SYNERGIES OF SENTINEL-1A SAR AND SENTINEL-2A MSI DATA FOR URBAN ECOSYSTEM SERVICE MAPPING

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ABSTRACT

The objective of the study is to evaluate the potential use and synergetic effects of novel ESA Sentinel-1A C-band SAR and Sentinel-2A MSI data for mapping of ecologically important urban and peri-urban space. Image resolutions between 5 m and 20 m provided by the Sentinel satellites introduce a new relevant spatial scale in-between high and medium resolution data at which not only urban areas but also their important hinterlands are expected to be effectively and efficiently mapped. The fusion of Sentinel-1/2 facilitates both the capture of ecologically relevant details but at the same time also enables large-scale urban analyses that draw surrounding regions into consideration. The combined use of Sentinel-1A SAR in Interferometric Wide Swath mode and simulated Sentinel-2A MSI (APEX) data is being evaluated in classification of a metropolitan area over Zürich, Switzerland. The SAR image was pre-processed using Range-Doppler terrain correction. A 5x5 adaptive Lee speckle filter was applied to the VH and VV intensity bands before co-registration to the simulated Sentinel-2 image. After radiometric and spatial resampling, the fused images were segmented by the KTH-SEG algorithm before being classified by SVM. After reclassification under masks and sieve-filtering, the resulting landscape patches were investigated in terms of spatial characteristics and topological relations that are deemed to be influential for ecosystem service provision. Based on the classification result, ecosystem service supply and demand values that account for spatial and topological patch characteristics were attributed to 14 different land cover classes. The method and underlying data were found suitable for urban land-cover and ecosystem service mapping. The introduction of spatial aspects into ecosystem service providing areas is believed to add another important aspect in currently existing valuation approaches.

INTRODUCTION

It is well-known that a continuous increase in urban population and growing cities can be expected in the future (1), leading to deteriorated living conditions if environmental issues that further urban growth raises are not integrated adequately into urban planning and policies. Remote sensing has the capability to efficiently and readily deliver reliable information about urban land cover, where in-situ data collection is labour-intensive and time-consuming and where there is currently a lack of well-established standardized methods to evaluate the quantity and quality of urban eco-space (2). The new Sentinel mission series is one component of the GMES (Global Monitoring for Environment and Security) programme by the European Union (EU) with the goal of providing us with reliable and timely information on land, ocean and atmosphere for energetic, climatological and security related topics (3). The Sentinel missions are expected to provide us with a global view of environmental parameters with high spatial and temporal resolutions crucial for climate and environmental research (4). Thus, one aspect and objective of this study to evaluate the recently launched Sentinel-1 C-band SAR satellite and a simulated Sentinel-2 multispectral image product regarding their combined suitability for the classification of ecologically important urban and peri-urban space. (5) discuss and categorize the potential use of the new sentinel missions for scientific observations. In the land surface variable category, the use of both Sentinel-1 and Sentinel-2 data for ecosystem relevant land cover mapping is summarized. One emerging concept that has been growing in popularity over the past decades to express both the importance as well as the quality of our natural capital around the globe is the one of ecosystem services. Having been an instrument of awareness raising for conservational measured in the beginning (6), the concept has been constantly further developed (7) resulting in one recent study (8) that presented an alternative relative ecosystem service valuation approach as opposed to traditional monetary valuation approaches (9,10) that are considered problematic (11). The promising approach of (8) was originally developed for regional assessments based on the CORINE land cover classification scheme (12). The second objective of this study is, based on the land cover classification result, to extend the concept of measuring ecosystem service supply by integrating spatial components into the valuation scheme.

STUDY AREA AND DATA

To exemplify the proposed method, Zürich as the largest city in Switzerland with an increasing urban population of over 400,000 inhabitants and about 1.8 million people residing in the metropolitan area has been chosen. Zürich's living quality is considered high with noticeable progress in terms of environmental quality over the past two decades. Major urban classes are continuous and discontinuous urban fabric, industrial/commercial areas, the infrastructural road/railroad network including Zürich airport, construction sites, green urban spaces, sports/leisure facilities and allotments. The urban hinterland is characterized by Lake Zürich, agricultural land and forest. Agriculture is predominately defined through crops (51%), pasture (24%) and natural grasslands (20%). Vineyards and orchards play a subordinate role. A 16x22 km^2 Sentinel-2A scene, simulated with high-resolution airborne imaging spectrometer (APEX) data and including all spatial and spectral characteristics corresponding to a Sentinel-2 level 1c product dating from 2011-06-26 was used in combination with Sentinel-1A C-band SAR IW mode dual polarisation (VV+VH) data as a Level-1 GRD product from 2015-03-16. The Level-1 GRD product consists of focussed detected, multi-looked SAR data projected to an Earth ellipsoid. The ellipsoid is corrected using the terrain height specified in the product general annotation. Figure 1 shows the Sentinel-2 image to the left and the Sentinel-1 image to the right.

Figure 1: RGB true-colour-composite of the Sentinel-2A APEX scene from June 2011 (left) and the Sentinel-1A 5x5 adaptive Lee speckle filtered intensity data from March 2015 (VV-VH-VV) (right).

METHODS

The main methodological steps involve image pre-processing and coregistration, image segmentation and classification, accuracy assessment, post-classification, spatial patch analysis and ecosystem service budget modeling as shown in Figure 2.

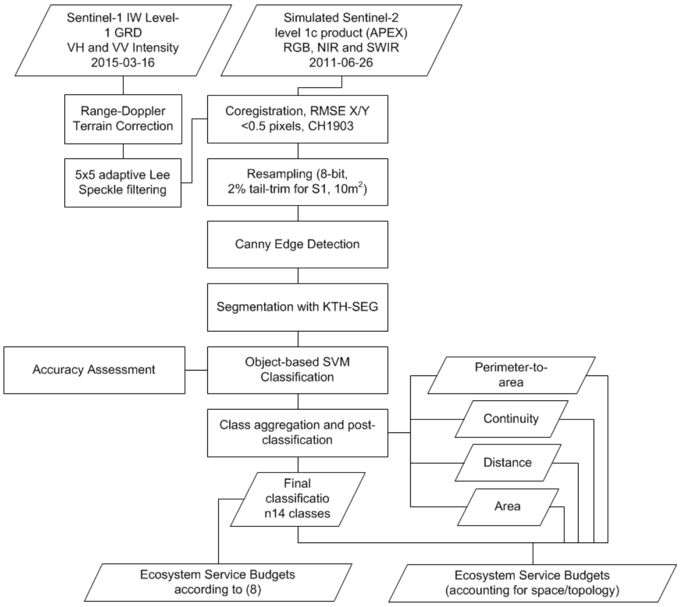

Figure 2: Methodology flowchart.

The Sentinel-1 SAR image was first geometrically corrected through Range-Doppler Terrain Correction with the method of (13) with a 3 second SRTM elevation model. Inherent speckle in SAR images is caused by the coherent interference of waves reflected from many elementary scatterers and complicates image interpretation by reducing the accuracy of image segmentation and classification (14). The reduction of speckle is therefore performed in this study by application of a 5x5 adaptive Lee filter applied on the VH and VV intensity bands that, empirically compared to kernel sizes from 3x3 to 11x11 and Frost and Gamma Map filters, yielded the best results. The applied filter with a 5x5 kernel size has already been found suitable previously (15). The Sentinel-1 image was then coregistered with RMSEs less than 0.5 pixels in X and Y directions to the Sentinel-2 image that is already nadir-normalized, spectrally resampled, geo-corrected and ortho-rectified to the Swiss National Grid (CH1903). An extensive description of the simulated Sentinel-2 scene can be found in (16). After coregistration, the filtered Sentinel-1 bands and the Sentinel-2 RGB, NIR and two SWIR bands were resampled to a 10 m spatial and to 8-bit radiometric resolution with a 2% tail trim.

Image segmentation was then performed with KTH-SEG, an edge-aware region growing and merging algorithm (17). By creating an edge/no-edge decision layer using an enhanced Canny edge detector, segment growing is divided off-edges and along edges. The homogeneity criteria for both growing and merging are defined by a weighted sum of change in mean and change in standard deviation. Merging is performed using a mutual best neighbour approach, followed by threshold merging. Growing is limited to the minimum segment size and merging to the maximum segment size. For the segmentations in this study, the following parameters were empirically determined and were found to generate the most suitable result: Canny threshold: 0.1-0.2; grow 0.5/0.5, merge 0.5/0.5, minimum and maximum segment sizes were chosen from 5 and 100 pixels.

The segment type was then determined by object-based Support Vector Machine (SVM) classification (18,19) into initially 19 spectrally different classes that were aggregated into 12 contextually coherent land use and land cover classes. After accuracy assessment, the classification result was sieved to remove small segments that are regarded as misclassifications. Forest and agricultural areas were reclassified into urban green spaces and urban forests under an urban mask. From the final classification, 4 spatial characteristics of natural green and blue land cover patches that are believed to influence ecosystem service provision capacities were derived under these following assumptions:

Distance: An increased ecosystem service provision of patches close to urban dwellers is expected. A Euclidean distance map from urban classes into natural land cover patches was generated. The closer the natural land cover patches are to the edge of urban areas, the higher their value.

Perimeter-to-area-ratio: The lower the ratio, the higher the service provision because less edge is shared with other classes (that might negatively affect the patch in question) and patch centres are considered more pristine. Perimeter-to-area ratios were calculated on a patch level.

Area: Larger patches are capable of providing more services. The area in hectare was calculated for all patches.

Contiguity: High patch connectivity and less fragmented landscapes are considered beneficent in several ways, e.g. for species dispersal or recreational purposes. Contiguity values were calculated for all land cover patches.

These four factor maps were all linearly scaled in a way that the lowest value in the map was set as 0.5 and the highest value as 1.5. As a final step two ecosystem service budget maps were derived. The first map was created by attributing the original ecosystem service demand and supply scores as presented in (8) to each land cover patch. A second supply and demand map was generated with modified service values. For this, each original per patch score from (8) was multiplied by each of the four factor maps, that through the scaling from 0.5 to 1.5 either decrease or increase the provisional value by a maximum of 50%. The 4 resulting values per patch were then averaged by summation and division by 4.

RESULTS

In total, 182,432 segments were generated by KTH-SEG that were then classified and aggregated into 12 classes. Table 1 below shows the classification confusion matrix. The classification into urban and peri-urban classes resulted in an overall accuracy of 79.81% with a Kappa coefficient of 0.78. Largest confusions occurred between construction sites and industrial/commercial areas and between the built-up classes discontinuous urban fabric, sport and leisure facilities and between airport runways and roads.

Table 1: Confusion matrix (C1=Water bodies; C2=Water courses; C3=Mixed forest; C4=Construction sites; C5=Discontinuous urban; C6=Airport; C7=Road/railroad network; C8 Industrial/commercial; C9=Agriculture and natural vegetation; C10=Continuous urban; C11=Sport/leisure facilities; C12=Allotment gardens.

	C1	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C9*	*C10*	*C11*	*C12*	**UA**
C1	100	0	0	0	0	0	0	0	0	0	0	0	**100**
C2	0.6	91.8	3.6	0	1.5	0	0.6	0.1	1.8	0	0.1	0	**91.7**
C3	0	0	95.4	0	0	0	0	0	4.6	0	0	0	**95.4**
C4	0	0	0	79.9	0.3	0	1.2	14.1	0	0	0.4	4.1	**79.9**
C5	0	0	1.2	0.7	81	0	1.9	4	0.5	4.1	1	5.5	**81.1**
C6	0	0	0	0	0	72.4	0.7	12.8	13.5	0	0.6	0.1	**72.4**
C7	0	0	0	0	6.4	0.1	86.9	1.7	2.1	0	0.3	2.5	**87**
C8	0	0	0	39.3	0.8	2.1	10.7	31.8	4	5.2	5.8	0.4	**31.8**
C9	0	0	0	0	1.1	2.4	0	0	95.1	0	0	1.4	**45.9**
C10	0	0	1.8	0	12.1	0	5.1	1	0	80	0	0	**80**
C11	0	0	0	3.7	13.8	0.5	0.9	1.6	14.8	0.5	51.1	13.2	**51.1**

C12	0	0	0	0	13	0	0	0	6.6	0	0	80.4	**80.4**
PA	**99.4**	**100**	**93.8**	**65.3**	**66.1**	**93.8**	**41.7**	**47.4**	**68.7**	**89.4**	**79.7**	**77.9**	**99.4**

Figure 3 shows the classification result after post-classification and sieving (left) a map displaying the combined topological and spatial influence of natural land cover patches on the provision of ecosystem services. The adjusted provision and demand scores are presented in the right map.

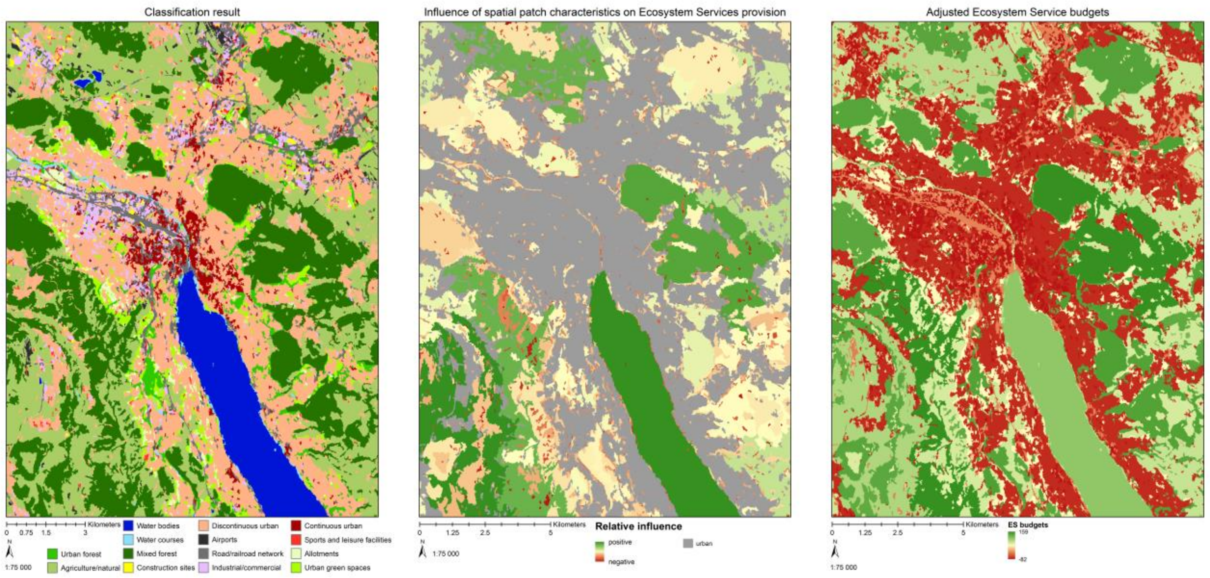

Figure 3: Classification result after sieving and reclassification (left), patch characteristics influence on ecosystem service provision (centre) and ecosystem service budgets map (right).

The scaling and weighting of spatial metrics and the choice of metric define the degree of influence on service provision. In this study, the importance of spatio-topological patch characteristics was considered equal. A more refined weighting process to mirror the influence of a particular factor or on a specific underlying ecological function or in respect to a distinct land cover class is believed to give a very different budget outcome. Thus, the service provision value should not be relied on as such, but they should rather be seen as an example of how spatial attributes or topological relations influence ecosystem services and how these aspects can be expressed and integrated.

CONCLUSIONS

Classification accuracies of ca. 80% suggest the suitability of the method and data for urban land cover mapping and classification of ecological important space and further use of the datasets in this application domain is recommended. The concept of expressing ecosystem service budgets according to (8) has been extended to include spatial properties and topological relations of landscape elements. The magnitude of influences these aspects have on service scores need however further reflections, i.e. each underlying function that is the base for the relative supply and demand values should be considered instead of applying the same adjustment factor to the aggregated score. This and further thoughts of how additional spatio-topological patch aspects might influence ecosystem service provision and also demands are suggested for future interdisciplinary research where valuable inputs from landscape ecologists would be an asset.

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