APPLICABILITY OF MULTI-SEASONAL X-BAND SAR IMAGERY FOR MULTIRESOLUTION SEGMENTATION: A CASE STUDY IN A RIPARIAN MIXED FOREST

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ABSTRACT:

The increasing availability of synthetic aperture radar (SAR) data from a range of different sensors necessitates efficient methods for semi-automated information extraction at multiple spatial scales for different fields of application. The focus of the presented study is two-fold: 1) to evaluate the applicability of multi-temporal TerraSAR-X imagery for multiresolution segmentation, and 2) to identify suitable Scale Parameters through different weighing of different homogeneity criteria, mainly colour variance. Multiresolution segmentation was used for segmentation of multi-temporal TerraSAR-X imagery, and the ESP (Estimation of Scale Parameter) tool was used to identify suitable Scale Parameters for image segmentation. The validation of the segmentation results was performed using very high resolution WorldView-2 imagery and a reference map, which was created by an ecological expert. The results of multiresolution segmentation revealed that in the context of object-based image analysis the TerraSAR-X images are applicable for generating optimal image objects. Furthermore, ESP tool can be used as an indicator for estimation of Scale Parameter for multiresolution segmentation of TerraSAR-X imagery. Additionally, for more reliable results, this study suggests that the homogeneity criterion of colour, in a variance based segmentation algorithm, needs to be set to high values. Setting the shape/colour criteria to 0.005/0.995 or 0.00/1 led to the best results and to the creation of adequate image objects.

1. INTRODUCTION

1.1 Background

The Synthetic Aperture Radar (SAR) backscatter signal, which depends on surface characteristics, provides valuable information about the surface roughness, texture, volumetric structure, canopy height and electrical properties of the targets (Baghdadi et al. 2009; Dobson et al. 1995; Gebhardt et al. 2012; Hess et al. 1995; Heumann 2011; Imhoff 1995; Koch 2010; Mahmoud et al. 2011; Wang et al. 2010). The increasing availability of SAR data necessitates efficient methods for extracting semi-automated information at multiple spatial scales for different fields of applications (Drăguţ and Eisank 2012; Hölbling et al. 2012). One approach for multi-scale representation is object-based image analysis (OBIA). An extensive review on OBIA concepts is provided by Blaschke (2010). The number of studies that use the concepts and methods of OBIA for different applications and datasets rapidly increase (Blaschke et al. 2014). OBIA can be applied for semi-automated classification and feature extraction, but is mainly applied on optical data, e.g. in the field of habitat mapping where both spectral and spatial information play a critical role.

Segmentation is commonly considered a the first step towards finding appropriate target objects (Burnett and Blaschke 2003). It can be divided into two main strategies, i.e. bottom-up approach (merge), based on starting from several single seed pixels and merging the neighbouring pixels to form the segments or primitive objects, and top-down approach (split), dealing the image as an initial region with internal homogenous sub-region (Haralick and Shapiro 1985; Zhang 1996). Among different available segmentation techniques, multiresolution segmentation gained attention because of its ability to partitioning the remote sensing imagery into “meaningful” objects at several scales(Benz et al. 2004). The multiresolution segmentation implemented in eCognition (Trimble Geospatial) software is controlled by two main criteria: the Scale Parameter (SP), and the homogeneity criteria or the degree of fitting of two adjacent image objects (Baatz and Schäpe 2000). The SP controls the maximum allowed variance/standard deviation of the resulting image objects in terms of the homogeneity criterion or criteria; with an increasing variance to be allowed, the size of the segments (image objects) grows naturally. Woodcock and Strahler (1987) argued that local variance can be used as an indicator to find the optimal size of objects in the remote sensing imagery. Based on this concept Drăguţ et al. (2010) introduced a tool called “Estimation of Scale Parameter” (ESP) to identify ideal scales, where the overall pattern of local variance changes. Drăguţ et al. (2014) further developed the ESP tool to be operational on multiple image layers. This latest version of the ESP tool was used in this study.

1.2 Objectives

The objective of this study is two-fold: a) to evaluate the applicability of multi-temporal TerraSAR-X imagery for deriving image object primitives (meaningful objects) that are suitable for habitat mapping in a riparian mixed forest in Salzburg, Austria, and b) to assess the validity of the derived image objects. Within this objective we tried to identify the relevant representation scale(s) of SAR image objects and the optimal parameterization of the multi-resolution segmentation algorithm.

2. METHODOLOGY

2.1 Study area

The study area is the Salzach river floodplain, which is located at the Austrian-German border (Figure 1). The area is a protected site according to the European NATURA 2000 environmental legalization (Lang et al. 2014), and characterized by alluvial forest (91E0) with Alnus glutinosa and Fraxinus excelsior (Alno-Padion, Alnion incanae, Salicion albae), and riparian mixed forest (91F0) with Quercus robur, Ulmus laevis and Ulmus minor, Fraxinus excelsior or Fraxinus angustifolia, along the great rivers (Ulmenion minoris).

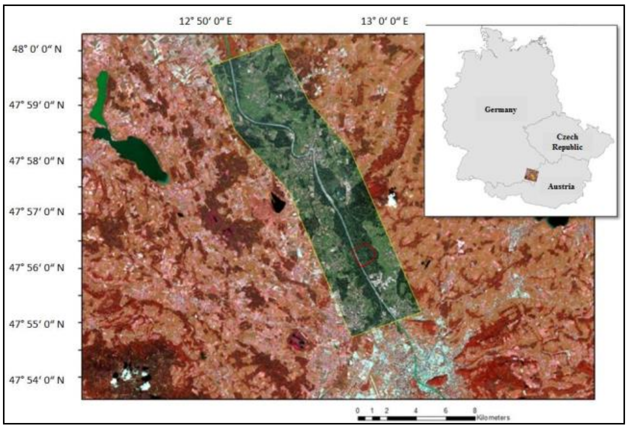


Figure 1. Salzach floodplain, located at the border of Germany and Austria. The red polygon indicates the test area.

2.2 Data Sets

For this study, two types of remote sensing data were used: a) multi-temporal archive TerraSAR-X (TS-X) images from 2012, acquired on 07 January, 09 February, 09 June, 01 July and 30 October, and b) a very high resolution (VHR) WorldView-2 (WV-2) optical image with 8 bands and 0.5 m spatial resolution from 09 July 2011. All TerraSAR-X images were acquired in a single HH polarization.

2.3 Segmentation of TerraSAR-X Imagery

Data pre-processing, i.e. calibration (Laur et al. 2003), orthorectification (Small and Schubert 2008), and speckle filtering (Frost et al. 1982; Lee and Pottier 2009; Mansourpour et al. 2006; Robinson 1977) were done using the open source software SENTINEL-1 Toolbox (S1TBX), provided by European Space Agency (ESA). All TS-X images were exported in GeoTIFF format. A spatial subset of the image was used in order to speed up the segmentation process.

The WV-2 image was used for comparison of the segmentation results. The WV-2 image was resampled to 3 m GSD in order to match the spatial resolution of TS-X imagery.

The multiresolution segmentation algorithm implemented in eCognition software was used to create segments, also known as image objects primitives, based on each SAR image as well as on the WV-2 image. As mentioned before, two main factors control the multiresolution segmentation: the Scale Parameter (SP) and the homogeneity criteria. SP determines the maximum standard deviation of the homogeneity criteria and affects the size of image objects. Furthermore, the shape factor can be optimized by defining smoothness and compactness parameters.

The multiresolution segmentation was supported by applying a statistical pre-evaluation with the ESP tool. The ESP tool identifies the relevant image object levels for an input layer (or a set of input layers) based on changes in local variance. The second version of the ESP tool suggests three levels of segmentation, whereby the first level is the most detailed one.

The weighing of shape vs. colour for multiresolution segmentation is arbitrary, however, in literature two combinations of colour variance are suggested for applying multiresolution segmentation on SAR imagery: a) heavy emphasis on colour variance, i.e. setting the weight of colour variance to 0.995 (Evans et al. 2014; Evans et al. 2010), or to 0.9 (Flores De Santiago et al. 2013). In addition to the value of colour variance suggested by Evans et al. (2014), we performed a segmentation with fully neglecting the shape effects and emphasized on the colour variance only (here the backscatter information) of SAR imagery, i.e. the colour variance was set to 1. These three different weightings of colour/shape were tested on all SAR images. The evaluation of the results was done by visual inspection and by comparison of the compactness values of the segments.

2.4 Validation of the Multiresolution Segmentation Results

Among research community, validation of the results of remote sensing derived thematic maps is highly important (Congalton 1994; Foody 2002). One of the most common ways to assess the accuracy is using a confusion matrix (Congalton 1991), and the Kappa coefficient (Smits et al. 1999). However, confusion matrix and Kappa coefficient only address the finally classified map by taking into account the thematic labels. In other words, these statistical approaches cannot be used to evaluate the accuracy of intermediate results, such as the segmentation result. Yet, there are several approaches suggested in the literature for addressing the accuracy of segmentation as well as classification (Albrecht et al. 2010; Hernando et al. 2012; Hoover et al. 1996; Lang et al. 2010; Lang et al. 2009). The segmentation results were compared to a reference map which has been created by an ecological expert through visual interpretation of the WV-2 image (Figure 2). The reference map consists of five main classes, namely: forest, riparian mixed forest, clear cut and young forest, meadow, and water. The quality of the multiresolution segmentations was assessed by considering the percentage of overlapping areas between each segmentation result and the respective thematic class and the number of classes covered by each segment.

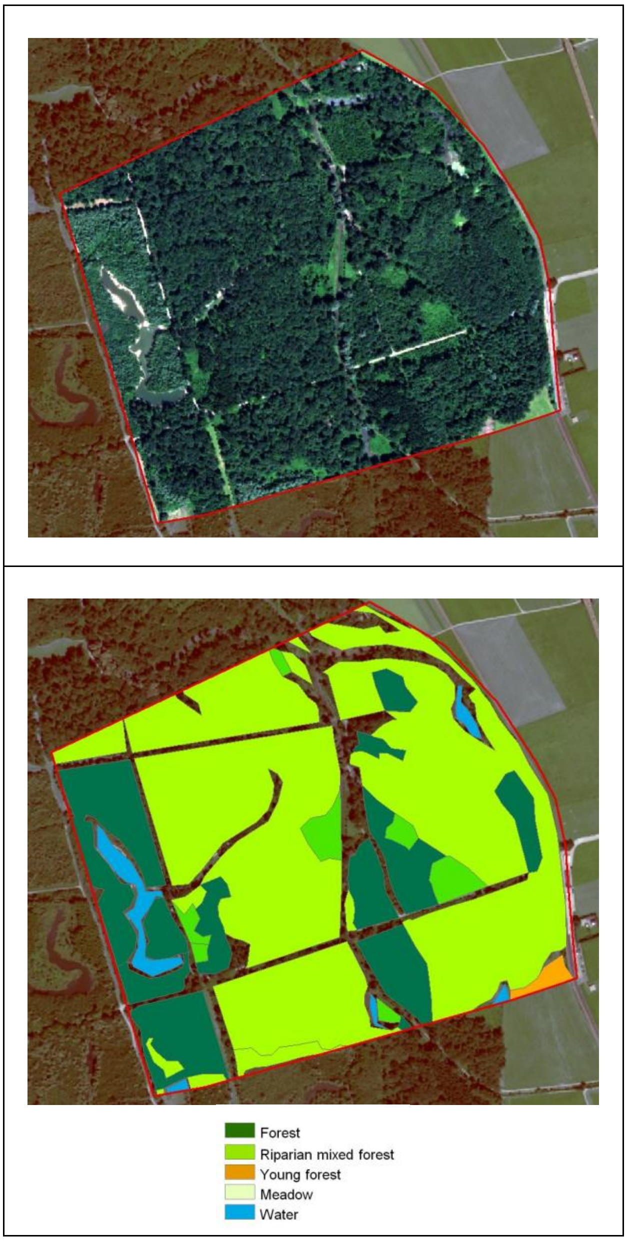


Figure 2. The study area showing the WV-2 image (above) and the visual interpretation of the same area, done by an ecological expert (below).

3. RESULTS

Table 1 shows the results of the multiresolution segmentation on the TS-X image acquired on 01 July 2012 and on the WV-2 image. Here, the segmentation levels are not organized in a strictly hierarchical manner, which means, image objects are built independently from the previous level and thus don not share common boundaries.

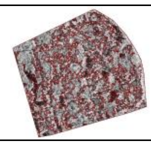
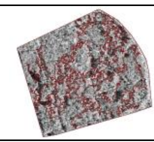
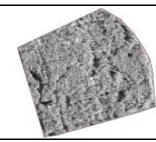
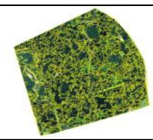
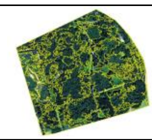
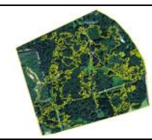
	Multiresolution segmentation results (shape vs. colour: 0.005/0.995)		
	Level 1	Level 2	Level 3
TS-X			
SP	37	81	201
Nr. of segments	66	9	1
WV-2			
SP	81	171	501
Nr. of segments	237	48	5

Table 1. Multiresolution segmentation results on the TS-X image from 01 July 2012 and on the WV-2 image. The three levels of segmentation suggested by the ESP tool are shown, whereby the weighing of colour variance has been set to 0.995 as suggested in the literature.

The visual interpretation of all the segmentation levels suggested by the ESP tool demonstrated that the first segmentation level (the most detailed one) was the most suitable one; thus, level 1 was further evaluated. For the validation of the segmentation results the visual interpretation of the area was used as reference. In order to assess the quality of the segmentation two criteria were taken into account (Figure 3):

1) The overlapping area between each segment and the reference classes
2) The number of the reference classes covered by each segment

The assumption is that the segments with a higher overlapping area in relation to the reference classes, as well as the segments with a lower number of covered reference classes have a higher potential to be correctly assigned to their respective class in further analysis. Based on this assumption, the quality map of the segmentation results for both images was created by considering the above mentioned criteria (Figure 4).

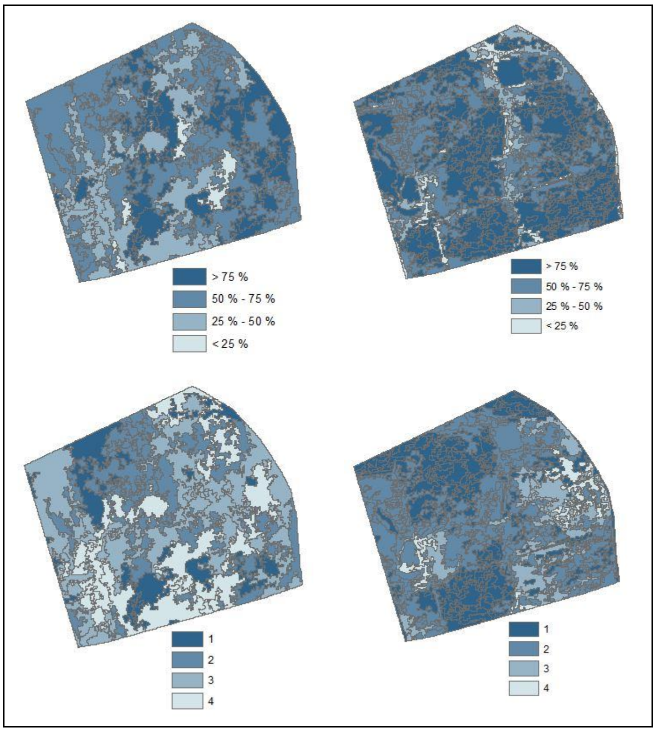


Figure 3. The overlapping area between each segment and the reference classes (TS-X: top left, WV-2: top right) and the number of the reference classes covered by each segment (TS-X: bottom left, WV-2: bottom right).

The following criteria were used to create the image segmentation quality map (Figure 4):

1. The class "high quality" comprises segments with an overlapping area of more than 75%, and the number of classes covered by each segment is equal to "1".
2. The class "good quality" comprises segments with an overlapping area between 50% and 75%, and the number of classes covered by each segment is equal to "2".
3. The class "average quality" comprises segments with an overlapping area between 25 % and 50%, and the number of classes covered by each segment is equal to "3".
4. The class "poor quality" comprises segments with an overlapping area of less than 25 %, and the number of classes covered by each segment is equal to "4".

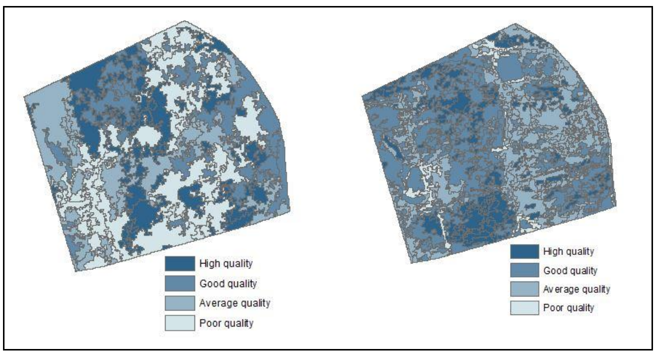


Figure 4. The quality map for the segmentation results on TS-X (left) and on WV-2 (right) imagery.

The segments of the classes "high quality" and "good quality" have potential to be directly assigned to their representative class, whereas the segments of the classes "average quality" and "poor quality" need more post-processing to be able to be labelled.

In general, the segmentation results are influenced by the different weighting of shape vs. colour criteria. Three combinations of shape vs. colour were tested on all TS-X images (Table 2).

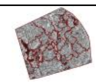
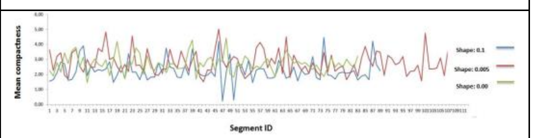
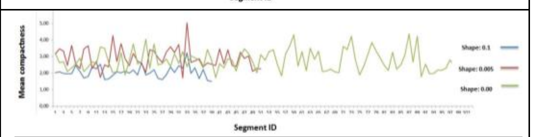
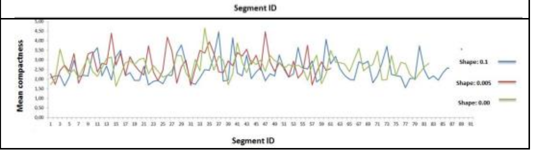
	07 Jan	09 Feb	09 June	01 July	30 Oct
Shape vs. colour: 0.1/ 0.9					
SP	30	32	40	44	29
Shape vs. colour: 0.005/ 0.995					
SP	27	34	41	37	34
Shape vs. colour: 0.00/ 1					
SP	27	24	35	33	33

Table 2. Comparison of three different weightings of shape vs. colour on TS-X images acquired in five different months in 2012. The ESP tool was used to select the SP.

The visual comparison of the results and the number of derived segments for each dataset reveals that using shape/colour with 0.005/0.995 or 0/1 results in more detailed segments compared to the shape/colour weighing of 0.1/0.9. Further comparison of the results was done using the compactness value of each segment (Table 3). Table 3 shows that setting the colour variance to 0.9 resulted in a more regular shape (mean compactness values between 2 to 3), whereas using 0.995 and 1 resulted in a more irregular shape (compactness values between 2 to 6). A compactness value of 1 indicates that the shape is close to a circle, thus higher compactness values may potentially indicate more complex natural objects.

TS-X imagery	Mean compactness value for each segment
Jan 2012	
Feb 2012	
June 2012	

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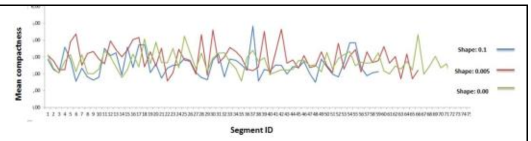
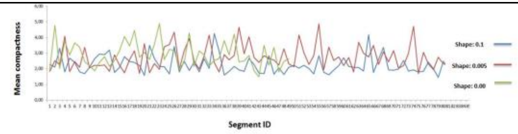
July 2012	
Oct 2012	

Table 3. Compactness values for the derived segments per TS-X image using different weighting of homogeneity criteria.

Based on visual inspection it seems that the weightings of colour variance with 0.995 and 1 resulted in more detailed segments, thus being more suitable for image segmentation of TerraSAR-X imagery. The segmentation results showed that waterbodies (Figure 2, reference map) were well delineated on all TerraSAR-X scenes, whereas significant deviations in terms of size and shape were identified for forest types.

4. CONCLUSIONS

This study assessed the applicability of multi-seasonal TerraSAR-X images for multiresolution segmentation. Based on statistical measures, SPs were automatically selected to produce image object primitives that can be used as a fundamental unit for subsequent classification. However, further refinements of the image object boundaries are necessary. Next to the scale parameter, we also studied the influence of shape vs. colour criteria on the size and shape of the objects. Setting the colour variance to 0.9 resulted in less image object primitives compared to 0.995 and 1 for multiresolution segmentation of TerraSAR-X images. Liu and Xia (2010) argued that the potential of classifying all pixels into their true classes in over-segmented images is higher compared to under-segmentation. When dealing with under-segmentation, each image object may consist of several objects, but it would be assigned to a single class. Therefore, we suggest the weighing of colour variance with 0.995 or 1 for multiresolution segmentation of SAR imagery. The visual inspection of the segmentation results on multi-temporal TS-X imagery revealed that water bodies were well delineated, however, the automated delimitation of forested areas just on SAR data seems to be difficult and needs further attentions.

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