Categorical Coefficients of Agreement for Assessing Soft-Classified Maps at Multiple Resolutions

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Abstract

An important issue regarding map comparison involves examining agreement of pixels between two categorical maps. Information in the maps can become less precise spatially as resolutions of the maps change from fine to coarse. This paper consists of two major components addressing this issue. First, cross-tabulation matrices are produced for multiple resolutions using hard classification and three different soft pixel classification operators: Multiplication, Minimum, and Composite. Second, the cross-tabulation matrices are analyzed through various statistical measures to produce the following categorical coefficients of agreement: user's accuracy, producer's accuracy, conditional kappa by row, and conditional kappa by column. These statistical measures are graphed to demonstrate their behavior over multiple resolutions. Land-cover maps of the same subject area for two different years are compared to illustrate the analysis. The area examined is a part of Worcester County, Massachusetts which has experienced about 10% change in land cover between 1971 and 1999. The results from the analysis show that over multiple resolutions, the Hard operator behaves chaotically, the Multiplication operator decreases agreement, the Minimum operator is difficult to interpret, while the Composite operator offers increasing agreement, is interpretable, and is recommended for a multiple resolution analysis.

1. Introduction

1.1 Purpose

Map comparison is an important issue among scientists in Remote Sensing and Geographic Information Science. Calculating agreement between two categorical maps is often performed using a cross-tabulation matrix, a valuable tool for presenting information regarding accuracy assessment (Stehman 1997). The columns within the cross-tabulation matrix represent categories of a reference map, and the rows represent categories of a comparison map. Each entry in the matrix indicates the proportion of pixels within the study area that coincide by category. The purpose of the matrix is to record the categorical agreement and disagreement of two maps, where agreement is calculated in the diagonal entries of the matrix and disagreement in the off-diagonal entries. Various statistics, or coefficients of agreement, are derived from the matrix by analyzing specific entries within the table. Many of these coefficients signify a percent agreement for either specific categories or all categories of the maps (Rosenfield and Fitzpatrick-Lins 1986, Stehman 1997, Binaghi et al. 1999, Pontius 2000, Lewis and Brown 2001, Pontius 2002, Pontius and Cheuk in review).

The cross-tabulation matrix has traditionally been used to compare maps that are of a hard classification. Such maps contain pixels that are uniquely identified with a single class or category. Hard classification allows for a simple representation of reality, but representation is limited due to over simplification where the entire pixel is assigned to the dominant category. Soft pixels of partial class membership offer a more appropriate representation of reality than hard-classified pixels by allowing for multi-membership within a pixel (Woodcock and Gopal 2000, Pontius and Cheuk in review). Operators have been developed to create a cross-tabulation matrix that accommodates pixels of a soft classification. This paper analyzes three of these operators: Multiplication, Minimum, and Composite. These operators differ based on their interpretation of pixel ontology, which defines class membership and location within a pixel.

Multiple resolution map comparison can reveal artifacts of classification that may not be visible at a single resolution. For instance, a cell-by-cell analysis of two maps at a fine resolution may indicate limited agreement if pixel classes do not correspond due to either map misregistration or misclassification at precise locations. Fine resolution analysis fails to account for spatial proximity of pixel agreement (Power et al. 2001, Pontius and Suedmeyer 2004). Spatial patterns within the data can be recognized and interpreted with a multiple resolution analysis. Pixel aggregation from a fine to a coarse resolution reveals how disagreement by location is spatially clustered between the two maps (Pontius 2002, Carmel 2003). Comparing maps over multiple resolutions allows for a thorough interpretation of a dataset by isolating disagreement of location from disagreement of quantity for each category.

Coefficients of agreement are derived from the cross-tabulation matrix to measure agreement between the maps. These coefficients determine the agreement per category based on the proportions correctly classified. There is no single coefficient that is best to meet all the objectives of accuracy assessment because many represent accuracy in dissimilar ways, leading to conflicting and contradicting conclusions (Stehman 1997). It is also known that many processes do not scale linearly (UCGIS 1998). Monitoring the agreement of categorical coefficients as resolution changes can aid in understanding the processes involved with different pixel ontologies. Therefore, this paper uses four categorical coefficients of agreement to investigate the performance of a hard operator and three soft-classified operators for a multiple resolution analysis.

1.2 Literature Review

Pixel ontology can have a dramatic effect on map comparison. The way we conceptualize a pixel can dictate or limit the measurement of agreement and disagreement between two categorical maps. The user should select a function of a pixel depending on the appropriateness for the specific application. The following paragraphs discuss the interpretations of a pixel regarding class membership and location for the four different operators.

1.2.1 Four Operators

The traditional interpretation of a pixel involves hard classification, which follows classical set theory. The entire pixel is assigned membership to a single dominant category. Location within the pixel is irrelevant because the pixel's content is homogenous with one class representing all locations of the pixel. In terms of accuracy assessment, when each location on a map belongs to a single class, then all other classes at that location are equally and completely wrong (Woodcock and Gopal 2000). Hard classification is commonly used because of ease regarding interpretation; however, loss and corruption of information occurs when a pixel is modified to represent one unique class (Pontius and Cheuk in review).

The first soft-classified operator examined is the Multiplication operator. For the Multiplication operator, class membership is interpreted as a proportion of the area within a pixel, with location defined in terms of points distributed randomly within a pixel (Pontius and Cheuk in review). Values of agreement and disagreement can be identified and placed within the cross-tabulation matrix by multiplying each category membership by every other category membership (Lewis and Brown 2001). Table 1 describes the formula used for this calculation. Equation 1 calculates both categorical agreement and disagreement using the same formula. The Multiplication Operator is based on conventional probability theory, where the probability of class membership is derived from uncertainty. Therefore, this operator is useful when the location of each category within each pixel is uncertain.

Table 1. The soft-classified operators for agreement and disagreement within one pixel where i and j indicate one of the J categories, n indicates the specific pixel, C_{ni+} is the membership to category i for pixel n in the comparison map, C_{n+j} is the membership to category j for pixel n of the reference map, and C_{nij} is the association in pixel n between category i of the comparison map and category j of the reference map.

Operator	Agreement *for j*	Disagreement *for* $i \neq j$	
Multiplication	$C_{njj} = C_{nj+} \times C_{n+j}$	$C_{nij} = C_{ni+} \times C_{n+j}$	(1)
Minimum	$C_{njj} = \mathrm{MIN}(C_{nj+}, C_{n+j})$	$C_{nij} = \mathrm{MIN}(C_{ni+}, C_{n+j})$	(2)
Composite	$C_{njj} = \mathrm{MIN}(C_{nj+}, C_{n+j})$	$C_{nij} = \dfrac{(C_{ni+} - C_{nii}) \times (C_{n+j} - C_{njj})}{1 - \sum_{j=1}^{J} C_{njj}}$	(3)

The second soft-classified operator is the Minimum operator developed by Binaghi et al. (1999). On-diagonal and off-digonal values are calculated by taking the minimum value of the two maps for each category combination in every pixel, which can then be entered and accumulated in a cross-tabulation matrix. Equation 2 in table 1 calculates categorical association. Similar to the Multiplication operator, formulas are identical for both on and off-diagonal entries within the matrix. The Minimum operator is based on fuzzy set theory and is designed for situations where classes are ambiguous or vague. Membership is represented as the degree to which the pixel contains that class. Individual class membership is constrained between 0 and 100%, but the sum of memberships over all classes within the pixel can be greater than 100% (Binaghi et al. 1999). Interpretation of the matrix becomes difficult because the sum of the matrix can be larger than 100% of the map, since off-diagonal values do not represent proportions of the landscape (Pontius and Cheuk in review).

The third soft-classified operator is the Composite operator developed by Pontius and Cheuk (in review). Class membership for the Composite operator is interpreted as the proportion of a pixel belonging to a class. The concept of location within a pixel does not exist for the ontology of the Composite operator. The Composite operator uses a two-step process for computing agreement and disagreement between two maps. First, the minimum value of similar classes from each corresponding pixel is determined as the agreement in a manner identical to the Minimum operator. Second, disagreement is calculated at the pixel level by multiplying the gains with the losses in class membership and dividing by one minus the total agreement in class membership as in equation 3 (Table 1). The sum of all agreement and disagreement within the pixel is equal to 100% of the pixel by allocating the disagreement over all categories. The Composite operator is designed for multiple resolution analysis, where soft membership is computed as the proportion of hard classified pixels at the finest resolution that comprise the coarser pixel.

Each of the four operators are used to calculate pixel agreement and disagreement between two categorical maps. It is important to understand the purpose of each operator when performing a multiple resolution analysis.

1.2.2 Converting Pixel Values into Proportions

Equation 4 is used to convert class membership agreement and disagreement of the individual pixels into proportions shown by the cross-tabulation matrix for the entire study area. At the finest resolution, each pixel in the study area has a weight of 1 and each pixel outside the study area has a weight of 0. Each coarse pixel is assigned a weight that is the proportion of the total number of fine-resolution pixels within the study area in the coarse pixel divided by the number of fine-resolution pixels in the coarse pixel.

$$p_{ij} = \frac{\sum_{n=1}^{N_g} W_n C_{nij}}{\sum_{n=1}^{N_g} W_n} \tag{4}$$

Table 2 illustrates a cross-tabulation matrix. Proportional values of agreement are placed in the diagonal entries of the matrix where *i* is the same as *j*. Proportional values of disagreement are placed in the off-diagonal entires where *i* does not equal *j*. The row totals are the sum of proportions by row for category *i* in the comparison map, and the column totals are the sum of proportions by column for category *j* in the reference map.

Table 2. The cross-tabulation table for *J* categories where entries are proportions of the study area.

	Reference data				
Comparison data	$j=1$	$j=2$	$\cdots$	$j=J$	Total
$i=1$	p_{11}	p_{12}	$\cdots$	p_{1J}	p_{1+}
$i=2$	p_{21}	p_{22}	$\cdots$	p_{2J}	p_{2+}
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$i=J$	p_{J1}	p_{J2}	$\cdots$	p_{JJ}	p_{J+}
Total	p_{+1}	p_{+2}	$\cdots$	p_{+J}	1

1.2.3 Coefficients of Agreement

There are many popular coefficients of agreement which can be derived from a traditional cross-tabulation matrix. Stehman (1997) discusses several coefficients which measure a single value of overall agreement between two categorical maps: overall proportion correct, Kappa, Kappa with random chance agreement, and Tau. Stehman also discusses several categorical coefficients which derive agreement per category: user's and producer's accuracy and conditional Kappa by row and by column. Overall coefficients and category specific coefficients can be derived directly from a cross-tabulation matrix of both hard and soft pixels, but with soft pixels, some of these measures become difficult to interpret while others maintain interpretability. This paper analyzes the categorical coefficients that measure agreement from the cross-tabulation matrix. Table 3 gives formulas for each of the statistics.

Table 3. The equations for categorical coefficients of agreement.

User's Accuracy	$U_i = \frac{p_{ii}}{p_{i+}}$	(5)	Producer's Accuracy	$V_j = \frac{p_{jj}}{p_{+j}}$	(6)
Conditional Kappa (row)	$k_i = \frac{U_i - p_{+i}}{1 - p_{+i}}$	(7)	Conditional Kappa (column)	$k_j = \frac{V_j - p_{j+}}{1 - p_{j+}}$	(8)

User's accuracy calculates the per category agreement with respect to the comparison map. Equation 5 gives its formula. It is the conditional probability that an area is classified correctly for a category given that it is classified as that category on the comparison map. Producer's accuracy calculates the per category agreement with respect to the reference map. Equation 6 gives its formula. It is the conditional probability that an area is classified correctly for a category given that it is classified as that category on the reference map. Both user's and producer's accuracy are directly interpretable, however, may be biased towards the dominant category with the largest number of pixels (Stehman 1997).

Conditional Kappa calculates the per category agreement while adjusting for the expected proportion correct due to chance (Rosenfield and Fitzpatrick-Lins 1986). Conditional Kappa can be calculated both by rows for the comparison map and by columns for the reference map. Equation 7 denotes conditional Kappa by row and equation 8 denotes conditional Kappa by column. Conditional Kappa adjusts agreement due to random chance on a per category basis. The adjustment is based on known proportions of pixels per category (Stehman 1997).

Each of these coefficients is based on different interpretations and representations of the cross-tabulation matrix. A good representation of categorical agreement is reached by examining each of these with a multiple resolution analysis of the four operators as the resolution moves from fine to coarse.

2. Methods

2.1 Data

A part of Worcester County, Massachusetts is used for this analysis. Figure 1 consists of maps of the study area. Land use maps of an identical area for two separate years, a) 1971 and b) 1999, are classified into four categories of land cover at Anderson level I: Built, Forest, Water, and Other. The study area has experienced approximately 10% land cover change among these four land cover types. The transition is due primarily to growth in Built from 44% in 1971 to just over 50% in 1999. The maps are created from land use maps provided by the Human-Environment Regional Observatory (HERO) program. At the finest resolution, each pixel represents a 30m by 30m square on the landscape. The maps from each year consist of 512 rows by 512 columns. The type of map comparison used in this study determines the change in landscape based on the four classes. There is no measured certainty of classification at the finest resolution since all pixels are hard classified at the 30m resolution. There is no measured vagueness or ambiguity of class because each pixel is assumed to have full membership in exactly one of the four classes at the finest resolution.

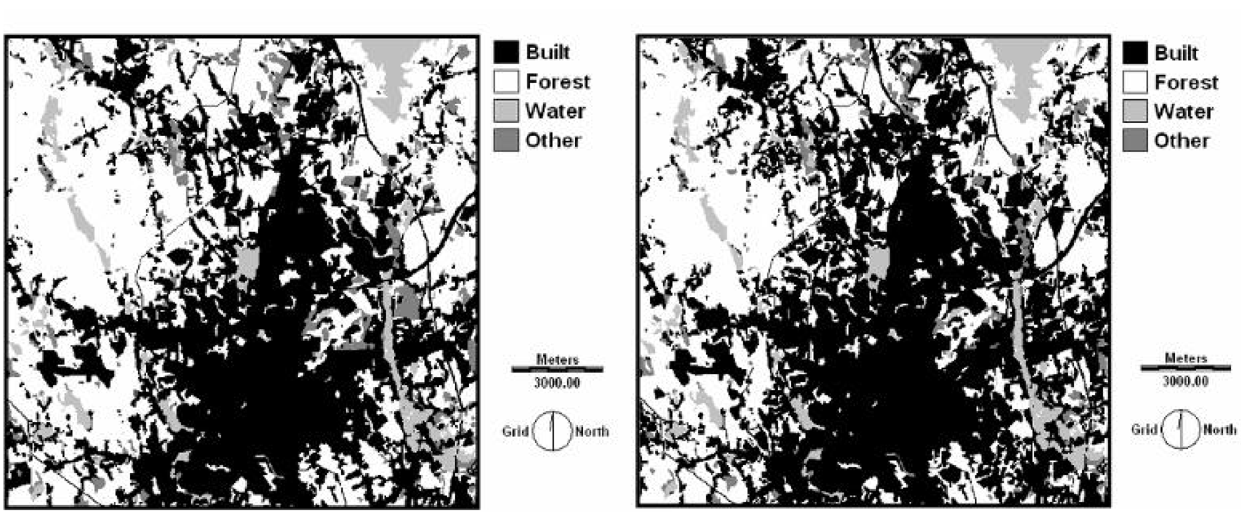

Figure 1. The Worcester County sample data for a) 1971 (left) and b) 1999 (right).

2.2 Scale Modification

Resolution for coarse pixels is the number of fine-resolution pixels constituting a side of a coarse-resolution pixel. The resolution size is 1 at the finest resolution since each cell consists of only one fine pixel. The resolution size is 512 at the coarsest resolution where the entire study area is contained inside one coarse pixel consisting of 512 rows and 512 columns of the finest pixels. Resolution grows in a geometric sequence by multiples of two as four neighboring pixels are aggregated to form the next coarser resolution. Ten resolutions are created for the multiple resolution analysis of this study. Ten separate matrices for each resolution are created for each operator. Partial membership for each class within a soft pixel is the proportion of fine pixels that constitute it for each class. The soft pixels are hardened to the dominant class at each coarser resolution for hard classification so that each pixel is homogenous. The hardening of pixels represents a loss and corruption of information. No such corruption occurs for soft classification.

2.3 Map Comparison

2.3.1 Four Operators

The pixels of each class of one map are compared with all other classes of the other map for hard classification. For the soft-classified operators, the pixel memberships of one map are compared with the corresponding pixel memberships of the other map based on the formulas contained in Table 1. Class membership agreement is calculated for similar classes while disagreement is calculated for dissimilar classes. Values of agreement are placed in the on-diagonal entries of the cross-tabulation matrix. Values of disagreement are placed in the off-diagonal entries of the matrix.

2.3.2 Calculating the Categorical Coefficients of Agreement

Each categorical coefficient of agreement is calculated from the cross-tabulation matrix after the matrix for each operator is generated at every resolution. Table 3 describes the equations used to calculate user's and producer's accuracy, as well as conditional Kappa by row and by column. All coefficients analyzed in this study are designed to be percentages ranging between 0 and 100%. The resulting coefficients are displayed graphically as a function of resolution for the four specific operators.

3. Results

Figures 2 through 5 display the graphical results for the four operators in the analysis over all resolutions. Percent agreement is the same with every coefficient for each operator at resolution 1. Percent agreement fluctuates based on the calculations performed by each operator as resolution becomes coarser.

Figure 2 displays the results of the coefficients of agreement for the Hard operator over all resolutions. Agreement is relatively stable for all coefficients at the finer resolutions. Agreement generally becomes less stable and more chaotic as resolution becomes increasingly coarse, especially beyond resolution 16. The categorical coefficients indicate complete disappearance of the Water and Other categories at the coarser resolutions. At resolution 512, there is 0% agreement because the 1971 hard pixel is Forest and the 1999 hard pixel is Built.

Figure 3 displays the results of the coefficients of agreement for the Multiplication operator over all resolutions. Percent agreement begins to decrease immediately for all categorical coefficients in the fine resolutions and continues steadily downward until the coarsest resolution. Nearly all coefficients have a percent agreement near zero at this resolution with the exception of user's and producer's accuracy for Forest and Built categories which have agreement near 50%.

Figure 4 displays the results of the coefficients of agreement for the Minimum operator over all resolutions. Similar to the Multiplication operator, percent agreement continually decreases as resolution moves from fine to coarse. Conditional Kappa by row and by column for Forest and Built fall below 0% agreement at resolution 16. All percent agreement generated by user's and producer's accuracy is higher than their corresponding conditional Kappa's in the coarser resolutions.

Figure 5 displays the graphical results of the categorical coefficients of agreement for the Composite operator over all resolutions. Percent agreement either remains stable or increases to a higher percentage

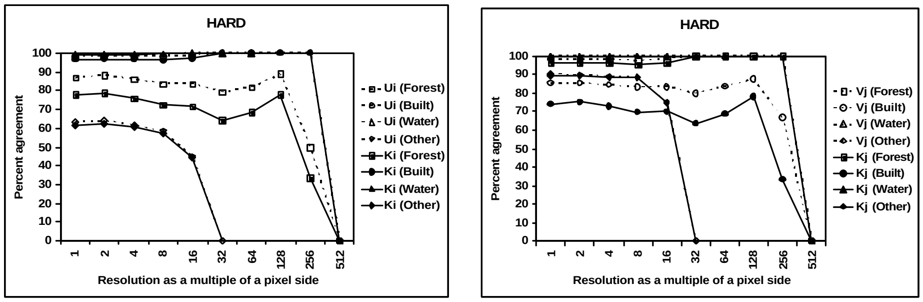

Figure 2. The comparison of categorical coefficients of agreement where the pixels are hardened at each coarser resolution. a) Coefficients by row are on the left and b) coefficients by column are on the right.

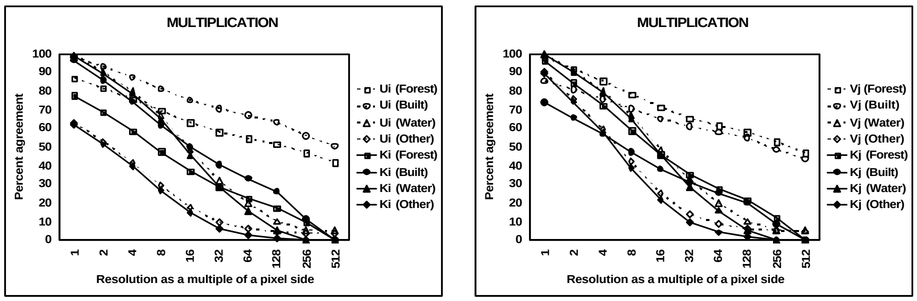

Figure 3. The comparison of categorical coefficients of agreement where the soft pixels are calculated using the Multiplication operator at each coarser resolution. a) Coefficients by row are on the left and b) coefficients by column are on the right.

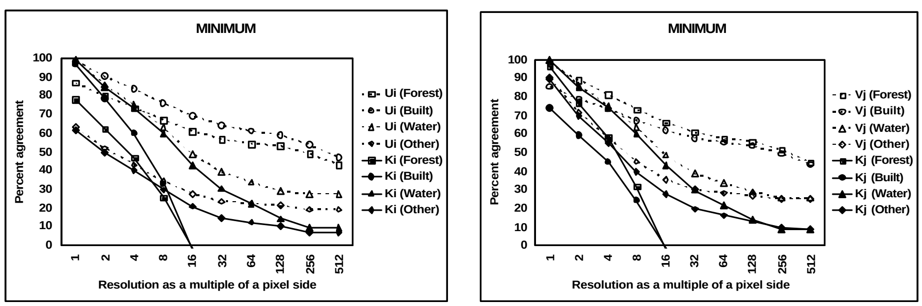

Figure 4. The comparison of categorical coefficients of agreement where the soft pixels are calculated using the Minimum operator at each coarser resolution. a) Coefficients by row are on the left and b) coefficients by column are on the right.

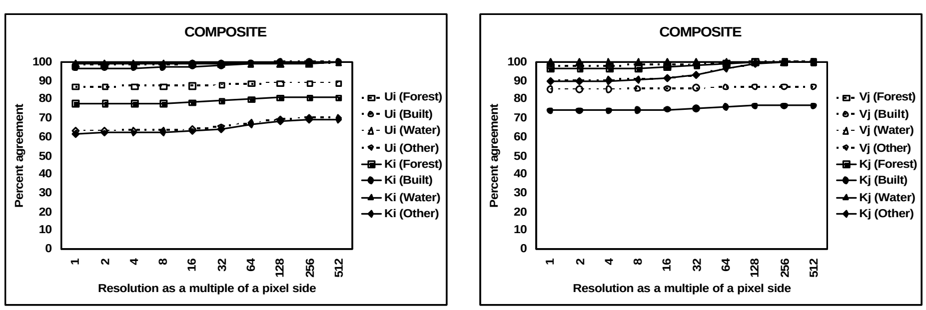

Figure 5. The comparison of categorical coefficients of agreement where the soft pixels are calculated using the Composite operator at each coarser resolution. a) Coefficients by row are on the left and b) coefficients by column are on the right.

for all coefficients as the resolution becomes coarser. Nearly all of the increase in agreement occurs in the medium resolutions from resolution 16 through to resolution 128. The increase in percent agreement is generally small for these coefficients. The trend for the Composite operator in this study tends to be stable over all resolutions.

4. Discussion

4.1 Interpretation of Each Operator

The four operators used in this study each use different methods for generating a cross-tabulation matrix based on their definition of what constitutes a pixel. These methods greatly affect the agreement of two maps when performing a multiple resolution analysis. The following subsections interpret the results of the analysis by evaluating the coefficients of agreement for each operator over all resolutions.

4.1.1 Hard Operator

The Hard operator compares pixels that are homogenous in order to determine agreement and disagreement between two maps. Loss and corruption of information occurs through the hardening process by assigning all the area within a pixel to the dominant class. In Figure 2, artifacts of this process are visible as the resolution moves from fine to coarse. Agreement falls to 0% for some of the categorical coefficients as the resolution becomes coarser. This is due to the loss of those categories. The dominant classes eliminate the smaller classes through the hardening process as pixel aggregation occurs. Categories such as Built and Forest dominate, while the categories which are smaller in area such as Water and Other disappear. The coarse resolution maps are clearly a corrupted representation of categories at the fine resolutions.

Percent agreement is relatively stable at the finer resolutions for each of the categorical coefficients. This is the result of the similarity in the clustering of classes on each of the maps. Neighboring pixels aggregate as resolution becomes coarser so the dominant class consumes the coarse pixel. These fine pixels are typically large clusters of the same class. The similarity between the two maps maintains the stability of the coefficients through resolution 16. It can be interpreted that class location and quantity is generally similar in blocks of 16 by 16 pixels on the maps. Beyond that, the quantity and location of classes alter the percent agreement at the coarser resolutions.

The row and column totals within the cross-tabulation matrix fluctuate as resolution moves from fine to coarse. The fluctuation is the result of the data corruption that occurs in the hardening process. The quantity of pixels within each class changes at each resolution when the pixels are reassigned to the dominant category value.

The hard operator is inappropriate for map comparison using a multiple resolution approach. The loss and corruption of information in the hardening process compromises the interpretation of the results. The chaotic behavior at the coarse resolutions is evidence that hard-classified pixels cannot offer easy interpretability over multiple resolutions.

4.1.2 Multiplication Operator

The Multiplication operator compares categories from two maps by multiplying the pixel memberships of one map with the memberships of the corresponding pixel of the other. Figure 3 shows the results of this analysis. It is clear that there is a common trend of decreasing percent agreement as resolution moves from fine to coarse. This can be attributable to the pixel ontology. The Multiplication operator determines class membership as the probability that a randomly selected point within a pixel falls on that class. The distribution of probability becomes more random spatially as pixel size becomes larger. This lowers the percent agreement when comparing a pixel to a corresponding pixel with an equally random distribution on another map. Corresponding pixels with identical probability of class membership can have small agreement when compared to each other. For example, if one pixel has 50% probability of containing a specific class and a corresponding pixel on another map also has 50% probability of containing that same class, multiplying the two pixels together results in an agreement of 25%. Therefore, agreement between identical pixels can be less than unity (Pontius and Cheuk in review). Each categorical coefficient in Figure 3 follows a decreasing behavior due to a perceived loss of spatial information.

The Multiplication operator is designed for situations where pixels in a map contain uncertainty of class membership. However, the softness of class membership in the coarser pixels does not represent uncertainty for this multiple-resolution study because membership is based on the proportion of fine pixels which constitute a coarse pixel. The Multiplication operator offers decreasing agreement over multiple resolutions due to the randomness of class membership and location within a pixel. The total quantity of each class does not change with resolution even though class membership is random within a pixel. This means the row and column totals remain constant over all resolutions.

Both user's and producer's accuracy for the Forest and Built categories have substantially higher agreement than the other categories at the coarser resolutions. This is due to large proportions of the two classes on both maps, where agreement is biased towards the dominant categories with the largest number of pixels (Stehman 1997). Water and Other have smaller proportions than the other two classes so the probability that the corresponding randomly distributed points coincide within coarse pixels on both maps is near zero. Conditional Kappa values for all categories are zero at resolution 512. This is because Kappa compares the agreement to the expected agreement with complete spatial randomness.

The Multiplication operator is not appropriate for a multiple-resolution approach because the random spatial distribution of class membership hinders agreement as pixel size changes. Interpretability of the results becomes misleading due to the continuously decreasing agreement as resolution moves from fine to coarse.

4.1.3 Minimum Operator

The Minimum operator compares categories from two maps by taking the minimum value of corresponding pixels. Figure 4 shows the results of this analysis. The sum of proportions in the cross-tabulation matrix is not necessarily constrained to 100% (Binaghi et al. 1999, Pontius and Cheuk in review). This becomes a drawback when performing a multiple resolution analysis. In the case of the Worcester County data, the sum of the proportions in the matrix increasingly surpasses 100% as resolution moves from fine to coarse. This is because the ontology of the Minimum operator allows for ambiguity and vagueness of categories. The row and column totals of the matrix also increase as resolution moves from fine to coarse as a result of overlapping class membership. Therefore, the entries in the matrix cannot be interpreted as proportions of the landscape (Pontius and Cheuk in review).

Percent agreement consistently decreases for the categorical coefficients as resolutions become coarser due to larger off-diagonal values in the matrix. This reduces the relative magnitude of the diagonal values. In the case of conditional Kappa for Forest and Built, agreement drops below 0% due to the growth of the column and row totals. These coefficients reveal problems of interpretability within the matrix generated by the Minimum operator over multiple resolutions.

The Minimum operator is designed to account for ambiguity and vagueness of category. The cross-tabulation matrix generated by the Minimum operator is unsuitable for a multiple resolution analysis since the purpose of a multiple resolution analysis is to examine the spatial distribution of known classes between two maps. Entries within the matrix cannot be interpreted as proportions of the landscape because they sum to greater than 100% as resolution becomes coarser. Examining the categorical coefficients of agreement over all resolutions reveals the inappropriateness by demonstrating the operator's inability to produce interpretable agreement and disagreement values.

4.1.4 Composite Operator

The Composite operator compares categories from two maps by using a combination of the Minimum and Multiplication operators, where the minimum values of similar classes represent agreement and the multiplication of the residual membership for dissimilar classes represents disagreement. Equations for these calculations are found in Table 1. Figure 5 shows the results of the Composite operator with a multiple resolution analysis. Percent agreement for all categorical coefficients either remains stable or increases as pixel resolution moves from fine to coarse. This is because the two maps being compared are very similar in respect to quantity and location of classes at the fine pixel level. This operator is designed for these types of studies where the fuzziness of the classification indicates spatial proximity, not necessarily uncertainty of class membership or the ambiguity of class. Class membership is determined as the proportion of fine pixels of a class that constitute a coarse pixel. The Composite operator is appropriate for multiple-resolution analysis because all classes and proportions from the finest resolution are still represented at the coarse resolutions (Pontius and Cheuk in review).

All increases in percent agreement as resolution moves from fine to coarse are attributable to increasing agreement of location, in other words, spatial proximity to agreement. Disagreement due to quantity does not change with resolution because coarse maps maintain the same proportions of fine pixels, so quantity of each category does not change. Consequently, the row and column totals of the matrix do not change with resolutions. The increase in percent agreement occurs when pixels are aggregated into coarser pixels and resolve any disagreement due to location. All disagreement at the coarsest resolution is attributable to quantity because location inside one coarse pixel does not exist according to the Composite operator's ontology (Pontius and Cheuk in review).

Similar to the Multiplication operator, proportion totals of the landscape for each class do not change with resolution. However, unlike the other soft-classified operators, the Composite operator offers either stable or increasing agreement over multiple resolutions as interpreted by the categorical coefficients. This behavior separates the Composite operator from the other soft-classified operators. Consistent proportion totals and increasing agreement attributable to spatial proximity allows for easy and useful interpretability of a multiple resolution approach. The Composite operator is recommended when performing a multiple resolution analysis.

4.2 Next Steps

The next important steps following this analysis would be to derive overall coefficients of agreement from the soft-classified operator matrices. Coefficients, such as overall proportion correct, Kappa, Kappa with random chance agreement, Kappa for Location, Nishii-Tanaka coefficient, and Cramer's V determine values for overall agreement between two categorical maps. These statistics would be analyzed at multiple resolutions to determine which operators produce useful information.

5. Conclusions

The focus of this paper has been to use categorical coefficients of agreement to interpret a multiple resolution analysis of four pixel operators: Hard, Multiplication, Minimum, and Composite. Each of these operators has a different interpretation of pixel ontology, which affects how agreement is calculated over various resolutions. The hard operator becomes chaotic and loses interpretability as resolution moves from fine to coarse because it modifies the basic information of the map. The Multiplication operator has limited interpretability because of decreasing agreement with changing resolution due to randomness of location within a pixel. The Minimum operator produces a matrix with proportions that sum to greater than one as resolution changes, thus matrix entries cannot be interpreted as proportions of the landscape. The Composite operator maintains information of class membership and offers a helpful interpretation of the landscape, making it appropriate for a multiple resolution analysis. The Composite operator also maintains interpretability over all resolutions, unlike the other operators. The supplemental knowledge provided by the categorical coefficients of agreement indicates that the Composite operator is ideal for a multiple-resolution analysis by giving a simple interpretation of the spatial structure of a pair of maps, without loss of information.

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