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ANIMAL PRODUCTION

Airborne cameras for natural grassland classification in the Pampa biome

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ABSTRACT: *The extension of the area occupied by the inter tussock stratum and tussock stratum in natural pastures is essential for the productive performance of grazing animals. Images obtained from unmanned remote sensors can provide useful information, especially because they have a high spatial resolution. Thus, this study evaluated the performance of the supervised adaptive classification applied to aerial images obtained from an onboard drone camera to map the area covered by tussocks in a natural pasture of the Pampa biome. The study was carried out in a natural pasture area managed since 1986 under different forage allowances, considering treatments of 8, 12, and 16 kg of dry matter per 100 kg live weight (% LW). An aerial image from September 2017, obtained with a Canon S100 camera onboard a drone at an altitude of 120 m, with a spatial resolution of 5 cm, was used. The random forest and support vector machine classifiers were tested associated with specific classification rules. False-color images showed considerable visual similarity in the large patterns of the vegetation distribution and the validation performed with independent samples when compared to the classified images. The tested classifiers were able to measure the area covered by the tussock stratum, which could be an indicator of the quality vegetation in a natural grassland of the Pampa biome.*
Key words: *supervised classification, aerial image, forage supply, random forest, support vector machine.*

Câmeras aerotransportadas para classificação da vegetação em pastagem natural no bioma Pampa

RESUMO: *A quantidade de área ocupada por estrato inferior e superior em pastagens naturais tem grande importância sobre o desempenho produtivo dos animais em pastejo. Imagens obtidas de sensores remotos não tripulados podem fornecer informações úteis, especialmente por possuírem alta resolução espacial. O objetivo deste trabalho foi avaliar o desempenho de classificação supervisionada adaptativa aplicada a imagem aérea obtida por câmera a bordo de drone, no mapeamento da área coberta por touceiras em pastagem natural do bioma Pampa. O estudo foi realizado em área de pastagem natural, manejada desde 1986 sob diferentes ofertas de forragem, tendo sido considerados os tratamentos 8, 12 e 16 kg de matéria seca por 100 kg de peso vivo (% PV). Foi utilizada uma imagem aérea, de setembro de 2017, obtida com uma câmera Canon S100, a bordo de um drone a 120 m de altitude, correspondendo a resolução espacial de 5 cm. Foram testados dois classificadores, Random Forest e Support Vector Machine associados a regras específicas de classificação. As imagens de falsa cor, quando comparadas às imagens classificadas, apresentaram considerável semelhança visual nos grandes padrões de distribuição da vegetação, bem como na validação feita com amostras independentes. Os classificadores testados foram capazes de mensurar a área coberta por estrato superior, podendo ser um indicador da qualidade da vegetação, em pastagem natural do bioma Pampa.*
Palavras-chave: *classificação supervisionada, imagem aérea, oferta de forragem, Random forest, Support Vector Machine.*

INTRODUCTION

Animal grazing can be considered indispensable for the maintenance of natural pastures and their biodiversity and has an important role in determining plant physionomy. A high grazing intensity leads to vegetation composed only of the inter tussock stratum dominated by rhizomatous or stoloniferous grasses. The vegetation becomes heterogeneous as grazing intensity decreases, with the development of a double stratum, that is, a inter tussock stratum dominated by rhizomatous species and a Tussock stratum dominated by cespitose grasses and shrubs. These cespitose grasses form

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tussocks that accumulate a lot of biomass, which leads to a reduction in the diversity of smaller species (OVERBECK et al., 2015).

Grazing animals explore the environment and adapt their feeding strategies to the environmental conditions to meet their nutritional needs (BAILEY, 2005), that is, they select their diet according to the available and most preferred forage species. Moreover, grazing intensity is one of the main drivers of pasture dynamics, as it affects the growth of vegetation, pasture structure, and forage nutritional value (PAVLU et al., 2006). The ability of animals to select their diet, together with grazing intensity, shape the pasture structure.

Pasture structure is defined as the distribution and arrangement of the aerial part of plants in the community (LACA et al., 2001), and directly influences the intake of forage by animals (PROVENZA et al., 2007). Thus, the structure of vegetation available to animals is an important factor for the productive performance of grazing animals. The area occupied by tussock in pastures characterized by double strata directly influences the grazing process. According to BREMM et al. (2012), the short-term intake rate of beef heifers was negatively affected when the area covered by the Tussock stratum was higher than 34%, showing that under situations of large areas covered by tussock the animals are faced with decisions about which plant to graze according to the cost-benefit of obtaining.

Considering the influence of the pasture structure on the productive performance of grazing animals, measuring the area covered by the Tussock stratum in natural pastures has a significant contribution to the management and consequent preservation of these ecosystems. It is especially true for the South of Brazil, where natural pastures are the basis of the feed for cattle and sheep. The difficulty associated with this problem is that the different stratum is commonly very similar in terms of appearance, with few attributes available to differentiate them.

A recent alternative for providing information on targets of agricultural interest, such as natural pastures, is images obtained from remote sensors, such as photographic cameras onboard-unmanned aerial vehicles (UAV). The great advantage of using cameras is the high spatial resolution, which allows the study of small targets, such as the identification of leaf diseases in soybean (TETILA et al., 2017) and corn phenotypes (SU et al., 2019). This characteristic, coupled with the increasingly frequent use of this type of image for the most varied fields of science, makes images from cameras become an alternative to be investigated for studies on the pasture structure in natural pastures.

After the image acquisition from cameras onboard UAVs, the challenge becomes the extraction and interpretation of the generated information. The digital classification process is one of the various methods that have been most frequently used. This classification process in digital remote sensing images is equivalent to determining, for each pixel, which category is present on the surface (ZANOTTA et al., 2019). The different responses observed in the image can serve, for example, to differentiate the Tussock and inter tussock stratum in natural pastures.

Several methods can be used for classifying digital images, which are divided into unsupervised and supervised classification methods. The support vector machine (SVM) and random forest (RF) stand out among the supervised classification methods, which use a subset of pixels (sample) as an example of the existing classes (ZANOTTA et al., 2019). The SVM classifier looks for a separate line called a hyperplane between data of two classes. A separation plane maximized the distance between the closest points relative to each of the classes. This distance between the hyperplane and the first point of each class is often called a margin. Thus, SVM defines each point belonging to each of the classes and then maximizes the margin (ZANOTTA et al., 2019). The RF classifier is similar to a decision tree but tends to avoid the phenomenon of overfitting while optimizing the use of sample information. Decision trees are a popular method for various machine-learning tasks. Tree learning is invariable in scale and robust to the inclusion of irrelevant characteristics. RFs are a way of averaging several deep decision trees, trained in different parts of the same training set to reduce variation. It occurs at the expense of a small increase in bias and some loss of interpretability, but it generally greatly increases performance in the final model (ZANOTTA et al., 2019).

The choice among the many classifiers available is not the only procedure task the user needs to define. Also, the number of classes and the quality of the available samples plays a crucial role in the performance of the methods. These definitions will greatly depend on the exact kind of problem faced by the user. Selecting the most appropriate classification technique and the most suitable setup strategy for each particular scenarios will impact positively the results, making the complex problem of differentiating very similar kinds of stratum more straightforward.

This study evaluated the performance of adaptive supervised classifiers applied to images obtained from a digital camera onboard a drone to map the area covered by tussock and inter tussock stratum in a natural pasture in the Pampa biome. The proposed methodology seeks to explore not only complex and modern classifiers for the differentiation between classes but also the optimization of the choice of attributes and adaptation of the technique to the different scenarios present in the environment.

MATERIALS AND METHODS

The study was carried out in a natural pasture area belonging to the Experimental Agronomic Station of the Federal University of Rio Grande do Sul – EEA/UFRGS, located under the geographical coordinates 30°05′27″ S and 51°40′18″ W and 46 m of altitude, in the municipality Eldorado do Sul in the Central Depression of Rio Grande do Sul, Brazil.

The regional climate is classified as humid subtropical (Cfa) (ALVARES et al., 2014). The average annual rainfall at EEA/UFRGS is 1,440 mm, with a monthly average rainfall of approximately 120 mm. The average air temperature varies from 13.5 °C in the coldest months (June and July) to 24.6 °C in the hottest months (January and February). The daily averages of global solar radiation range from 206 (June) to 509 cal cm^{-2} day^{-1} (December) (BERGAMASCHI et al., 2012). Three soil types can be reported in the experimental area, according to the Brazilian Soil Classification System, that is, Planossolo Háplico Distrófico êndico (Planosol), Argissolo Vermelho Distrófico típico (Acrisol), and Plintossolo Argilúvico Distrófico típico (Plinthosol) (MELLO et al., 1966; MACHADO & GIASSON, 2016).

The study area is located in a long-term experiment, composed of 64 ha of natural pasture, which has been receiving the same level of anthropic interference since 1986. The experimental design was randomized in blocks with two replications of area per treatment, which consisted of different forage supplies (FS), that is, fixed over the year and variable in the spring season. The following fixed forage supplies were considered in this study: 8, 12, and 16 kg DM 100 kg^{-1} live weight (% BW) corresponding to the experimental units (EU) 7A, 3A, 5A, 1B, 6B, and 4A, in which each EU represents a treatment. The continuous grazing method with a variable stocking rate (MOTT & LUCAS, 1952) was used to adjust the recommended forage supplies. The carrying capacity was adjusted at intervals of approximately 28 days, according to the forage mass available for grazing in the experimental units. The animals used in the experimental units consisted of beef heifers from crosses between Angus, Hereford, and Nellore breeds, with an average live weight of 244.8 ± 39 kg and the initial average age of 12 months.

The proportion of area covered by tussock (%) was obtained through random sampling, using metal frames of 0.25 m^2. Fifty sites were sampled at each EU, in which the evaluator classified the forage as inter tussock stratum. The proportion of tussock present at the EU was obtained by the proportion of frames that sampled tussock relative to the total number of frames sampled.

An aerial image was acquired in September 2017 by using a Canon S100 camera onboard a drone to obtain the data related to the spectral response of the vegetation that makes up the study area. The camera was altered by adding a vegetation sensor filter, which filters out all the red light and instead allows the near-infrared band, which is normally blocked, to be collected. This manipulation allows a camera to collect light in the near-infrared, green, and blue. This adaptation is considered important in studies involving vegetation, as the near-infrared band is the one that most reflects these targets. The flight was performed at a height of 120 m, with a frontal overlap (in the flight direction) of 80% and lateral overlap (between the flight lines) of 60%. The spatial resolution of the image was 5 cm.

The target classification was carried out using the software MATLAB R2014b by adaptive methodology, derived from exploratory experiments on the classes present in the study area. Samples from each class were collected by visual interpretation and used to train classifiers. The number of samples varied from three to seven, depending on the variability of color hues of each class. The classifiers support vector machines (SVM) and random forest (RF) were tested.

The classification used attributes of brightness and shape/texture of the targets. In the first stage, only brightness (spectral) attributes were used. In the second stage, some combinations also used elements of shape and texture to differentiate spectrally similar classes. The texture attributes used were standard deviation and entropy, as well as shape and size in some specific cases. The result presented measures of accuracy of the classification by re-substitution of sample elements.

The validation was performed through a set of samples collected specifically for this purpose, different from those used in the training stage of the classifiers. Therefore, any contamination or defect of the classifiers is exempt, and the precision results obtained can be considered reliable. The choice of the best classifier (SVM or RF) for each EU was made based on its global accuracy and the visual observation in the classified images confronted with the false-color image (NIR-G-B).

The area covered by each class was quantified by counting the number of pixels belonging to each class, multiplied by the pixel area, generating a total area that is part of the total area of each EU. Subsequently, the results reported through the classification were compared with the data obtained in loco.

RESULTS AND DISCUSSION

For each of the selected tussocks, a set of samples were collected and the best classifier and space of features used (spectral or textural) were individually defined based on the results. There were two different sets of samples, one used for training and selection of the appropriate method, and another for validation purposes (confusion matrix). As expected, the classifier performance and the set of classification features were different according to the EU. The classifier SVM presented the best performance for EUs 3A, 1B, 5A, and 6B and RF for 7A and 4A. These differences are due to the peculiarities of each environment, whose quantities and characteristics of the classes vary. Six different classes were identified: water (WH), shade (SH), tussock stratum 1 (TS1), tussock stratum 2 (TS2), inter tussock stratum 1 (ITS1), and inter tussock stratum 2 (ITS2). Tussock stratum 1 class was observed in areas with dry tussock stratum, while tussock stratum 2 class occurred in areas with tussock stratum in wetlands, presenting water interference in the spectral behavior of this class. The inter tussock stratum 1 class represented the inter tussock green stratum in dry areas, while the inter tussock stratum 2 was classified as the inter tussock stratum in wetlands or areas other than green.

The false-color images obtained from the drone camera showed visual similarities compared to the classified images (Figure 1), showing the quality of the classification performed based on the spectral attributes of the vegetation present in the evaluated EUs.

Table 1 shows the confusion matrices or error matrices, which allows for a quantitative evaluation of the classification precision for each EU. The overall accuracy (OA) of classifiers varied from 75 to 87% at EUs 4A and 5A, respectively, which can be considered a satisfactory result depending on the type of targets evaluated, the number of classes, and similarity between them. The OA magnitudes were similar to those observed by LU & HE (2017), who tested classifiers to identify plant species in pastures. These authors reported OA values ranging from 82 to 86% also using images obtained from unmanned aerial vehicles to identify ecologically and economically important species and investigate their phenological characteristics.

In general, ITS1 and ITS2 were the classes that generated the highest confusion with each other. It can be observed at EUs 3A and 7A, with Inter Tussock Stratum user accuracies of 60 (for ITS1) and 65% (for ITS2), respectively (Table 1). Also, classes TS1 with TS2 generated classification errors, as shown at units 7A and 5A (Table 1), with user accuracies of 77 (for TS1) and 70% (for TS2), respectively. This type of classifier error was not considered problematic, as it occurred between subclasses of the same target. The presence of water in the wetland areas contributed to differentiating the spectral response of the same target under different water conditions, due to the spectral behavior of water that is distinct from the spectral behavior of vegetation (JENSEN, 2009). However, the water content is possibly not constant throughout the wetland area and; therefore, there is a transition in the response of a given class under a drier and more humid condition, which may have confused the classification.

Classes TS1 with ITS2 also showed confusion, as occurred at EUs 6B and 4A. The confusion between classes TS1 and ITS2 can be related to two main factors. One is the floristic diversity, which is affected by grazing intensity, soil type, soil moisture, and distribution of plant species, among others, which may have generated spectral similarities (ANDRADE et al., 2019). The second factor is the process of collecting samples, both for training the classifier and for the evaluation of classification. Sampling in natural pastures is dependent on the operator’s experience and knowledge, as each class has different colors and, often, the same hue can be present in more than one class, which makes sampling complex. It is important to remember that in both classes, Tussock and Inter Tussock stratum, there is a reasonably similar spectral pattern and arranged almost randomly at EUs.

The success of the supervised classification depends on a series of factors such as the measurements obtained by the sensor, which allow the differentiation of the user’s interest classes. The spatial, spectral, radiometric, and temporal resolutions of the data are compatible with the problem to be treated; and finally, data with different spectral bands capable of differentiating spectrally similar classes are important to classify agricultural

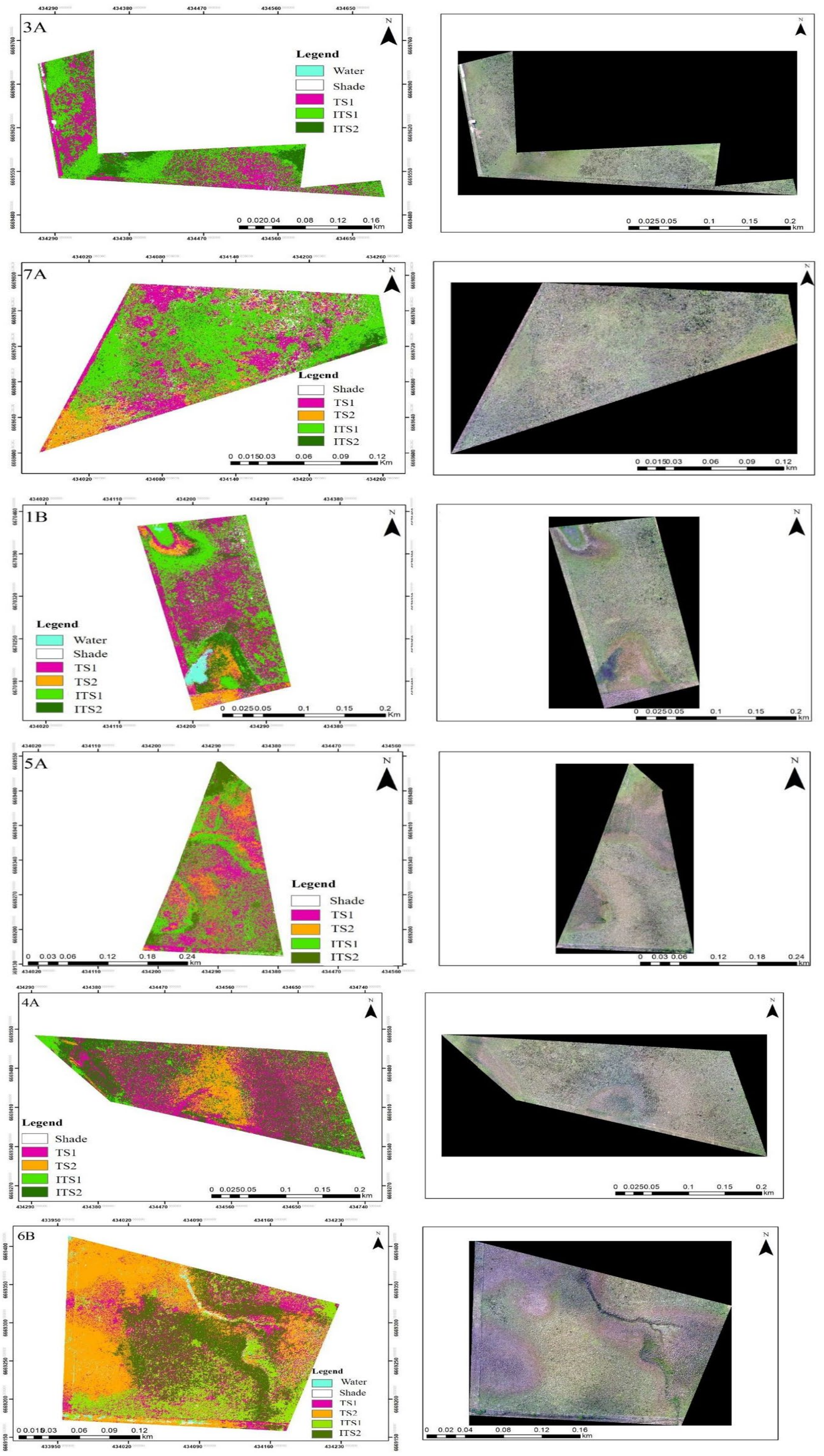

Figure 1 - Classified maps (left) and false-color images (infrared, green, and blue) (right) at the six evaluated experimental units (3A, 7A, 1B, 5A, 4A, and 6B). Eldorado do Sul, Brazil, 2019. Legend: Water; Shade; Tussock Stratum 1 (TS1); Tussock Stratum 2 (TS2); Inter Tussock Stratum 1 (ITS1); Inter Tussock Stratum 2 (ITS2).

Table 1 - Confusion matrices generated at each experimental unit (3A, 7A, 1B, 5A, 6B, and 4A) in the classification process. Eldorado do Sul, Brasil, 2019.

---3A---										
	Water	Shade	TS1	ITS1	ITS2	Total	PE (%)	UE (%)	GA (%)	
Water	312	0	43	0	0	355	88	96	78	
Shade	0	81	0	0	3	84	96	100		
TS1	4	0	1792	12	109	1917	93	83		
ITS1	0	0	14	8642	371	9027	96	60		
ITS2	8	0	312	5721	12683	18724	68	96		
Total	324	81	2161	14375	13166	30107				
---7A---										
	Shade	TS1	TS2	ITS1	ITS2	Total	PE (%)	UE (%)	GA (%)	
Sombra	894	0	0	2	0	896	100	99	80	
TS1	3	2220	312	13	401	2949	75	77		
TS2	2	505	707	0	0	1214	58	69		
ITS1	0	16	0	5137	1457	6610	78	94		
ITS2	0	135	12	299	3503	3949	89	65		
Total	899	2876	1031	5451	5361	15618				
---1B---										
	Water	Shade	TS1	TS2	ITS1	ITS2	Total	PE (%)	UE (%)	GA (%)
Water	16111	0	6	0	0	3	16120	100	95	82
Shade	756	420	0	22	5	9	1212	62	100	
TS1	0	0	2619	317	631	3299	6866	79	79	
TS2	37	0	168	2888	0	1568	4661	184	86	
ITS1	0	0	11	0	10187	22	10220	100	89	
ITS2	15	0	530	139	669	6285	7638	82	56	
Total	16919	420	3334	3366	11492	11186	46717			
---5A---										
	Shade	TS1	TS2	ITS1	ITS2	Total	PE (%)	UE (%)	GA (%)	
Shade	176	0	0	0	0	176	100	100	87	
TS1	0	4186	847	150	35	5218	80	84		
TS2	0	445	2007	115	25	2592	77	70		
ITS1	0	129	9	6601	161	6900	96	94		
ITS2	0	207	11	393	3479	4090	85	89		
Total	176	4967	2874	7054	3905	18976				
---6B---										
	Water	Shade	TS1	TS2	ITS1	ITS2	Total	PE (%)	UE (%)	GA (%)
Water	1051	0	0	100	0	0	1151	91	97	80
Shade	0	159	0	0	2	0	161	99	100	
TS1	0	0	1999	504	6	192	2701	74	54	
TS2	34	0	260	3072	0	38	3404	90	83	
ITS1	0	0	69	0	3768	536	4373	86	98	
ITS2	0	0	1405	38	51	2552	4046	63	77	
Total	1085	159	3733	3714	3827	3318	15836			
---4A---										
	Shade	TS1	TS2	ITS1	ITS2	Total	PE (%)	UE (%)	GA (%)	
Shade	150	4	1	0	0	155	97	98	75	
TS1	0	4299	567	10	1671	6547	66	65		
TS2	0	332	3906	0	77	4315	91	85		
ITS1	0	25	0	4079	369	4473	91	96		
ITS2	3	1927	134	143	3057	5264	58	59		
Total	153	6587	4608	4232	5174	20754				

Class TS1 refers to the tussock stratum in the dry area, class TS2 refers to the tussock stratum in the wetland area, class ITS1 refers to the inter tussock stratum in the dry area, and class ITS2 refers to the inter tussock stratum in the wetland area or with a color other than green. PE is the producer efficiency and UE is the user efficiency. GA is the global accuracy.

areas (ZANOTTA et al., 2019). In this study, the used image showed only three spectral bands, which may have limited the differentiation of targets. Conversely, the spatial resolution was adequate for the evaluated classes, as the pixel size was smaller than the targets of interest.

The percentage of area covered by tussock obtained in the classification process showed similar values at EUs 3A, 7A, 1B, and 4A compared to the data obtained in loco. However, the percentage of area covered by the tussock stratum obtained by the classification at EUs 5A and 6B was higher than that obtained by field evaluation (Table 2). This difference in the percentages of area covered by tussock may have occurred due to the complexity of separating different types of vegetation, which often presented a similar spectral response (KATTENBORN et al., 2019).

As a strategy for a better understanding of the classification results, figures 2 and 3 show the magnification of some specific areas, in which there were facilities or difficulties in the classification process. The two EUs with higher differences between the values classified and sampled in the field (5A and 6B) showed some areas in which the classifier satisfactorily differentiated the tussock and Inter Tussock stratum classes (Figure 2). In these cases, the classification was successful, given the evident spectral differences between the classes in question, which is also perceived visually, mainly in figure 3 (6B), where the tussock are presented with defined borders and a contrast of colors evident compared to the inter tussock stratum.

Figure 3, shows a detailed classification result for the same EUs (5A and 6B), but in areas where problems were observed in the classification. In these cases, the complexity of separating the inter tussock stratum and tussock classes was higher and the algorithm classified some areas of the inter tussock stratum as tussocks. This type of error brought problems for the dimensioning of the area covered by tussocks.

The use of digital images captured through UAVs is an interesting methodology when associated with the use of classifiers appropriate to the type of problem to be solved. This type of methodology can be used to assist in the management of natural pastures due to the ability to classify and quantify the different vegetation strata.

CONCLUSION

The diversity of plant species that make up the inter tussock stratum and tussock stratum of natural pastures, whose proportion varies according to the forage supply, makes the spectral pattern of the set insufficient to determine classes accurately. However, plant groups that make up the inter tussock stratum and tussock can be differentiated with data collected by a digital camera onboard a drone in the

Table 2 - Percentage of area of each experimental unit (EU) covered by tussock obtained through field evaluation (%T – field) and supervised classification (%T – image) in the different treatments of forage allowances (FA, % LW). Eldorado do Sul, Brasil, 2019.

EU	Treatment (FA, % LW)	No. of evaluations	%T – field	SD	%T – image
3A	8	17	29	±5	31
7A	8	17	31	±8	37
1B	12	17	35	±5	40
5A	12	17	38	±3	50
6B	16	17	40	±3	52
4A	16	16	50	±7	50

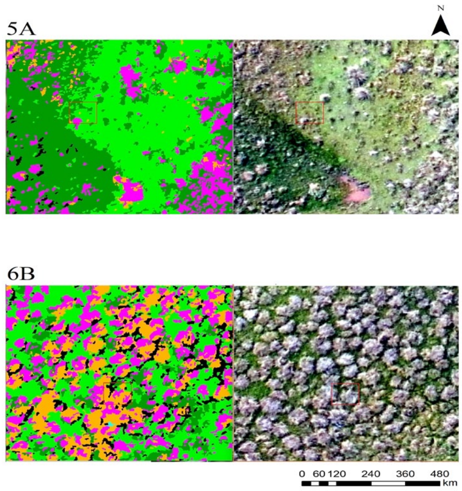

Figure 2 - Details of maps classified at EUs 5A and 6B. Cases in which the algorithm properly classified the different classes. On the left is the classified image and, on the right, the false-color image. Eldorado do Sul, Brazil, 2019.

infrared, green, and blue bands and using varying feature space and adaptive SVM and RF classifiers. The classification and mapping of vegetation in natural pastures give spectral data the characteristic of being an indicator of pasture quality, with an objective methodology, with a low cost, fast, and easy to implement. Moreover, it can be used to complement the already established methodologies.

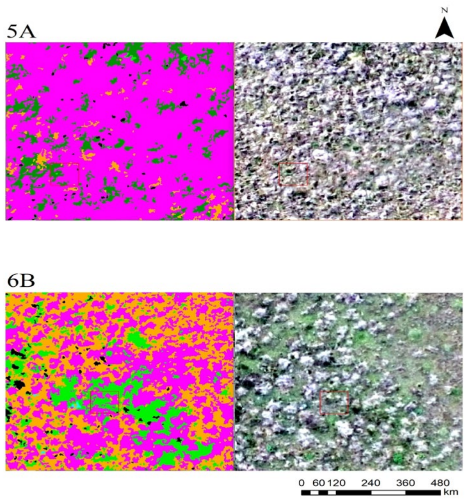

Figure 3 - Details of maps classified at EUs 5A (a) and 6B (b). Cases in which the algorithm failed to properly classify the different classes. On the left is the classified image and, on the right, the false-color image. Eldorado do Sul, Brazil, 2019.

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DECLARATION OF CONFLICT OF INTEREST

The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

AUTHORS' CONTRIBUTIONS

All authors contributed equally for the conception and writing of the manuscript. All authors critically revised the manuscript and approved of the final version.

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