International Journal of Applied Earth Observations and Geoinformation 95 (2021) 102263

Contents lists available at ScienceDirect

International Journal of Applied Earth Observations and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Assessing the performance of different OBIA software approaches for mapping invasive alien plants along roads with remote sensing data

P. Lourenço [a,b,c,*], A.C. Teodoro [d,e], J.A. Gonçalves [d], J.P. Honrado [f,g], M. Cunha [b,d,h], N. Sillero [b]

[a] *MED – Mediterranean Institute for Agriculture, Environment and Development, Departamento de Engenharia Rural, Escola Ciências e Tecnologia, Universidade de Évora, Pólo da Mitra, Ap. 94, 7006-554 Évora, Portugal*

[b] *CICGE: Centro de Investigação em Ciências Geo-Espaciais, Faculdade de Ciências da Universidade do Porto, Portugal*

[c] *CAESCG - Centro Andaluz para la Evaluación y Seguimiento del Cambio Global, Universidad de Almería, Ctra. Sacramento s/n, La Cañada de San Urbano, 04120 Almería, Spain*

[d] *Departamento de Geociências, Ambiente e Ordenamento do Território, Faculdade de Ciências da Universidade do Porto, Portugal*

[e] *Instituto Ciências da Terra, Faculdade de Ciências da Universidade do Porto, Portugal*

[f] *Departamento de Biologia, Faculdade de Ciências da Universidade do Porto, Portugal*

[g] *InBIO - Rede de Investigação em Biodiversidade e Biologia Evolutiva, Laboratório Associado, CIBIO - Centro de Investigação em Biodiversidade e Recursos Genéticos, Universidade do Porto, Portugal*

[h] *INESCTEC - Institute for Systems and Computer Engineering, Technology and Science, Porto, Portugal*

A R T I C L E I N F O

Keywords:
Invasive alien plants
Remote sensing
Segmentation
Very high spatial resolution images
Open source software
Proprietary software

A B S T R A C T

Roads and roadsides provide dispersal channels for non-native invasive alien plants (IAP), many of which hold devastating impacts in the economy, human health, biodiversity and ecosystem functionality. Remote sensing is an essential tool for efficiently assessing and monitoring the dynamics of IAP along roads. In this study, we explore the potentialities of object based image analysis (OBIA) approach to map several invasive plant species along roads using very high spatial resolution imagery. We compared the performance of OBIA approaches implemented in one open source software (OTB/Monteverdi) against those available in two proprietary programs (eCognition and ArcGIS). We analysed the images by two sequential processes. First, we obtained a land-cover map for 15 study sites by segmenting the images with the algorithms Mean Shift Segmentation (MSS) and Multiresolution Segmentation (MRS), and by classifying the segmented images with the algorithms Support Vector Machine (SVM), Nearest Neighbour Classifier (NNC) and Maximum Likelihood Classifier (MLC). We created a mask using the polygons classified as non-vegetation to crop the images of the 15 study sites. Second, we repeated the previous segmentation and classification steps over the 15 masked images of vegetated areas using the same algorithms. OTB/Monteverdi, with MSS and SVM algorithms, showed to be a good software for land-cover mapping (OA = 87.0%), as well as ArcGIS, with MSS and MLC algorithms (OA = 84.3%). However, these two programs, using the same segmentation algorithms, did not achieve good accuracy results when mapping IAP species ($OA_{OTB/Monteverdi}$ = 63.3%; OA_{ArcGIS} = 45.7%). eCognition, with MRS and NNC algorithms, reached better classification results in both land-cover and IAP maps ($OA_{Land\text{-}cover}$ = 95.7%; $OA_{Invasive\text{-}plant}$ = 92.8%). 'Bare soil' and 'Road', and '*A. donax*' were the classes with best and worst overall accuracy, respectively, when mapping land-cover classes in the three programs. 'Other trees' was the class with the most accurate and significant differences in the three programs when mapping IAP species. The separation of each invasive species should be improved with a phenology-based design of field surveys. This study demonstrates the effectiveness of sequential segmentation and classification of RS data for mapping and monitoring plant invasions along linear infrastructures, which allows to reduce the time, cost and hazard of extensive field campaigns along roadsides.

* Corresponding author at: MED – Mediterranean Institute for Agriculture, Environment and Development, Departamento de Engenharia Rural, Escola Ciências e Tecnologia, Universidade de Évora, Pólo da Mitra, Ap. 94, 7006-554 Évora, Portugal.

E-mail addresses: pmrlourencov2@gmail.com (P. Lourenço), amteodor@fc.up.pt (A.C. Teodoro), jagoncal@fc.up.pt (J.A. Gonçalves), jhonrado@fc.up.pt (J.P. Honrado), mccunha@fc.up.pt (M. Cunha).

https://doi.org/10.1016/j.jag.2020.102263
Received 27 July 2020; Received in revised form 21 October 2020; Accepted 22 October 2020

1. Introduction

Invasive alien plants (IAP) can cause devastating impacts in the economy, human health, biodiversity and ecosystem functioning of invaded regions (Bock et al., 1986; Pyšek and Richardson, 2010; Williams and Baruch, 2000). Despite the efforts to control and eradicate IAP, their impacts continue to increase worldwide (Andreão et al., 2016; Hulme et al., 2010). Invasions by IAP are difficult to manage and prevent due to their ability to disperse and attain high abundances (Pluess et al., 2012; Rejmánek and Pitcairn, 2002). Further information is needed on the invasion process itself and on the role that environmental conditions and landscape structures play during invasions (Andrew and Ustin, 2010; Minor and Gardner, 2011).

IAP frequently spread along roads and roadsides (Christen and Matlack, 2006; Kalwij et al., 2008; Mortensen et al., 2009). The high density of roads in Europe enables a rapid expansion of IAP (Hulme, 2009), with vehicles acting as vectors for the propagation of seeds and vegetative parts of plants (Dar et al., 2015; Joly et al., 2011; Lelong et al., 2007). Our understanding about the underlying dispersion mechanisms must improve in order to minimize the related negative effects (Lemke et al., 2019). In this sense, fast and repeatable detection methods are essential for cost-effective monitoring (Nielsen et al., 2005; Pyšek and Hulme, 2005; Vilà and Ibáñez, 2011; Wittenberg and Cock, 2005), thereby enabling a more efficient management of IAP (Baard and Kraaij, 2019; Müllerová et al., 2017; Sharma, 2019).

Remote sensing (RS) thus emerges as an important tool for assessing and monitoring the dynamics of IAP along roads, providing information in a quick, efficient, continuous, consistent and repeatable way over large areas. High spatial resolution images provide an intuitive and direct RS method to visually detect the spatial distribution of IAP (Huang and Asner, 2009). Current and historical very high spatial resolution (VHR) aerial photographs provide important information about landscape changes over time, helping to identify the target species through the acquisition of appropriate period images and good time series (Brook and Bowman, 2006; Laliberte et al., 2004). This approach can complement the traditional field monitoring of IAP, which can be logistically difficult and expensive.

Object-based image analysis (OBIA) presents new possibilities of automated or semi-automated processing of high spatial and low spectral resolution data (Laliberte et al., 2004; Pringle et al., 2009). OBIA is characterized by sequential segmentation and classification processes. Segmentation involves grouping contiguous pixels (image objects) where features based on spectral variables, shape, texture, size, thematic data, and spatial relationship (contiguity) are assigned to each object (Blaschke, 2010). The classification process consists in classifying each object based on the assigned features. The characteristics of VHR images, large amount of shadow, low spectral information or low signal-to-noise ratio, favor the use of OBIA, obtaining better results than pixel-based analyses (Hodgson et al., 2003). Still, the availability of a large amount of spectral, spatial and contextual data for each image object can make the process subjective or time consuming (Laliberte et al., 2012).

The number of studies using OBIA for classifying IAP has recently increased (Alvarez-Taboada et al., 2017; Gonçalves et al., 2019a, 2019b; Jones et al., 2011; Khare et al., 2018; Ouyang et al., 2011; Pande-Chhetri et al., 2017). For instance, VHR aerial imagery is now commonly used to map non-native IAP, with satisfactory results for the giant hogweed (*Heracleum mantegazzianum*) in the Czech Republic (Müllerová et al., 2005; Müllerová et al., 2013) and for the Japanese knotweed (*Reynoutria japonica*) in the UK (Jones et al., 2011). Michez et al. (2016) mapped three riparian invasive taxa derived from Unmanned Aerial Systems (UAS) imagery using OBIA analysis. However, OBIA methods with VHR images to map IAP along roads remain unexplored.

OBIA methods are considered relatively complex and are mainly included in different commercial software (e.g. Bas, 2016; eCognition, 2013). However, their availability, as well as integration in open source software and tools, has increased in recent years (Gonçalves et al., 2019a, 2019b; Knoth and Nust, 2016; Teodoro and Araujo, 2016). The importance of using OBIA in open source software is related to the low cost and ease of networking through reproducibility and collaboration (Knoth and Nust, 2016). In this context, here we explored the potentialities of open source OBIA approaches to map IAP along roads using VHR aerial imagery. Specifically, we aimed to compare the performance of sequential OBIA algorithms implemented in the open source software Orfeo Toolbox/Monteverdi 5.6.1 (hereafter OTB/Monteverdi) and the proprietary software eCognition Developer 8.9 (hereafter eCognition) and ESRI ArcGIS 10.4.1 (hereafter ArcGIS). This study is motivated by the importance of developing fast, repeatable and cost-efficient methods for timely monitoring of non-native IAP, using RS in order to reduce the time, cost and hazard of extensive field campaigns along roadsides.

2. Material and methods

2.1. Study area

The study area includes the roadsides of the national roads EN4 and EN114 located in the Alentejo region (Southern Portugal; Fig. 1), with a total length of ca. 112 km (WGS84 coordinates: from 8.39 W, 38.57 N to 7.53 W, 38.84 N).

The climate is of the Mediterranean type, characterized by cold and wet winters and by hot and dry summers when temperatures reach up to 40 °C (Corte-Real et al., 1998). The topography of the two studied roads is relatively flat, with altitude ranging between 100 and 400 m a.s.l. The landscape of the national roads EN4 and EN114 is characterized by a diverse mosaic of land-cover types, including: (i) a savannah-like Mediterranean agroforestry system based on evergreen cork (*Quercus suber*) and holm oak (*Q. rotundifolia*) trees; (ii) intermixed with extensive open agricultural areas (non-irrigated arable land, permanently irrigated land), olive groves, vineyards, pastures; iii) forest plantations mainly of pines (*Pinus pinea*) and eucalypts (*Eucalyptus* spp.), broad-leaved forest, coniferous forest, and transitional woodland-shrub; and iv) artificial surfaces, such as continuous urban fabric, discontinuous urban fabric, industrial or commercial units, mineral extraction sites, sport and leisure facilities (Gonçalves et al., 2019a, 2019b; Meneses et al., 2018). All this landscape surrounds the roadsides of the study roads on which expansion and/or colonization of IAP species may occur.

The study area also includes the IAP species Silver wattle (*Acacia dealbata*), Australian blackwood (*Acacia melanoxylon*), Black locust (*Robinia pseudoacacia*), Tree of heaven (*Ailanthus altissima*) and Giant reed (*Arundo donax*), which are the target species of this study (Table 1). These IAP have the ability to produce a lot of seeds that can be accumulated in different seed banks and remain viable in the ground for many years. Seeds germinate after a space opening and/or fire occurrences, or if they have humidity. These plant species are considered invasive in a number of European countries and are listed among the hundred most aggressive invaders in Europe (DAISIE database, www.europe-aliens.org, invasoras.pt). In Portugal, the regulation of the introduction of IAP species was recognized in 1999 (Decreto-Lei n°. 565/99, of 21 December) and in 2019 considered the existence of 200 IAP species. Since 2013, the 'project invasoras.pt' is increasing knowledge and raising awareness of the Portuguese population on biological invasions which help to tackle the IAP problem.

2.2. Image data

An aerial flight was conducted in May of 2016 to collect VHR aerial images of the study area, covering the roads, the roadsides and the neighbouring land for IAP mapping (Fig. 2). According to the references (Table 1), the month of May corresponds to a particular phenological stage that captures the flowering and the peak of high productivity of most of the target IAP species. The spatial resolution of the aerial imagery was 10 cm/pixel with three bands in the visible spectrum, i.e. Red (R), Green (G) and Blue (B), and one band in the Near-Infrared (NIR).

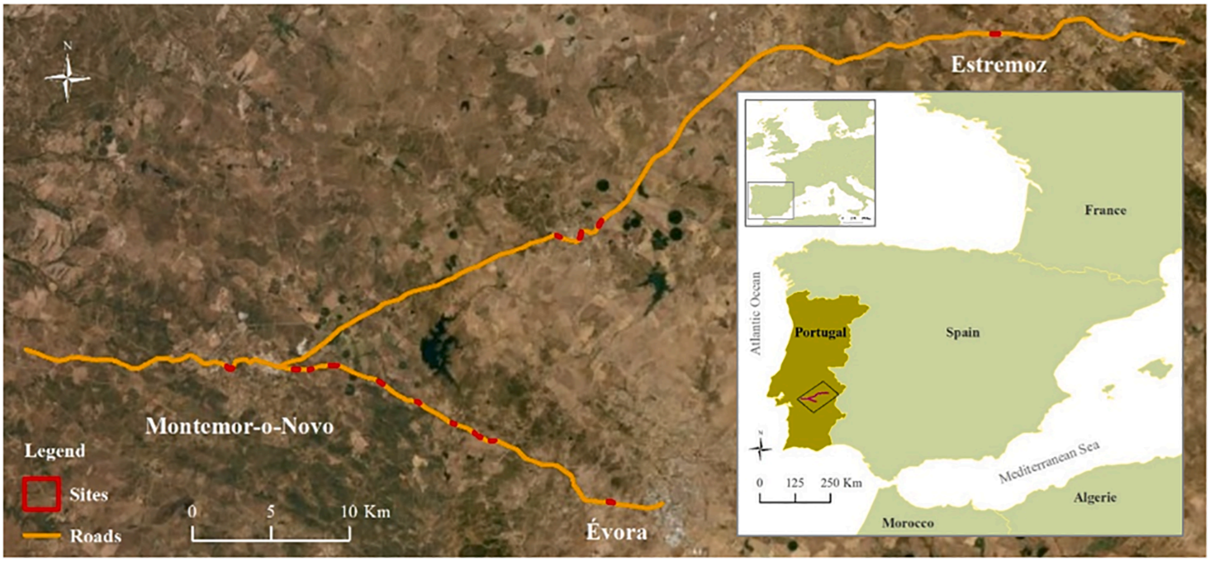

Fig. 1. Map of the study area and its location in Portugal and Europe. We defined 15 study sites (red dots) along the two focal roads (yellow lines) as representative of the land-cover diversity of the study area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Images were acquired with the support of high accuracy GPS and inertial navigation equipment, which allowed for precise georeferencing. All image bands were georeferenced and orthorectified. The images were orientated in the Agisoft Photoscan software, based on the coordinates of the projection centres given by precision GPS on board the plane. Then, we extracted a point cloud and generated a digital surface model. Finally, we computed the orthorectification and mosaic composition.

2.3. Field data

We conducted a field survey in May of 2016 along the roadsides of the study area (EN4 and EN114). We identified 96 individuals of IAP species, such as *A. dealbata, A. melanoxylon, R. pseudoacacia, A. altissima* and *A. donax*, that were located with the aid of a real-time kinematic (RTK) GPS receiver with 2 cm + 2 parts per million (ppm) of accuracy (Fig. 2). We used 70% of these occurrence data to train the classifier and 30% of the data as ground truth.

The final set of target IAP species included the Silver wattle (*A. dealbata*), the Australian blackwood (*A. melanoxylon*), the Black locust (*R. pseudoacacia*), the Tree of heaven (*A. altissima*) and the Giant reed (*A. donax*). These plant species are considered invasive in a number of European countries and are listed among the hundred most aggressive invaders in Europe (DAISIE database, www.europe-aliens.org, invasoras.pt).

Based on the location of the individuals of IAP recorded during the field survey, we defined 15 sites representative of the land-cover diversity in the study area (Fig. 1; Supplementary Material 1 – SM1). Each of the 15 study sites comprised a maximum of three of the target IAP species (Table 2). Since IAP are located along the roadside, we cropped the images of the 15 sites considering a 30 m buffer area from the roads (Fig. 2).

2.4. Overview of the software used

We computed the segmentation and classification procedures using one open source program, OTB/Monteverdi, and two proprietary programs, eCognition and ArcGIS, using different algorithm parametrisations.

From several available open source programs with OBIA algorithms, e.g. OTB/Monteverdi (ORFEO Toolbox, 2014), Spring (Spring-DPI/INPE, 2014), GRASS (GRASS GIS, 2014) and SegOptim (R package), we selected OTB/Monteverdi, designed for processing high resolution optical, multispectral and radar images (Christophe and Inglada, 2009). It supports raster and vector data and provides a wide variety of applications from *ortho*-rectification to classification and processing (Calleja et al., 2019).

Most studies based on OBIA algorithms use the proprietary software eCognition (now called Definiens Professional), an object-based image analysis software (Laliberte and Rango, 2009; Peña et al., 2013). eCognition is used in Earth sciences to develop rule sets for automatic analysis of RS data (Tarantino et al., 2019). The ArcGIS software has incorporated OBIA algorithms for segmentation (MSS) and classification (ISO Cluster, Maximum Likelihood, Random Forest and SVM classifiers). These two proprietary programs allow efficient inclusion of spatial concepts by segmenting an image into multipixel objects according to both spatial and spectral features. These objects are defined to maximize between-object variability and minimize within-object variability for user-chosen inputs. Rule-based decisions may then be applied to assign a class to each object. The fuzzy logic classifier provides additional adaptability.

2.5. OBIA methods

2.5.1. Segmentation

Segmentation is the process of partitioning the images into a spatially contiguous set of objects, each composed of a neighbouring group of pixels with homogeneity or semantic significance. We used the Mean Shift Segmentation (MSS) algorithm (Comaniciu and Meer, 2002) present at OTB/Monteverdi and ArcGIS, and the Multiresolution Segmentation (MRS) algorithm (Baatz and Schäpe, 2000) available in eCognition.

The MSS is a non-parametric method designed for the analysis of a complex space (Comaniciu and Meer, 2002). It is based on three main parameters: the spatial radius used to define the neighbourhood; the radius of the interval used to define the colour space interval (expressed in radiometry unit); and the minimum size for regions to be maintained after grouping (in pixel unit). These parameters are adjusted to build the segments based on a pixel, creating a set of neighbouring pixels within a given spatial radius and colour range. We tested different MSS scale parameters in OTB/Monteverdi and ArcGIS to obtain the best segmentation result. Although we used the same segmentation algorithm, the programs present different scale parameters to select. In OTB/Monteverdi, we defined after several trails the spatial radius and range radius of 20, and minimum region size of 500 pixels, while in ArcGIS, we

Table 1
Biological and biogeographical features of Invasive alien plants (IAP) considered as target species in the study area.

Scientific name	Native distribution area	Growth form and size	Leaves	Flowers	Fruits	Flowering	References
Acacia dealbata Link	Southeast Australian states of New South Wales, Victoria and Tasmania	Trees and shrubs (up to 15 m)	Evergreen, grey-green, bipinnate, with 10–26 pinnae pairs	Bright yellow arranged in globular flower heads of 5–6 mm diameter, forming large panicles	Brownish-red pods, compressed, pruinose, ± constricted between the seeds	January to April	Correia (2012)
Acacia melanoxylon R. Br.	Southeast Australia and Tasmania	Trees and shrubs (up to 15 m)	Evergreen, where the young leaves can be bipinnate and the others reduced to phyllodes as in adult leaves	Pale yellow, arranged in globular flower heads of 10–12 mm diameter	Brownish-red pods, compressed, contorted; seeds completely encircled by an orange funicle	February to June	Correia (2012)
Ailanthus altissima (Mill.) Swingle	Temperate Asia (China)	Trees and shrubs	Deciduous, alternate, odd-pinnate	Small (7–8 mm), greenish and arranged in panicles of 10–20 cm	Samaroid monocarps of 3–4 cm, reddish on the beginning	April to July	Silva et al. (2008)
Arundo donax L.	It is presumed to be native to eastern Europe, temperate and tropical Asia.	Robust perennial grass of large dimensions	From 1 to 8 cm wide, linear–lanceolate, of knifelike margins	Arranged in violet panicles of 30–90 cm, oblong, dense and ± constricted, generally with a short peduncle and a glabrous rachilla	Oblong caryopses that don´t produce viable seeds outside the native distribution area.	August to October	Pilu, Badone, and Michela (2012)
Robinia pseudoacacia L.	Central and Eastern North America	Trees and shrubs (up to 25 m)	Deciduous, odd-pinnate, with 3–11 pairs of elliptic or ovate leaflets	White, flashy, arranged in pendulous racemes	Pods of 3–12 × 1–1,5 cm, flat, slightly constricted between the seeds	April to June	Hunter (2000)

selected spectral detail of 17, spatial detail of 2 and minimum segment size of 10 pixels. All bands were equally balanced in the segmentation parameter in both programs. For segmentation and classification in OTB/Monteverdi we used all bands, while in ArcGIS we used only three bands (G, R, and NIR), the most related to vegetation, which is the maximum number of bands allowed.

The MRS algorithm consists of the consecutive fusion of pixels or image objects that partitions the image into image objects based on homogeneity criteria controlled by user-defined parameters such as shape, compactness/smoothness and scale parameter (Baatz and Schäpe, 2000). After testing different scale parameters, we defined the scale analysis of 70. We set the homogeneity criteria (shape and compactness) to default values of 0.1 and 0.5, respectively. We assigned an image layer weight 1 to the RGB bands and 2 to the NIR band due to its importance for mapping vegetation, which presents a high peak of reflectance at this wavelength. The chosen combinations correspond to the best conjugations of the four segmentation parameters obtained in the identification (segmentation) of the different available objects.

2.5.2. Classification

Training of the classifier was done using field data and expert knowledge. The Jeffries-Matusita index (JM) was applied to quantify the pair-wise classes' spectral separability and to allow the improvement of data quality (Richards and Richards, 1999) of land-cover and IAP species maps.

We tested three supervised classification algorithms to accurately classify the 15 images: (1) Support Vector Machine (SVM) available in OTB/Monteverdi; (2) Nearest Neighbour classifier (NNC) available in eCognition; and (3) Maximum Likelihood classifier (MLC) available in ArcGIS. The purpose of supervised classification is to categorize all pixels of the image in land-cover classes (Lillesand et al., 2014). Since we are using OBIA methods, we categorized the segments, composed by a set of pixels with similar characteristics. We used segments as training samples. In this way, we expected to obtain a very high classification accuracy and high quality of the information generated (Blaschke, 2010).

SVM is a machine learning non-parametric supervised classifier that analyses data used for classification and regression analysis (Vapnik, 1999). This algorithm has been used in various RS applications, such as mapping IAP (e.g. Gil et al., 2013; Shiferaw et al., 2019). The SVM algorithm, from a set of class-identified training examples, builds a model that assigns new examples to one class or another. SVM constructs a linear separation rule between examples in a higher-dimensional space induced by a mapping function in training samples.

NNC is a non-parametric method that uses a representative set of samples from each class to assign class values to segmented objects. This sample set is used by the algorithm to predict the class values of image objects, i.e. sample image objects closest to an image object of a given class will be assigned to that class (eCognition, 2013).

MLC algorithm considers that the distribution of a sample is Gaussian and the decision making is based on the Bayes Theorem. Based on these two characteristics, the statistical probability of each object is calculated to determine the membership of the object to the class, and an object is classified to the class to which it has the highest probability of being a member (Lillesand et al., 2014).

2.6. Accuracy assessment

We computed the overall accuracy (OA) and the Kappa coefficient, commonly used in accuracy assessment, to determine the accuracy of the land-cover and IAP species classified images. OA is calculated considering the error matrix by dividing the correctly classified pixels by the total number of pixels checked. Kappa coefficient is a multivariate technique for accuracy assessment that provides a measure of whether the confusion matrix is significantly different from a random result (Congalton, 1991; Congalton et al., 1983). This coefficient varies

Fig. 2. Examples of Invasive alien plants (IAP) in the study sites along roads, and their location (red rectangles) in the corresponding VHR images: *Ailanthus altissima* (S1 and S11), *Arundo donax* (S9) and *Acacia dealbata* (S14). See Table 2 for information on the IAP species recorded by site. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Numbers of individuals of each invasive alien plant (IAP) species recorded in the 15 sites (S1 to S15).

Species	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	Total
Acacia dealbata	1	4			2		3						3		2	15
Acacia melanoxylon		1		5	6	3		3		7				2		27
Ailanthus altissima	5		3			1	1				3					13
Arundo donax	6								2		12					20
Robinia pseudoacacia		2	4									1	5	8	1	21
Total	12	7	7	5	8	4	4	3	2	7	15	1	8	10	3	96

between<0 (random) and 1 (perfect agreement) (Landis and Koch, 1977).

The results of the accuracy assessment are presented in a confusion matrix where the allocated class crosses the reference data for the sample locations (Foody, 2002). From the confusion matrix, we computed producer's accuracy (PA) and user's accuracy (UA) of the land-cover and IAP species classes, which are the mapmaker (producer) and the map user accuracies, respectively.

We compute Kruskal-Wallis test and the *post-hoc* Dunn test to compare and to assess significant differences in the groups of the classes of land-cover and IAP species classification maps among the three programs. The Kruskal-Wallis test is a non-parametric method, alternative to the One Way ANOVA, used to compare two or more groups (Vargha and Delaney, 1998). The Dunn Test is a *post-hoc* non-parametric test, recommended to the Tukey test, used to assess significant differences in a small subset (Dunn, 1964).

2.7. Workflow

We mapped the target IAP species in the study area through a sequential process (Fig. 3). First, we established a legend with 8 classes for land-cover classification supported by JM pair-wise classes' spectral separability to separate the vegetation classes from non-vegetation classes in the 15 study sites by segmentation, using the algorithms MSS and MRS, and by classification, using the algorithms SVM, NNC, MLC (Fig. 3). This first classification included the following classes: (1) 'Bare soil', (2) '*Arundo donax*', (3) 'Grass', (4) 'Road', (5) 'Shadow', (6) 'Trees', (7) 'Urban', and 8) 'Water' (for more information see SM2). We considered '*Arundo donax*' a class apart from 'Grass' due to its distinctive size and its high dispersal ability along the roadsides in the study area. The class 'Trees' include all trees present in the study area, such as *Quercus* spp., *P. pinea*, *Eucalyptus spp.*, IAP trees species and others. Based on the vegetation areas obtained from the land-cover map (first segmentation followed by classification), we created a vegetation mask using the polygons classified as vegetation, i.e. the classes: (2) '*A. donax*'; (3) 'Grass'; and (6) 'Trees'. We used the mask to crop the images of the 15 study sites. Second, we mapped the target IAP species and calculated JM pair-wise classes' spectral separability in the 15 study sites with a second segmentation and classification, using the same algorithms of the first segmentation (MSS and MRS) and classification (SVM, NNC and MLC) on the cropped images (Fig. 3). This second classification included the classes: (1) '*Acacia dealbata*', (2) '*Acacia melanoxylon*', (3) '*Ailanthus altissima*', (4) '*Arundo donax*', (5) 'Grass', (6) '*Robinia pseudoacacia*', (7) 'Shadow', and (8) 'Other trees' (for more information see SM3). The class 'Other trees' include all trees species that are not the target IAP trees species.

3. Results

3.1. Classification accuracy for land-cover classes

eCognition obtained the higher accuracy when classifying land-cover classes (OA = 95.7%; Kappa = 0.95; PA = 93.0%; UA = 96.9%), while ArcGIS obtained the lower accurate map (OA = 84.3%; Kappa = 0.77; PA = 80.0%; UA = 68.2%) (Fig. 4; SM4). OTB/Monteverdi yielded intermediate accuracy (OA = 87.0%; Kappa = 0.84; PA = 78.0%; UA =

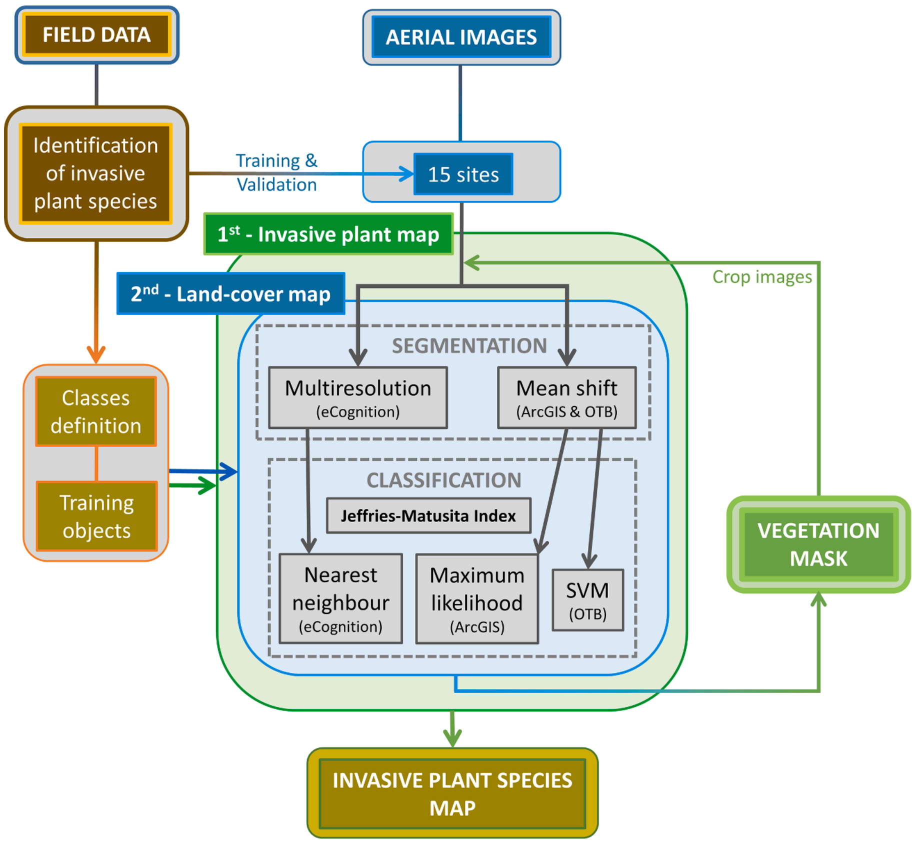

Fig. 3. Workflow of the sequential methodology applied to map invasive alien plants (IAP) species in the 15 study sites: 1st segmentation and classification to obtain the land-cover map of the study area, followed by a 2nd segmentation and classification to map the target IAP species.

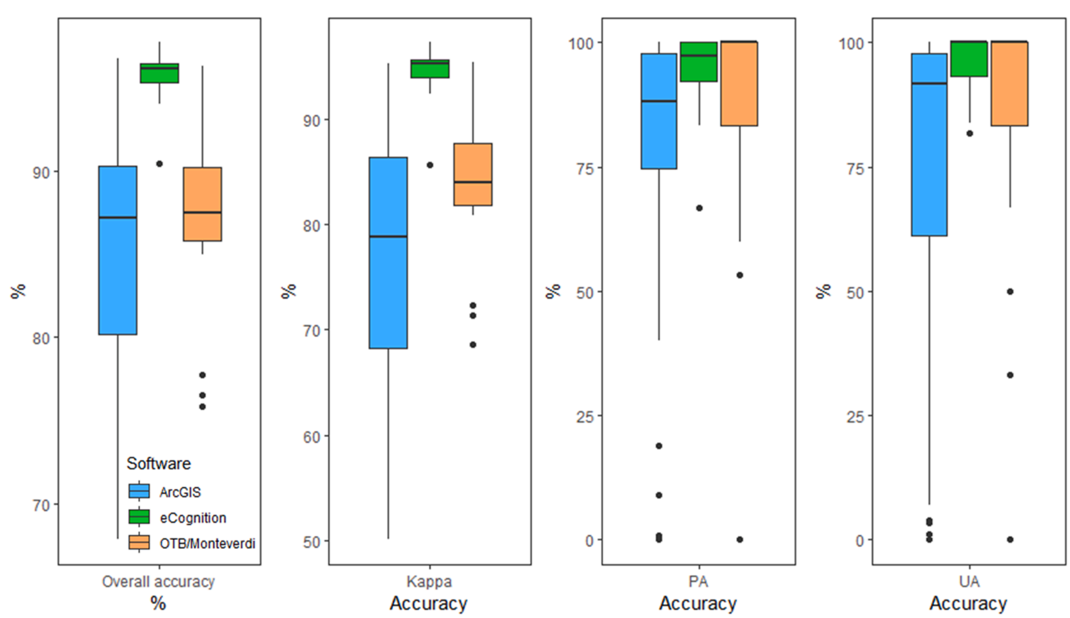

Fig. 4. Overall accuracy, Kappa coefficient, producer's and user's accuracy (PA and UA) of land-cover classes in the 15 study sites by OTB/Monteverdi (orange), eCognition (green) and ArcGIS (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

77.0%). The OA and Kappa coefficient obtained by eCognition were significantly different to those attained by ArcGIS and OTB/Monteverdi (p-value = 0.0003), while PA and UA obtained by eCognition and OTB/Monteverdi were significantly different to those obtained with ArcGIS (p-value < 0.0001).

The classes with the best PA in the three programs were 'Bare soil' and 'Road' (PA ≥ 92.4%) (Fig. 5a; SM5; SM6). The classes with the lowest PA values in eCognition were 'Water', 'Urban' and '*A. donax*' (PA = 83.3%, PA = 88.5% and PA = 89.3%), in ArcGIS were '*A. donax*' and 'Trees' (PA = 56.2% and PA = 67.2%), and in OTB/Monteverdi were '*A. donax*' and 'Urban' (PA = 22.2% and PA = 48.9%). The classes with the best UA in the three programs were 'Water' (UA = 100%), followed

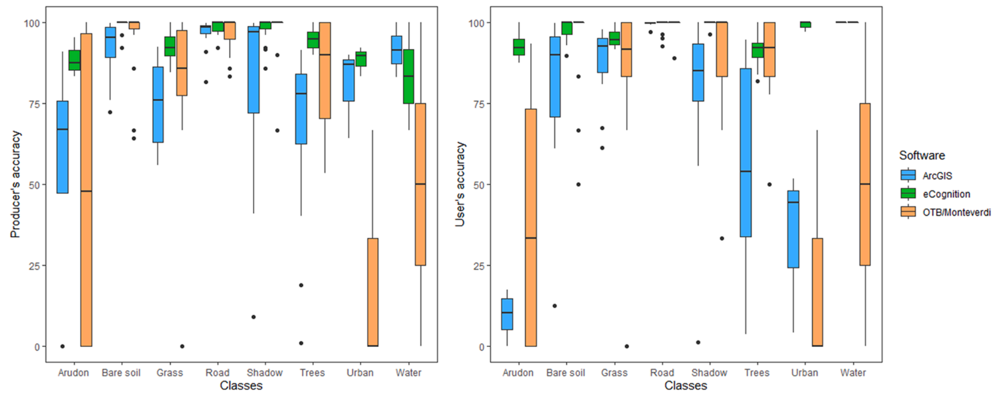

Fig. 5. Producer's accuracy (a) and user's accuracy (b) of the land-cover classes in the 15 study sites by OTB/Monteverdi (orange), eCognition (green) and ArcGIS (blue). Arudon: *Arundo donax*. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

by 'Shadow' in eCognition (UA = 99.8%) and 'Road' in ArcGIS and OTB/Monteverdi (UA ≥ 98.5%) (Fig. 5b; SM5; SM6). The classes with the lowest UA in the eCognition were 'Trees' and '*A. donax*' (UA = 91.5% and UA = 92.9%), and '*A. donax*' and 'Urban' in ArcGIS (UA = 9.5% and UA = 33.3%) and OTB/Monteverdi (UA = 40.0% and UA = 22.2%). The Fig. 6 shows an example of the land-cover classification map of the S14.

The separability between non-vegetation ('Bare soil', 'Road', 'Urban' and 'Water') and vegetation ('*A. donax*', 'Grass' and 'Trees') classes was very good, with a minimum value of 1.5 for the JM index in the land-cover map. The exception occurred between 'Bare soil' and 'Grass' which separability was good, with JM = 1.3. Regarding the separability between 'Water' and, '*A. donax*' and 'Urban', there is no information because only the sites 4 and 15 have the class 'Water' and none of the last two classes (SM1, SM2). The separability between 'Shadow' and, '*A. donax*' and 'Grass' was very good (JM = 1.6), and between 'Trees' was good (JM = 1.1). There was also a very good separability among the non-vegetation ('Bare soil', 'Road', 'Urban' and 'Water') with JM > 1.6, except between 'Bare soil' and 'Urban' which presented a low separability (JM = 1.0). The separability between the vegetation classes was low (JM < 1). In addition, the vegetation classes, i.e. '*A. donax*', 'Grass', 'Trees', and 'Urban' were significantly different from 'Bare soil' (p-value = 0.0000 for all), 'Road' (p-value = 0.0000 for all), 'Shadow' (p-value = 0.0000 for all) and 'Water' (p-value = 0.0005; p-value = 0.0323; p-value = 0.0038; p-value = 0.0041) (Fig. 7; SM5; SM6).

3.2. Classification accuracy for invasive alien plants

The best classification map of IAP species, i.e. the result of the second segmentation and classification map, was obtained with the eCognition

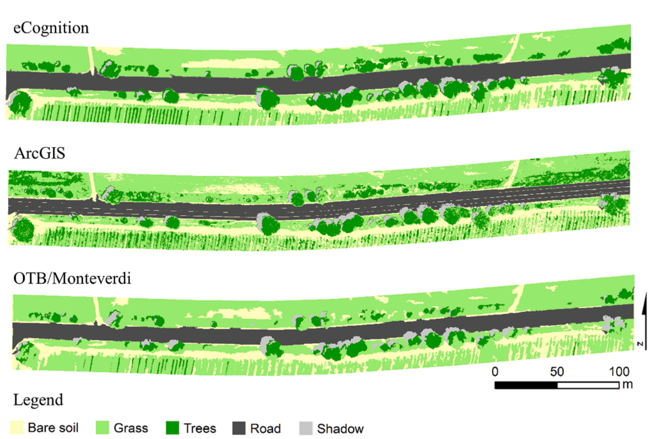

Fig. 6. Land-cover classification map of S14 (see also Fig. 2 and Table 2) in the eCognition, ArcGIS and OTB/Monteverdi programs.

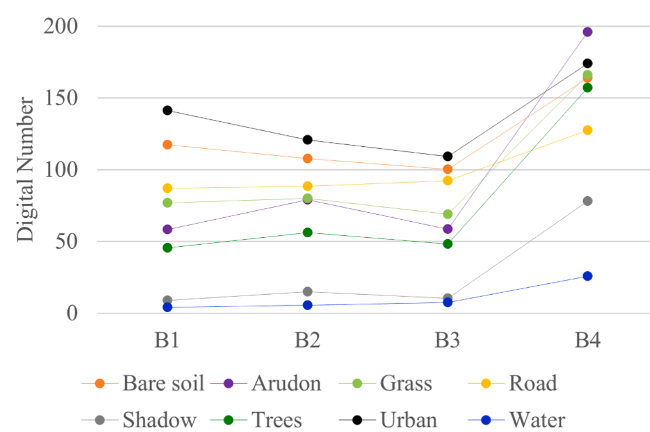

Fig. 7. Spectral signatures of the mapped land-cover classes in the four bands of the aerial images (B1 = Blue, B2 = Green, B3 = Red and B4 = NIR). Arudon: *Arundo donax*. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(OA = 92.8%; Kappa = 0.89; PA = 90.1%; UA = 91.7%) (Fig. 8; SM7). According to the OA and Kappa values, ArcGIS achieved the least accurate map (OA = 45.7%; Kappa = 0.24). OTB/Monteverdi attained better results for OA and Kappa than ArcGIS (OA = 63.3%; Kappa = 0.29). However, it obtained the lowest values of PA and UA overall (PA = 28.1%; UA = 30.4%), compared to ArcGIS (PA = 50.5%; UA = 37.5%), both distant from eCognition. The OA was significantly different among the three programs (p-value = 0.017). The Kappa, PA and UA of eCognition were significantly different (higher) to OTB/Monteverdi and ArcGIS (p-value = 0.000).

The classes with the best PA were 'Shadow' in eCognition (PA = 95.5%) and ArcGIS (PA = 75.6%), and 'Other trees' in OTB/Monteverdi (PA = 61%) (Fig. 9a; SM8; SM9). The classes with the lowest PA were '*A. dealbata*' in eCognition (PA = 84.5%) and ArcGIS (PA = 34.0%), and '*A. altissima*' in OTB/Monteverdi (PA = 0.0%). The class with the highest UA was '*A. donax*' in eCognition (UA = 96.4%) and 'Other trees' in ArcGIS (UA = 81.0%) and OTB/Monteverdi (UA = 87.0%) (Fig. 9b; SM8; SM9). The classes with the lowest UA were 'Grass' (UA = 84.4%) and '*A. altissima*' (UA = 87.6%) in eCognition; '*A. dealbata*' (UA = 13.9%) and 'Grass' (UA = 17.8%) in ArcGIS; and '*A. altissima*' (UA = 0.0%) and '*A. melanoxylon*' (UA = 5.7%) in OTB/Monteverdi. In OTB/Monteverdi the classes with the lowest PA and UA were the IAP trees, i.e. '*R. pseudoacacia*', '*A. dealbata*', '*A. melanoxylon*' and '*A. altissima*'. The Fig. 10 shows an example of the IAP species classification map of the S14.

The separability between IAP tree species ('*A. dealbata*', '*A. melanoxylon*', '*A. altissima*', '*R. pseudoacacia*') and 'Other trees' was

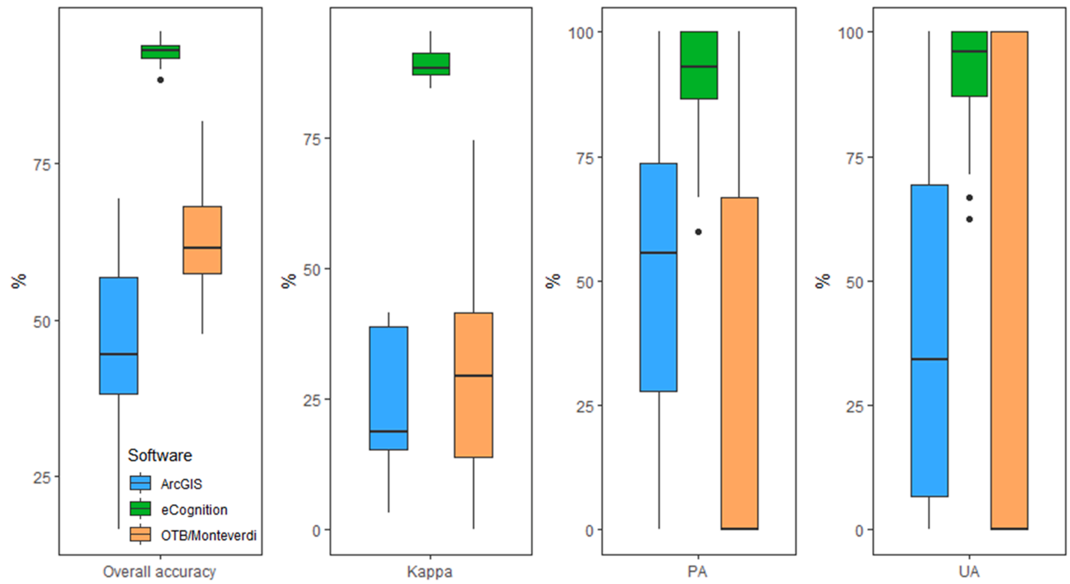

Fig. 8. Overall accuracy, Kappa, producer's and user's accuracy (PA and UA) of IAP in the 15 study sites by OTB/Monteverdi (orange), eCognition (green) and ArcGIS (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

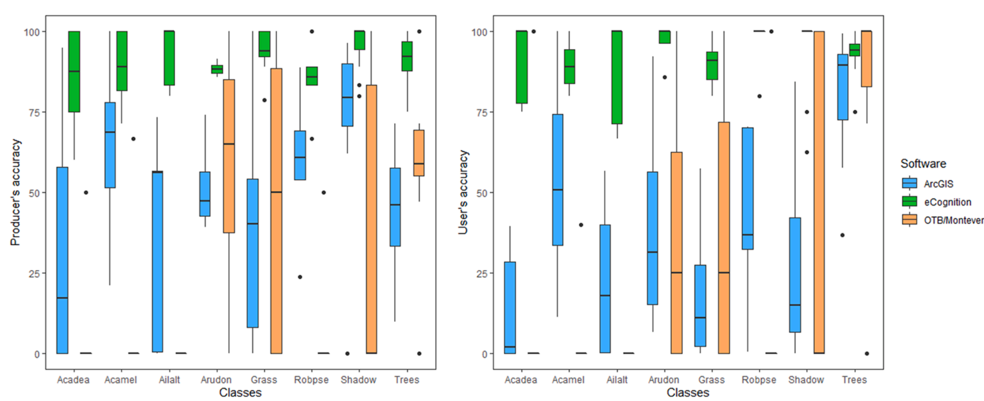

Fig. 9. Producer's accuracy (a) and user's accuracy (b) of invasive alien plants (IAP) in the 15 study sites by OTB/Monteverdi (orange), eCognition (green) and ArcGIS (blue). Acadea: *Acacia dealbata*. Acamel: *Acacia melanoxylon*. Ailalt: *Ailanthus altissima*. Arudon: *Arundo donax*. Robpse: *Robinia pseudoacacia*. Trees: Other trees. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

weak, with a JM index value of 0.8 in the IAP species map. The separability between '*A.* melanoxylon'and '*R. pseudoacacia'* was very good, with a value of 1.6 for the JM index. The separability between '*A. dealbata*' and, '*A. altissima*' and '*R. pseudoacacia*' was good with values of 1.2 and 1.3 for the JM index. On the other hand, '*A. melanoxylon*' and, '*A. dealbata*' and '*A. altissima*' presented weak separability, with JM index values of 0.8 and 0.9. The separability between '*A. altissima*' and '*R. pseudoacacia*' was also weak with a JM index value of 0.8. The separability was weak between '*A. donax*' and, '*A. altissima*', 'Grass' and 'Shadow' (JM = 0.8), and between 'Trees' (JM = 0.7). There is no separability information between '*A. donax*' and the other classes because only the sites S1, S9, S11 and S15 have this class. The class 'Other trees' held significant differences in accuracy from all IAP trees species, i.e. '*A. dealbata'* (p-value = 0.0008), '*A. melanoxylon'* (p-value = 0.0006), *'A. altissima'* (p-value = 0.0002), '*R. pseudoacacia'* (p-value = 0.0122), and from 'Grass' (p-value = 0.0000) and 'Shadow' (p-value = 0.0037) (Fig. 11; SM8; SM9). There were no significant differences among IAP trees species.

4. Discussion

4.1. Software performance

The proprietary software eCognition obtained higher accuracy results, followed by the open source software OTB/Monteverdi and then by the proprietary software ArcGIS. Our results corroborate the effectiveness of the OBIA methods of eCognition in producing high-quality classification maps as reported by other authors (Benz et al., 2004; Michez et al., 2016; Moran, 2019; Neubert and Meinel, 2003). Neubert and Meinel (2003) evaluated the segmentation of high-resolution images using several programs: the best overall results were reached by eCognition, which deals efficiently with the high complexity of VHR remote sensing imagery. eCognition applies a multi-scale segmentation with fuzzy logic based image classification capabilities (Meinel and Neubert, 2004). The great advantage of eCognition is its capacity to perform segmentation and classification together as a whole, i.e. the parameters of segmentation and classification are chosen automatically in order to optimize the results.

In general, the OTB/Monteverdi SVM algorithm showed a better classification performance than the ArcGIS MLC algorithm when computing classification maps. Several authors demonstrated that SVM

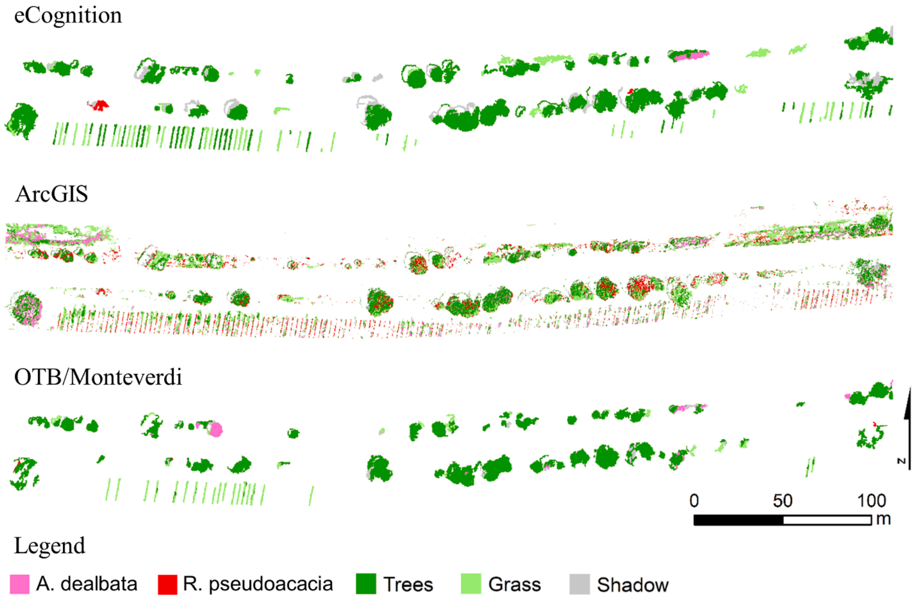

Fig. 10. IAP species classification map of S14 (see also Fig. 2 and Table 2) in the eCognition, ArcGIS and OTB/Monteverdi programs.

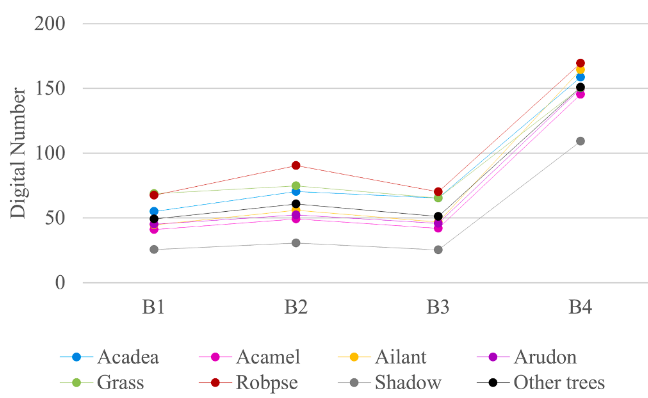

Fig. 11. Spectral signature of the classes in the invasive alien plants (IAP) map, in the four bands of the aerial images (B1 = Blue, B2 = Green, B3 = Red and B4 = NIR). Acadea: *Acacia dealbata*. Acamel: *Acacia melanoxylon*. Ailalt: *Ailanthus altissima*. Arudon: *Arundo donax*. Robpse: *Robinia pseudoacacia*. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

is indeed a more accurate classifier compared to MLC (Deilmai et al., 2014; Mondal et al., 2012; Nitze et al., 2012). The SVM classifier has proved its effectiveness in the classification of VHR ground cover images (Bruzzone and Carlin, 2006; Inglada, 2007; Tuia et al., 2009), while MLC is known to face some problems when handling complex images (Deilmai et al., 2014).

At the moment of software selection for OBIA techniques, one must not forget the cost-effectiveness of an open source software solution compared to proprietary software. Open source software solutions have an advantage over proprietary software because they are freely available and accessible to all users, including those without purchasing capacity (Rocchini and Neteler, 2012; Wegmann et al., 2016). Another advantage of open source software is that the source code can be shared and modified to meet the needs of each user. However, proprietary software is frequently more user-friendly despite its price. Currently, open source software (such as R, GRASS, QGIS, OTB, SAGA, and GDAL) offer similar features to proprietary software (Esri, ERDAS, ENVI / IDL, and eCognition) at no cost.

4.2. Accuracy assessment and implications for monitoring

The land-cover classification provided generally higher overall accuracy values than the IAP classification. These differences are due to the low range of spectral separability of the classes related to IAP species with JM index minimum and maximum values of 0.7 and 1.6, while the separability among land-cover classes vary between 0.7 and 2.0 of JM index minimum and maximum values. These differences are observed also in the digital number range per land-cover classes varying from 4 and 196, while the digital number range per IAP classes varies between 28 and 163 (Figs. 7 and 11). Indeed, we performed the second segmentation and classification to maximise the spectral differences between IAP species in order to obtain a good classification of IAP. However, OTB/Monteverdi (PA_{min} = 0% and PA_{max} = 57.5%; UA_{min} = 0% and UA_{max} = 37.5%) and ArcGIS (PA_{min} = 34% and PA_{max} = 64.1%; UA_{min} = 13.9% and UA_{max} = 53.9%) showed a poor OBIA performance in the classification of IAP classes compared with the good IAP mapping performance of eCognition (PA and UA > 84.4%). Moreover, the rather high accuracy attained for the land-cover classification map may be explained by the high spectral separability of the more distinct landscape classes.

Our results showed that there is some spectral difference between IAP tree species and 'Other trees' (mainly pines, eucalypts and evergreen oaks). OTB/Monteverdi showed good OBIA performance in accurately classify the class 'Other trees' (PA = 61.0% and UA = 87.0%) but not the IAP trees *per se* (PA_{min} = 0% and PA_{max} = 10.0% and UA_{min} = 0% and UA_{max} = 20.0%). The differences observed among IAP classes may be due to the date of the image acquisition (beginning of May) which corresponds to the period of greatest greenness for most, but not all, IAP species. For example, the Tree of heaven (*Ailanthus altissima*) is characterized by a later seasonal development than other tree species because it requires high temperatures for leaf sprouting (Kowarik and Säumel, 2007). In May, temperatures begin to rise in the study region (Alentejo) in an average of ± 22 °C to ± 27 °C and, on the date of acquisition of the images, the branches of the trees of *A. altissima* did not have their maximum foliage. Consequently, the reflectance of this species was low, compared to other tree species (e.g. *A. melanoxylon* and *R. pseudoacacia*). In the case of *A. dealbata*, the overall accuracy was lower compared to *A. melanoxylon*, because in May the flowering period of the former has already ended (January to April; Table 1) whereas the latter is still within the flowering period (February to June; Table 1)

(Correia, 2012).

We also observed some misclassification between the classes '*A. donax'* and 'Grass' despite the high values of accuracy assessment, which may be related to their similar spectral signature. In May, native grasses are very vigorous in the study area due to water availability and moderate temperatures, while *A. donax* is still not in its flowering period (August to October; Table 1) (Pilu et al., 2012). A good date of image acquisition should correspond to the phenological period that allows better detection and differentiation among the target species, e.g. the peak of flowering (high greenness) (Huang and Asner, 2009), when the canopy structure is dense, or there is a high spectral difference between the region of the visible and the NIR (Dorigo et al., 2012; Jones et al., 2011; Somodi et al., 2012). Therefore, when mapping many plant species, it becomes challenging to find a suitable date of image acquisition, particularly in the case of IAP species.

This study also showed that the expansion of AIP species along roads is conditioned by surrounding anthropic areas, as in the study area, for instance by agroforestry systems, agricultural and urban areas around the road. Further, most of the *A. donax* areas were located close to roadsides and on the limit of the agricultural area and agroforestry systems, or in areas with high water availability, e.g. near bridges and depressions on the ground. This observation is in agreement with Pilu et al. (2012) which state that the invasion of *A. donax* is located mainly in riparian and along the roadside and can reach several kilometres. In the study area, some of IAP trees species, e.g. *Acacia* spp, *A. althissima* and *R. pseudoacacia*, are used for ornamentation of the housing area, fence rows, cracks in sidewalks and road embankments and colonize roadsides, as described by several authors (Correia, 2012; Ivajnšič et al., 2012; Kowarik and Säumel, 2007). Thus, the expansion along the roads of the IAP trees species is limited, despite their fast germination and seedling growth, because the owners will control their colonization. Furthermore, in Portugal, there is an action plan for cleaning the roadsides and fuel management tracks to "contribute effectively to the Forest Fire Protection System" (Resolution of the Council of Ministers n.° 161/2017, Portugal) that indirectly prevent the expansion and colonization of IAP species.

5. Conclusions

Our results highlight that it is possible to analyse VHR images with OBIA methods and with open-source software similarly to proprietary software. More importantly, not always proprietary software is the best solution. In our case, eCognition provides OBIA methods and tools for mapping land-cover and IAP, but ArcGIS showed to be the less appropriate software for this type of RS applications due to its limited capacities of OBIA performance. However, the open source software OTB/Monteverdi proved to be a good cost-effective classification option for 'Other trees' using OBIA methods but not for IAP species. It is necessary therefore to consider the specific characteristics of the study case in order to choose the suitable date of image acquisition and the best software. Further, our study showed that IAP species along the study roads, characterized as vectors of propagation of seeds and vegetative parts of plants, do not have many opportunities to expand into the adjacent land because the roadsides are actively managed.

Declaration of Competing Interest

None.

Acknowledgements

This work is funded by the LIFE LINES project (LIFE 14/NAT/PT/001081), and by the National Funds through FCT - Foundation for Science and Technology under the project UIDB/05183/2020 and the project UIDB/04683/2020. NS is supported by a FCT contract (CEECIND/02213/2017).

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jag.2020.102263.

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