

NOVEL PARAMETERS FOR EVALUATING THE SPATIAL AND THEMATIC ACCURACY OF LAND COVER MAPS

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ABSTRACT:

Correct delineation and classification of land cover maps is an important aspect for its management and monitoring. Based on orthophotos, object-based image analysis (OBIA) can be used to produce detailed land cover maps. However, these new products require measures to evaluate and quantify both thematic (difference in assigned labels) and spatial (difference in delineated object boundaries) accuracy of the outputs. We propose to extend the Object Fate Analysis (OFA) comparison approach with an *OFA-matrix* to validate thematic and spatial accuracy together. Its diagonal shows the relative area of spatial and thematic coincidence between a reference map and a classification map. Novel parameters *STL* (Spatial Thematic Loyalty), *STL_{OVERALL}* (Spatial Thematic Loyalty Overall) and *MIO* (Maximal Interfering Object) summarize the new *OFA-matrix* accuracy assessment. Land cover map generated by OBIA (classification) was compared with the map performed using photo interpretation and field data (reference). The results show for the *OFA-matrix* good spatial and thematic accuracies (>65 %) for all the classes except for one of them, with a good *STL_{OVERALL}*=69.8 %. Overall, *OFA-matrix* could be used for OBIA accuracy assessment.

1. INTRODUCTION

Object Based Image Analysis (OBIA) has been recently applied for processing land cover maps using automated methods for the analysis of very high resolution images (Hay *et al.*, 2005; Hernando *et al.*, 2012). OBIA, alternative to the traditional pixel approach, describes the imaged reality using spectral, textural, spatial, topological and hierarchical objects characteristics (Lang, 2008; Blaschke, 2010). This method raises concerns about the subsequent validation strategies. It was suggested that OBIA products would preferably be assessed by replacing the standard sampling units by objects (Congalton and Green, 2009). Accuracy assessment of object-based maps should include both thematic and spatial components. Therefore, for the OBIA accuracy assessment new methods explicitly built on the concept of objects are needed (Albrecht, 2010; Lang *et al.*, 2010).

Considering the thematic accuracy (difference in assigned labels), in a review of 20 recent papers on OBIA the point-based sampling, error matrix (Congalton and Green, 1999) was still used in the majority of the cases (Radoux *et al.*, 2010). However, even if it is recommended to set up the accuracy assessment on an object-based sampling, there is no state-of-the-art approach available at the present. Nevertheless, some strategies using the bias and the variance of the overall accuracy have been proposed (Radoux *et al.*, 2010). Related to the spatial accuracy (difference in delineated object boundaries),

boundaries are more relevant for OBIA than had been for traditional pixel-based image analysis approach. For this purpose new methods for validation are being developing such as positional error (Radoux and Defourny, 2007) or object fate analysis (Schöpfer *et al.*, 2008). The methodology presented by Radoux and Defourny (2007) showed that the use of simple statistics, bias and standard deviation, provide robust quantitative spatial quality assessment. The Object Fate Analysis (*OFA*) is a method presented by Schöpfer *et al.* (2008) for investigating the spatial relationships of corresponding objects in two different representations. *OFA* was successfully applied for object-based change detection and for the assessment of object boundary accuracy (Schöpfer *et al.*, 2008).

Both methods summarize spatial quality and thereby complement thematic accuracy assessments. In any case, none of the above studies undertook both thematic and spatial accuracy at the same time. In this paper we propose to extend the *OFA* comparison approach with an *OFA-matrix* and derived *OFA-parameters* to validate thematic and spatial accuracy simultaneously.

2. METHODS

2.1 Thematic and spatial assessment: *OFA-matrix*.

Within *OFA* the topological relationships between overlapping objects are categorized by an error band and by evaluating

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whether the centroid of the classification object fell inside the reference object (C2: *Good I, Good II, Expanding*) or not (C1: *Invading, Not interfering I, Not interfering II*), (Tiede *et al.*, 2010). The two data sets are named classification and reference. For the spatial comparison, all classified objects were compared to all reference objects in the manner illustrated in Fig. 1.A. Then, the reference object boundary and a buffer applied to this boundary serve for subdividing the relationships for each cluster into its three sub-types. The OFA concept is implemented in a tool called LIST (Landscape Interpretation Support Tool) as an extension for ArcGIS (Weinke *et al.*, 2007). To illustrate this concept we explain a possible case. We compare a one reference object A (area: s_1) with different classified objects (a, b, c,...) as illustrated in Fig. 1.B.

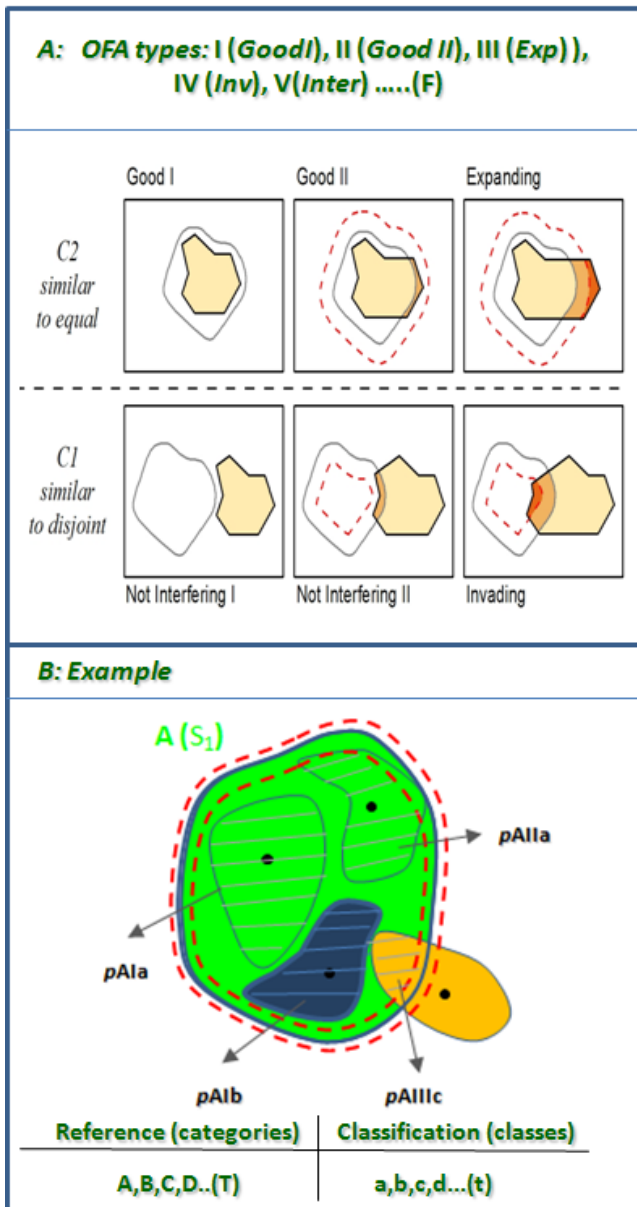


Figure.1.A: Interaction between classified objects (rose solid color), reference objects (grey outline) and buffer (dashed red outline). 1.B: Comparison between one reference object A (area: S_1) with different classified objects (a, b, c,...) and (p) the overlapping part (e.g. $pA1a$: correct thematic classified object (a) compared to the reference (A) and OFA type spatial delineation: I (Good I).

Considering the thematic accuracy some of them are correct thematic classified (a) while others (b and c) are not. Each classified object is compared to the reference only with the overlapping part between the reference object and the classified object (p). For a reference (A) those classified (a) are correct thematically. Besides, we can distinguish the OFA spatial accuracy (I) *Good I*, (II) *Good II*. Therefore, we obtain $pA1a$, $pA11a$. Other examples would be $pA1b$ thematic wrongly classified and good I spatial classified and $pA11c$ both thematic and spatial incorrectly classified.

We propose now to combine the OFA concept with the traditional error matrix structure to create the OFA-matrix, for validating both thematic and spatial assessments. The OFA-matrix is a square array of numbers set out in rows and columns that considering a reference category (T) expresses the relative area (r_{TCt}) of classified objects (t) regarding the OFA types (C) –Good I; Good II; Expanding; Invading; Not Interfering II- and the thematic correspondence (Fig. 2).

If finally we compare all these relationships following these criteria in an OFA- matrix, we formulate that r_{TCt} is the sum of the relative areas of the t classified objects considering a OFA type (C) defined by Eq. (1):

$$r_{TCt} = \sum_{i=1}^t \frac{P_{TCti}}{S_T} \quad (1)$$

where p_{TCti} are the areas within the reference compared to the reference category area S_T . The diagonal shows the relative area of spatial and thematic coincidence between the reference and the classification.

Furthermore, to characterize overall spatial and thematic accuracy we group the total OFA-matrix information into clusters C2 and C1 (Fig. 3.A).

We proposed three specific measures. Firstly, *STL* (Spatial thematic Loyalty) indicates the percentage of spatial and thematic loyalty between one reference (T) and the classified objects (t) for a C2 OFA type given by Eq. (2):

$$STL_{TC2t} = \frac{r_{TC2t}}{R_{TC2}} \quad (2)$$

where R_{TC} is the total relative area in a reference T in a type C1 or C2 given by Eq. (3):

$$R_{TC} = \sum r_{TCt} \quad (3)$$

Secondly, $STL_{OVERALL}$ (Spatial Thematic Loyalty Overall) is the mean of the *STL* defined in Eq. (4):

$$STL_{OVERALL} = \frac{\sum STL_{TC2t}}{w} \quad (4)$$

where w is the number of the references categories (A, B, C...w...T).

Thirdly, *MIO* (Maximal Interfering Object) is the percentage of the class (different from the reference) invading more the reference for a C1 OFA type given by Eq. (5).

$$MIO = \frac{r_{TC_1max}}{R_{TC_1}} \quad (5)$$

OFAMatrix

		REFERENCE						
		A	B	C	D	E	T	
CLASSIFICATION	GoodI							
	a							
	b							
	c							
	d							
	e							
	t							
	GoodII							
	a							
	b							
	c							
	d							
	e							
	t							
	Exp							
	a							
	b							
	c							
	d							
	e							
t								
Inv								
a								
b								
c								
d								
e								
t								
NontI								
a								
b								
c								
d								
e								
t								

Figure 2. Structure of the OFA-matrix where each of the cells contain r_{TCt} which is the sum of the relative areas of the classified objects (t) considering a OFA type (C).

3. RESULTS

In our case of study we considered two land cover maps: the first one is one performed using photo interpretation and field data (considered as the reference) and the stands map obtained with the OBIA (considered as the classification). The reference map was obtained delineating visually homogeneous vegetation patches and confirming the class assignment with a field survey (a regular grid of 156 circular plots, $r=10$ meters). The study site is a forest public land, called “Dehesa Boyal” (815 ha), located in central Spain, Ávila, Region of Castilla y León (Fig.1). It is on flat or gently sloping area (altitudes 1220-

1395 m, slope 5-12%) with oligotrophic acid soils. The climate is Temperate Mediterranean, with dry hot summers, cool and rainy winters and a mean annual rainfall between 600-2000 mm. This site is included in the Mediterranean biogeographic region of the Natura 2000 network. Based on field work, we can distinguish within this area the following land cover classes: *shrub* (<1 m tall); *low pole* (> 1 m tall and a diameter breast height (DBH) < 10 cm); *high_pole* (10 cm < DBH < 20 cm); *High_forest* (20 cm < DBH < 35 cm), the largest trees in the forest *tall_shrubs* and *pasture* (Hernando *et al.*, 2010).

The summarized *OFA-matrix* shows the results (Fig.3.B). We appreciate that more than $\frac{3}{4}$ of the classified objects belong to the cluster C2 for all the categories (77.9%, 83.4%, 79.9%, 78.9%, 74.4%, 84.2%) which means a good relative spatial coincidence. For example, the *shrub* has a 77.9% spatial accuracy but there is only a thematic coincidence with *shrub* for the 24.7%, that is a $STL_{(shrub)} = 31.8\%$. Even if the class *shrub* was adequately segmented there is thematic confusion with the *high polewood* (33.6%). The highest *STLs* belong to *tall_shrubs* (83.6 %) and *high_pole* (87.2%) which represent the best spatial and thematic assignment.

The $STL_{OVERALL}$ for all the classification is 69.8%, it indicates the percentage which was correctly segmented of the type C2 and well classified thematically. Regarding the C1 group we obtain a different view for the incorrectly classified objects (type C1). For example, regarding the class *s-shrub* (22.1%) is mainly invaded by the *low_pole* (9.9%) and therefore the $MIO_{shrub} = 44.6\%$. The highest *MIO* (75.8%) belongs to the reference *High_forest* which is invaded by the 16% of *High_forest*.

4. DISCUSSION

The presented approach to assess the accuracy of the object-based image classification of “Dehesa Boyal” showed that with the OFA-matrix it is possible to compare the classification to the reference on the basis of objects. Spatial boundary inconsistencies are accounted for by assigning each spatial relationship between a classification object and a reference object to an OFA category. Thematic comparisons then are handled separately within each category.

Each object comparison is taken into account by its overlapping area that is covered by both involved objects. By this approach, each area segment of the reference is only counted once in the matrix and all matrix cells add up to form the total area of the reference. On this basis the *OFA-matrix* is comparable to the traditional thematic error matrix. As an advantage, the *OFA-matrix* enhances the thematic object comparison by distinguishing between objects that are spatially sound (and well delineated C2) and objects that do not meet this spatial accuracy C1. Obviously the categorization process has to be lead with care in order to get optimal information about the implications of spatial accuracy on thematic accuracy. Furthermore, the proposed new parameters *STL* (Spatial Thematic Loyalty), $STL_{OVERALL}$ (Spatial Thematic Loyalty Overall) and *MIO* (Maximal Interfering Object) summarize the accuracy assessment. These parameters could be use to compare different Object-based Image studies as we used to do with the Kappa index (Congalton and Green, 1999; Congalton, 2001) in the traditional pixel approach.

A		REFERENCE DATA (T)					
		A	B	C	D	E	T
CLASSIFIED DATA (t)	C2 (TOTAL)	R_{AC_2}	R_{BC_2}	R_{CC_2}	R_{DC_2}	R_{EC_2}	R_{TC_2}
	a	r_{AC_2a}					
	b		r_{BC_2b}				
	c			r_{CC_2c}			
	d				r_{DC_2d}		
	e					r_{EC_2e}	
	t						r_{TC_2t}
	STL_{TC_2} (%)	STL_{AC_2a}	STL_{BC_2b}	STL_{CC_2c}	STL_{DC_2d}	STL_{EC_2e}	STL_{TC_2t}
	$STL_{OVERALL}$ (%)	STL_{Total}					
	C1 (TOTAL)	R_{AC_1}	R_{BC_1}	R_{CC_1}	R_{DC_1}	R_{EC_1}	R_{TC_1}
	a	r_{AC_1a}					
	b		r_{BC_1b}	r_{CC_1max}			
	c	r_{AC_1max}		r_{CC_1c}	r_{DC_1max}		r_{TC_1max}
	d		r_{BC_1max}		r_{DC_1d}	r_{EC_1max}	
e					r_{EC_1e}		
t						r_{TC_1t}	
MIO (%)							

B		REFERENCE DATA (T)					
		shrub	low pole	high pole	High forest	tall shrubs	pasture
CLASSIFIED DATA (t)	C2 (TOTAL)	77.9	83.4	79.4	78.9	73.4	84.2
	shrub	24.7	1.5	0.1		2.5	14.4
	low pole	3.8	63.1	8.6		1.2	1.0
	high pole	33.6	10.1	66.4	28.6	2.9	
	High forest		3.0		50.3		
	tall shrubs	3.8	4.3	4.2		64.0	4.1
	pasture	12.0	1.4	0.1		2.8	64.7
	STL (%)	31.8	75.7	83.6	63.7	87.2	76.9
	$STL_{OVERALL}$ (%)	69.8					
	C1 (TOTAL)	22.1	16.6	20.6	21.1	26.6	15.8
	shrub	0.1	1.1	0.8		0.3	0.6
	low pole	9.9	1.2	0.9	4.1	6.1	0.9
	high pole	7.5	7.4	13.6	16.0	7.0	3.1
	High forest	0.2		2.6		0.1	
tall shrubs	3.2	5.6	1.7	0.6	7.7	6.1	
pasture	1.1	1.1	1.0	0.4	5.4	5.1	
MIO (%)	44.6	44.9	12.6	75.8	26.3	38.3	

Figure 3. A: Example of the structure of the summarized OFA-matrix and structure 3.B: application for the “Dehesa Boyal” example.

5. CONCLUSION

The OFA-matrix is explicitly built on the concept of objects and fulfills this initial requirement for an object-based accuracy assessment. Thematic accuracy and spatial accuracy can be assessed together in a single approach. The proposed OFA-matrix, with its parameters $STL_{OVERALL}$ and MIO, assesses about the thematic and spatial accuracy jointly for the OBIA. This matrix has shown to be a useful and alternative tool to the confusion matrix for validation or comparison in classifications based on objects. This fact confirms the transferability of OFA-matrix to other OBIA application contexts.

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