific weed management, reducing production costs as well as reducing environmental impacts.

CONCLUSION

- • It can be concluded that the analysis of spectral curves of black oat, ryegrass and wheat plants allows their differentiation in the full bloom stage of the species.
- • Yellow and orange spectral bands have higher spectral differentiation efficiency of black oats, ryegrass and wheat.
- • Hyperspectral sensors are of paramount importance in defining wavelengths or spectral bands for the purpose of identifying distinct targets in agricultural systems.
- • Studies using hyperspectral data of weed and cropped plants provide important information for composing a bank of spectral signatures for weed control in a targeted manner.

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