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FOREST RESTORATION MONITORING THROUGH DIGITAL PROCESSING OF HIGH RESOLUTION IMAGES

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Abstract

Monitoring and evaluating forest restoration projects is a challenge especially in large-scale, but the remote monitoring of indicators with the use of synoptic, multispectral and multitemporal data allows us to gauge the restoration success with more accurately

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and in small time. The objective of this study was to elaborate and compare methods of remote monitoring of forest restoration using Light Detection and Ranging (LIDAR) data and multispectral imaging from Unmanned Aerial Vehicle (UAV) camera, in addition to comparing the efficiency of supervised classification algorithms Maximum Likelihood (ML) and Random Forest (RF). The study was carried out in a restoration area with about 74 hectares and five years of implementation, owned by Fibria Celulose S.A., in the southern region of Bahia State, Brazil. We used images from Canon S110 NIR (green, red, Near Infrared) on UAV and LIDAR data composition (intensity image, Digital Surface Model, Digital Terrain Model, normalized Digital Surface Model). The monitored restoration indicator was the land cover separated in three classes: canopy cover, bare soil and grass cover. The images were classified using the ML and RF algorithms. To evaluate the accuracy of the classifications, the Overall Accuracy (OA) and the Kappa index were used, and the last was compared by Z test. The area occupied by different land cover classes was calculated using ArcGIS and R. The results of OA, Kappa and visual evaluation of the images were excellent in all combinations of the imaging methods and algorithms analyzed. When Kappa values for the two algorithms were compared, RF presented better performance than ML with significant difference, but when sensors (UAV camera and LIDAR) were compared, there were no significant differences. There was little difference between the area occupied by each land cover classes generated by UAV and LIDAR images. The highest cover was generated for canopy cover followed by grass cover and bare soil in all classified images, indicating the need of adaptive management interventions to correct the area trajectory towards the restoration success. The methods employed in this study are efficient to monitor restoration areas, especially on a large scale, allowing us to save time, fieldwork and invested resources.

Keywords: Light Detection and Ranging (LIDAR), Unmanned Aerial Vehicle (UAV), Random Forest (RF), Maximum Likelihood Algorithm, Recovery of Degraded Areas, forest restoration

1. Introduction

Due to the high demand for environmental regularization of big companies and farmers and the need to mitigate environmental impacts generated by human activities, restoration projects have been increased across the globe (Li et al., 2017). The expansion of works and techniques used in restoration initiatives and successive evaluations of what was done in the past made it possible to correct and to adapt the previously used methods to favor functional ecosystem reestablishment (Rodrigues et al., 2009).

Long-term follow-up of large-scale restoration projects is critical because it allows us to evaluate their success or to correct their trajectory through the generation of ecological management recommendations (enrichment, invasive species control, and othres). Therefore, the application of these corrective actions can guarantee the success of the project already in the first years of the planting (Ruiz-Jaen and Aide, 2005; Melo et al., 2013; Zahawi et al., 2015). However, monitoring restoration is a challenge especially in large-scale projects (Viani et al., 2017, Ockendon et al, 2018), mainly because the field assessment of several indicators can be time consuming, costly, and require trained technicians (Zahawi et al., 2015; Reif and Theel, 2017). Additionally, a clear definition of which indicator should be measured and the frequency of assessment still lack (Rodrigues et al., 2009). Alternative approaches to evaluating and monitoring different restoration parameters using remote sensing and digital image processing techniques are considered promising to reduce the need for field measurement methods (Reif and Theel, 2017; Viani et al., 2017), especially for large scale restoration projects and for areas that are difficult to access (Mascaro et al., 2014; Zahawi et al., 2015). Additionally, with the use of remote monitoring it is possible to evaluate restoration in landscape scale, not only in selected samples, as it is usually done in field monitoring (Zahawi et al., 2015).

Land cover composition is an important indicator to evaluate landscape condition and to monitor status and trends of ecosystem change over a specific time (Xian et al., 2009). In our study, land cover indicator was separated in three classes: canopy cover, grass cover and bare soil. According to Harris et al. (2012), canopy cover influences forest structure, amount of light entering the forest, water infiltration, facilitates the growth of understory native seedlings and controls of undesirable grasses, among others. The evaluation of invasive grass cover is considered of high importance in the early stages of the forest restoration process, because these species are spreading rapidly and compete with native species impeding or hindering their growth (Rocha-Nicoleite et al, 2017). Bare soil should be monitored because when it occurs in large spots also compromises the seedlings survival preventing the water infiltration and inducing soil erosion and nutrient loss, among others (Muñoz-Rojas et al., 2016).

Out of the new remote sensing techniques that have been widespread Light Detection and Ranging (LIDAR) enables to determine the distance between the sensor and the target surface using laser pulses (Lefsky et al., 2002). Additionally, this sensor is able to generate the pulse return intensity image, which can be useful to classify land cover (Song et al., 2002). According to Giongo et al. (2010) this sensor has proved to be efficient for different forestry applications, since it allows the measurement of canopy topography (Dubayah and Drake, 2000), biomass (Bortolot and Wynne, 2005), volume (Ioki et al., 2010), species identification (Kim et al., 2007; Holmgren et al., 2008) and several other applications. Another remote sensing technique that has been widely used is high-resolution imagery acquired from Unmanned Aerial Vehicle (UAV) camera. Several studies have demonstrated the efficiency of these image processing, e.g. in the mapping of invasive species (Michez et al., 2016), land use and cover planning (Silva et. al., 2016), to monitor tropical forest recovery (Zahawi et al., 2015) and biodiversity (Koh and Wich, 2012; Getzin et al. 2012; Paneque-Galves et al., 2014).

Supervised classification is a process of image information extraction where the user selects representative samples of different classes found in the image (Campbell, 1996). A widely used algorithm for image classification is the Maximum Likelihood (ML), which considers the classes involved in a Gaussian probability density function (Hagner and Reese, 2007). Another more robust algorithm that has been shown to be very efficient in the classification of satellite images is the Random Forest (RF) (Gislason et al., 2006; Lawrence et al., 2006; Puissant et al., 2014). This algorithm is based on the generation of multiple decision trees that vote for the most popular class (Breiman, 2001) to produce more accurate classification (Cutler et al., 2007; Puissant, 2014).

The aim of the present study was 1) to elaborate and compare methods of remote monitoring of forest restoration using images from LIDAR data and UAV camera, 2) to compare the efficiency of supervised classification algorithms ML and RF and 3) to obtain land cover composition by classified images.

2. Materials and methods

2.1. Study site

The present study was carried out in conservation areas under restoration process owned by Fibria Celulose S.A., on a farm named "Project Maria Mirreis T734", 39.68° S, 17.71° W, located in the municipality of Caravelas, extreme south of Bahia state, Brazil (Figure 1).

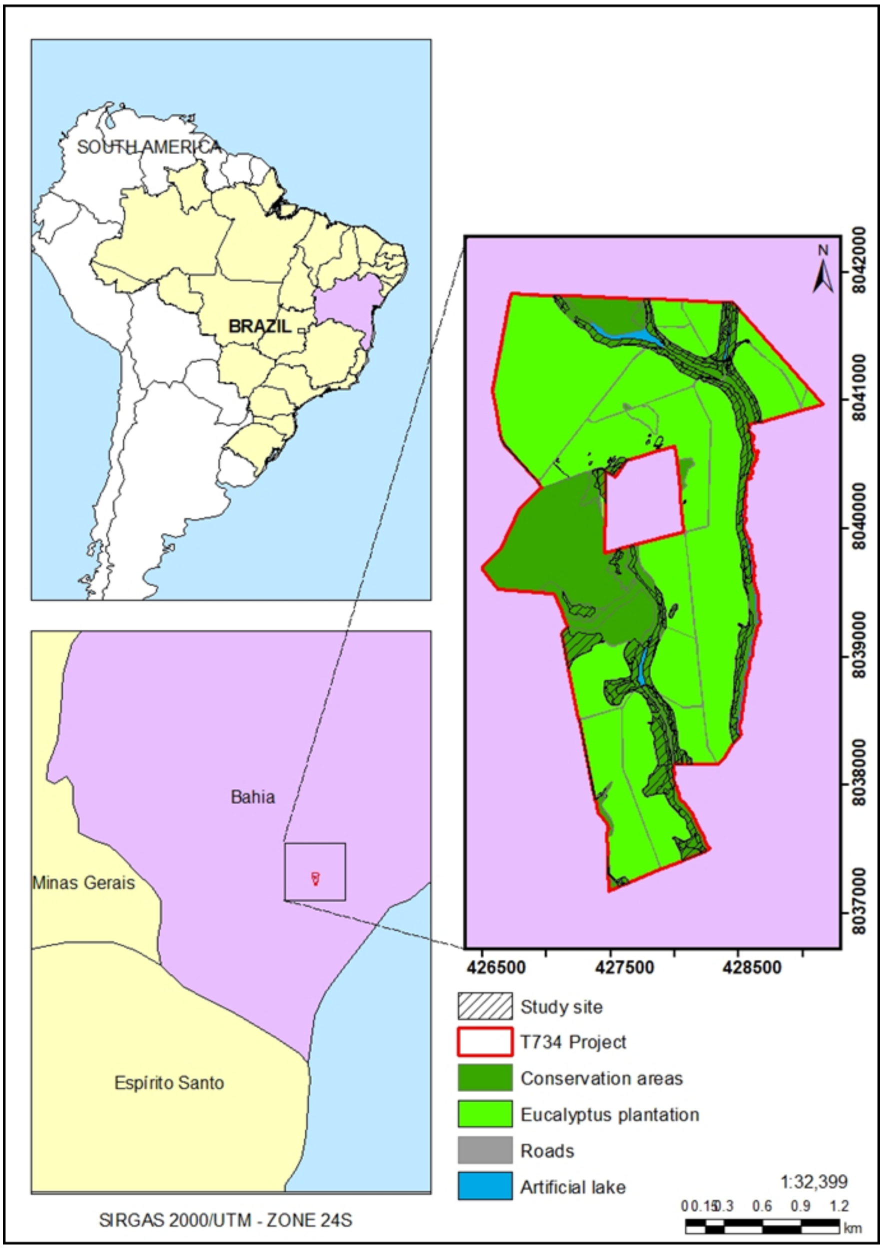

Fig. 1. Location and Land Use of the study site called "Project T734 Maria Mirreis", in south of Bahia state, Brazil.

According to the classification of Köppen, the region is in the transition between Tropical rainforest climate, hot and humid tropical climate on the coast and seazonal climate, with dry winter in the interior (Zonete et al., 2010). The average annual rainfall is around 1,100 mm (Almeida et al., 2008) and the average temperature is 25°C, without defined dry season (Costa et al., 2009). The predominant soils in the region are the kaolinitic Latosols and Yellow or Red-Yellow Argisols, presenting low fertility, and, in case of Argisols, presence of a dense layer in the subsurface (Moreau et al., 2006). The natural vegetation in the region includes Atlantic forests (Dense Ombrophilous Forest and Seasonal Semideciduous Lowland Forests) (Saporetti, 2012).

The farm that included our study area has a total area of 664.42 ha, where 432.09 ha are planted with eucalyptus, 207.17 ha is conservation areas, 15.78 ha of roads and 9.38 ha for various uses. Among the conservation areas, there are natural forests in different successional stages and degraded pastures dominated by the exotic grass *Urochloa decumbens* (Stapf) R.D.Webste (74 ha). Restoration projects are being carried out mainly in these degraded pastures, which were originally occupied by Dense Ombrofilous forest, and native grasses do not occur (Veloso, 1991; Ivanauskas and Assis, 2012). Aiming to achieve the restoration success, interventions were implemented in 2010 through the methodologies of natural regeneration or planting native species seedling.

2.2. Image gathering from UAV and LIDAR

Aerial images of the study area were obtained from Canon S110 NIR cameras, coupled to UAV in the spring season. The resolution of the images captured by the cameras is 4000 x 3000 pixels, and the spatial resolution is 0.08 meters. The camera captures images in the spectral region of green, red, and near infrared (NIR). The Normalized Difference Vegetation Index (NDVI) (Rouse et al, 1973) (Equation 1) and Soil Adjusted Vegetation Index (SAVI) (Huete, 1988) (Equation 2) were calculated. Then, three spectral bands and two spectral transformations were combined.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \qquad \text{(Equation 1)}$$

where: *NIR* = Near Infrared band and Red = Red band

$$SAVI = \frac{(1+Ls)*(NIR-Red)}{(Ls+NIR+Red)} \qquad \text{(Equation 2)}$$

where: *Ls* is a constant denominated factor of adjustment of the SAVI index, being able to assume values from 0.25 to 1 depending on the land cover. In this case, the value of 0.5 was considered, representing vegetation with intermediate density (Huete, 1988)

Images were also obtained through a RIEGL LMS - Q680I Airborne Laser system denominated LIDAR, which works on Near Infrared region with a wavelength of 1,036 nm. The images were taken in spring season. From LIDAR point clouds, it was possible to generate the pulse return intensity image, Digital Surface Model (DSM), Digital Terrain Model (DTM) and normalized Digital Surface Model (nDSM) using ArcGIS 10.2 (ESRI, 2015). nDSM stores information of the objects height, obtained through the difference between DSM and DTM. According to Song et al. (2002), the intensity is defined as the ratio of strength of reflected light to the emitted light and can be useful to classify the land cover. By using the obtained data, a 0.5 m spatial resolution image composed of four bands (Intensity, nDSM, DTM, DSM) was generated. Thus, in addition to the information of the vegetation height, there is also the spectral information related to the pulse return intensity.

2.3.Land cover monitoring

The monitored restoration indicator was the land cover separated in three classes: canopy cover, bare soil and grass cover. These classes were chosen due to the feasibility for obtaining results from aerial images classification. All these classes are easily identified by visual image interpretation and digital image processing due to clear differences between their spectral signatures. They also have ecological importance in early stages of restoration process and relevance for generating adaptive management recommendations, which aim to correct the trajectory of a restoration area allowing its ecological succession (Atlantic Forest Restoration Pact, 2013; Viani et al., 2017).

UAV camera is a passive sensor, which requires sunlight as an illumination source for obtaining images. Therefore, the presence of clouds and shadows modifies the reflectance of the objects and can reduce the classification accuracy. For this reason, besides the three mentioned classes, it was necessary to establish another class representing objects in shadows, which was called “shadow”.

2.4. Sample selection, classification, accuracy, comparison and class area quantification

Fifty representative samples of each class (canopy cover, bare soil and grass cover, shadow) were selected over UAV camera images. The same number of samples per class (canopy cover, bare soil and grass cover) were chosen over LIDAR return intensity channel. These samples were polygons with the same size, 450 pixels on average for the UAV camera images and 55 pixels for LIDAR images due to the different spatial resolution between both sensors. The software ArcGIS 10.2 (ESRI, 2015) was used for sample acquisition. Seventy percent of the samples polygons were randomly selected for training and thirty percent them was left for validation of both algorithms (ML and RF).

The supervised classification using ML algorithm was done with ArcGIS 10.2 software, whereas the RF algorithm was done with R 3.3.2 software (R Core Team, 2016). The fifty samples used for classification were randomly divided into training and validation samples ten times, and for each division classification models were fitted. RF algorithm also permitted to generate the variable importance, which represents the most important variables for creating algorithm's decision trees, through two methods: randomization and Gini Index, described by Hastie et al. (2009).

Thirty percent of the selected samples from UAV and LIDAR images were used for the validation phase to verify the accuracy of the methods. The classification accuracy was assessed with the confusion matrix approach. From this matrix, classification accuracy indicators, such as Producer's accuracy, User's accuracy, Overall classification accuracy, and Kappa coefficient, were calculated. Additionally, ten samples of each class were collected in the field, totaling 30 validation samples, and the coordinates of each sampling point was obtained with GPS. This sampling was done to evaluate whether the sampling on UAV and LIDAR images may have some bias that leads to over or underestimated accuracy. After obtaining the Kappa Index, it was possible to classify its value according to the literature (Landis and Kock, 1977).

As it was mentioned before 10 classifications were performed by each combination between imaging method and algorithm, therefore we calculate the average of Producer's accuracy, User's accuracy, Overall classification accuracy, and Kappa coefficient, in each situation. The Z test was used to compare Kappa values among all different classified images with a 95% confidence level, $Z > 1.96$ (Foody, 2004; Congalton and Green, 2009).

We calculated the land cover composition based on percentage class area (canopy cover, grass cover, bare soil and shadow) generated by the most accurate classification (from the 10 classifications), for each classified image using ArcGIS software (ESRI, 2015) and R software (R Core Team, 2016) for ML and RF, respectively.

The complete procedure that we used to classify UAV and LIDAR images with different classifying algorithms and the validation performed to verify the classifiers accuracy is presented in Figure 2.

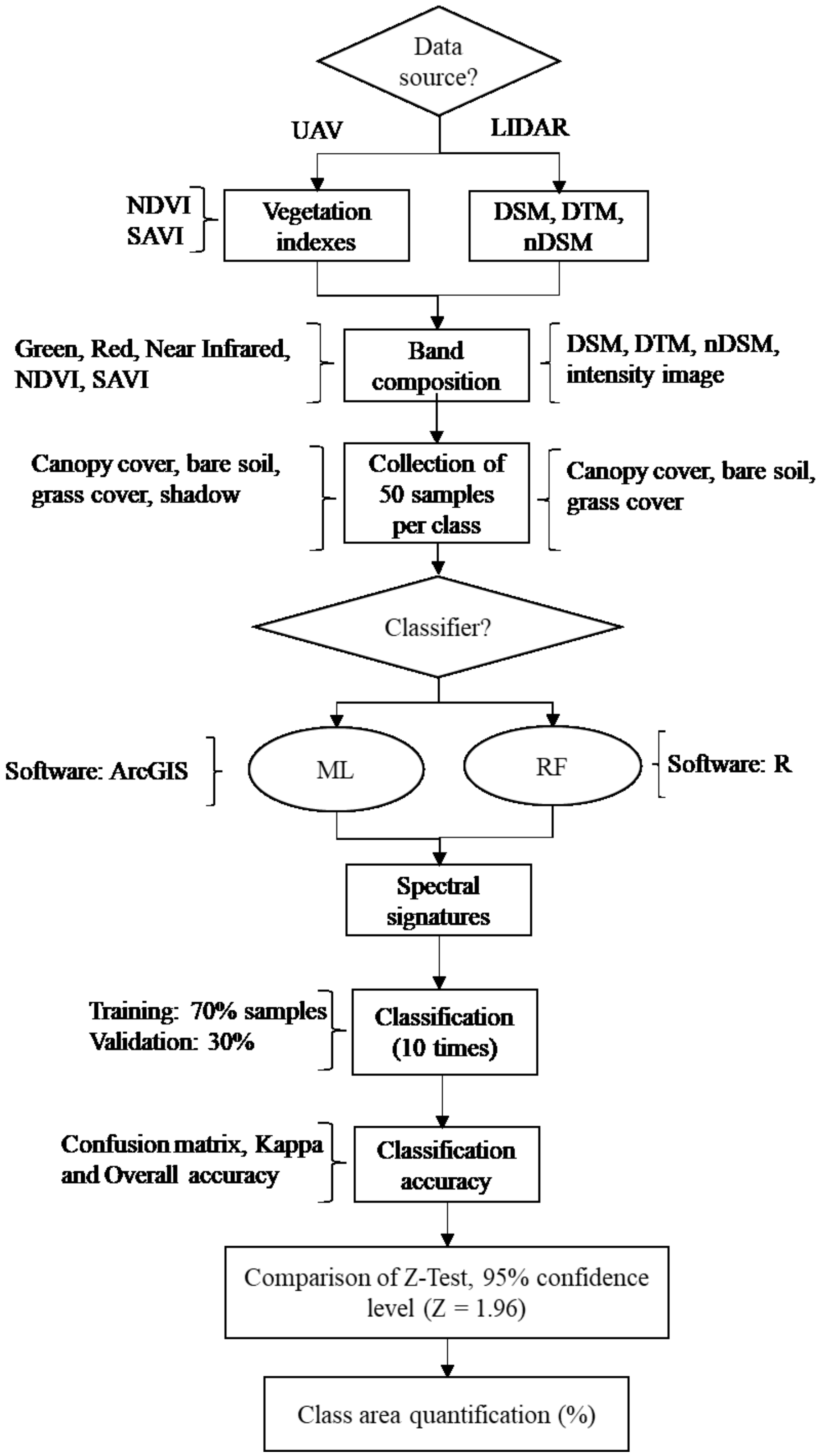

Fig 2. Flowchart representing the methodology used to classify LIDAR and UAV images, using the ML and RF algorithms, and the accuracy of the classifications. DTM: Digital Terrain Model, DSM: Digital Surface Model, LIDAR: Light Detection and Ranging, ML: Maximum Likelihood, nDSM: normalized Digital Surface Model, NDVI: Normalized Difference Vegetation Index, RF: Random Forest, SAVI: Soil Adjusted Vegetation Index, UAV: Unmanned Aerial Vehicle.

3. Results

3.1. Classification by the Maximum Likelihood and Random Forest algorithms from UAV camera images

The images obtained by UAV camera classified using ML and RF algorithms is presented in Figure 3, and it represents part of the restoration project.

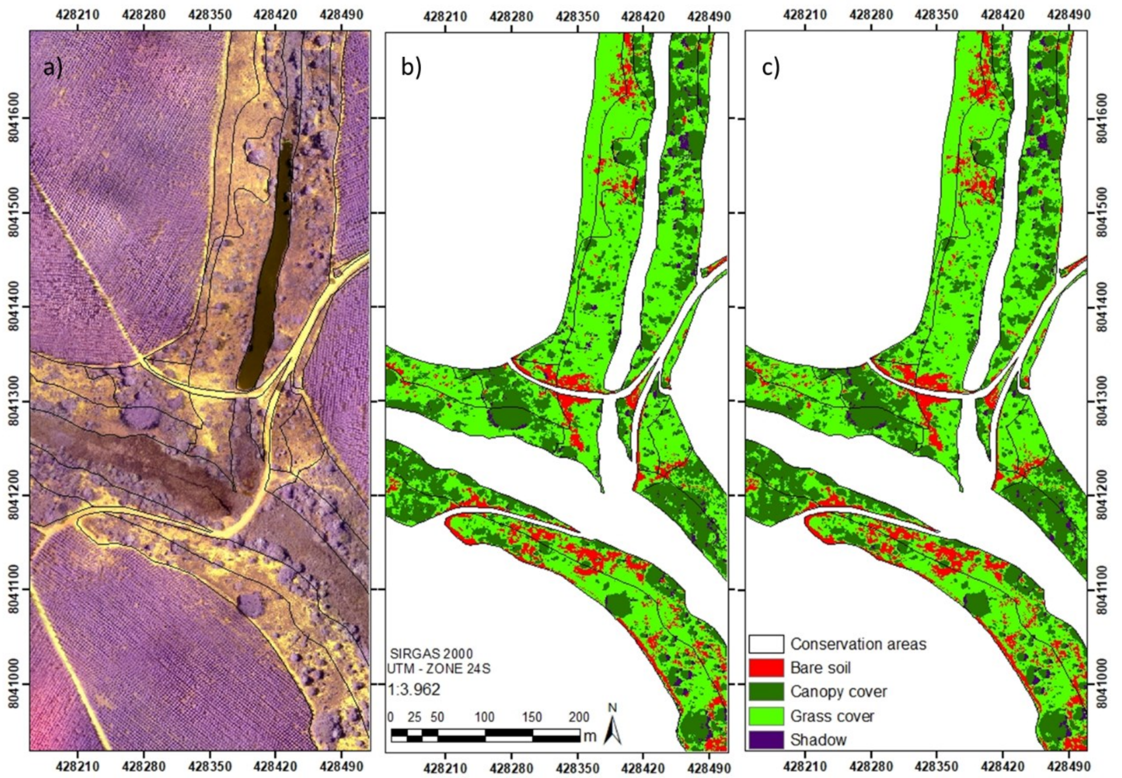

Fig. 3. a) UAV camera images (Red, Green, Near Infrared, NDVI, SAVI), which represent part of the study area; b) Image classified by Maximum Likelihood algorithm; c) Image classified by Random Forest algorithm.

It is noticed that all the classes were well delimited on UAV classified images by both algorithms and they were quite similar (Fig.3).

The Tables 1 and 2 represents the mean values generated from the ten confusion matrices for both classifiers. It was observed that Kappa and Overall Accuracy were high and ranked as excellent (Landis and Kock, 1977) for both algorithms. The classes separation was also assessed through user's and producer's accuracy. The values of these indices were high in both classifications, indicating a good level of discrimination between classes. Additionally, "shadow" was the class that most generates confusion, especially with "bare soil" and "grass cover" for both classifiers.

Table 1
Mean values generated from the ten confusion matrices, with the Maximum Likelihood classifier, for UAV camera images

CLASS	Bare Soil	Canopy cover	Grass cover	Shadow	Total	PA (%)
Bare soil	**6463**	3	91	388	6945	93.17
Canopy cover	0	**8097**	184	94	8375	96.75
Grass cover	21	65	**7929**	440	8455	94.02
Shadow	376	282	114	**3858**	4630	81.55
Total	6860	8447	8318	4779	**28404**	
UA (%)	96.21	96.45	95.63	90.00		
Average Kappa					0.90	
Average OA					0.93	

OA: Overall Accuracy, PA: Producer's Accuracy, UA: User's Accuracy.

Table 2
Mean values generated from the ten confusion matrices, with the Random Forest classifier, for UAV camera images

CLASS	Bare Soil	Canopy cover	Grass cover	Shadow	Total	PA (%)
Bare soil	**6408**	3	43	0	6454	99.34
Canopy cover	1	**6992**	109	1	7103	98.65
Grass cover	186	244	**5836**	172	6438	89.43
Shadow	1	80	63	**2493**	2637	93.88
Total	6596	7319	6051	2666	**22632**	
UA (%)	96.46	95.35	96.84	93.12		
Average Kappa					0.94	
Average OA					0.96	

OA: Overall Accuracy, PA: Producer's Accuracy, UA: User's Accuracy.

From the ten generated confusion matrices, the minimum Kappa value found with ML algorithm was 0.69, and the maximum value was 0.99, with a mean of 0.90

and a standard deviation of 0.094. For RF, the minimum Kappa value found was 0.85 and the maximum was 0.99, with a mean of 0.94 and a standard deviation of 0.043.

A significant difference was verified by the Z test ($Z > 1.96$ at 95% of confidence level) (Table 5) among Kappa values for each classifier. In addition, RF algorithm presented the best Kappa and OA results, being considered the best alternative for image processing.

When validation was performed using the field samples, the Kappa indexes remained in the excellent range for both algorithms, 0.97 for ML and RF. The OA was also considered high (0.98 for both algorithms), proving that the field data are consistent with the results obtained through training and validation when using samples selected in the image itself.

The variables importance generated by the RF for UAV image, in decreasing order, were red band, green, SAVI, NDVI and near infrared.

3.2. Classification using Maximum Likelihood and RF algorithms from LIDAR data composition images

The images obtained by LIDAR data composition, classified using ML and RF algorithms is presented in Figure 4, and it represents part of the restoration project.

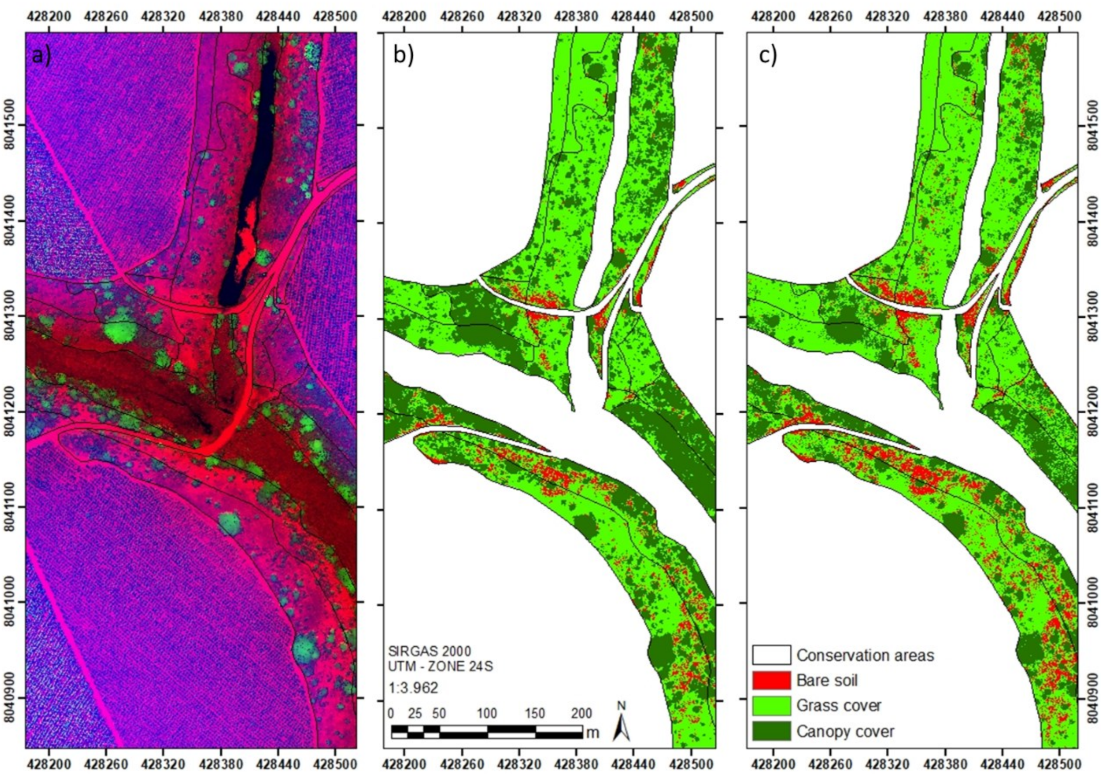

Fig. 4. a) LIDAR data composition images (Intensity, nDSM, DSM, DTM); b) Image classified by Maximum Likelihood algorithm; c) Image classified by Random Forest algorithm.

It is noticed that all the classes were well delimited on classified LIDAR images by both algorithms and they were quite similar (Fig.4).

According to Tables 3 and 4, Kappa and Overall Accuracy were high and ranked as excellent (Landis and Kock, 1977). User's and producer's accuracy values were also considered high for both algorithms indicating few confusions among classes. The greatest confusion was between "bare soil" and "grass cover" for both classifiers.

Table 3
Mean values generated from the ten confusion matrices, with the Maximum Likelihood classifier, for LIDAR data images

CLASS	Bare soil	Grass cover	Canopy cover	Total	PA (%)
Bare soil	**817**	0	1	817	99.38
Grass cover	62	**557**	31	649	86.16
Canopy cover	72	8	**678**	758	89.50
Total	950	565	710	**2225**	
UA (%)	89.24	98.32	96.12		
Average Kappa				0.88	
Average OA				0.92	

OA: Overall Accuracy, PA: Producer's Accuracy, UA: User's Accuracy.

Table 4
Mean values generated from the ten confusion matrices, with the Random Forest classifier, for LIDAR data images

CLASS	Bare soil	Grass cover	Canopy cover	Total	PA (%)
Bare soil	**493**	14	0	507	97.29
Grass cover	53	**595**	1	649	92.13
Canopy cover	0	0	**642**	642	100
Total	547	608	643	**1798**	
UA (%)	91.80	97.77	99.85		
Average Kappa				0.94	
Average OA				0.96	

OA: Overall Accuracy, PA: Producer's Accuracy, UA: User's Accuracy.

The minimum Kappa value found with ML was 0.61, and the maximum value was 0.98, with a mean of 0.88 and a standard deviation of 0.14. For RF, the minimum Kappa was 0.76, and the maximum was 0.98, with a mean of 0.94 and a standard deviation of 0.07.

A significant difference was verified by the Z test ($Z > 1.96$ at 95% of confidence level) (Table 5) among the Kappa values for each classifier. RF algorithm presented the best Kappa and OA results, then this algorithm was considered the best alternative for LIDAR images processing.

When field samples were used to validate the classifications, the Kappa Index remained in the excellent range, 0.86 for ML algorithm and 0.95 for RF. The OA was also considered high, with 0.91 and 0.97 for ML and RF, respectively, proving that field data are consistent with the results obtained through training and validation, using samples collected in the image itself.

The variables importance generated by RF for LIDAR image, in decreasing order, were intensity band, nDMS, DSM and DTM.

3.3 Comparison between imaging methods: LIDAR and UAV camera

Considering that the best classification result was obtained using RF algorithm, LIDAR and UAV methods were compared first for that algorithm. The difference between LIDAR and UAV methods was nonsignificant ($Z < 1.96$ at 95% of confidence level) (Table 5), demonstrating that method selection does not significantly affect the results. On the other hand, when using ML, a significant difference ($Z > 1.96$ at 95% of confidence level) (Table 5) was found between LIDAR and UAV images classifications. In this case, the image from UAV camera produced a higher accuracy classification.

Table 5 is a summary of Kappa and Z test values for each method evaluated on this study.

Table 5. Kappa Index found for UAV and LIDAR images classified by Maximum Likelihood and Random Forest algorithms. The Table also presents the Z values for comparison among the algorithm (RF and ML) for each imaging methods (UAV and LIDAR), and the comparison between imaging methods (LIDAR and UAV) for each algorithm (RF and ML)

Kappa Values	ML	RF	Z test ML x RF
UAV	0.90	0.94	14.55*
LIDAR	0.88	0.94	5.74*
Z test UAV x LIDAR	2.58*	0.06	

* Significant difference ($Z > 1.96$ at 95% of confidence level). LIDAR: Light Detection and Ranging, ML: Maximum Likelihood; RF: Random Forest; UAV: Unmanned Aerial Vehicle.

3.4 Land cover composition obtained by classified images

The area covered by canopy, grass and bare soil in the studied project generated through different image classification methods is represented in Figure 5. The highest percentage cover was generated for canopy cover followed by grass cover and bare soil in all classified images.

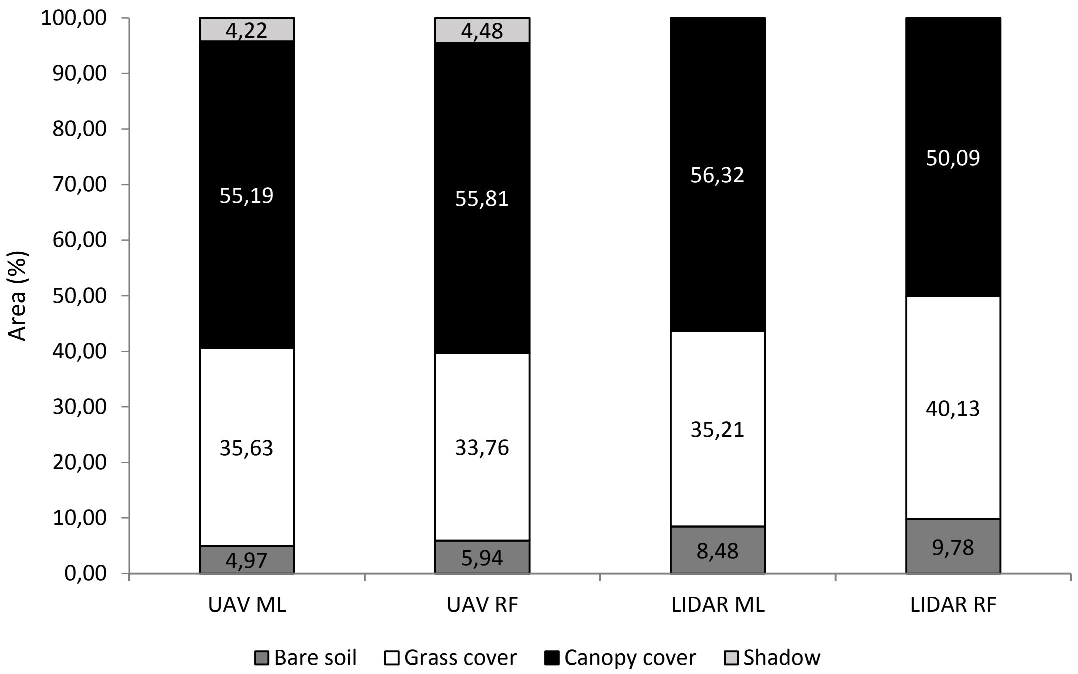

Fig. 5. Percentage area for canopy cover, grass cover and bare soil found through different image classification methods: UAV camera images classified with ML and RF algorithms, LIDAR images classified with ML and RF algorithms. LIDAR: Light Detection and Ranging, ML: Maximum Likelihood; RF: Random Forest; UAV: Unmanned Aerial Vehicle.

4. Discussion

We elaborated and compared methods of remote monitoring of forest restoration using LIDAR data and multispectral imaging of UAV camera and compared the efficiency of supervised classification algorithms ML and RF that proved to be reliable tools for assessing land cover composition. Field monitoring and evaluation of restoration requires a great deal of efforts mainly in large-scale projects (Zahawi et al., 2015; Reif and Theel, 2017; Ockendon et al, 2018), but the use of remote monitoring of land cover indicators with synoptic, multispectral and multitemporal data (Paneque-Galves et al., 2014; Reif and Theel, 2017) allow us to save time, fieldwork and resources (Zahawi et al., 2015).

4.1 Comparison between algorithms: Maximum Likelihood and Random Forest

As previously mentioned, Kappa index and OA were chosen to evaluate the accuracy of the classification since those measures are still the most used in image classification, although they have recently been questioned (Lyons et al., 2018). Similar values of Kappa and OA were found in all classifications and these values were also high, denoting the classifier precision.

Although Kappa values were similar and ranked as excellent in all combinations of images and algorithms, RF presented higher values of accuracy than the ML. This is in accordance with studies carried out by Gislason et al. (2006), which RF efficiency (Overall Accuracy = 82.8%) proved to be better when compared with other classifiers (ensemble methods and CART - decision trees) for land cover classification with an image composition (Landsat satellite images, elevation, slope and aspect) in Colorado. RF algorithm has been widely used by ecologists because of its simple interpretation, high accuracy, rapid processing, robustness to outliers and noises and ability to characterize complex interactions between variables (Breiman, 2011; Cutler et al., 2007).

An interesting feature of RF classification is the possibility of obtaining the variables importance, especially in situations where it is necessary to classify hiperspectral images (Gislason et al., 2006). In our study with multispectral images, intensity band and nDSM were the most important variables of LIDAR image classification. This can be justified by the fact that intensity band has spectral information and nDSM has height information, in other words, they are poorly correlated, providing less redundant data for the classifier (Lu and Weng, 2007). For UAV images, the most important variables were the red and green bands, followed by SAVI index, which also are the less correlated variables of the composition.

Although the ML algorithm was slightly less assertive than the RF, it also presented results ranked as excellent, which makes it eligible for this type of monitoring. This classifier is widely used for remote sensing, displaying good results when the data have a normal distribution and when sample selection represents well the spectral diversity of the class to be mapped (de Oliveira et al., 2013). ML has already proved efficient in several studies, such as the study by Silva et al. (2016), who tested the efficiency of this classifier, after segmentation, for monitoring Brazilian Savanna (*Cerrado)* land cover with UAV image, and obtained high values of similarity (0.94) with the visual interpretation. In the case of de Oliveira et al. (2013), who mapped forest fragments with monodominant *aroeira* (*Myracrodruon urundeuva*), ML classifier presented the best performance (Kappa = 80) in RapidEye images classification when compared to Neural Networks.

4.2 Comparison between imaging methods: LIDAR and UAV camera

No significant difference was found when comparing the sensors (LIDAR or UAV camera) using RF algorithm. Therefore, regardless the method choice, good results are expected to be obtained when RF is used. In case of ML, there was significant difference between the methods, so UAV images presented better results than LIDAR.

The "shadow" class was the one that mostly generated confusion in UAV camera images for both classifiers. This confusion can be justified by the fact that shadows cause partial or total loss of radiometric signature in the analyzed areas thus this can affect the performance of image classification process, object identification and consequently the land-cover mapping (Adeline et al., 2013; Movia et al., 2016). Shadow in images can be considered as a disadvantage of the use of UAV camera images when compared to LIDAR. The latter is considered an active sensor that have their own light source and does not require sunlight, so shadow interference does not occur in images (Song et al, 2002; Giongo et al., 2010) reducing the probability of class confusions in classification.

Little confusion was found between the classes when LIDAR data were evaluated. In this case, the greatest confusion was between bare soil and grass cover. In a study conducted by Song et al. (2002) using LIDAR, it was found that only with intensity band it would be difficult to separate grass cover from canopy cover, but with the addition of nDSM band, this becomes possible. According to Thenkabail et al. 2004, an increase in spectral bands quantity may improve the accuracy of classification, but only when these bands are useful for discriminating the classes. The low spectral information of the analyzed images does not show an adverse influence on the classifications since both Kappa and OA values were high, with few confusing errors. However, selecting samples within LIDAR images was more difficult since the small number of spectral bands hinder the visual differentiation among classes.

The use of LIDAR has been shown to be efficient for forest applications because it mobilizes many points with high precision, low cost and high speed of data acquisition (Giongo et al., 2010). Additionally, LIDAR data has already been proved to be successful (Overall Accuracy = 75%) for grassland habitats classification with RF algorithm as showed on the study developed by Zlinszky et al. (2014) in Hungary. According to data provided by Fibria and to Zahawi et al., 2015, the use of LIDAR is more financially feasible for large areas. On the other hand, UAV is feasible for small area imaging (Paneque-Galves et al., 2014; Zahawi et al., 2015).

To achieve better results on remote monitoring and make the evaluation of a greater number of indicators possible, such as arboreal individual density, species richness, invasive tree cover and vegetation strata, it is suggested the use of aerial cameras with high resolution and LIDAR sensor coupled, or Ecosynth (new aerial remote sensing system with similar properties to LIDAR, but with RGB spectral attributes for each point, e.g. Zahawi et al., 2015). In this case, in addition to increase spectral information, there will be geometry data (Persson et al., 2004). Additionally, the use of region-based image classification, through segmentation of images it is suggested to improve accuracy values. In the study carried out by Holmgren et al. (2008) in Scandinavia to identify local occurrence of species, higher value of OA (96%) was found when segmentation was used before the classification of aerial camera images combined with LIDAR data by the ML algorithm. The combination of both devices allows us to evaluate a greater number of indications with high accuracy, but it makes the monitoring process more expensive.

4.3 Land cover composition by classified images

Slight variations in the area occupied by different classes were observed between the image classification methods. These little variations may be associated with the presence of shaded areas in UAV camera images (cf. Adeline et al., 2013; Movia et al., 2016), that probably consist of bare soil or grass in the field or, additionally, by wrongly classified pixels in the digital image processing.

The highest cover was generated for canopy cover by all methods, followed by grass cover and then bare soil. According to the Atlantic Forest Restoration Pact (2013) and Viani et al. (2017), after four years of restoration implementation the canopy cover should achieve at least 70% to be capable to reduce invasive grass cover and to facilitate tree establishment. Our study area has not reached the desired value yet, probably due to the planting methodology, which used lines of early seral tree species interspersed with late seral species that have slower development and higher mortality. The high grass cover found in this study can be explained by the fact that the project area was covered by degraded pastures dominated by *Urochloa decumbens* before restoration activities and by the short time period since the restoration process has started. The invasive grass cover also competes with native tree seedlings species impeding or hindering their growth (Rocha-Nicoleite et al, 2017), and this can be seen in our restoration area. Bare soil cover was not high, but when it occurs in large areas, it induces soil erosion and nutrient loss (Muñoz-Rojas et al., 2016) that call for further restoration interventions.

According to the Atlantic Forest Restoration Pact (2013) and Viani et al. (2017), after checking the land cover indicators, a field ecological monitoring (phase II) has to be done in areas where canopy cover is greater than 70%. This monitoring is to verify species composition indicators (e.g. richness, density, regeneration) based on field sampling and it will guide adaptive management techniques aiming to correct the restoration trajectory of the areas if necessary. This two-step evaluation (remote sensing and field monitoring) should reduce the costs associated with monitoring, since it will not be necessary to measure field indicators in all areas. The field study related to this monitoring will be presented in a future paper.

5. Conclusions

The methods employed in this study are efficient to monitor restoration areas, bringing gains in quality and precision, synoptic analysis and reduction of field efforts, especially on a large scale. RF algorithm presented the greatest assertiveness in the image classification by UAV camera and LIDAR. The land cover composition found on this research suggests that the study area has not achieved the restoration success yet, therefore adaptive management strategies must be adopted to correct their trajectory towards the desired target state for restoration projects.

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