MAP ACCURACY ASSESSMENT ISSUES WHEN USING AN OBJECT-ORIENTED APPROACH

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ABSTRACT

When a land cover map is created using an Object Based Image Analysis (OBIA) approach, the pixels are grouped so that within-segment variances are less than between-segment variances and the thresholds for both minimum size and maximum variability of the segments are defined by the analyst creating the map. Therefore, the segments are generally not all the same size and are dependent on the properties of the image. In order to validate maps created using an OBIA approach, the reference sample units should be the same as the segments (i.e. polygons), rather than pixels, so that the units are directly comparable to the map segments. However, unlike in more traditional pixel-based mapping techniques, each unit will have a unique size, which should be accounted for in the assessment process. Therefore, an error matrix that incorporates the reference unit area into each cell is proposed for reporting the thematic accuracy of a map created using an OBIA approach. This study reports the new area-based error matrix in conjunction with the traditional error matrix, to provide a more complete representation of an accuracy of a land cover map created using an OBIA approach.

Keywords: Object-based image analysis, accuracy assessment, area-based accuracy

INTRODUCTION

Today's land cover maps are generally created using computer-based classification techniques using remotely sensed images (McGarigal & Cushman, 2002; Xiuwan, 2002; Jensen, 2005; Turner, 2005). There are generally two ways of analyzing images using computer-based land cover classifications: the traditional pixel-based approach; and the newer object-based image analysis (OBIA) approach (Blaschke & Strobl, 2001; Jensen, 2005; Congalton & Green, 2009). Pixel-based approaches classify the pixels of an image individually without using the context of the pixels, while the OBIA approach groups contiguous pixels with similar properties into segments or polygons. The resulting segments represent areas of similar spectral response that can be classified as a whole, rather than pixel by pixel (Baatz et al., 2001; Desclee et al., 2006). In a successful segmentation, all of the pixels within a single segment should have the same land cover type. The segments also have additional attributes, such as size, shape, and texture, which can be used to help identify the pixels within each segment (Baatz et al., 2001; Desclee et al., 2006; Lu & Weng, 2007). This new process mimics how a human interprets an image, and is considered an improvement over the traditional pixel-based approaches (Warner et al., 1998; Blaschke & Stroble, 2001; Desclee et al., 2006; Congalton & Green, 2009).

Although there are many advantages to using the OBIA approach over the pixel-based approach, there are some caveats when dealing with segments rather than individual pixels. In OBIA classification approaches, the image is broken into segments of unknown pixels with similar spectral properties. However, land cover types are naturally heterogeneous. Therefore, the segmentation of the image may or may not always place conterminous pixels of the same land cover type into the same segment and the pixels within each of the segments will all have slightly different spectral properties (Blaschke & Strobl, 2001). The heterogeneity of the data can make the process of classifying each of the segments more complex than classifying individual pixels.

SAMPLING TECHNIQUES

When generating a land cover map from remotely sensed data, reference data are needed for use in both training and validation (Congalton et al., 1983; Congalton, 1991; Gopal & Woodcock, 1994; Foody, 2002; Congalton & Green, 2009). Training data are used to in the classification process and validation data are used to assess the accuracy of the land cover maps. The reference data are usually either collected through photo-interpretation or ground visits (Congalton & Green, 2009). The accuracy of the reference data is incredibly important, since the accuracy of the training data will influence the success of the classification. Also, when performing an accuracy assessment, the validation data are assumed correct, so that any discrepancies between the land cover map and the validation data are assumed to be errors in the map (Congalton, 1991; Gopal & Woodcock, 1994; Stehman, 1995; Foody, 2002; Congalton & Green, 2009). Therefore, the accuracy of both the training and validation data is of upmost importance when creating a land cover map.

When the image being used for pixel-based classification is of medium to high spatial resolution, acceptable thematic accuracies of ground collected reference sample units are generally easy to attain (Stehman & Czaplewski, 1998). In a pixel-based classification, the recommended size of a reference unit is an area within a single land cover type of at least 3x3 pixels in size (Congalton & Green, 2009). Since pixels in medium to high spatial resolution images are relatively small, the reference units also cover a relatively small area, and each reference unit is the same size. The reference units should also contain only one land cover type, so the variability of the land contained within the reference units should be small. Therefore, since the variability of the reference unit is low, the reference unit can often easily be classified accurately using a single sample observation within the unit. However, as the pixels get larger or more variability is captured within a single pixel, it may be more difficult to classify a reference unit using a single observation (Stehman & Czaplewski, 1998).

In an OBIA approach, the pixels are grouped based on the spectral variation of the pixels within the image and the thresholds for both minimum size and maximum variability of the segments are defined by the analyst creating the map (Blaschke & Strobl, 2001). Therefore, the polygons created during segmentation are generally not all the same size and are dependent on the properties of the image (Desclee et al., 2006; Congalton & Green, 2009; Blaschke, 2010). When classifying these polygons, the training and validation data must be the same as the segments of the map, so that the map and reference sample units are directly comparable (Congalton & Green, 2009; Radoux et al., 2010). In an effective OBIA approach, the average segment usually contains significantly more pixels than a 3x3 pixel square, and the polygons range in size from the minimum mapping unit (mmu) to considerably larger (Desclee et al., 2006; Blaschke, 2010; Radoux et al., 2010), meaning the reference sample units should also vary in size. These variably sized reference units present issues with both the training and the validation data. Since the average reference unit is larger than the 9 pixel squares recommended in the pixel-based approach, there is a wider variety of pixels within each reference unit, making it more difficult to classify the those reference sample units (Stehman & Czaplewski, 1998; Congalton & Green, 2009), making collecting accurate training and validation data more difficult. Currently, there isn't a recommended sampling method for determining the map class of polygon reference units in remote sensing (Stehman & Czaplewski, 1998; Jensen, 2005). However, since the larger reference sample units generally are more variable, a single sample within the reference unit may not be sufficient for many land cover types (MacLean & Congalton, 2011). The variable size of the reference units also changes how an accuracy assessment is completed with a land cove map created using an OBIA approach.

ACCURACY ASSESSMENT

Assessing the accuracy of a land cover map created using an OBIA approach has some additional considerations beyond a pixel-based approach. The statistics for calculating accuracy when using polygons as validation sample units is different than those used in a pixel-based approach, since the size of each reference sample unit varies (Radoux et al., 2010). In the traditional pixel-based approach, or when all reference units are the same size, overall accuracy is estimated using:

$$\hat{\pi} = \frac{\sum_{i=1}^{n} C_i}{n} \tag{1}$$

where π is overall accuracy, C_i is equal to 1 or 0 if the validation sample unit i is correctly classified (yes and no, respectively), and n is the number of validation units collected. Unfortunately, many researchers still use the same equation to calculate accuracy with polygon reference units (Radoux et al., 2010). However, this equation does not account for the variable sizes of the polygons in the accuracy assessment. The accuracy of a map created using OBIA should be computed using:

$$\pi = \frac{\sum_{i=1}^{N} C_i S_i}{\sum_{i=1}^{N} S_i} \tag{2}$$

where N is the total number of segments in the image, and S_i is the area of a single sample unit i. However, accuracies for all polygons within the map are usually not known, so Radoux et al. (2010) presented two estimates of overall accuracy. The first just replaces N with n:

$$\hat{\pi} = \frac{\sum_{i=1}^{n} C_i S_i}{\sum_{i=1}^{n} S_i} \tag{3}$$

which weights the accuracy assessment by the area of the validation polygons (Radoux et al., 2010). Radoux et al. (2010) propose another estimate of OBIA accuracy which includes the added information of the size of the remainder of the polygons that were not used as validation polygons. Radoux et al. (2010) state that while the accuracy, C_i, is not known for each segment, the size or area, S_i, is in most OBIA projects. The researchers propose that the information gained from knowing the S_i of the unsampled polygons can reduce the variance of the estimate of overall accuracy. Their estimate of accuracy is:

$$\hat{\pi} = \frac{1}{S_T}\left(\sum_{i=1}^{n} C_i S_i + \hat{p} \sum_{i=n+1}^{N} S_i\right) \tag{4}$$

where S_T is the total area of the map and $\hat{p}$ is the estimate of the probability of an object being classified correctly. As long as C_i is independent of S_i, $\hat{p}$ can be estimated using:

$$\hat{p} = \frac{1}{n}\sum_{i=1}^{n} C_i \tag{5}$$

Radoux et al. (2010) found that when using equation (4), fewer polygons were needed as validation sample units than the number of sample units necessary for accuracy assessment in a pixel-based approach to achieve the same accuracy and variance estimates.

Since the accuracy of maps created using an OBIA approach must be weighted by the area of the reference units, an error matrix that incorporates area into each cell is appropriate for reporting thematic accuracy. This new area weighted error matrix should be reported in conjunction with the traditional error matrix. The new OBIA error matrix is set up similarly to the traditional error matrix, but instead of each reference unit having the same weight, the individual cells reflect the total area of the reference units that fall into that cell (Table 1).

Table 1. OBIA error matrix where S_{ij} represents the total area of the reference data in map class i and reference data class j and S is the total area of the reference data.

		Reference Data (j)				
		1	2	…	k	Total Area
Classified Data (i)	1	S_{11}	S_{12}	…	S_{1k}	S_{1+}
	2	S_{21}	S_{22}	…	S_{2k}	S_{2+}
	⋮	⋮	⋮	…	⋮	⋮
	k	S_{k1}	S_{k2}	…	S_{kk}	S_{k+}
	Total Area	S_{+1}	S_{+2}	…	S_{+k}	S

Using the above OBIA error matrix, overall accuracy can be computed. If overall accuracy is being computed using equation (3) above, the same overall accuracy would be computed in the error matrix using:

$$\hat{\pi} = \frac{\sum_{i=1}^{k} S_{ii}}{S} \tag{6}$$

where the sum of S_{ii} is the sum of the major diagonal cells, similarly to how overall accuracy is computed in the traditional error matrix.

If overall accuracy is being computed using equation (4) above, the values from the OBIA error matrix can also compute the same overall accuracy using:

$$\hat{\pi} = \frac{\sum_{i=1}^{k} S_{ii} + \hat{a}(S_T - S)}{S_T} \quad (7)$$

where $\hat{a}$ is the overall accuracy of the map calculated using a traditional pixel-based error matrix.

When computing the overall accuracy using equation (4), it is especially important that both the OBIA and the traditional error matrix are reported. Users' and producers' accuracies can be computed in the OBIA error matrix using the same procedures as with a traditional pixel-based error matrix. Kappa statistics can also be computed using the same methods as the traditional error matrix. For an example using the new OBIA error matrices, please see Campbell & Congalton (2012) in these proceedings.

CONCLUSIONS

As with the pixel-based approach, the new method of accuracy assessment for maps created using an OBIA approach still assumes that the reference polygons are 100% correct (Radoux et al., 2010). However, the accuracy of the reference sample units can be affected by the positional and thematic accuracy of the sampling method used to decide the label of the reference polygons. As discussed above, the variability within a polygon, or segment, often makes it difficult to identify a polygon with a single observation (MacLean & Congalton, 2011). Therefore, the number of necessary observations for each reference polygon should be determined so that the reference polygon labels can be as close to 100% accurate as possible. With the reference labels as accurate as possible, the accuracy assessment of the map created using the OBIA approach should reflect the accuracy of the map, rather than the accuracy of the reference data.

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