Machine learning applied to the classification of riverine species using UAV-based photogrammetric point clouds

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Abstract*— Riverine areas are of great importance for their high nature conservation and biodiversity value. These zones are also areas of high human activity, negatively affecting the ecosystem with the modification of riverbeds, construction of dams, or introduction of invasive species. In this sense, to achieve balance in the riverbed, it is essential to have periodic information on the area to be able to implement management plans. From photogrammetric RGB point clouds, our study conducted a classification of species using geometric and spectral features to classify the predominant species of a stretch of the river Palancia (Spain). These species were *Arundo donax* L., *Tamarix gallica* L., *Pinus halepensis* Mill., other riverine species, and ground. The classification was done applying the Random Forest algorithm, obtaining a mean cross-validation score of 82%, and individually by species a score of 88% for giant reed, 70% for French tamarisk, 82% for Aleppo pine, 92% for ground and 62% for other riverine species. The good results obtained show the feasibility of using digital aerial photogrammetry in unmanned aerial vehicle (UAV-DAP) for periodic monitoring of river species, improving the information provided to river administrators to implement management plans.

Keywords*— *Point cloud classification, UAV-DAP, Random forest, Riverine species

I. INTRODUCTION

One of the most important ecosystems of the nature is the riverine, where the exchange between the aquatic systems of the rivers and the terrestrial systems of the shore takes place, being perfect habitat for a large number of species of flora and fauna [1]. The vegetation of these areas allows the fixation of CO_2 as well as the soil, preventing soil erosion and keeping the geomorphology more stable [2], [3]. Nevertheless, this area is quite fragile due to human action, making necessary to find a balance between its ecological and economic functions [4], [5].

The most significant events in Mediterranean riverine areas are periods of torrential rainfall, which can cause flooding [6]. To avoid the consequences of flooding, it is necessary to have up-to-date information on the distribution of plant species in the river bed in order to plan pruning or thinning actions [7].

Traditionally, flights by aircraft have been carried out to obtain orthophotographs and Light Detection and Ranging (LiDAR) data for the classification of plant species, but the emergence of UAVs in forestry has changed this paradigm. UAVs allow the capture of data with higher spatial, temporal, radiometric and spectral resolution, if they are equipped with appropriate cameras, using only photogrammetric techniques. In addition, the use of these techniques allows the obtention of three-dimensional structure of plant species, without the need of LiDAR data capture [8]–[10]. Some studies have demonstrated the ability of photogrammetric products to classify tree species [11], but these studies have not been applied to particularly complex areas such as riverine zones.

Therefore, the aim of this project is the development of a new methodology allowing for the study of fluvial species using UAV-DAP.

A. Study area

The study area had an extension of 43.11 ha of the riverbed of the river Palancia, located in the province of Valencia, in the eastern of the Iberian Peninsula (Fig. 1).

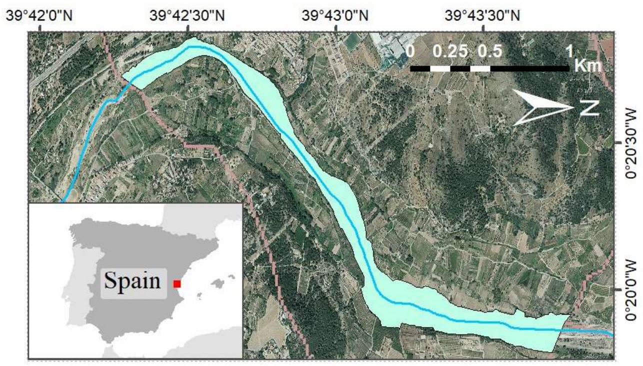

Fig. 1. Location of the study area, represented in aquamarine, with the Palancia's thalweg in blue.

The Mediterranean climate of this area is characterised by dry and hot summers, mild winters, and variable autumns and springs, both in terms of temperature and rainfall. Spring and autumn accumulate the highest annual precipitation (500 mm). These climatic conditions affect the fluvial regime, with periods when the riverbed is practically dry and periods when the riverbed is overflowing. These factors mean that the dominant species in the stretch of river studied are shrubs, *Tamarix gallica* L. (French tamarisk) and the invasive species *Arundo donax* L. (giant reed). Regarding the tree structure, it is relevant the presence of individuals of *Pinus halepensis* Mill. (Aleppo pine) in the riverbanks. The fact that we are studying a riverside area makes it possible to find a great diversity of plant species, with the occasional individual of *Acacia karroo* Hayne (Karroothorn), *Agave Americana* L. (American aloe), *Celtis australis* L. (Mediterranean hackberry), *Nerium oleander* L. (Nerium), *Nicotiana glauca* Graham (tree tobacco), *Opuntia maxima* Mill. (prickly pear), *Pistacia lentiscus* L. (lentisk), *Populus alba* L. (silver poplar), *Populus nigra* L. (black poplar), *Rhamnus lycioides* L. (Mediterranean buckthorn), *Ricinus communis* L. (castor bean) and *Tamarix africana* Poir. (African tamarisk), being all of them are very sparsely represented in the study area.

B. *Data collection*

Fieldwork consisted of collecting photogrammetric data using an UAV and taking ground control points using a differential GPS.

To cover the entire study area (43.11 ha), seven flights were carried out using an ATyges FV8 UAV (Fig. 2). The Atyges FV8 is an octocopter with a weight of 3.5 kg and a payload of 1.5 kg. Its flight time is up to 25 minutes, depending on meteorological conditions and payload. For this data collection, the ATyges FV8 was equipped with a Sony A5000 RGB camera of 20.1 MP of resolution. The sensor is a CMOS Exmor™ APS HD with a size of 23.2 × 15.4 mm, which has a diagonal of 28.21 mm.

The flights were set up at an altitude of 120 m. with an average speed of 25 km/h, taking more than 1250 images.

Fig. 2. ATyges FV8 UAV equipped with a camera Sony A5000.

The position of the control points in the field was obtained using two differential GPS models, Topcon GR-5 and Leica Viva GS16. In this campaign, 262 Ground Control Points (GCPs) were taken randomly.

II. Methods

The methodology for carrying out the mapping of plant species is based on the classification of the photogrammetric point cloud. This methodology is divided into 3 sections: photogrammetric process, height normalisation, point classification of the point cloud, and validation.

A. *Photogrammetric process*

The photogrammetric process was carried out using Pix4D© software. The first step in this process is the creation of tie points based on the extraction and matching of keypoints, camera model optimization and geolocation of ground control points. After this process the point cloud is densified, creating additional tie points.

B. *Normalisation of heights*

The next step was to normalise the heights of the obtained point cloud. This normalisation was carried out using LASTools© software. This software performs the normalisation process in two steps. First, classifies the ground points, and subsequently creates a digital terrain model (DTM). The DTM is lowered to zero elevation to obtain the normalised heights. Once the heights were normalised, the points classified as ground were removed, obtaining a point cloud of 30 million of points for the whole area.

C. *Point cloud classification*

In this step, we classified the point cloud using the Random Forest algorithm. Random forest is an ensemble learning method for classification, based on the construction of different decision trees during training, being the most repeated class in the classification of the individual trees, the prediction of the model.

In this study we defined five classes: "A*rundo donax*", "P*inus pinaster*" and "*Tamarix africana*" (the most representative species in the study area); the class "other riverine species", which encompasses the rest of the species in the study area; "ground", which includes the points that were not removed as ground in the height normalisation process.

The features input to the model were the normalised height (Z), the red (R), green (G), blue (B), the normalised green-red difference index (NGRDI), the normalised green-blue difference index (NGBDI), and the normalised red-blue difference index (NBRDI) of each point in the point cloud.

D. *Validation*

To validate the results, cross-validation was applied on the fitted model. The cross-validation technique is based on dividing the data sample into subsets, training on one subset of the data, while validating on another subset. In this case the number of subsets was set at 10-fold, in the iterative process one of the subsets is used as test data and the rest (9) as training data. The result of this validation is the average obtained from the evaluation measures on the different subsets.

III. Results and discussion

The point cloud obtained after the photogrammetric process had more than 85 million of points, i.e.,197 points/m^2. This point cloud had a root mean square error in the GCPs of 0.015 m in the x-component, 0.013 m in the y-component and 0.021 m in the z-component. This indicates that the use of the UAV-DAP technique is appropriate for riverside areas, where vegetation does not form a continuous mass, avoiding the existence of shaded areas and allowing the visualisation of points on the ground.

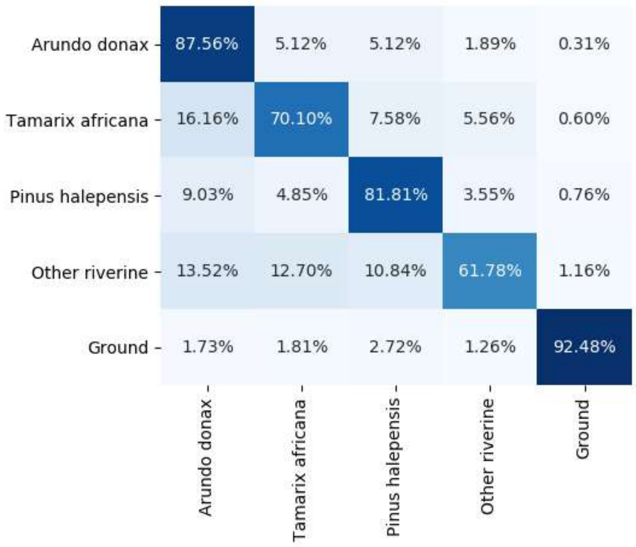

Fig. 3. Confusion matrix of the classification applying cross-validation with 10 folds in the random forest algorithm on the classes "*Arundo donax*", "*Tamarix africana*", "*Pinus halepensis*", "other riverine" and "ground".

The results of the mean cross validation score by class can be seen in the Fig. 3, where a global mean cross-validation score of 0.82 among all classes is obtained. Based on the results, the use of perform oversampling over the training samples obtained good results, as previous studies have shown [12].

Analysing each class in detail, the class that is best explained by the model is the "ground" class with 0.88 recall, that is the ability of the classifier to find all the positive samples. This was due to the large spectral difference between this class and the others. The precision for this class was of 0.85, the precision is the ability of the classifier not to label as positive a sample that is negative. The f1-score of this class was 0.86, the f1-score can be interpreted as a weighted average of the precision and recall.

The classes "*Arundo donax*" and "*Pinus halepensis*" obtained similar precision (0.85 and 0.84, respectively) and f1-score (0.86 and 0.83, respectively), but their recall values (0.88 and 0.82) indicate that the class "*Pinus halepensis*" has been classified more reliably, mainly because tree species had the greatest height of all the species in the study area.

The "*Tamarix africana*" class obtained the same values of recall, precision, and f1-score, 0.70. These values indicate that this class has also been classified correctly. Finally, the "other riverine species" class was the worst classified, predictably, with 0.62 recall, 0.64 precision and 0.63 f1-score. This is due to the diversity of classes that have been merged in this class, with different species, spectral responses, and geometries.

Fig. 4 shows the comparison between the normalised RGB point cloud and the classified point cloud. Visualising the classified point cloud can be observed that most of the riverbed is colonised by *Arundo donax*, this species is the majority species in the entire study area. The creation of a species map at centimetre resolution opens the possibility of implementing specific management plans for the elimination of this invasive species. Similarly, the image shows how the bridge in the lower left corner has been correctly classified as "ground".

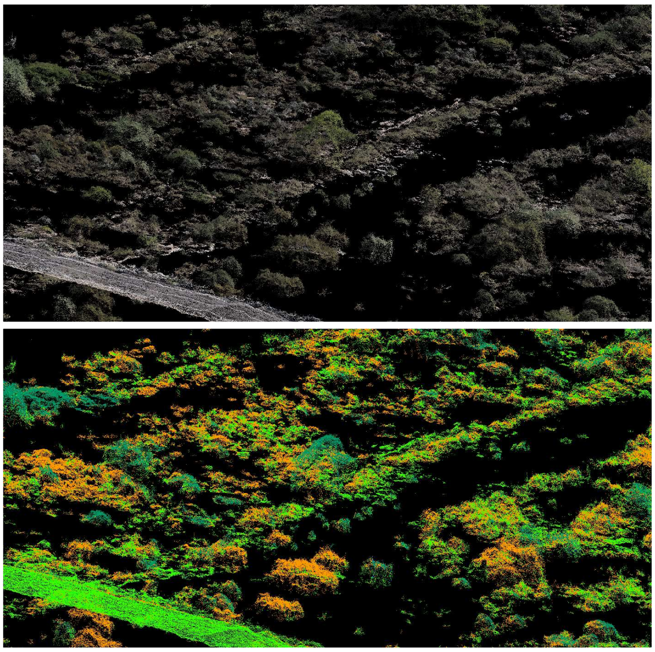

Fig. 4. Top: Oblique display of the normalised RGB point cloud. Bottom: Oblique display of the classified point cloud with the classes "*Arundo donax*" (aquamarine), "*Tamarix africana*" (orange), "ground" (green), "P*inus halepensis*" (blue), and "other riverine species" (yellow).

IV. Conclusions

This study showed that it is possible to classify riverine species from RGB images and the UAV-DAP technique, applying the Random Forest algorithm based on variables extracted from the point cloud. The proposed methodology can help to improve riverine zone management, allowing species maps to be obtained with high geometric and temporal accuracy at low cost.

Riverside areas are ideal for the use of the UAV-DAP technique due to the high dispersion of vegetation, making it unnecessary to use data from other techniques, such as LiDAR to obtain ground points that allow us to obtain a quality DTM for height normalisation. Therefore, in areas with low-dense vegetation it is not necessary to use high-cost sensors for species classification. Future studies will explore the possibility of merging LiDAR point clouds with UAV-DAP data for the classification of dense forest areas.

In addition, a future idea derived from this work is the use of multispectral and hyperspectral cameras for the classification of a larger number of plant species, without the need to merge different plant species into a single class. The methodology proposed in this work can be easily transferred to other fields.

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REFERENCES

[1] M. R. V.-A. Gutiérrez and M. L. S. Alonso, "Which are, what is their status and what can we expect from ecosystem services provided by Spanish rivers and riparian areas?," *Biodivers. Conserv.*, vol. 22, no. 11, pp. 2469–2503, 2013.

[2] W. Elmore and R. L. Beschta, "Riparian areas: perceptions in management.," *Rangelands Arch.*, vol. 9, no. 6, pp. 260–265, 1987.

[3] R. Naiman, S. Elliott, J. Helfield, and T. O'Keefe, "Biophysical interactions and the structure and dynamics of riverine ecosystems: The importance of biotic feedbacks," *Hydrobiologia*, vol. 410, pp. 79–86, Sep. 1999.

[4] G. Muñoz, E. Canadas Sanchez, M. F. M.C., and F. Valle, "Los SIG como herramienta para la gestión de la vegetación riparia," *Medio Ambient. Recur. y riesgos Nat. análisis Median. Tecnol. SIG y teledetección*, vol. 1, pp. 155–178, 2004.

[5] National Research Council, *Riparian Areas: Functions and Strategies for Management*. Washington, DC: The National Academies Press, 2002.

[6] D. Arizpe, A. Mendes, and J. E. Rabaça, "Áreas de ribera sostenibles: una guía para su gestión," *General. Valencia.*, 2008.

[7] A. A. Apan, S. R. Raine, and M. S. Paterson, "Mapping and analysis of changes in the riparian landscape structure of the Lockyer Valley catchment, Queensland, Australia," *Landsc. Urban Plan.*, vol. 59, no. 1, pp. 43–57, 2002.

[8] A. Fernández-Sarría, J. Estornell, I. López-Cortés, B. Velázquez-Martí, and D. Salazar, "Comparación de parámetros dendrométricos en almendros utilizando láser escáner terrestre (TLS) y fotogrametría digital automatizada (SfM)," in *Nuevas plataformas y sensores de teledetección*, 2017, no. 1, pp. 341–344.

[9] A. Michez, H. Piégay, L. Jonathan, H. Claessens, and P. Lejeune, "Mapping of riparian invasive species with supervised classification of Unmanned Aerial System (UAS) imagery," *Int. J. Appl. Earth Obs. Geoinf.*, vol. 44, pp. 88–94, 2016.

[10] J. P. Carbonell-Rivera, J. Estornell, L. Á. Ruiz, J. Torralba, I. López-Cortés, and D. Salazar, "Comparación de medidas de Nerium oleander L. mediante medición clásica, láser escáner terrestre (TLS) e imágenes derivadas de drones (UAV)," in *Hacia una visión global del cambio climático*, 2019, pp. 81–84.

[11] O. Nevalainen *et al.*, "Individual tree detection and classification with UAV-Based photogrammetric point clouds and hyperspectral imaging," *Remote Sens.*, vol. 9, no. 3, 2017.

[12] B. W. Yap, K. Abd Rani, H. A. Abd Rahman, S. Fong, Z. Khairudin, and N. N. Abdullah, "An application of oversampling, undersampling, bagging and boosting in handling imbalanced datasets," in *Proceedings of the first international conference on advanced data and information engineering (DaEng-2013)*, 2014, pp. 13–22.

[13] A. F. Abdullah, Z. Vojinovic, R. K. Price, and N. A. A. Aziz, "Improved methodology for processing raw LiDAR data to support urban flood modelling–accounting for elevated roads and bridges," *J. Hydroinformatics*, vol. 14, no. 2, pp. 253–269, 2012.