Sub-object examination AIMED AT improvING detection and distincTION of objects with similar ATTRIBUTE characteristics

T. Veljanovski [a, b,] *, N. • uri• [b], U. Kanjir[a], K. Oštir [a, b]

[a] Institute of Anthropological and Spatial Studies, Scientific Research Centre of the Slovenian Academy of Sciences and Arts, Novi trg 2, Ljubljana, Slovenia – (tatjanav, ursa.kanjir, kristof)@zrc-sazu.si
[b] Space-SI – Centre of Excellence for Space Sciences and Technologies, Ašker•eva 12, 1000 Ljubljana, Slovenia - (tatjana.veljanovski, natasa.dzuric, kristof)@space-si

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ABSTRACT:

Traditionally, remote sensing employed pixel-based classification techniques when attempting to obtain land use/cover information. Pixel-based approaches have proven to work well with low and medium spatial resolution imagery. Due to the increased scale and detail of surface features high spatial resolution images (e.g. from aerial and VHR satellite sensors) have proven to be problematic for pixel-based analysis and over the last decade this has driven the research towards object-oriented approaches. Despite that object-based classification is more applicable to VHR data we still face challenges in improving the semantic classification accuracy. Post-classification often reveals considerable numbers of misclassified objects (irrespective of the used classifier). The erroneous outcomes indicate the difficulty of separating objects that share similar attribute characteristics (i.e. Japanese knotweed and blackberry). Contrary to this, certain evidently dissimilar objects (i.e. forest patch and grassland) can occasionally be placed into a forest class due to the over generalised computed list of segment attributes. This article proposes a hybrid approach with the aim to incorporate the advantages of pixel-based classification into an object-based image analysis frame. At first the general spatial structure information is obtained through segmentation, which is followed by the sub-object analysis in the spectral and geometric domain. The object's spectral signature is obtained and tested for similarity with a reference object class using the Kolmogorov-Smirnov test. The sub-object spectral and structural analyses are incorporated into a classification scheme by a ruleset. The experimental results for detecting Japanese knotweed showed that the proposed approach allows for the extraction of different stages of knotweed growth, and this considerably improves the knotweed classification accuracy. This method has also shown improvement in the delineation from the similar blackberry and other species on aerial photographs and WorldView-2 satellite data.

1. Introduction

1.1 Motivation

The continuous progress in the field of remote sensing systems produces increasingly detailed data, which leads to improved interpretation possibilities. With the increased spatial resolution we have also observed greater between-class spectral confusion and within-class spectral variation (Mathieu and Aryal, 2007). The scale and detail of the mapping thus emphasise the difficulties in the classification and land use mapping routines.

Conventional pixel-based classification methods rely on the spectral information contained within an individual pixel and classify each pixel into an appropriate class according to the classification rules. Object extraction then requires specific generalisation measures that diminish the "Salt and Pepper" noise phenomena and approach the basic cartographic standards. Over the past decade object-based image analyses (OBIA) responded to these drawbacks (Lang and Blaschke, 2006; Blaschke et al., 2008; Addink and Van Coillie, 2010). OBIA processing involves steps that are based on homogenous pixel groups (segments) – representations of geographic features – and the relations between them. In order to create meaningful image objects, suitable for geographical feature analysis, the process integrates contextual, spectral, geometric and textural information as well as all auxiliary data. The classification is performed with the use of these segments rather than single pixels. OBIA of satellite data provides an interpretation that is close to the human perception of the environment. Thus, it enables a more coherent understanding of geographical features in nature and their representations (i.e. geographical objects) on remote sensing data (Hay and Castilla, 2006). Although the object-based approach has proven successful, some of its shortcomings remain a challenge in its practical application.

In our experience object-based classification (Veljanovski et al., 2011) achieves moderate classification accuracy and requires considerable post-processing (corrections of incorrectly classified objects). Post-classification is labour-demanding and in most cases a manual procedure based on visual inspection. Misclassifications are a result of the poor ability of distinguishing between various segments that share similar attributes within a given semantic list of target object classes (Fig. 1). Besides, they are associated with complex

* Corresponding author.

relations between geographical features and their detection, analysis and representation in semantic-oriented modelling procedures.

Single geographic features can exhibit multiple characteristic manifestations, however the aim of land use/cover mapping and classification is to achieve an explicit abstraction of each geographical feature in the appropriate classification-driven (target) object class. In cases in which the material composition of the land cover is diverse and heterogeneous, object sub-division and appropriate definition of multiple sub-objects can be required for training and classification needs. The sub-classes might exhibit a variety of spectral characteristics, thus they might have unique spectral signatures in the spectral domain and a typical geometric subdivision. These characteristics should be represented separately in the training and classification phases of the object-based image analysis.

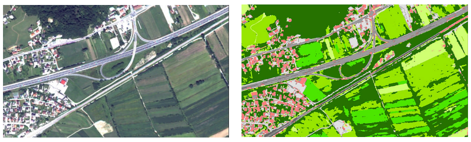

Figure 1. The results of object based classification for vegetation elements from a WorldView-2 satellite image clearly indicate that the dark fields can be misclassified as forest (dark green) and bright rooftops as open soil.

Considering the capabilities of the currently available software (i.e. Definiens Imaging Developer, ENVI Feature Extraction, Erdas Objective) on one hand, and the potential of the object-based paradigm for analysis on the other, we can state that the possibilities for a complex analysis of the sub-object spectral and geometrical domain are rather unexploited. Thus, we propose a shift towards the expansion of the set of computed attributes towards the description of the object's spectral signature and geometrical (sub)structure on the sub-object level. The introduction and proper use of such complex attributes could substantially facilitate the detection and distinction of objects that share similar attribute characteristics in remote sensing data (ploughed fields – paved surfaces, bright rooftops – gravel roads, forest patch – field, knotweed – blackberry).

1.2 References to related work

Only a few published works deal with the sub-object analysis within object-based classification. Rarely do they consider the use of more complex descriptors of spectral and structural characteristics on the object sub-level in order to support the classification. Lloyd et al. (2004) exposed the problems related to the fact that pixels included in the segments do not necessarily exhibit normal distribution, thus using the mean or standard deviation (conventionally used in OBIA) may not fully capture and properly describe the signatures of pixels within the segment. They also stated that the shapes of histograms that belong to the pixels within a segment for a certain geographical feature may be characteristic and thus diagnostic.

Sridharan (2010) presented the capability and potential of the sub-object spectral domain exploration with the Kolmogorov-Smirnov (K-S) test used for classifying trees in urban environments (on WorldView-2 data). The analysis and tree species classification is based on the candidate object's (or region) empirical cumulative frequency distribution and its comparison to the referential (target class) cumulative frequency distribution. The results proved that using the K-S based classifier was successful. Stow et al. (2012) explored the potential and evaluated the capabilities of the curve matching approach with the classification of the multi-pixel frequency distribution. Object histogram signatures were used for determining the characteristic frequency distribution. Through this they quantified the similarity between the histogram curves that represent the within-object pixels. Their application context was to classify and map the general land use types and socio-economic status of the residential areas within Accra (Ghana) with the use of VHR satellite imagery. The curve matching based classifier gave results that were more effective than the standard classifiers based on the closest neighbour classifier.

The recent approach to a number of issues related to the use of object-oriented classification and sub-structure characteristics with aerial images in the detection of the invasive species of Japanese knotweed was elaborated by Jones et al. (2011).

1.3 Aims of the study

The objectives of this study were to: (1) examine the sub-object and between objects class variability within the spectral and structural domain, on the sub-object level, using cumulative frequency distribution and the Kolmogorov-Smirnov test to determine within-class similarity and between class separability, and (2) exploit the potential of combining object- and pixel-based routines in order to improve the overall classification of complex landscapes represented on remote sensing data.

The application context is to identify and map the invasive plant (Japanese knotweed) in the urban fringes of Ljubljana, Slovenia. The ENVI object-based feature extraction module was supplemented by the sub-object pixel-based approach (developed in Matlab), in combination with VHR data from multispectral satellite data (WorldView-2) and orthophotos.

2. Study area, data and USED approach

2.1 Study area and data

Recently the field of biological invasion investigation has shown considerable interest in remote sensing techniques (Jones et al., 2011). A key prerequisite for effective management of invasive species is to delineate the spatial extent and information on the severity of the invasion in a particular area or environment (Ustin et al., 2002). Our study area is the urban fringe of Ljubljana, the capital of Slovenia (Fig. 2). Recent studies of tree-species and Japanese knotweed delineation in urban environments attempt to integrate VHR satellite (WorldView-2) and aerial (orthophoto) data and object-based classification with the goal of obtaining a tree-species and Japanese knotweed land use map (• uri•, 2011). As Japanese knotweed belongs to one of the fastest growing and highly invasive plants, which is hard to permanently eliminate from the environment, it is necessary to obtain information on its spatial distribution and start a regular inventory of its new occurrences. Therefore, it was necessary to develop a methodology that would be capable of recognizing the various stages of growth in Japanese knotweeds.

Figure 2. Sites investigated in the study area of the Ljubljana urban fringe. Data used and their overlap area: WorldView-2 false colour composite and digital orthophoto.

The WorldView-2 satellite image of the Ljubljana area was acquired on 10.08.2010, in 8-band multispectral resolution and a panchromatic band. The applied pre-processing involved precise orthorectification and pan-sharpening to a spatial resolution of 0.5 m. The aerial dataset (digital orthophotos – DOF) was obtained from the Surveying and Mapping Authority of the Republic of Slovenia (2006 and 2011 imaging cycles). We considered images acquired in colour and infra-red wavelengths with 0.5 m (RGB: DOF050) and 1 m spatial resolution (CIR: DOF100 IR). Two dates (summer 2006 and 2011) were tested for colour orthophotos (RGB bands), but only 2006 imagery was available for infrared orthophotos (IRRG bands). Referential data for Japanese knotweed occurrences was obtained through a field survey performed on 5.9.2011 and 6.10.2011. Individual spots were documented by photographs.

2.2 Japanese knotweed

The World Conservation Union listed the Japanese knotweed (*Fallopia japonica*) as one of the world's top 100 invasive species. There are several subspecies and all of them form persistent, pervasive, dense and suppressive monocultures that trigger severe problems throughout Europe, North America and Asia (Jones et al., 2011). In Slovenia, Japanese knotweed grows mainly in riparian zones and habitats influenced by human activities (within green areas of new residential zones, along communication infrastructures and multi-purpose agro-recreational zones). It is mainly spread by constructions and natural soil materials, while natural dispersal mechanisms such as rivers and wind also play their role.

Once fully established in the new environment, it grows rapidly and forms dense and mono specific strands, excluding other native and endemic floral and faunal species (Gerber et al., 2007). The removal and elimination of Japanese knotweed is extremely hard as it forms a deep and branched root system (up to 10 meters deep) and has extremely high capabilities for re-growth from minor root residuals found in the soil. The typical representation of Japanese knotweed on high resolution remote sensing data is shown in Fig. 3.

Figure 3. Typical texture and colour representation of Japanese knotweed. Upper row: DOF050 (2006), DOF100 IR (2006), DOF050 (2011). Lower row: DOF050 (2006), DOF100 IR (2006), DOF050 (2011), WorldView-2 (2010).

2.3 Delineation, classification and mapping

Object extraction from VHR data typically covers several steps: data pre-processing and preparation, segmentation, computation of segment characteristics (attributes), contextual object classification and object extraction, post-classification and accuracy evaluation. The data processing flow chart used in the experimental study for Japanese knotweed detection is shown in Fig. 4 (• uri•, 2011). The upper part (white boxes) that deals with the classification for defining the broader landscape elements, masking the vegetation and vegetation re-segmentation, belongs to the object-based approach. The lower part of the flow chart (grey boxes) belongs to the pixel-based approach and involves the candidates' selection (on the finer scale) to capture individual Japanese Knotweed plants and the subsequent sub-object analysis. The object spectral signature characteristics of the candidates are tested against a referential (representation) knotweed object class and evaluated with the Kolmogorov-Smirnov test. Ground validation (field survey) data was used to define the training examples and develop a reliable algorithm for detecting Japanese knotweed. The results were visually evaluated and compared to the field survey data.

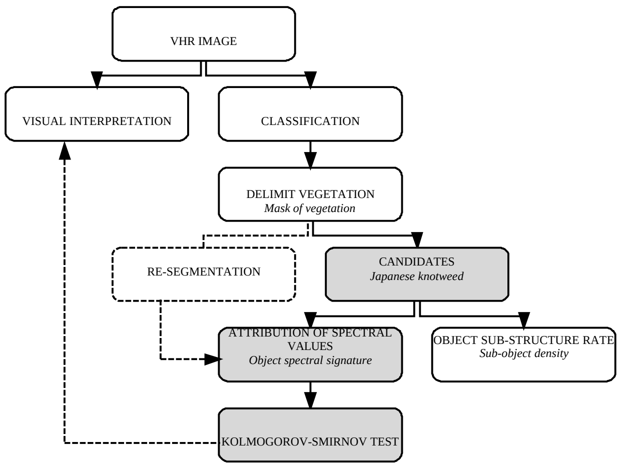

Figure 4. Data processing and flow chart used in the study of Japanese knotweed detection with the hybrid (supervised object- and pixel-based) approach.

3. Sub-object IMAGE analysis

3.1 Preparation of object-level information imagery

Extracting land use structure data from remote sensing imagery requires methods that are capable of providing an appropriate level of observed details. The segmentation delimits a digital image into smaller parts (image segments), in accordance to a given homogeneity criteria. The segmentation used in the ENVI EX is controlled by two parameters: the initial segmentation rate (scale level) and the merge level, both with a range between 1 and 100%. The degree of fragmentation (details) is determined by a single input parameter (scale level). Following the merge parameter (merge level) segments can be combined according to the combination of spectral and spatial properties, which leads to merging smaller segments into larger ones. Both parameter values have a critical influence on the classification results and must therefore be carefully selected.

The next step applies the different attributes (geometric, spectral, textural and the ratio between two bands) to the segments. Based on the values of the attributes, the segments are classified into classes based on training examples set or controlled by rule-based definitions. The classification links the selected attribute and its value, and this determines which segments are classified into a selected (target) class. We used this procedure for the first classification level – creating the vegetation mask and establishing the Japanese knotweed candidates (see Fig. 4).

The vegetation mask that excludes anthropogenic and water related surfaces was obtained with the classification of the normalised difference vegetation index (NDVI) layer (Table 1). NDVI can be achieved either from WorldView-2 data (as Red-Edge NDVI from RE and R band) or as modified NDVI from infrared orthophotos (from R and G band, since DOF100 IR does not contain the source original of the R and IR band).

Then, using the vegetation masks, attributes were used to define the candidates for Japanese knotweed in the process of rule-based classification (Table 2). Appropriate thresholds were defined so that they provided the best description of the spectral, textural and/or other characteristics representative of the Japanese knotweed on a given image. We assumed that not all objects found in the Japanese knotweed class candidates were in fact Japanese knotweed. We captured several other objects that behave like Japanese knotweed in the spectral region or selected attribute values: blackberry bush, goldenrod, arable land (field, grassland), green zones in urban areas and shrubs.

	DOF100 IR	WorldView-2
Segmentation level	54	54
Merge level	58	58
Attribute (Input data)	Modified NDVI	Red-Edge NDVI
Rule	Attribute > 0.295	Attribute > 0.36

Table 1. Parameter values and attributes used to create vegetation masks in the ENVI FE module on IR orthophoto and WorldView-2 data.

	DOF100 IR	WorldView-2
Segm. level	33	36
Merge level	58	74
Attributes	Red band Mean (Att.1) Green band Mean (Att.2) Modified NDVI (Att.3)	Red-Edge NDVI (Att.1), Red-Edge band Mean (Att.2) IR2 band Mean (Att.3)
Rule	*1. set of attributes:* Att.1 [177, 210] AND Att.2 [27, 51] *2. set of attributes:* Att.1 [185, 210] AND Att.3 [0.64, 0.67]	Att.1 [0.900, 0.984], Att.2 [690, 776], Att.3 [1016, 1172]

Table 2. Parameter values and attributes used to extract Japanese knotweed candidates on IR orthophoto and WV-2 data.

In the next step objects from the candidate class were sorted into selected (target) object classes. First step in this process used the criteria of sub-object density as a measure for object structural domain while in the second step the Kolmogorov-Smirnov test was used in order to determine the object spectral domain fit.

3.2 Sub-object structural domain

The sub-object structural domain encompasses a variety of descriptions of the object's geometrical (structural) characteristics. The sub-object density used in this study is defined (Jones et al., 2011; • uri•, 2011) as the ratio between the total area of the object (outer boundaries) and the number of segments (sub-objects) in the object at a given observation scale (Fig. 5). This represents the average area of the segment and provides a measure of the object fragmentation (texture) characteristic that can be distinguished in certain (land) uses. This measure predominantly distinguishes between arable or anthropogenic surfaces and vegetation.

The segments for sub-object density were obtained through the use of the minimum segmentation level (a segmentation level of 10% was used in the study). The segments were not merged; we calculated their attributes and exported them to a vector layer. The procedure was implemented in ArcGIS. The examples of object sub-density calculation are shown in Fig. 5 (the sub-object density is given by the mean). It turns out that the value of farmland density is significantly higher than for other uses that occur within a candidate layer. Besides, we also discovered that the majority of Japanese knotweed polygons share a similar value of sub-object density (<7 on orthophotos), yet the sub-object density of blackberry and bush approached this value.

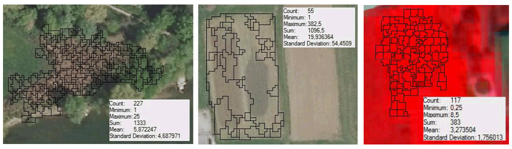

Figure 5. Sub-object density is a measure of the object fragmentation rate at a given observation scale. Japanese knotweed on an orthophoto and WorldView-2 (left, right), compared to farmland (centre).

The use of the sub-object density criterion is an optional classification step, which allows for the removal of predominantly arable land and facilitates further work on the candidate class classification.

3.3 Sub-object spectral domain

The sub-object spectral domain is associated with the object spectral signature, a concept known from pixel-based spectral analysis. In opposition to the pixel-based approach, in which the spectral signature represents multi spectral characteristics of an individual pixel, the spectral signature in this case is obtained for a selected region – object or segment.

The spectral object signature can be represented as a distribution function similar to the histogram distribution or as a cumulative frequency distribution (CDF) function. The latter provides better support for various statistical investigations. Two samples of the Kolmogorov-Smirnov (K-S) test represent the nonparametric statistical test, and through the comparison of the empirical distribution functions of the two samples we estimate their similarity. The empirical distribution function (EDF) is the CDF associated with the empirical measure of the sample. In this way we account for every pixel within the object (region) instead of merely one or two summary measurements (Sridharan, 2010).

The two sample K-S statistic quantifies the distance between the EDFs of two samples (Wikipedia, 2012). The null distribution of this statistic is calculated under the null hypothesis that the samples are drawn from the same distribution. In each case the distributions considered under the null hypothesis are continuous, yet otherwise unrestricted. The test does not specify the common distribution (normal or not normal; the statement that suits the remote sensing data characteristics), and is thus one of the most useful and general nonparametric methods for comparing two samples. It is sensitive to the differences in both, the location and shape of the two samples' EDF.

A connection between the object polygons and the multispectral image enables the attribution of all spectral values (through all spectral bands) to the given objects. The outputs are therefore regions in which each pixel is defined by the following attributes: the identification label of the pixel, geographical and pixel coordinates and the spectral value in each spectral band. The described regions constitute the starting point for the K-S test. The main assumption of the test is that different types of geographical entities (for example, different bush-like species) exhibit characteristic EDFs, which are determined according to the spectral values of all pixels in all wavelengths in the region (i.e. object spectral signature). The comparison of EDFs from various geographical entities (with the use of the K-S test) enables us to distinguish between them.
In the first step of the classification EDFs are provided for regions for which we know with certainty which features they represent (reference regions). This means that we choose the reference samples and through them define the information classes, and this makes the K-S based classification supervised. It is important to select representative and sufficiently large samples. The presence of a geographical entity type in a given area should thus be confirmed by a field survey or appropriate topographic or thematic maps. Selection of referential regions in which Japanese knotweed was detected was conditioned by the used data and the characteristics of the study area.

The next step is to compare an unknown region to all of the reference regions, i.e. compare the EDF of an unknown region to the EDF from a reference sample, for each spectral band, and determine the statistics significance measure (maximum absolute difference between the EDFs). The unknown region in each band belongs to a class with the lowest value of this statistic (Sridharan, 2010; • uri•, 2011). Each distribution pair with a 95% confidence level needs to have its value *h* ascertained (value 0 or 1). If the value is 1, the null hypothesis is rejected (the unknown region does not belong to the target class), otherwise it is accepted (the unknown region belongs to the target class). Described procedure was developed in Matlab.

The classification capabilities of the K-S test were analysed in the orthophoto area for which we know that Japanese knotweed is present, but was not included in the formation of the candidate class. We want to determine how many and which areas will be classified as Japanese knotweed with the K-S test. For referential use we selected verified samples of Japanese knotweed, blackberry bush and field. Fig. 6 shows the distribution function of the reference uses and the object that has not been classified as Japanese knotweed in the process of rule-based classification.

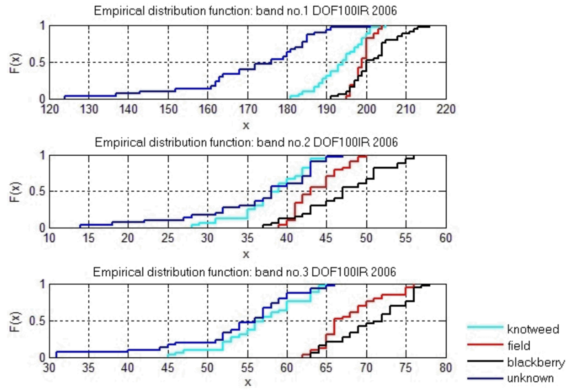

Figure 6. Empirical distribution functions of 3 reference uses and an unknown object; for the orthophoto spectral bands.

4. RESULTS AND DISCUSSION

4.1 Classification results and evaluation

Figs. 7 and 8 show the detection of Japanese knotweed in a riparian and suburban area, at which the sub-object spectral signature classification approach was used.

The coincidence of the reference data and the detected polygons is relatively large; yet some false-negative sites are present. A large part of the overlooked areas represent embankments of streams, where tree crowns hide the Japanese knotweed. For accurate validation one should also consider the temporal component: classification involved an orthophoto from 2006, while the field visit was performed 5 years later. In some cases, it is known that Japanese knotweed was not present on the orthophoto image, though it was observed in the field (Fig. 9).

Figure 7. Classification results for Japanese knotweed, obtained with the first set of attributes in riparian and communication areas. Green polygons are the identified candidates from the candidate layer, while the red dots represent actual knotweed occurrences.

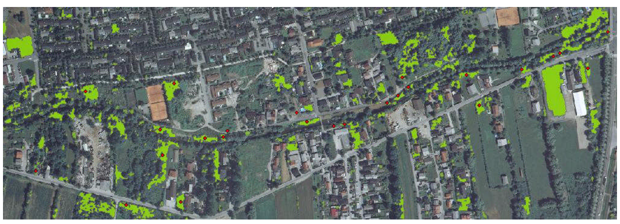

Figure 8. Classification results for Japanese knotweed,

obtained with the first set of attributes in the city suburbs. Green polygons are the identified candidates from the candidate layer, while the red dots represent actual knotweed occurrences.

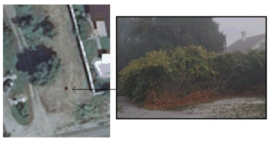

Figure 9. Time constraints are highly relevant in the identification of invasive plants. Ortopohoto from 2006 on the left and Japanese knotweed at the spot in 2011.

The quality determination of Japanese knotweed detection was assessed only visually (Fig. 10). The individual layers of the candidates, obtained through the use of different attribute sets, were compared to reference (field) data. Results are optimal for ortopohoto and WorldView-2 datasets. We can conclude that by selecting appropriate values for the attributes we can exclude (detect) the majority of knotweed strands in the broader area.

Figure 10. An example of correct classification results for Japanese knotweed detection (based on the first set of attributes).

Taking into account the spectral resolution of the involved imagery we have to promote the use of multispectral data, particularly the Red Edge NDVI index, for the results based on it are truly promising. The period in which the image was acquired (August) coincided with the top annual harvest cycle of Japanese knotweed (blooms in late summer, August and September). Thus, the Red Edge NDVI index is a highly appropriate indicator for detecting the occurrence areas of Japanese knotweed. The use of attributes from WorldView-2 band 6 (Red Edge) and 8 (IR2) also play an important role in determining these areas.

In our classification of Japanese knotweed we performed an evaluation of the candidate layer (not presented herein) and of the classification results using the K-S test, in which the candidate layer represented starting point for the classification.

4.2 Accuracy assessment of the Kolmogorov-Smirnov based classification results

We used the K-S test to check the efficiency of Japanese knotweed detection in overlooked areas (areas where strands were not detected). We analyzed all 32 areas on the selected orthophoto subset in which we used the first set of attributes to classify the candidate class. From the 32 mistreated areas of Japanese knotweed, 17 additional sites were classified as Japanese knotweed using the K-S tests, i.e. 53% of the otherwise neglected areas. The remaining undetected areas were mainly characterized by the occurrence of small areas of Japanese knotweed or areas in which knotweed is hidden under the tree foliage, making it impossible to see.

5. Conclusion

This paper provides an insight into the authors' current thoughts on object-based classification challenges with regard to the potential elements and technical capabilities necessary to move beyond the current OBIA commercial software support. The main challenge is to improve the classification accuracy so that the post-classification work would be significantly reduced. We conducted an experimental approach that combines the advantages of object- and pixel-based classifications. At first segmentation was used to provide the basic processing units, and this was followed by sub-object (pixel- and object-based) analyses with which we analysed the object's spectral and structural domain in greater detail. In the object's spectral domain we used the Kolmogorov-Smirnov test to compare the object's spectral signatures and thus facilitate a better distinction between the candidates. In the object's structural domain we implemented a measure of object sub-density in order to improve the characterisation of the object fragmentation rate at a given observation scale. The proposed hybrid approach was implemented in the detection of Japanese knotweed in the urban fringe of the city of Ljubljana. The results have shown that the classification accuracy obtained from the K-S based classifier for invasive species was improved greatly when compared to conventional object based classifiers. The K-S test classification algorithm is currently being implemented into the IDL programming language, and this will enable further extensive testing within ENVI.

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