SITE-SPECIFIC AREA-BASED VALIDATION OF CLASSIFIED OBJECTS

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ABSTRACT:

The establishment of geographic object based image analysis (GEOBIA) as a group of methodologies for analysing and classifying remotely sensed data as objects suggests accuracy assessment should incorporate some form of geometric validation of the classified objects against the real world objects they are meant to represent. Site-specific accuracy assessment methods, such as those associated with per-pixel classifications provide information on the accuracy of a classification at particular locations (x,y) across an image. Applied to GEOBIA classifications, there is uncertainty whether that class is consistent across the entire object. In addition, as the output of an object-based classification is ready for inclusion in GIS analysis, it should be assessed for the geometric accuracy (shape, symmetry and location) of the classified objects. This study describes a novel method of validating both the geometric and thematic accuracy of a multi-class classification against reference data. The accuracy assessment used a hierarchical object-based approach applied to randomly selected sample areas containing both classified (*C*) and reference (*R*) objects. Proportional overlap between the *C* and *R* objects, is used in the calculation of a number of measures of similarity that provide both thematic and spatial accuracies for the sample areas and classified objects within. In this study, the GEOBIA classification showed an overall accuracy of 72%, 90% sample areas showed a good match (>50% overlap) between *C* and *R* objects within and of these 11 out of 20 have over 70% correspondence. The measures of similarity also indicate strong correspondence between *C* and *R* objects within these samples. In the sample areas where there was poorer accuracy, and the omission and commission errors greater, the values for the dissimilarity measures were noticeably higher. Visual inspection of the sample areas shows that error is greatest in the sample areas with greater heterogeneity in cover types. Most of the non-matching objects occurred on the boundaries between land covers. This paper presents a novel application of area-based methods for the quality or accuracy assessment of object-based image analysis that have an advantage over the conventional site-specific assessment. Given appropriate reference data, the measures provide not only an overall accuracy for the image but also per object, per class and per sample area accuracies. In addition, classification uncertainty can be visualised enabling further analysis of error and where it occurs.

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1. INTRODUCTION

1.1 Accuracy and GEOBIA

The establishment of geographic object based image analysis (GEOBIA) as a group of methodologies for analysing and classifying remotely sensed data implies accuracy assessment should incorporate some geometric validation of image objects against the real world objects they are meant to represent. Site-specific accuracy assessment methods, typically associated with pixel-based classifications (Congalton 1991, Congalton and Green 2009), provide information on the quality or accuracy of a classification but only assess the thematic accuracy at particular locations (x,y) across the image (Zhan *et al.* 2005) and there is uncertainty whether that class is consistent across the entire object (Figure 1a). In applying such assessment methods to GEOBIA classifications, where the output is a collection of classified objects with geometric extent that are ready for inclusion in GIS analysis (Benz *et al.* 2004), there needs to be an assessment of the geometric accuracy (shape, symmetry and location) (Figure 1b) of the objects (Schöpfer and Lang 2006).

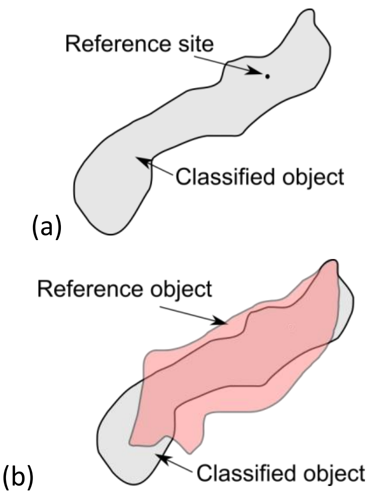


Figure 1: (a) The relationship between a classified object and site-specific reference. (b) The relationship between a classified object and reference object.

Acccuracy assessment of GEOBIA has been identified as an area of research need (Blaschke 2010), and the literature on spatial accuracy measures for object-based image analysis is limited (Winter 2000, Zhan *et al.* 2005, Schöpfer *et al.* 2008, Weidner 2008, Clinton *et al.* 2010, Stehman and Wickham 2011). Research has been undertaken on assessment of building extraction (single class) where spatial accuracy is a requirement (Winter 2000, Weidner 2008). There has been little research applying spatial accuracy measures for GEOBIA for mapping multi-class land cover (Lang and Tiede 2008, Schöpfer *et al.* 2008, Lang *et al.* 2009) in landscapes or natural environments where land cover is spatially and spectrally variable.

This study describes a novel application for validating spatial (both geometric and thematic) accuracy of a multi-class classification against reference data.

1.2 Spatial accuracy and object relationships

In this instance, spatial accuracy refers to how well the classified object spatially matches the real world object it is intended to represent. There are two aspects to consider when assessing spatial accuracy: location and shape. Location accuracy refers to the position in space of a classified object in relation to the corresponding reference object. Shape-based accuracy refers to the degree of similarity of two objects based on certain shape-based criteria (such as area, perimeter, length, and width). These measures can be undertaken by including a reference map and/or reference objects for comparison against classified objects, provided the reference data has temporal and spatial relevance to the image data.

Whole of image area-based approaches tend to provide little spatial information on where commission or omission occur (Congalton and Green 2009). Therefore, if area-based approaches are to be effective, they require some form of locational specificity. An advantage of GEOBIA is that objects have spatial extents. It is therefore, possible to introduce site specificity to area-based assessment by using sample reference objects or sample reference areas containing a number of objects or portions of objects (Schöpfer and Lang 2006, Möller *et al.* 2007).

There are several measures that have been used to determine similarity between classified objects and reference objects. These measures utilise the spatial relationships (i.e. proportional overlap) between two sets of objects (classified and reference). Winter (2000) and Straub and Heipke (2004) identify five relevant topological relationships that exist between two sets of objects (Figure 2):

1. *Disjoint* – where there is no locational overlap between two objects;
2. *Overlap* – where two objects share a proportion of the same space;
3. *Contains* – where one object is located entirely within the other;
4. *Contained by* – where one object is located entirely within the other; and
5. *Equal* – where the two objects occupy exactly the same space or location.

In terms of proportional overlap between the two objects, relationship 1 (disjoint) has a value of 0, relationship 5 has a value of 1, and relationships 2-4 are between 0 and 1. A minimum proportional overlap of 0.5 is considered adequate to show correspondence between a classified object and its corresponding reference object (Winter 2000, Zhan *et al.* 2005).

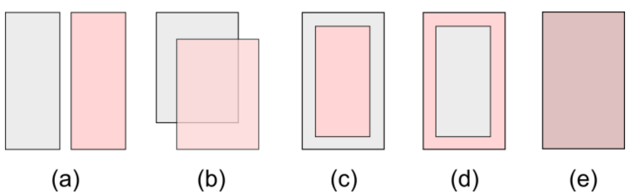


Figure 2: Five topological relationships between two objects: (a) Disjoint, (b) Overlap, (c) Contains, (d) Contained by, and (e) Equal.

When comparing a classified object (*C*) and a reference object (*R*), four spatial objects can be derived (Figure 3):

- The intersection $C \cap R$ - the inclusive area of overlap;
- The union $C \cup R$ – the area of both *C* and *R*;

- Commission $C \cap \neg R$ – the area of C outside the boundary of R; and
- Omission $\neg C \cap R$ – the area of R outside of C.

The four spatial objects can be displayed in an object hierarchy (Figure 4) and described in the equation (1).

$$C \cup R = C \cap R + C \cap \neg R + \neg C \cap R \quad (1)$$

Using equation (1), the 5 spatial relationships between C and R can be described as thus: All relationships (1-5) are within the $C \cup R$ object. Relationships 2-5 are associated with the $C \cap R$ object, while relationships 1-4 concern the $C \cap \neg R$ and $\neg C \cap R$ objects. Where $C \cup R = C \cap R$ the relationship is *Equal*, where $C \cap R = 0$ the relationship is *Disjoint*. Where either $C \cap \neg R$ or $\neg C \cap R = 0$, the relationship is either *Contains* or *Contained by*. Where $C \cap R$, $C \cap \neg R$ and $\neg C \cap R$ are all >0 then the relationship is *Overlap*.

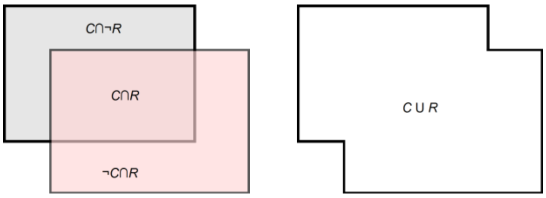


Figure 3: Spatial objects derived by overlapping classified objects (shown in grey) and reference objects (pink). $C \cup R$ is the spatial extent of both objects.

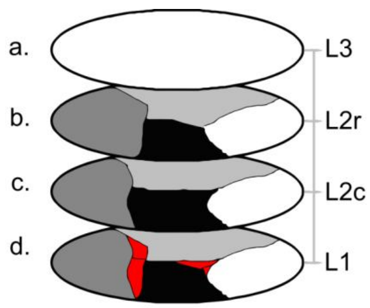


Figure 4: Hierarchy of multi-class validation layers. (a) Level 3 - total area of sample ($C \cup R$), (b) Level 2r - reference object layer (R), (c) Level 2c - classified object layer (C), (d) Level 1 - agreement layer where areas of agreement between C and R ($C \cap R$) are shown in class colours, and areas of omission and commission ($C \cap \neg R$ and $\neg C \cap R$) are shown in red.

1.3 Similarity measures

A number of similarity measures have been proposed to compare two sets of objects (Winter 2000, Zhan *et al.* 2005, Weidner 2008). These measures combine the spatial objects described in section 1.2 and displayed in Figure 3. The measures used in this paper are shown in Table 1 (Equations 2-5).

Table 1: Similarity measures (after Winter 2000, Zhan *et al.* 2005, Weidner 2008). Note: *s12* is a measure of dissimilarity.

Measure	Equation	
OQ, s11	$C \cap R / C \cup R$	(2)
s31	$C \cap R / \max\lvert C\rvert, \lvert R\rvert$	(3)
*s41**2	$(C \cap R / \lvert C\rvert + \lvert R\rvert) \times 2$	(4)
s12	$\lvert C \cap \neg R\rvert + \lvert\neg C \cap R\rvert / C \cup R$	(5)

2. DATA AND METHODS

2.1 Data

The study used a subset of an ASTER image captured on 28 July 2000. Data were the VNIR bands and corresponding digital elevation model. The subset covers a 1376 ha study site which lies within Litchfield National Park approximately 120 km south of Darwin in Australia's Northern Territory. Vegetation in the area is mostly a tropical savanna matrix of Eucalypt dominated canopy and annual grass understorey interspersed with linear forests associated with permanent water and grasslands associated with seasonally inundated areas.

2.2 Classification

The image classification assessed in this paper was a multi-class object-based image analysis conducted using a combined segmentation, supervised classification and rule-based driven approach and is described in detail by Whiteside *et al.* (2011).

2.3 Accuracy assessment

The reference data used for this assessment were derived from the ASTER dataset. Polygons of land cover classes were visually identified within the imagery and manually digitised to create a thematic layer within a geographical information system (GIS). The land cover polygons were verified against a high spatial resolution multispectral QuickBird image captured in 2004 and refined.

The accuracy assessment used a hierarchical object-based approach to create the spatial objects needed. Using GIS, 20 random points were created over the study area and buffered to a 200 m radius to provide sample areas representing land cover of the area. The circle polygons were used to clip both the reference and classified layers creating 20 samples of corresponding objects. These field boundary samples were then imported into eCognition Developer software to undertake the analysis. An object hierarchy with four levels of objects was created. The top level (L3) contained the $C \cup R$ object - a union of the reference and classified objects (Figure 4a), the second top layer (L2r) contains the reference (R) objects and the third top layer (L2c) contains the classified (C) objects (Figure 4b and Figure 4c respectively). At the bottom level of the hierarchy (L1), the suite of accuracy objects ($C \cap R$, $C \cap \neg R$, and $\neg C \cap R$) were then created (Figure 4d). Proportions of $C \cap R$, $C \cap \neg R$, and $\neg C \cap R$ within $C \cup R$, and between the C objects and R objects, were then used in the calculation of the measures of similarity (Table 1) that provided both thematic and spatial accuracies for the sample areas and classified objects within.

3. RESULTS AND DISCUSSION

Using a confusion matrix, a comparison of the areas of each land cover assigned in the GEOBIA classification showed an overall accuracy of 72% (Table 2). Applying the *s11* measure to the entire area covered by the samples, the overall quality was 71% (Table 3). Using the *s11* measure at a per object level, 18 out of the 20 (90%) sample areas showed a good match (>50%)

between C and R objects within the image (Figure 5) and of these samples, 11 have over 70% correspondence. The measures of similarity also indicate strong correspondence between C and R objects within these samples (Table 4). In sample areas where there was poorer accuracy and the omission and commission errors greater, the values for the dissimilarity measures were noticeably higher. Visual inspection of the sample areas shows that error is greatest in the sample areas with greater heterogeneity in cover types.

Table 2: Summary of confusion matrix for multiclass object-based classification based on area within samples.

Class	User Accuracy (%)	Producer Accuracy (%)
Grassland	41	22
Open Forest	69	74
Open Woodland	50	78
Riparian	64	86
Woodland	90	67
Overall (%)	72	

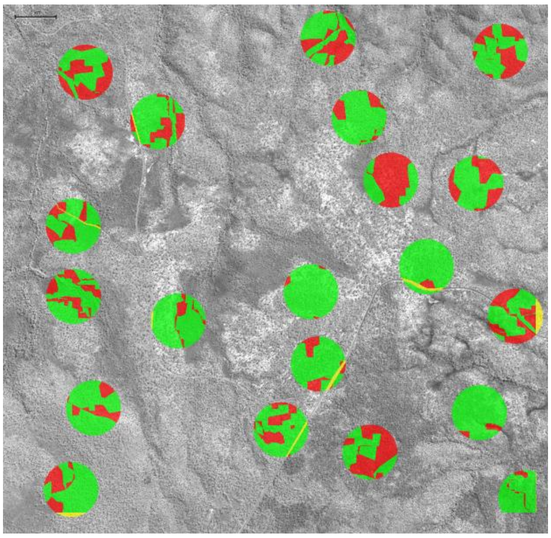


Figure 5: Accuracy image. Green objects within the sample areas have been classified correctly according to reference objects, whereas, red objects have been incorrectly classified. Yellow objects are unclassified.

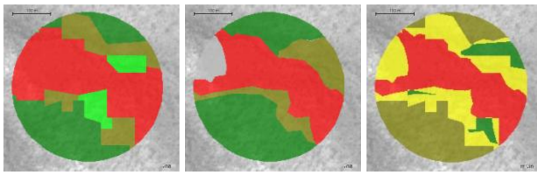
Table 3: Overall area-based measures of multiclass object-based classification including *Overall quality* (OQ_a, *s11*, ρ_q), another measure of similarity (*s41**2), and measure of dissimilarity (*s12*).

Measure	Value
OQ	0.71
s12	0.28
*s41**2	0.71

Table 4: Area-based measures per class over all sample areas.

	Measure			
Class	*OQ*	*s31*	*s41**2	*s12*
Open woodland	0.43	0.50	0.60	0.57
Woodland	0.63	0.68	0.19	0.37
Riparian	0.57	0.63	0.72	0.43
Open forest	0.55	0.68	0.71	0.45
Grassland	0.17	0.22	0.28	0.83

Most of the non-matching objects occurred on the boundaries between land covers as evidenced when looking at the sample object in Figure 6. As the same dataset was used for the classification and reference there would be no geometric discrepancy. In this instance, the uncertainty more than likely can be attributed to how the classified and reference objects were derived.



(a) (b) (c)

Figure 6: Example of one sample created for validation (a) classified objects at Level 2c, (b) reference layer at Level 2r, and (c) Level 1 agreement objects between the classification (2c) and reference objects (2r) are shown in red ('Riparian' class), green ('Open forest' class) and brown ('Woodland' class), while non-agreement objects are shown in yellow.

The method used here not only provides overall measures and per class measures, but each sample and objects within each sample can be analysed. When examining the similarity measures for the 'Riparian' class object from a selected sample (Figure 6) it can be seen in this case there is strong similarity between the classification and the reference (Table 5).

Table 5: Selected similarity measures for the 'Riparian' object in sample area shown in Figure 6.

	Similarity measure		
Object class	*s11*	*s31*	*s12*
Riparian	0.70	0.74	0.30

4. CONCLUSION

This paper presents a novel application of area-based methods for quality or accuracy assessment of object-based image analysis. These approaches have been used infrequently in the literature, and prior to this research have not been used for the assessment of GEOBIA of natural landscapes. These methods have an advantage over the conventional site-specific methodology in that classified objects are assessed both thematically and geometrically. Given appropriate reference data, the measures provide not only an overall accuracy for the image but also per object, per class and per sample area accuracies. In addition, classification uncertainty in the form of these measures can be visualised enabling further analysis of error and where it occurs.

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