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Mapping invasive alien *Acacia dealbata* Link using ASTER multispectral imagery: a case study in central-eastern of Portugal

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Abstract

Aim of the study: *Acacia dealbata* is an alien invasive species that is widely spread in Portugal. The main goal of this study was to produce an accurate and detailed map for this invasive species using ASTER multispectral imagery.

Area of study: The central-eastern zone of Portugal was used as study area. This whole area is represented in an ASTER scene covering about 321.1 x 10^3 ha.

Material and methods: ASTER imagery of two dates (flowering season and dry season) were classified by applying three supervised classifiers (Maximum Likelihood, Support Vector Machine and Artificial Neural Networks) to five different land cover classifications (from most generic to most detailed land cover categories). The spectral separability of the land cover categories was analyzed and the accuracy of the 30 produced maps compared.

Main results: The highest classification accuracy for acacia mapping was obtained using the flowering season imagery, the Maximum Likelihood classifier and the most detailed land cover classification (overall accuracy of 86%; Kappa statistics of 85%; acacia class Kappa statistics of 100%). As a result, the area occupied by acacia was estimated to be approximated 24,770 ha (*i.e.* 8% of the study area).

Research highlights: The methodology explored proved to be a cost-effective solution for acacia mapping in central-eastern of Portugal. The obtained map enables a more accurate and detailed identification of this species' invaded areas due to its spatial resolution (minimum mapping unit of 0.02 ha) providing a substantial improvement comparably to the existent national land cover maps to support monitoring and control activities.

Keywords: remote sensing; invasive alien species; land cover mapping; vegetation mapping.

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Introduction

Fire and invasive species are becoming two of the most important global problems in natural and anthropogenic ecosystems (Pimentel *et al.,* 2005; Keeley, 2006; Arán *et al*., 2013). Invasive species constitute a major environmental problem, as they have profound consequences on biodiversity conservation and on ecosystem processes and functioning (Parker *et al*., 1999; González-Muñoz *et al*., 2012). In the past few centuries, thousands of woody plant species have been moved out of their natural ranges around the world. As a result, in recent decades many species of trees and shrubs have become naturalized or invasive. Many have spread from planting sites and some are now among the most widespread and damaging of invasive organisms (Richardson & Rejmánek, 2011).

The naturalization/invasion process may be explained by the following key terms: 'introduction' means that the plant (or its propagule) has been transported by humans across a major geographical barrier; 'naturalization' starts when abiotic and biotic barriers to survival are surmounted and when various barriers to regular reproduction are overcome; 'invasion' further requires that introduced plants produce reproductive offspring in areas distant from sites of introduction. Taxa that can cope with the abiotic environment and biota in the general area may invade disturbed, semi-natural communities (Richardson *et al.*, 2000). Asner *et al.* (2008) also consider that some of the life strategies that correlate a plant invasive success are: 1) an ability to grow through the native canopy, or in gaps, and eventually replace it (*e.g.* Yamashita *et al.*, 2000); 2) alteration of fundamental ecosystem processes such as nitrogen (N) cycling (*e.g.* Ehrenfeld, 2003; May & Attiwill, 2003; Hughes & Denslow, 2005); and 3) an ability to alter disturbance regimes such as fire frequency (*e.g.* Hughes *et al.*, 1991; D'Antonio & Vitousek, 1992).

Characterization and distribution of *Acacia dealbata* Link

Australian acacias are a group of leguminous woody plants that include some of the most important plant invaders on a global scale (Richardson & Rejmánek, 2011; Souza-Alonso *et al.*, 2013). Australian acacias have a wide range of impacts on ecosystems that increase with time and disturbance, transform ecosystems and alter and reduce ecosystem service delivery. A shared trait is the accumulation of massive seed banks, which enables them to become dominant after disturbances (Le Maitre *et al.*, 2011). As a result, the invasion of acacias species poses a threat to natural habitats by competition and replacement of native species, decreasing the native biodiversity and homogenizing the community (Lorenzo *et al.*, 2010). In general, invasion takes over sites that have been disturbed by fire, harvesting or other types of anthropogenic disturbance as a result of this species high colonization capacity (Fuentes-Ramírez *et al.*, 2011). Therefore, control and restoration operations should be promoted, particularly active restoration. Despite requiring substantial short to medium term investments these operations can reduce losses of biodiversity and ecosystem services as well as the costs to society in the long term (Le Maitre *et al.*, 2011).

The species *Acacia dealbata* Link (silver wattle) was introduced in Europe during the 19th century and is currently causing huge ecological concerns in Southern Europe (Souza-Alonso *et al.*, 2013; Vazquez-de-la-Cueva, 2014). In Portugal, the species was introduced in 1850 and used for ornamental purpose, for its products (flowers, tannin and timber either for construction or for firewood) and for soil fixation. Despite its invasive behaviour has been reported during the 19th century, restrictive legislation to acacia plantation occurred only in 1937. Nevertheless, its status as an invasive species was only legally established in 1999 (Marchante *et al.*, 2005). At the present, the species acacia can be found all over the country and its high invasive potential comes from the high seed production, dispersal and longevity in the soil, as well as the stimulation of seeds by fire (quite frequent in Mediterranean climates such as Portugal) allowing that recently burnt areas of this species easily recover their stands (Marchante *et al.*, 2005). According to the last National Forest Inventory (AFN, 2010), 35% of the territory (3.2 x 10^6 ha) is covered by forests whereas the afforested area of *Acacia* sp. (stands) in 2010 was 5,351 ha (*i.e.* 0.2%). Furthermore, between 1995, 2005 and 2010 (a 15 year period) an enormous increase of this species afforested area was observed (2,701 ha in 1995, 4,726 ha in 2005 and 5,351 ha in 2010, *i.e.* + 98%). Moreover, when considering acacia's total area as a dominant species its expression is fairly higher (12,278 ha in 1995 that has decreased to 11,803 in 2010) representing around 0.4% of Portuguese forest area (ICNF, 2013). Even so, it must be stressed that in this National Forest Inventory forest areas estimation considered only areas with a minimum of 0.5 ha, a minimum width of 20 m, and a ground cover higher than 10% (ICNF, 2013).

According to Marchante *et al.* (2005) this species grows preferably in fresh valley soils or along water streams banks and it is also very frequently located along road sides. It is also known that the species acacia is widely spread in patches much smaller than 0.5 ha nearby localities and on main road sides (*e.g.* linear patches of width smaller than 20 m). Therefore, it is expected that this species invaded area to be much higher than those from the National Forest Inventory statistics. Acacia areas are characterized as both dense and very short vegetation structures (*e.g.* ground cover around 90%) wherein this species dominates all height classes under 16 m (*e.g.* mean height around 4 m). This species invasion is mainly found in maritime pine (*Pinus pinaster* Aiton), umbrella pine (*Pinus pinea* L.) and eucalyptus (*Eucalyptus* sp.) stands (Godinho-Ferreira *et al.*, 2005).

Application of RS and GIS techniques in mapping biological invasions

The spread of invasive species has generated interest in mapping their present distribution worldwide as the patterns of plant invasions, and the ecological processes which generate these patterns, vary across spatial scales. Thus, consideration of spatial scale may help to illuminate the mechanisms driving biological invasions, and offer insight into potential management strategies (Pauchard & Shea, 2006). Therefore, it becomes essential to have tools to identify and monitor invasive species distributions, in order to obtain reliable and updated information for better management of invaded areas (Joshi *et al*., 2006; Underwood & Ustin, 2007). This implies being able to delineate the spatial extent and to ascertain the severity or intensity of the invasion, providing therefore a baseline for monitoring future expansion, increasing the effectiveness of control efforts, and assisting in identifying specific targets for control activities such as satellite populations and 'invasion fronts' (Underwood *et al*., 2003).

Remote sensing (RS) has been an important tool for large-scale ecological studies in the past three decades, but it was not commonly used to study alien invasive plants until the mid 1990s (Huang & Asner, 2009). RS and Geographic Information Systems (GIS) are useful tools for mapping and monitoring invasive species and to predict areas of susceptibility for exotic species invasion (Joshi *et al*., 2004). RS provides multi-temporal records that can be integrated and used into a GIS in order to support monitoring and control activities of invaded sites (Gil *et al*., 2013; Gil *et al*., 2014). Additionally, researchers have sought to exploit unique phenological, spectral, or structural characteristics of invasive species in digital multispectral imagery to distinguish them from the species around them (Underwood *et al*., 2003; Underwood & Ustin, 2007; Resasco *et al*., 2007). According to Huang & Asner (2009), moderate resolution satellite imagery (*e.g.* spatial resolution between 10-100 m and spectral resolution with less than twenty spectral bands) such as the ones captured by the satellites LANDSAT (*e.g.* Thematic Mapper and Enhanced Thematic Mapper Plus), SPOT (*Satellite pour l' Observation de la Terre*) and TERRA (particularly, ASTER – Advanced Spaceborne Thermal Emission and Reflection Radiometer) are well suited for mapping at the community level and have been used to map invasive species before (*e.g.* Cobbing, 2007; Lawes & Wallace, 2008; Viana & Aranha, 2010; Gil *et al*., 2014).

In Portugal the latest official land cover map (COS2007) was produced in 2007 at the scale of 1:25,000 (with a minimum mapping unit of 1 ha, a minimum distance between lines of 20 m, and a minimum polygon width of 20 m). Despite using a five-level classification system of 238 land cover categories, the COS2007 map considers broad classes of invasive species only (*e.g. A. dealbata* and *Ailanthus altissima* Mill.) either as, pure or mixed forest (ground cover higher than 30%) or open forest (ground cover between 10 to 30%) (DGT, 2007). Therefore, the use of moderate resolution satellite imagery to produce detailed presence maps for the species acacia by supervised classification techniques should be explored.

Viana & Aranha (2010) performed a comparison study between ASTER/TERRA and ETM+/LANDSAT 7 imagery for mapping the species acacia, in a study area in the center of Portugal, using two supervised classifiers and a classification system with three categories. These authors obtained overall accuracies of 89% for the ETM+ imagery classification (24 January 2003) and 87% for the ASTER imagery classification (7 October 2003) using the best classifier (*e.g.* maximum likelihood classifier). Despite of the ASTER imagery having a better special resolution (*e.g.* 15 m) than the ETM+ imagery (*e.g.* 30 m) it was the imagery acquisition date that proved to be the most relevant factor on imagery classification accuracy.

Therefore, due to the success of those previous studies and also because of ASTER imagery specific characteristics (low economic cost allied to moderate spatial and spectral resolutions), the aim of this study was to explore ASTER imagery from two acquisition dates (*Acacia* sp. flowering season vs. dry season), five land cover classifications with different degree of generalization and three supervised classifiers, in order to assess the best approach to accurately map this species. The working hypothesis essayed was that ASTER imagery from March (*i.e.* the species flowering season) will allow a better spectral separability and classification/mapping of the species than the imagery from August (dry season) when using the most detailed land cover classification essayed and the maximum likelihood classifier. To test this hypothesis, ASTER imagery from 25 August 2005 and from 24 March 2007 were used. First, both imagery datasets were assessed in terms of spectral separability using the five land cover classifications with different degree of generalization. After, the images were classified using three supervised classifiers (*e.g.* the parametric Maximum Likelihood classifier and the two non-parametric Support Vector Machine and Artificial Neural Networks classifiers). In the end, the accuracy of the produced maps was compared to assess the best approach to accurately map this species. The most accurate map was used to evaluate species' invasion area at a minimum mapping unit of 0.02 ha providing a substantial improvement comparably to the COS2007 map and/or the National Forest Inventory statistics.

Material and methods

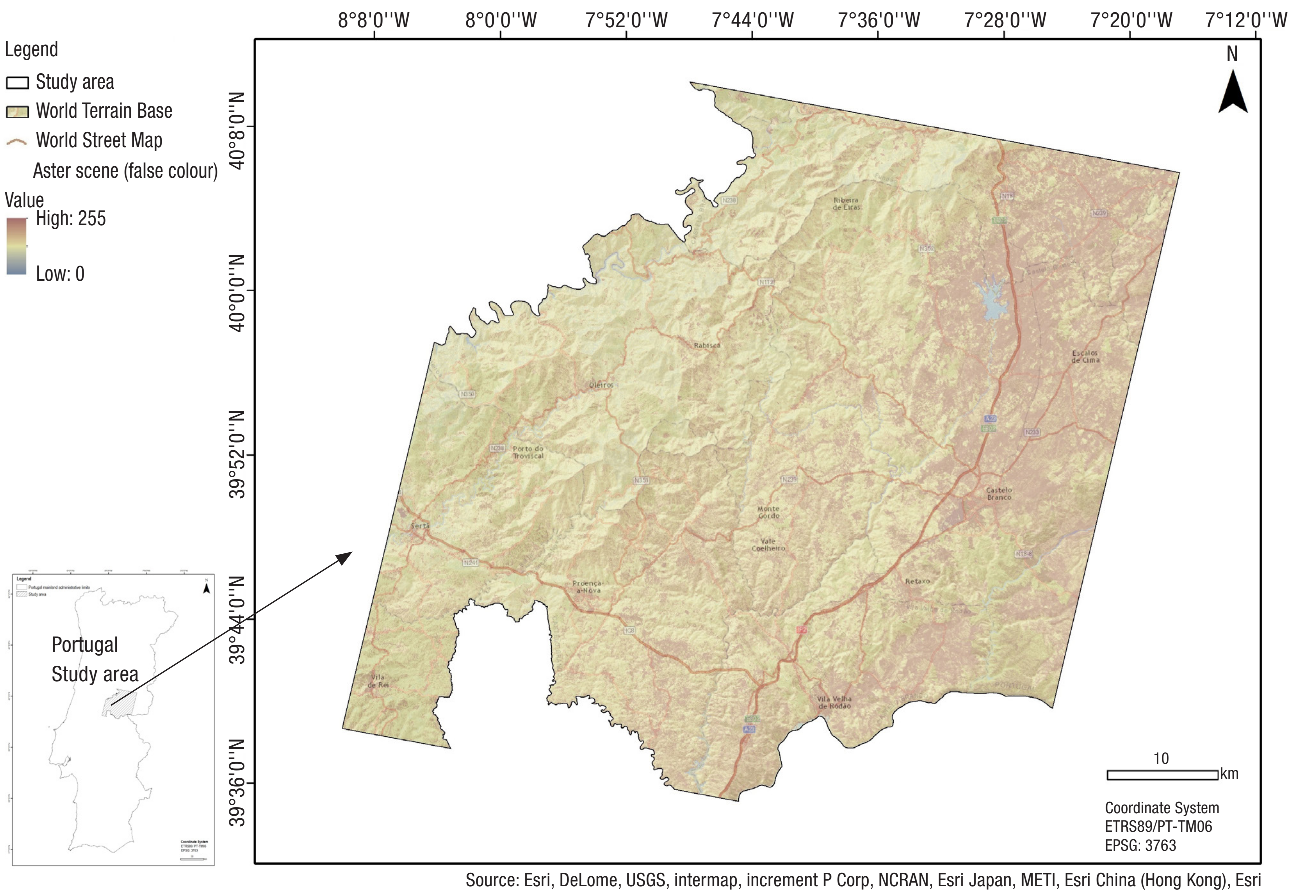
Study area and ASTER imagery

The study area consists of an ASTER scene of 321.1 x 10^3 ha located in the central-eastern of Portugal covering 49% of 11 municipalities of the Castelo Branco's district (Fig. 1), located between 40º9´47´´N - 39º34´49´´N and 8º10´36´´W – 7º16´46´´W. The imagery obtained was of two dates: the first, on 25 August 2005 with a cloud cover of 20% and the second, on 24 March 2007 without cloud cover as there were no images available from the same year to performed valuable work (*e.g.* high cloud cover). The months of March and August were chosen, as the first corresponds to acacia flowering season by contrast to the second (dry season).

The multispectral sensor ASTER produces images with moderate spectral and spatial resolutions, namely: three visible and near-infrared bands (VNIR bands 1, 2, 3N and 3D) with a spatial resolution of 15 m; six mid-infrared bands (SWIR bands 4, 5, 6, 7, 8 and 9) with a spatial resolution of 30 m; and five far-infrared bands (TIR bands 10, 11, 12, 13 and 14) with a spatial resolution of 90 m. The imagery used in this study (VNIR and SWIR bands) was acquired as raw data (L1A) that has radiometric correction but no geometric and atmospheric corrections. Therefore, imagery geometric correction was performed using the digital elevation model (DEM) developed from both bands 3N and 3B to ortho-rectify the ASTER images by the resampling method of cubic convolution. Atmospheric correction was accomplished using the FLAASH model (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) through the MODTRAN algorithm (Adler-Golden *et al*., 1999). To do so, both VNIR and SWIR bands were first aggregate in one file (layer stacking) and the spatial resolution of the SWIR bands expanded to a pixel size of 15 m using the resampling method of cubic convolution once more. Subsequently, the layer stacking was converted to the BIL format so the FLAASH module could be processed (Fig. 2).

Methodology – RS classification scheme

Five land cover classification schemes with different degree of generalization (Table 1 – Level 1 to Level 5) were essayed which allowed studying the spectral separability of acacia class in comparison to the other land cover categories considered (Fig. 2). The classification system of the Portuguese official land cover map for 2007 (COS2007) was used as reference (DGT 2007) and further adapted to the purpose of this study. It should be emphasized that the COS2007 classifica-



Source: Esri, DeLome, USGS, intermap, increment P Corp, NCRAN, Esri Japan, METI, Esri China (Hong Kong), Esri (Thailand), MapmyIndia, OpenStreetMap contributors, and the GIS User Community; Sources: Esri, USGS, NOAA

Figure 1. Geographic location of the study area – ASTER scene of 3,211 km^2 (false colour composite with elevation, cities names and main roads).

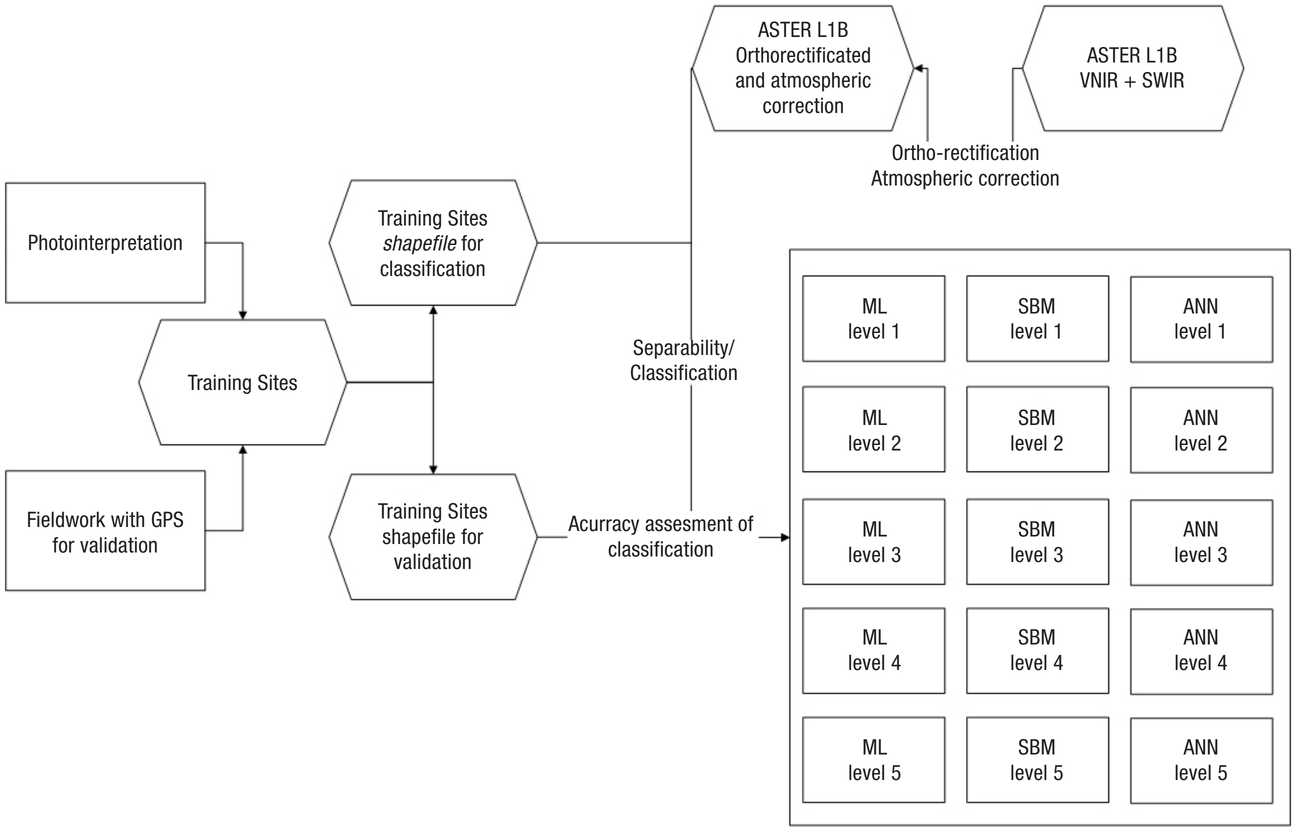


Figure 2. Methodological approach to test acacia mapping using ASTER imagery of two dates (25 August 2005 and 24 March 2007) and three classifiers (ML – Maximum Likelihood; SVM – Support Vector Machine; and ANN – Artificial Neural Networks).

tion system is standardized with the Corine Land Cover (CLC) classification system until the third level of detail (Caetano *et al*., 2009).

The categories "artificial areas", "agricultural areas", "forests" and "water bodies" used in this study follow the nomenclature referred to above for the broader classification level (Table 1 – Level 1). However, when moving to a more detailed classification (Table 1 – Level 2), the "acacia" category is isolated from the "forests" category. After, the "natural areas" category (*e.g.* scrub and/or herbaceous vegetation associations and open spaces with little or no vegetation) is isolated from the "forests" category (Table 1 – Level 3). Next, "forests" category is sliced into "broadleaves" and "coniferous" categories (Table 1 – Level 4). In the end, "broadleaves" category is divided into "holm oak/cork oak" category (Qr/Qs – *Quercus rotundifolia* Lam. and *Quercus suber* L), "chestnut/other oaks" category (Cs/Q – *Castanea sativa* Mill. and *Quercus* sp.) and "eucalyptus" category (Ec – *Eucalyptus* sp.) (Table 1 – Level 5). In this study area the "coniferous" category comprises essentially the species maritime pine (*Pinus pinaster* Aiton). The goals of sub-dividing the "broadleaves" category (Level 4) into more specific forest categories in Level 5 were: (1) testing spectral separability among more specific and homogeneous forest assemblages; and (2) testing the potential of ASTER imagery for mapping these same more specific and homogeneous forest assemblages, as represented in the Portuguese National Forest Inventory.

A total of 1080 sites (120 for each land cover class, Table 1 – Level 5) were selected over the ASTER imagery. The training sites were obtained by applying a stratified random sampling, in order to cover the whole study area (Congalton, 2001). Ancillary information such as the CLC land cover maps (2000 and 2006), the COS land cover map (1990 and 2007), ortho-rectified aerial photographs (2005) and Google Earth™ 5.2.1 imagery (several dates) were used to cross-validate the sites selection by photo-interpretation and field work with GPS (undertaken between 2011 and 2012). These 1080 field sites identified over both ASTER imagery were randomly divided in two sub-sets as follows: 75% as training sub-set (810 sites: 90 for each land cover class, Table 1 – level 5) and 25% as testing sub-set (270 sites: 30 for each land cover class, Table 1 – level 5). The training sub-set was used to create the spectral signatures, for each land cover category by classification level, needed to support the imagery classification stage. While, the training sub-set was used to assess the accuracy of the 30 imagery classifications produced

Table 1. Land cover categories by classification level (*i.e.* increasing degree of detail)

Land cover categories				
Level 1	**Level 2**	**Level 3**	**Level 4**	**Level 5**
Artificial areas	Artificial areas	Artificial areas	Artificial areas	Artificial areas
Agricultural areas	Agricultural areas	Agricultural areas	Agricultural areas	Agricultural areas
Forests	Acacia	Acacia	Acacia	Acacia
	Forests	Forests	Broadleaves	Qr/Qs
				Cs/Q
				Ec
			Coniferous	Coniferous
		Natural areas	Natural areas	Natural areas
Water bodies	Water bodies	Water bodies	Water bodies	Water bodies

Legend: Broadleaves – Qr/Qs (holm oak/cork oak); Cs/Q (chestnut/other oaks); Ec (eucalyptus); Coniferous (*e.g.* maritime pine).

(*i.e.* two dates imagery x five land cover classifications x three supervised classifiers).

Prior to the ASTER imagery classification stage, the signatures were used to assess the spectral separability between every land cover categories referred to above (Table 1) by calculating the Transformed Divergence (TD). The TD is a measure of the statistical separation between categories response patterns computed for all pairs of categories and presented in the form of a matrix. It is based on the covariance of the samples for each category at the pixel level and estimates a weight which exponentially decreases to enlarge the distances between categories (Richards, 2013). The TD values are normalized to the range of [0 , 2] and as a general rule it can be accepted that good spectral separability occurs for values higher than 1.9, moderate spectral separability for values between 1.7 and 1.9 and poor spectral separability (*i.e.* spectral similarity or spectral confusion) for values below 1.7 (Jensen, 1996).

After, the ASTER imagery for each date was classified at the pixel level wherein three supervised classifiers were applied (Fig. 2). The classifiers essayed were the following: the parametric Maximum Likelihood classifier (ML) and the two non-parametric Support Vector Machine (SVM) and Artificial Neural Networks (ANN) classifiers (Xu *et al*., 2005; Foody & Mathur, 2004; Filippi & Jensen, 2006).

In the end, the accuracy of the 30 classified images produced (Fig. 2) was assessed by calculating the error matrix (or confusion matrix). This matrix is obtained by comparing the land cover category found in the testing sub-set (ground-truth) to that which was mapped in the image for the same location and it shows the distribution of the percentage of pixels classified correctly and in an erroneous way (Congalton, 1991). The statistical assessments of accuracy derived from the error matrix that were considered are: the producer's accuracy (*P*), the user´s accuracy (*U*), the overall accuracy (*O*) and the Kappa statistics (*K*). Producer's accuracy (*P*) is a measure of omission error that indicates the probability that a sample is correctly classified. User's accuracy (*U*) is a measure of commission and indicates the probability that a classified pixel does represent that category in the field. Overall accuracy (*O*) allows evaluating the overall thematic classification of the map produced (Congalton & Green, 1999). The Kappa statistics measures model accuracy with respect to the accuracy expected with a random assignment of pixels to categories. The Kappa statistics takes into account all elements of the confusion matrix in its evaluation (*i.e.* also includes the elements off the main diagonal, which represent disagreements in classification) as opposed to the overall accuracy which uses only the diagonal elements (real agreement) (Congalton, 1991).

Acacia spatial distribution

The accuracy measures referred to above were used to select the best image classification (from all classifications performed during the previous methodological step) in order to obtain the spatial distribution of the species acacia in the study area. Then, an estimate of the invasion area of this species was obtained with a 15 m spatial resolution (*i.e.* a minimum cartographic unit of 0.02 ha). Additionally, the previous acacia spatial distribution was compared to the one obtained by the overlay of the common areas classified as acacia in all high accuracy (*i.e.* $U \geq 80.00$ and/or $K \geq 0.8$) image classifications for the species, in order to minimize classification uncertainty and errors regarding this same class. After, the estimated areas of acacia spatial distribution were compared to the area of acacia stands over the study area according to the National Forest Inventory statistics in 2005 (AFN, 2010).

Results

Spectral separability of land cover categories

The analysis of the transformed divergence (TD) matrices for each one of the five tested land cover classifications proved that there were more spectral confusion when using the ASTER imagery of August 2005 (dry season) than when using the image of March 2007 (acacia flowering season – bright yellow flowers). In August, spectral separability among categories in the most detailed classifications (Table 2 – Level 5) were mainly moderate to good. Whilst in March, good spectral separability was found between almost all of these same categories of land cover (Table 3 – Level 5). Furthermore, overall separability assessments performed for more generic land cover classifications (*e.g.* Levels 1, 2 and 3; Table 1) for both flowering season and dry season images did not demonstrate to be unequivocally higher than those reached for the most detailed land cover classifications (Levels 4 and 5; Table 1).

It was found spectral confusion between the categories "acacia" and both "forests" (*i.e.* broadleaves – holm oak/cork oak, chestnut/other oaks and eucalyptus – and coniferous – *e.g.* maritime pine) and "natural areas" when using the imagery of August 2005 (Table 2 – Level 5). Whilst, spectral confusion was only found between the categories "acacia" and both "agricultural areas" and "coniferous" (*e.g.* maritime pine) when using the imagery of March 2007. Finally, good spectral separability between the "acacia" category and the remaining categories was observed (Table 3 – Level 5).

Table 2. Land cover categories spectral separability in level 5 (ASTER imagery of 25 August 2005) – Transformed Divergence matrices obtained using the training sub-set

Land cover categories	Transform divergence matrices								
Level 5	**Artificial areas**	**Agricultural areas**	**Acacia**	**Qr/Qs**	**Cs/Q**	**Ec**	**Coniferous**	**Natural areas**	**Water bodies**
Artificial areas	0								
Agricultural areas	1.79	0							
Acacia	1.98	1.78	0						
Qr/Qs	1.99	1.51	1.38	0					
Cs/Q	2.00	1.84	0.97	1.29	0				
Ec	2.00	1.91	1.64	1.54	1.43	0			
Coniferous	2.00	1.99	1.46	1.87	1.48	1.33	0		
Natural areas	1.99	1.88	1.61	1.86	1.67	1.65	1.84	0	
Water bodies	1.90	1.79	1.83	1.75	1.82	1.93	1.97	1.89	0

Legend: Good separability – > 1.9; Moderate separability – 1.7 - 1.9; Poor separability – < 1.7; Qr/Qs – holm oak/cork oak; Cs/Q – chestnut/other oaks; Ec – eucalyptus; Coniferous – *e.g.* maritime pine.

Table 3. Land cover categories spectral separability in level 5 (ASTER imagery of 24 March 2007) – Transformed Divergence matrices obtained using the training sub-set

Land cover categories	Transform divergence matrices								
Level 5	**Artificial areas**	**Agricultural areas**	**Acacia**	**Qr/Qs**	**Cs/Q**	**Ec**	**Coniferous**	**Natural areas**	**Water bodies**
Artificial areas	0								
Agricultural areas	2.00	0							
Acacia	2.00	1.29	0						
Qr/Qs	2.00	2.00	2.00	0					
Cs/Q	2.00	1.90	1.93	2.00	0				
Ec	1.99	2.00	2.00	2.00	2.00	0			
Coniferous	2.00	1.84	1.21	2.00	1.95	2.00	0		
Natural areas	1.52	1.99	1.97	2.00	1.98	1.99	1.99	0	
Water bodies	1.97	1.99	1.98	2.00	1.99	1.99	1.99	1.92	0

Legend: Good separability – > 1.9; Moderate separability – 1.7 - 1.9; Poor separability – < 1.7; Qr/Qs – holm oak/cork oak; Cs/Q – chestnut/other oaks; Ec – eucalyptus; Coniferous – e.g. maritime pine.

Imagery classifications accuracy

The analysis of the evaluated accuracy measures (*P*, *U*, *O* and *K*) for the classified images produced by the three classifiers essayed (ML, ANN, SVM) when using the imagery of August 2005 (dry season) proved that the ML classifier was the one that performed best for all tested land cover classifications. The same result was found when analysing the classified images produced by the three classifiers essayed (ML, ANN, SVM) while using the image of March 2007.

Regarding the classified images overall accuracy (for both *O* and *K*) it was verified that it was higher in all cases when using ASTER imagery of March 2007 (flowering season) when compared to the results obtained by processing the dry season image of August 2005 (Table 4). An explicit trend of increasing or decreasing accuracy associated to the change of land cover classifications (from level 1 to level 5) was not found. The highest overall accuracies ($O \geq 80.0$ and/or $K \geq 0.80$) were always obtained by applying the ML classifier to the flowering season image, which has slightly decreased from the most generic (Table 4 – Level 1: $O = 92.45$ and $K = 0.89$) to the most detailed land cover classification (Table 4 – Level 5: $O = 85.21$ and $K = 0.83$). Conversely, overall accuracy results obtained by processing the dry season image (August 2005) were significantly lower (Table 4 – Level 1: $O = 79.17$ and $K = 0.70$; Table 4 – Level 5: $O = 73.44$ and $K = 0.70$) than those obtained with the flowering season image (March 2007).

To what concerns to the classifiers tested, the ML classifier showed very good accuracies especially when using the flowering season imagery (Table 4 – *K* between 0.83-0.89). As opposed to the lower accuracies observed either with the ANN classifier (Table 4 – *K* between 0.50-0.78) or the SVM classifier (Table 4 – *K* between 0.36-0.54). In fact, the ML classifier obtained the best results in all land cover classifications but the highest overall Kappa was obtained at level 1 (Table 4 – $K = 0.89$). By contrast, the remaining classifiers (ANN and SVM) showed a very low global accuracy (Table 4; ANN always below $K = 0.65$; SVM always below $K = 0.54$).

Acacia spatial distribution

Regarding the "acacia" category, the highest accuracy (Table 5 – Level 5: $U = 100.00$, P = 69.57 and $K = 1.0$) was reached by applying the ML classifier to the March 2007 (flowering season) image while using the most detailed land cover classification. Good accuracies were also obtained by applying to this same image the ML classifier to level 4 ($U = 84.21$ and $K = 0.81$) and level 2 ($U = 80.77$ and $K = 0.75$) land cover classifications. Finally, applying the ANN classifier to the flowering season image while using the level 2 classification scheme also allowed to reach a good mapping accuracy for acacia ($U = 84.62$ and $K = 0.80$).

Accuracy results of acacia mapping obtained by processing the dry season image (August 2005) were significantly lower than those obtained with the flowering season image (March 2007), as shown in Table 5. Best results for this image were obtained by applying the ANN classifier to level 5 ($U = 66.67$ and $K = 0.61$) as well as the ML classifier to level 2 land cover classification ($U = 66.67$ and $K = 0.57$), to level 4 ($U = 60.61$ and $K = 0.53$) and to level 5 ($U = 60.00$ and $K = 0.54$).

As a result, to estimate the area of acacia spatial distribution over the study area the best image classification that resulted from the application of ML to the March 2007 image using the level 5 land cover classification (*i.e.* best image classification only; Table 5 – Level 5: $U = 100.00$, $P = 69.57$ and $K = 1.0$) was used (Fig. 3). According to this output, the total area covered by acacia in the study area was estimated approximately in 24,770 hectares.

Table 4. Accuracy assessments – Overall accuracy and Kappa statistics of the 30 imagery classifications *vs.* the testing sub-set: ASTER imagery of two dates (25 August 2005 and 24 March 2007), three supervised classifiers (Maximum Likelihood, Support Vector Machine and Artificial Neural Networks) and five levels of land cover classification with different degree of generalization

Land cover categories	ASTER imagery classification of 25 August 2005 *vs.* testing sub-set						ASTER imagery classification of 24 March 20075 *vs.* testing sub-set					
	ML		SVM		ANN		ML		SVM		ANN	
	O	***K***	***O***	***K***	***O***	***K***	***O***	***K***	***O***	***K***	***O***	***K***
Level 1	79.17	0.70	60.42	0.41	79.17	0.70	92.45	0.89	65.09	0.79	84.90	0.78
Level 2	83.96	0.79	39.58	0.24	63.54	0.54	88.54	0.86	63.20	0.54	72.64	0.65
Level 3	77.42	0.73	42.98	0.31	55.26	0.46	87.72	0.85	53.26	0.43	66.13	0.59
Level 4	72.53	0.68	44.70	0.35	49.24	0.41	87.12	0.85	47.18	0.38	55.63	0.48
Level 5	73.44	0.70	40.21	0.32	47.93	0.42	85.21	0.83	43.50	0.36	55.93	0.50

Legend: ML – Maximum Likelihood; SVM – Support Vector Machine; ANN – Artificial Neural Network; *O* – overall accuracy; and *K* – *Kappa* statistics.

Table 5. Accuracy assessments – Confusion matrices of imagery classifications *vs.* the testing sub-set: ASTER imagery of two dates (25 August 2005 and 24 March 2007), three supervised classifiers (Maximum Likelihood, Support Vector Machine and Artificial Neural Networks) and the most detailed level of land cover classification (Level 5)

Land cover categories Level 5	ASTER imagery classification of 25 August 2005 *vs.* testing sub-set								
	ML			SVM			ANN		
	P	*U*	*K*	*P*	*U*	*K*	*P*	*U*	*K*
Artificial areas	77.78	100.00	1.00	44.44	42.11	0.35	72.22	41.94	0.35
Agricultural areas	81.82	85.71	0.84	50.00	75.00	0.72	55.56	90.91	0.90
Acacia	78.26	60.00	0.54	69.57	32.65	0.22	8.70	66.67	0.61
Qr/Qs	35.00	100.00	1.00	56.52	30.95	0.20	39.13	47.37	0.39
Cs/Q	77.27	51.52	0.45	26.67	50.00	0.45	40.00	50.00	0.45
Ec	88.89	80.00	0.78	11.11	20.00	0.10	16.67	30.00	0.22
Coniferous	66.67	66.67	0.63	0.00	0.00	0.00	72.22	27.08	0.18
Natural areas	61.11	64.71	0.61	44.44	57.14	0.52	66.67	75.00	0.72
Water bodies	94.44	100.00	1.00	44.44	53.33	0.48	72.22	68.42	0.65
O		73.44			40.24			47.93	
K		0.70			0.32			0.42	
Land cover categories Level 5	**ASTER imagery classification of 24 March 20075 *vs.* testing sub-set**								
	ML			**SVM**			**ANN**		
	P	*U*	*K*	*P*	*U*	*K*	*P*	*U*	*K*
Artificial areas	83.33	93.75	0.93	88.89	69.57	0.66	77.78	70.00	0.67
Agricultural areas	88.89	84.21	0.82	81.82	58.06	0.52	77.27	77.27	0.74
Acacia	69.57	100.00	1.00	56.52	26.00	0.15	56.52	59.09	0.53
Qr/Qs	86.96	90.91	0.89	55.00	32.35	0.24	45.00	60.00	0.55
Cs/Q	86.67	92.86	0.92	4.55	33.33	0.24	13.64	100.00	1.00
Ec	83.33	68.18	0.64	22.22	66.67	0.63	44.44	47.06	0.41
Coniferous	94.44	80.95	0.79	0.00	0.00	0.00	66.67	46.15	0.40
Natural areas	94.44	77.27	0.75	5.56	100.00	1.00	44.44	25.00	0.17
Water bodies	83.33	88.24	0.87	72.22	44.83	0.39	83.33	75.00	0.72
O		85.21			43.5			55.93	
K		0.83			0.36			0.50	

Legend: ML – Maximum Likelihood; SVM – Support Vector Machine; ANN – Artificial Neural Network; *P* – producer's accuracy; *U* – user's accuracy; *O* – overall accuracy; *K* – *Kappa* statistics; Qr/Qs – holm oak/cork oak; Cs/Q – chestnut/other oaks; Ec – eucalyptus; Coniferous – *e.g.* maritime pine.

Additionally, the acacia spatial distribution obtained by the overlay of the common areas classified as acacia in all high accuracy (*i.e.* $U \geq 80.00$ and/or $K \geq 0.8$) image classifications for the species was produced (Fig. 4). Therefore, the aforementioned imagery classifications meeting those conditions were the following: (1) March 2007 image, ML classifier and Level 5 legend ($U = 100.00$ and $K = 1.0$); (2) March 2007 image, ANN classifier and Level 2 legend ($U = 84.62$ and $K = 0.80$); (3) March 2007 image, ML classifier and Level 4 legend ($U = 84.21$ and $K = 0.81$); and (4) March 2007 image, ML classifier and Level 2 legend ($U = 80.77$ and $K = 0.75$). According to this output, the total area covered by acacia in the study area was estimated approximately in 12,178 hectares.

By analysing both acacia spatial distribution maps (Figs. 3 and 4) it can be stated that although acacia vegetation patches occur all over the study area, they are especially dense in the western and northern zones.

Discussion

Spectral separability of land cover categories

The analysis of the spectral separability of the land cover categories used in each of the five tested land cover classifications showed that the flowering season ASTER imagery provided higher spectral separability between almost all categories of land cover considered (*e.g.* good spectral separability) than the dry season ASTER imagery (*e.g.* moderate to good spectral separability). This result highlights how detection by RS can be facilitated by the timing of image acquisition to correspond with particular phenological periods of a target

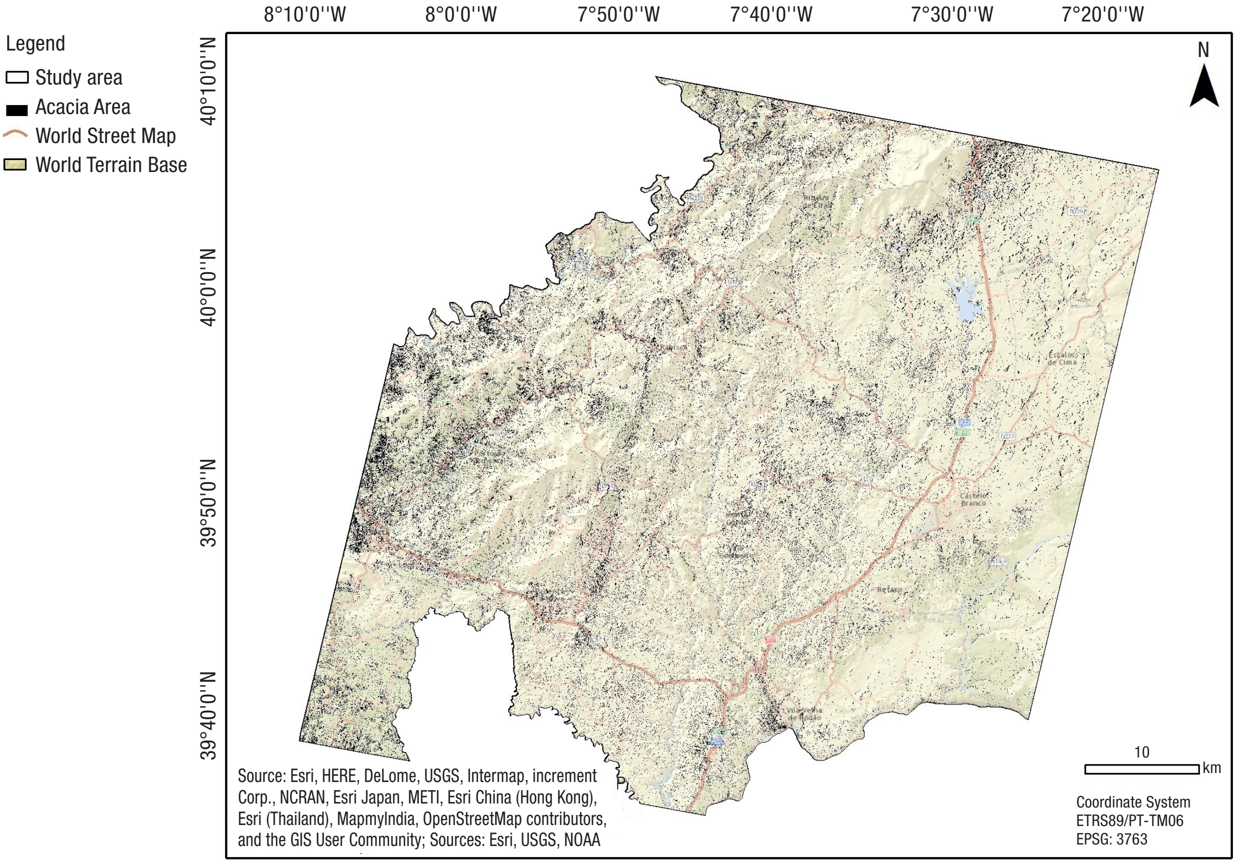


Figure 3. Spatial distribution of acacia over the study area (with elevation, cities names and main roads) according to the best accuracy classification for acacia category (*i.e.* ML classification using the level 5 land cover classification and the ASTER imagery of March 2007).

invasive species (*e.g.* maximizing phenological differences between the invasive plant species and the native species) (see Underwood & Ustin, 2007; Pauchard & Maheu-Giroux, 2007). In this case, the species acacia provides a clear and intense yellow pattern during its flowering season (*e.g.* between January and March) (*e.g.* Marchante *et al.*, 2005; Pauchard & Maheu-Giroux, 2007) that can be distinguished by RS techniques, providing a tremendous potential for monitoring the spread of invasion of this species. Therefore, the analysis of the spectral separability between land cover categories allows to identify where spectral confusion exists which is useful to better define optimal imagery acquisition date for each species. The findings in this study showed that in March some spectral confusion between "acacia" and "coniferous" category was observed thus suggesting that maybe a late winter imagery acquisition date (*e.g.* January-February) would be more suitable.

Imagery classifications accuracy

The analysis of the accuracy of the 30 classification maps proved that the highest classification accuracy was found using both the imagery of flowering season and the Maximum Likelihood classifier ($K \geq 0.80$). Moreover, acacia mapping accuracy obtained excellent results when using the most detailed land cover classification ($K = 1.00$) which indicate the high potentiality of ASTER imagery for mapping this species distribution when the most appropriate imagery date is used. As a result, mapping the spatial distribution of the species acacia across central-eastern Portugal was achieved with good accuracy by applying both the ML classifier and the most detailed land cover classification to the ASTER image of March (flowering season).

These findings are in accordance to the study of Viana & Aranha (2010) in which the imagery acquisition date was found to be the most relevant factor on imagery classification accuracy. The ML classifier was the one that performed the best as well. However, the accuracy of ASTER imagery classification, having an acquisition date of 7 October 2003 and using only three land cover categories, was slightly lower (O=86.69 and K=0.81) when compared to the ones obtained in the present study using the flowering season imagery, the ML classifier and five land cover categories (Level 2: O=88.54 and K=0.86). Despite producer´s accuracy

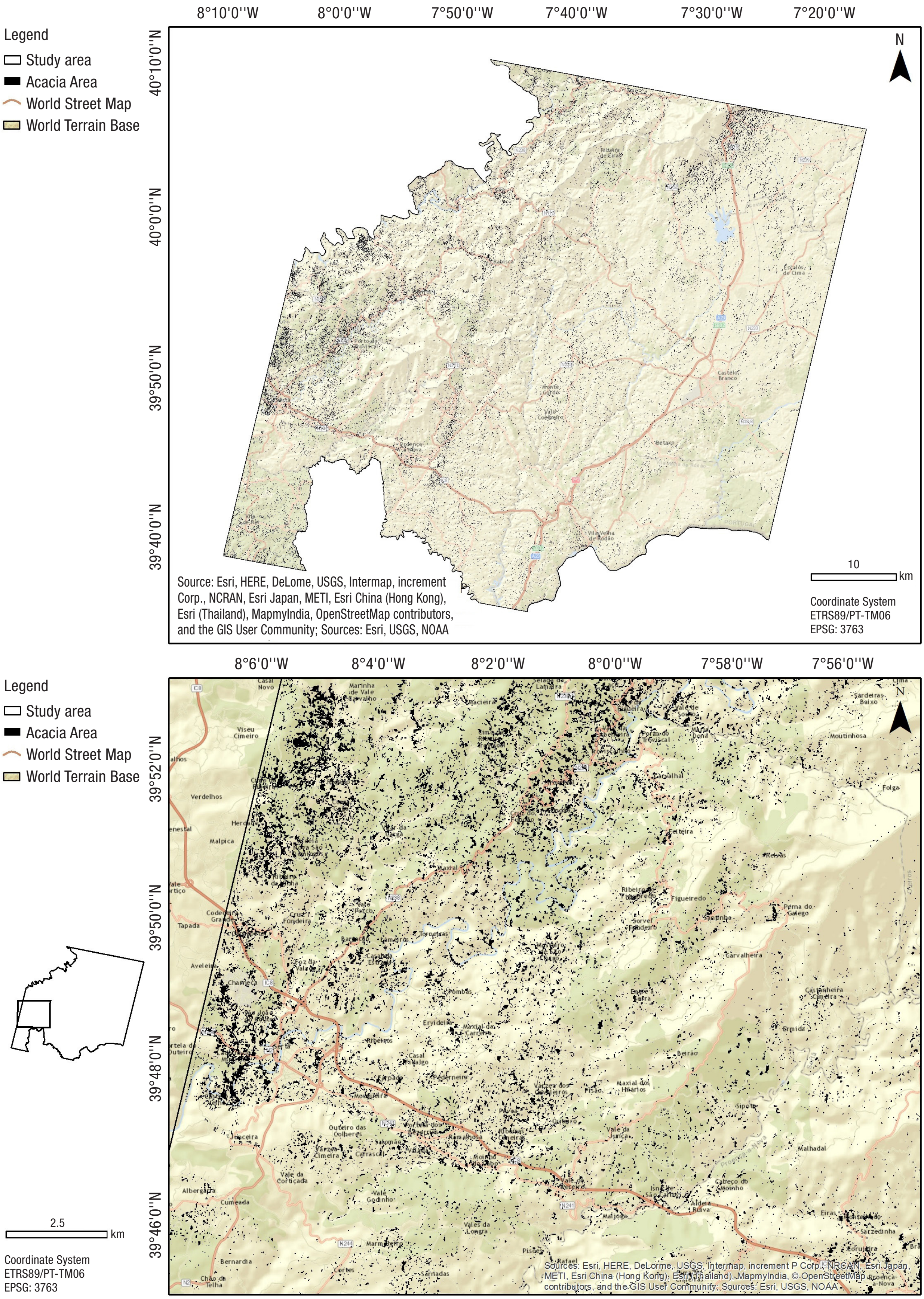


Figure 4. a) Spatial distribution of common areas classified as acacia in all high accuracy (*i.e.* $U \geq 80.00$ and/or $K \geq 0.8$) image classifications obtained for the species over the study area (with elevation, cities names and main roads); **b)** Zoom over an area located at the western zone of the study area having a vast incidence of acacia invasion (*e.g.* nearby localities and along roads).

being the same in both studies (P=100), a paramount improvement in user's accuracy was attained in the present study (Level 2: U=80.77) when compared to the one of those authors (U=11.10).

Acacia spatial distribution

The approximated total area occupied by this invasive woody species was estimated in 24,770 hectares (8% of the study area) according to the most accurate image classification for the species (i.e. applying both the ML classifier and the most detailed land cover classification to the ASTER image of March). An estimate of approximately 12,178 hectares was obtained when considering only the common areas classified as acacia in all high accuracy (*i.e.* $U \geq 80.00$ and/or $K \geq 0.8$) image classifications for the species.

By contrast, according to the National Forest Inventory in 2005 (AFN, 2010), the surface covered by acacia stands in the study area was estimated in 225 hectares only (0.1% of the study area). This can be explained by the standards used in this forest inventory (*e.g.* area with a minimum of 0.5 hectares, a minimum width of 20 meters and a ground cover higher than 10%). Therefore, due to this species fragmented distribution pattern it is argued that the estimated area in this study (24,770 hectares) is a more realistic approach of acacia occupation and geographic distribution as a spatial resolution of 15 m was used (*i.e.* minimum cartographic area of 0.02 ha) and no generalization process was applied.

Despite of the results obtained in this study, it is expected that acacia mapping accuracy may be slightly increased if both the number of training sites are increased and ancillary GIS-based information (*e.g.* roads, distance to water lines, altitude, slope, soil type, lithology, etc.) are included in the classification process (Van der Wouw *et al.*, 2011; Gil *et al.*, 2014) to overcome the poor spectral separability (TD < 1.7) observed between some of the land cover categories.

The spatial distribution map of acacia obtained allows decision-makers, stakeholders and landowners to both setup and implement more realistic, adequate and cost-effective invasive woodland management in central-eastern Portugal, by clearly identifying the location, the dimension and the logistics constraints (distance to roads, distance to water streams, slope, etc.) associated to the sites to be intervened and managed. Additionally, this new and more detailed data on acacia spatial distribution also allows more accurate ecological modeling studies of this invasive alien species in this same geographic area (*e.g.* Bradley & Mustard, 2006; Andrew & Ustin, 2009).

Directions for future research – Satellite Remote Sensing and acacia mapping

At the present the numbers of satellites for earth observations are constantly changing as new are being launched while others are getting inoperative (*e.g.* Richards, 2013). Available commercial imagery is not always cheap or has the desired resolutions (spatial, spectral, radiometric and temporal) for the study to be developed (*e.g.* ASTER imagery offer only four bands and a spatial resolution of 15 m; Landsat (E)TM imagery offer 6 or 11 bands but a spatial resolution of 30 m). However, the ASTER imagery proved to constitute a cost-effective solution for acacia mapping in central-eastern of Portugal. Furthermore, the use of flowering season date ASTER imagery with the application of the ML classifier when using levels 1, 2 and 3 land cover classifications also provided an effective and reliable solution to perform generic land cover mapping for both this species and type of landscape (rural territories in central inland of Portugal).

In sum, the use of ASTER imagery obtained during the species flowering season may therefore be recommended for detailed land cover/vegetation and especially acacia mapping purposes and management decision-support on this type of southern Europe's ecosystems. Despite of the ASTER SWIR detectors no longer function since April 2008 (only VNIR and TIR sensors are still operational), the archived and currently available ASTER multispectral data may be used for multi sensor-based acacia temporal studies (*e.g.* Lawes & Wallace, 2008), in order to assess its invasive distribution trends and to enable a more effective control of these populations.

Finally, further efforts on improving acacia mapping are needed to overcome the poor spectral separability observed between "acacia" category and both "agricultural areas" and "coniferous" categories when using the flowering season date imagery. This situation is tightly related to this specific rural landscape under study where maritime pine forest dominates (flowering season March-April; golden yellow masculine flowers) and the distribution pattern of this invasive species consists mostly of both very small patches nearby agricultural areas and very narrow strips along main road sides.

Although all the positive results achieved in this study and their potential application for improving decision-making on acacia management in Portugal, spatial and spectral information provided by moderate spatial and spectral resolution satellite images as ASTER is still insufficient to decipher the complexity of natural environment and further fully delineate the distribution of alien plants, as stated by Huang & Asner

(2009) and Joshi *et al.* (2004). Nevertheless, due to its innovative technical features, applying a multi-method processing approach to the new ESA Copernicus Sentinel-2 sensor data might be able to cost-effectively address this relevant information gap at regional level, by providing accurate, detailed and periodic thematic cartography and change detection assessment (*e.g.* Immitzer *et al*., 2016; Gil *et al*., 2012). Furthermore, observing alien plants as acacia requires data collected from sensors pushing the limits of at least one type of resolution (spatial, temporal or spectral resolution) since the profiles of these species may be quite similar to those of native plants, from a RS perspective (Asner, 2008). For instance, the use of very high spatial resolution in several studies on mapping invasive species has pointed out very encouraging results (*e.g.* Gil *et al*., 2013). On the other hand, hyperspectral images are currently the most heavily used imaging source for studies of alien plants because detailed spectral profiles can be developed for native and non-native plants, allowing the analysis of specific spectral regions that are most sensitive to the abundance of the species of interest (Underwood *et al*., 2003). Therefore, as stated by Gillespie *et al.* (2008) and Bradley (2014), future research on satellite RS of alien invasive plants as the species acacia should focus on the collection and dissemination of high-quality field data coupled with the incorporation and integration of available data acquired by existing (especially the most recent) spaceborne multispectral (*e.g.* WorldView-3, Landsat-8 OLI, Sentinel-2), hyperspectral (*e.g.* Chris-Proba, Hyperion) and synthetic aperture radar (*e.g.* Sentinel-1) sensors. Finally, this improved data (in quality and quantity) on the spatial distribution of this alien invasive plant species may also allow more accurate ecological modelling studies (*e.g.* Gutierres *et al*., 2011; Costa *et al*., 2015, 2013; Pereira & Figueiredo, 2015).

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