# Using Classification Error Matrices to Improve the Accuracy of Weighted Land-Cover Models

*Stephen P. Prisley* and *James L. Smith*
School of Forestry and Wildlife Resources, Virginia Tech, Blacksburg, VA 24061

ABSTRACT: Digital land-cover data are used frequently in resource analysis in geographic information systems (GIS). One common technique involves summing of weighted areas of various land-cover categories to derive a score for the resource bing analyzed. Erroneous or misleading results are obtained when the modeling procedure ignores errors in the land-cover data. When information on classification errors is available, adjustments to the weights are appropriate. The distribution of misclassified pixels reported in the error matrix can be used to modify weights to compensate for such errors. In many instances, conclusions reached from using adjusted weights may be different than conclusions based on unadjusted weights. This finding suggests that current procedures could be modified to improve the results of GIS land-cover modeling analyses.

## INTRODUCTION

DIGITAL SATELLITE DATA are now a common source of land-use/land-cover information. This information, usually presented in the form of a map, is critical to natural resources management and planning. However, in recent years, these land-use/land-cover maps have been increasingly used as intermediate data sources for quantitative models in digital geographic information systems (Mead *et al.*, 1982; Lauer, 1986). These models typically result in a number which represents the quality or suitability of a given region for a particular use or management practice. The accuracy of this quantitative assessment, of course, depends primarily upon the accuracy of the map(s) from which it is derived. The purpose of this report is to propose a method which uses the results of a standard accuracy assessment procedure for a land-cover map to improve the accuracy of quantitative models which use the map. The proposed method is contrasted with what is perceived as the current standard practice in these situations.

## ACCURACY ASSESSMENT PROCEDURES

The most common means of reporting the reliability of a land-cover map derived from satellite data is the error or confusion matrix, also called a contingency table (Congalton *et al.*, 1983). These tables are typically the result of a sampling effort in which the land cover depicted on a map is compared with the land cover found at corresponding locations on the ground. The error matrix represents a tabulation of errors made in a classification, and usually takes the form of Table 1, where the columns represent categories as noted on the ground during the accuracy assessment, and the rows represent the categories assigned in the mapping project.

TABLE 1. EXAMPLE CLASSIFICATION ERROR MATRIX.

| Category as Classified | Reference ("Ground Truth") Data $j=1$ | . . . | $j=k$ | Total |
|---|---|---|---|---|
| $i=1$ | $x_{11}$ | . . . | $x_{1k}$ | $x_{1\cdot}$ |
| . | . | . . . | . | . |
| . | . | $x_{ij}$ | . | $x_{i\cdot}$ |
| . | . | . . . | . | . |
| $i=k$ | $x_{k1}$ | . . . | $x_{kk}$ | $x_{k\cdot}$ |
| Total | $x_{\cdot 1}$ | . . . | $x_{\cdot k}$ | $x_{\cdot\cdot}$ |

$x_{i\cdot}$ = total for row $i$;
$x_{\cdot j}$ = total for column $j$;
$x_{\cdot\cdot}$ = total number of pixels in error matrix;
$x_{ij}$ = number of pixels classified as category $i$ which are found to belong to category $j$ on the ground;
$k$ = number of categories;
$i$ = row index (classification); and
$j$ = column index (reference data).

The error matrix can yield several values which summarize the classification accuracy. First, the overall accuracy is the sum of the diagonal elements divided by the total number of pixels in the table. This number represents an average accuracy for the classification over all categories, but provides no information about accuracies of individual categories. Story and Congalton (1986) discuss "producer's" and "user's" accuracies, which reflect the perspective from which the accuracy is interpreted, and which provide accuracy information for each land-cover category. The producer's accuracy relates to the probability that a *ground sample* will be correctly classified, and is calculated by dividing the number of pixels correctly classified in a given category by the total number of pixels of that category that were sampled on the ground. The user's accuracy will reflect the proportion of pixels in a *category on the map* which are correctly classified. This value is obtained by dividing the number of pixels in a category that were classified correctly by the total number of pixels that were assigned to that category in the classification. A crucial assumption in this use of error matrices is that the distribution of errors in the contingency table is representative of the types of misclassification made in the entire area classified. Without this assumption, no inferences can be made about probabilities of correct or incorrect assignments of pixels to land-cover categories.

## LAND-COVER WEIGHTING PROCEDURES

The purpose and use of land-cover maps has undergone a transition from that of physical cartographic products to key components of digital spatial databases used in geographic information systems (GIS). With this transition has come an opportunity to better use the details of classification accuracy reported in error matrices.

The quantitative analysis of land cover in a GIS may be performed for many reasons. One example is the analysis of wildlife habitat. In this situation, vegetation categories may be ranked and weighted to indicate their ability to provide important components of habitat such as food and cover (Gysel and Lyon, 1980). Generally, the goal is either to compare the habitat score for two areas to determine which has more potential for supporting wildlife populations, or to measure the habitat score before and after some treatment of a single area to assess the treatment's impact upon wildlife (Heinen and Mead, 1984).

Wildlife habitat is not the only application of such weighting and ranking schemes. Others may be land-use planning, recreation suitability evaluation, or watershed modeling. In applications such as watershed modeling for erosion potential, land cover may be used as a surrogate for land attributes which are used as variables in predictive models (Robinove, 1981). In con-

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trast to the habitat evaluation example, these applications may produce a number which has meaning in itself, and is not used merely as a score for comparison of two areas.

The typical weighting procedure, then, may be seen as first identifying the region for which a score is desired, such as a watershed, a management unit, or a parcel of a given ownership. The number of pixels classified into each land-cover class in the specified region is counted ($A_i$), and multiplied by a weight assigned to that class ($w_i$). Such weights are typically, but not necessarily, between zero and one. These weighted counts are summed to form a total score ($Q$) for the study area (Equation 1). In order to compare scores for regions of different size, this number may be expressed on a per-unit basis ($Q'$) by dividing the score by the total number of pixels in the study area (Equation 2).

$$Q = \sum_{i=1}^{k} w_i A_i \quad (1)$$

where $Q$ = score for study area,
$A_i$ = number of pixels (or area) within study area classified as type $i$,
$w_i$ = weight for category $i$, and
$k$ = number of land-cover categories.

$$Q' = \frac{Q}{\sum_{i=1}^{k} A_i} = \frac{\sum_{i=1}^{k} w_i A_i}{\sum_{i=1}^{k} A_i} \quad (2)$$

where $Q'$ = score per unit area.

## THE PROPOSED PROCEDURE

Assuming the category weights have been derived in a reliable manner, the major weakness in the above procedure lies in the fact that not all pixels classified into a given land-cover type truly belong to that type. Therefore, misclassified pixels are weighted incorrectly, and the final score will be incorrect to the extent that the classification is inaccurate. A solution to this problem may be to use the information that is provided in the classification error matrix which describes the observed distribution of misclassifications in the map.

For example, consider a habitat model in which weights are assigned to land-cover categories according to their ability to produce forage. Suppose that agricultural land-cover types are extremely important in terms of forage production; pixels mapped as agriculture will be assigned a high weight relative to other types. However, simple weighting of the categories as classified ignores the distribution of observed errors as reported in the contingency table. If a significant proportion of the mapped agriculture class contains something other than (and less important than) agriculture, the agriculture class weight should be adjusted downwards accordingly. Conversely, if the accuracy assessment indicates that a lower-weighted class as mapped contains considerable confusion with higher-weighted agricultural land, its weight should be adjusted upward.

The first step in the proposed procedure is to divide every cell in an error matrix by its row total. This produces what we will call the User Probability Matrix (Table 2), in which the cell entries represent the proportion of a mapped category (the row) that has been found to belong to the various reference categories (the columns). The diagonal elements of this table can be viewed as the probability that a pixel in a given mapped class is classified correctly. Similarly, the off-diagonal elements of Table 2 can be viewed as the probability that a given pixel on the map has been misclassified as another particular category. This step is similar to part of a procedure proposed by Card (1983) to improve estimates of thematic map accuracy.

Two possibilities exist for modifying a weighting procedure to incorporate information on misclassifications. First, the count of pixels in a category on the map ($A_i$) can be modified by

TABLE 2. EXAMPLE USER PROBABILITY MATRIX; CELLS CONTAIN PROPORTIONS OF THE ROW TOTALS OF THE ERROR MATRIX (FROM TABLE 1).

| Category as Classified | Reference ("Ground Truth") Data $j=1 \ldots\ldots j=k$ | | | Total |
|---|---|---|---|---|
| $i=1$ | $p_{11}$ | ... | $p_{1k}$ | 1.00 |
| . | . | ... | . | . |
| . | . | $p_{ij}$ | . | 1.00 |
| . | . | ... | . | . |
| $i=k$ | $p_{k1}$ | ... | $p_{kk}$ | 1.00 |

$p_{ij} = x_{ij} / x_{i\cdot}$ = proportion of all pixels classified as $i$ which were found to belong to category $j$;
$k$ = number of categories;
$i$ = row index (classification); and
$j$ = column index (reference data).

multiplying by the proportions in the appropriate column of the User Probability Matrix (Equation 3). This adjusts the pixel counts using an estimate of the number of misclassified pixels in a category, and apportions those pixels to other categories which were shown to be confused in the error matrix. These adjusted pixel counts ($A_i^*$) would then be multiplied by the appropriate weights ($w_i$) and summed to arrive at a score. A significant drawback to this procedure is that, whenever a new area is selected for study, new pixel counts are made and must again be adjusted.

$$A_i^* = \sum_{j=1}^{k} A_j p_{ji} \quad \text{(Eq. 3)}$$

where $A_j$ = original pixel count for category $j$;
$p_{ji}$ = value in row $j$, column $i$ of User's Probability Matrix; and
$A_i^*$ = adjusted pixel count for category $i$.

A second way of achieving the same final score is to adjust the weights ($w_i$) instead of the pixel counts. This is the preferred technique because, once the weights have been adjusted, they can be used for any area on the map. The adjustment of weights is performed as shown in Equation 4: a new weight for category i ($w_i^*$) as calculated by multiplying the proportions in row $i$, Table 2 ($p_{ij}$), by the original weights corresponding to each column ($w_j$), i.e.,

$$w_i^* = \sum_{j=1}^{k} w_j \, p_{ij} \quad \text{(Eq. 4)}$$

where $w_j$ = original weight for category $j$;
$p_{ij}$ = value in cell $i$, $j$ from User's Probability Matrix; and
$w_i^*$ = adjusted weight for category $i$.

These adjusted weights are then substituted for the original weights in Equation 1. The new score calculated for the region ($Q_a$) should express the fact that the mapped categories are not 100 percent correct by adjusting the final score according to the distribution of errors indicated by the error matrix.

## A NUMERICAL EXAMPLE

To demonstrate this procedure, an example error matrix and modeling situation has been adapted from Ormsby and Lunetta (1987). In their study, Landsat data were used to classify land cover for use in a wildlife habitat evaluation model. The error matrix from their land-cover classification is shown in Table 3. From this table, producer's user's, and overall accuracy can be calculated (Table 4). In the habitat modeling example reported by Ormsby and Lunetta, a portion of a wildlife refuge was evaluated for deer habitat suitability. For their model, land-cover types were weighted according to their ability to produce winter

TABLE 3. CLASSIFICATION ERROR MATRIX ADAPTED FROM ORMSBY AND LUNETTA (1987).

| | Reference Data | | | | | | |
|---|---|---|---|---|---|---|---|
| Classification | Corn | Beans | Pasture | Grass | Wheat | Other | Total |
| Corn | 65410 | 18323 | 2749 | 24482 | 299 | 25568 | 136831 |
| Beans | 15357 | 279107 | 6005 | 17647 | 1316 | 15907 | 335339 |
| Pasture | 3454 | 7136 | 9049 | 4542 | 1543 | 12196 | 37920 |
| Grasses | 192 | 560 | 634 | 4826 | 12 | 7392 | 13616 |
| Wheat | 180 | 1297 | 612 | 51 | 13298 | 1173 | 16611 |
| Other | 7951 | 19707 | 7387 | 23598 | 1601 | 301723 | 361967 |
| Total | 92544 | 326130 | 26436 | 75146 | 18069 | 363959 | 902284 |

TABLE 4. PRODUCER'S AND USER'S ACCURACY FIGURES, DERIVED FROM TABLE 3.

| Category | No. pixels Correctly Classified | Total pixels in column | Total pixels in row | Producer's Accuracy (percent) | User's Accuracy (Percent) |
|---|---|---|---|---|---|
| Corn | 65410 | 92544 | 136831 | 70.68 | 47.80 |
| Beans | 279107 | 326130 | 335339 | 85.58 | 83.23 |
| Pasture | 9049 | 26436 | 37920 | 34.23 | 23.86 |
| Grasses | 4826 | 75146 | 13616 | 6.42 | 35.44 |
| Wheat | 13298 | 18069 | 16611 | 73.60 | 80.06 |
| Other | 301723 | 363959 | 361967 | 82.90 | 83.36 |
| Total | 673413 | 902284 | 902284 | 74.63 | 74.63 |

TABLE 5. LAND-COVER CATEGORY WEIGHTS FOR WINTER FORAGE PRODUCTION FOR WHITE-TAILED DEER (FROM ORMSBY AND LUNETTA, 1987).

| Land-Cover Category | Winter Forage Weight |
|---|---|
| Corn | 0.80 |
| Beans & beets | 0.15 |
| Pasture | 0.10 |
| Wetland grasses | 0.10 |
| Wheat | 0.05 |

food for white-tailed deer (Table 5). (Categories classified by Ormsby and Lunetta that did not have any weight for winter food potential were grouped into the category "Other" for our illustration.) Pixel counts for each land-cover category within their study area were then multiplied by these weights to produce a score for food potential. For the purposes of our example, the "study area" will be represented by the data from the accuracy assessment. Therefore, the pixel counts for each category in the area of interest are equivalent to the row totals of the error matrix. (Our use of the reference data as a study area is merely a convenience; normally, an area would be delineated and pixels within it counted.) Using the traditional method, category scores are obtained by multiplying the weights by the pixel counts. The individual category scores are then summed to arrive at a food potential score for the study area: i.e.,

$$\begin{aligned} Q = \quad & (0.80 \times 136831) = & 109464.80 \\ & + (0.15 \times 335339) = & 50300.85 \\ & + (0.10 \times 37920\ ) = & 3792.00 \\ & + (0.10 \times 13616\ ) = & 1361.60 \\ & + (0.05 \times 16611\ ) = & 830.55 \\ & + (0.00 \times 361967) = & \underline{0.00} \\ & = & 165749.80 \end{aligned}$$

$Q' = (165749.80/902284) = 0.1837$ per unit area

Now, in order to incorporate information from the error matrix in an adjustment of the weights, the cell values from the error matrix in Table 3 have each been divided by their row totals to produce the User Probability Matrix shown in Table 6. Note that the diagonal elements of this table are identical to the user's accuracy values given in Table 4. Next, each weight is adjusted in turn using the values from the appropriate row in Table 6 multiplied by the respective original weights as in Equation 4 (see Table 7). Finally, these adjusted weights are multiplied by the pixel counts as before, and summed:

$$\begin{aligned} Q_a = \quad & (0.4225 \times 136831) = & 57814.50 \\ & + (0.1687 \times 335339) = & 56582.65 \\ & + (0.1390 \times 37920\ ) = & 5269.85 \\ & + (0.0576 \times 13616\ ) = & 784.20 \\ & + (0.0643 \times 16611\ ) = & 1069.75 \\ & + (0.0345 \times 361967) = & \underline{12494.40} \\ & & 134016.35 \end{aligned}$$

$Q'_a = 134016.35 / 902284 = 0.1485$ per unit area

## DISCUSSION

At this point, three questions are pertinent. First, does the adjustment procedure result in a meaningful difference in scores? Second, would a different in scores result in different decisions regarding the resource? Third, if adjusted scores are truly different from unadjusted scores, which is "better"?

The answer to the first question is yes; a dramatically different score can be obtained if weights are adjusted. In fact, the only way that adjustment would not result in different scores is if there were no error in the classification, or if the misclassifications occur uniformly across all categories. In the example, the adjustments of the weights has resulted in a 19 percent decrease in the calculated score for forage production potential. This would be expected if, in general, higher-weighted cover categories has been confused with lower-weighted categories, thus diluting the weight for the higher-weighted categories. This is indeed the case in the above example. The highest weight is assigned to the corn category, which has an accuracy of only 47.8 percent (from the user's perspective). This category is confused considerably with the "Other" category, which has a weight of zero, and the wetland grass category, which has a weight of 0.10. This confusion has caused the weight of the corn category to be reduced almost in half (from 0.80 to 0.4225). Conversely, the weight for the pasture category has increased from 0.10 to 0.139, primarily because of a high degree of confusion with the higher-weighted categories of Beans and Corn.

In response to the second question, the different scores obtained by adjusting weights will often result in a different conclusion. For example, the relative importance of certain categories

TABLE 6. USER PROBABILITY MATRIX DERIVED FROM TABLE 3.

| | Reference Data | | | | | | |
|---|---|---|---|---|---|---|---|
| Classification | Corn | Beans | Pasture | Grass | Wheat | Other | Total |
| Corn | 0.4780 | 0.1339 | 0.0201 | 0.1789 | 0.0022 | 0.1869 | 1.0000 |
| Beans | 0.0458 | 0.8323 | 0.0179 | 0.0526 | 0.0039 | 0.0474 | 1.0000 |
| Pasture | 0.0911 | 0.1882 | 0.2386 | 0.1198 | 0.0407 | 0.3216 | 1.0000 |
| Grasses | 0.0141 | 0.0411 | 0.0466 | 0.3544 | 0.0009 | 0.5429 | 1.0000 |
| Wheat | 0.0108 | 0.0781 | 0.0368 | 0.0031 | 0.8006 | 0.0706 | 1.0000 |
| Other | 0.0220 | 0.0544 | 0.0204 | 0.0652 | 0.0044 | 0.8336 | 1.0000 |

TABLE 7. CALCULATION OF ADJUSTED LAND-COVER CATEGORY WEIGHTS.

$$\text{Adjusted weight} = w_i^* = w_1 \times p_{i1} \times w_2 \times p_{i2} + w_3 \times p_{i3} + w_4 \times p_{i4} + w_5 \times p_{i5} + w_6 \times p_{i6}$$

So, for the adjusted corn weight,

$$\begin{aligned} w_1^* &= 0.80(0.4780) + 0.15(0.1339) + 0.10(0.0201) + 0.10(0.1789) + 0.05(0.0022) \\ &= 0.3824 + 0.0201 + 0.0020 + 0.0179 + 0.0001 \\ &= 0.4225 \end{aligned}$$

Similarly, the other weights are

Beans ($w_2^*$):

$$\begin{aligned} &= 0.80(0.0458) + 0.15(0.8323) + 0.10(0.0179) + 0.10(0.0526) + 0.05(0.0039) \\ &= 0.0366 + 0.1248 + 0.0018 + 0.0053 + 0.0002 = 0.1687 \end{aligned}$$

Pasture ($w_3^*$):

$$\begin{aligned} &= 0.80(0.0911) + 0.15(0.1882) + 0.10(0.2386) + 0.10(0.1198) + 0.05(0.0407) \\ &= 0.0729 + 0.0282 + 0.0239 + 0.0120 + 0.0020 = 0.1390 \end{aligned}$$

Wetland grasses ($w_4^*$):

$$\begin{aligned} &= 0.80(0.0141) + 0.15(0.0411) + 0.10(0.0466) + 0.10(0.3544) + 0.05(0.0009) \\ &= 0.0113 + 0.0062 + 0.0047 + 0.0354 + 0.0000 = 0.0576 \end{aligned}$$

Wheat ($w_5^*$):

$$\begin{aligned} &= 0.80(0.0108) + 0.15(0.781) + 0.10(0.0368) + 0.10(0.0031) + 0.05(0.8006) \\ &= 0.0086 + 0.0117 + 0.0037 + 0.0003 + 0.0400 = 0.0643 \end{aligned}$$

Other ($w_6^*$):

$$\begin{aligned} &= 0.80(0.0220) + 0.15(0.0544) + 0.10(0.0204) + 0.10(0.0652) + 0.05(0.0044) \\ &= 0.0176 + 0.0082 + 0.0020 + 0.0065 + 0.0002 = 0.0345 \end{aligned}$$

may change after adjustment of weights. Notice that the weight for the wetland grass category was initially higher than the weight for the wheat category. Consequently, a reasonable interpretation might have been: "Another area of the same size with more pixels classified as wetland grass and fewer classified as wheat will have a *higher* score and, thus, more potential winter food value." However, if adjusted weights are used, the situation is reversed. Because the adjusted weight for wheat is higher than the adjusted weight for wetland grass, the correct conclusion would be: "Another area of the same size with more wetland grass pixels and fewer wheat pixels will have a *lower* score and less potential winter food value." In many cases, however, the adjustment of weights may not reverse the relative ranking of categories, as it did with wetland grass and wheat. In such instances, the rankings of different areas in the same map will not be affected by the adjusting of weights. Areas with higher scores using unadjusted weights will still have higher scores using adjusted weights; the conclusions would not be altered.

A second instance in which the adjustment of weights will change the results is if the evaluation or assessment is meant to yield an interpretation in terms of an absolute quantity, such as a carrying capacity or erosion potential. In this case, the magnitude of the number is important, and itself will carry meaning. Because the adjustment will likely change the magnitude of the number, the procedure may be warranted.

The third case in which the adjustment procedure will probably result in a different interpretation is when comparing areas for which separate classifications of land cover were performed. In this case, there is a different classification error matrix and a different adjustment of weights for each area. Therefore, the use of adjusted weights may result in different relative scores for the areas than if unadjusted weights were used. Note that this case could include comparing areas across time. It is not always possible to foresee whether future studies will use today's results as a comparison; therefore, using the adjustment procedure even in current "single-map" analyses will provide a more consistent basis for future comparison and change evaluations.

It is evident that the adjustments of weights will result in different scores, and possibly different interpretations; but to what extent are they better or worse than results obtained using the conventional techniques? In the example above, the error matrix contains information on the "true" identity of the pixels in our study area (the accuracy assessment data set), so the "true" total forage score for the area ($Q_t$) can be calculated. This number represents the score that would be obtained if the land-cover areas (pixel counts) were calculated from ground data, rather than from the classified land-cover map. The "true" forage quantity is obtained by using the column totals instead of the row totals, and the original weights: i.e.,

$$\begin{aligned} Q_t = \; & (0.80 \times 92544) \\ & + (0.15 \times 326130) \\ & + (0.10 \times 26436) \\ & + (0.10 \times 75146) \\ & + (0.05 \times 18069) \\ & + (0.00 \times 363959) = 134016 \end{aligned}$$

$$Q'_t = 134016 / 902284 = 0.1485$$

Now, we find the adjusted score (134016) to be identical to the "true" score (134016). It can be shown algebraically that the adjusted score $Q_a$ will always equal the score $Q_t$ obtained by using the original weights and the "true" reference data pixel counts. Obviously, in general practice, the accuracy assessment data will not be used as the study area; the "true" land-cover composition of the study area will not be known, and a $Q_t$ could not be calculated. The important point, though, is that, if the error matrix reflects the expected distribution of misclassifications, the adjusted scores can be considered a more accurate representation of the site conditions than the traditional, unadjusted scores.

The drastic difference between scores obtained with and without the adjustment procedure supports two recommendations. First, these results emphasize the point made by Story and Congalton (1986) and others that error matrices should be made available to the users of land-cover classification products. Second, when a classification is performed with a specific purpose such a habitat mapping, and a specific model or weighting scheme has been previously selected, it may be desirable to orient the classification procedure to get higher accuracies in the higher-weighted categories. This can be done by varying sampling intensities or by using classification algorithms which allow for variable misclassification costs.

## SUMMARY

Digital land-cover maps classified from remotely sensed data are being used frequently in quantitative GIS models. In such cases, the use of the accuracy assessment information presented in the error matrix can be used to enhance the accuracy of subsequent analyses.

A technique has been proposed to incorporate information on misclassification errors in the adjustment of typical weighting and ranking schemes. This procedure uses simple manipulations of the error matrix from a classification to alter land-cover category weights to reflect the types of confusion found in the classification. The method proposed has been shown to produce the same results that would be obtained if "ground-truth" data were used in place of classified data.

In an example of the proposed procedure, the adjustment of weights resulted in a 19 percent decrease in the computed score. This difference may or may not lead to different decisions regarding the resource being analysed. The cases in which adjustments may be crucial are:

- If the adjustment results in a different relative ranking of land-cover categories;
- If the result is a quantity that is interpretable in terms of its magnitude, and not only in a comparison; and
- If scores are to be compared between maps with different error matrices (from either different areas or dates).

These results suggest that, if a classification is performed specifically for a quantitative analysis such as the example described, efforts to enhance the classification accuracy of highly weighted classes may be worthwhile. Even if classifications are performed with no such specific purpose in mind, then the error matrices can be a valuable tool for improving any subsequent analyses using the classified data.

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