11 Advanced Topics

This chapter begins with a discussion of change detection accuracy assessment. The complexities of conducting such an assessment are presented along with the formulation of the change detection error matrix. A key issue in any change detection accuracy assessment is the realization that change is a rare event and sampling must occur to specifically deal with this issue. While it is possible to create a change detection error matrix, it requires a tremendous amount of work. A compromise two-step method is proposed and demonstrated that may provide a more practical approach to assessing the accuracy of change. The chapter concludes with a short discussion of multilayer accuracy assessment.

CHANGE DETECTION

An increasingly popular application of remotely sensed data is for use in change detection. Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). Four aspects of change detection are important: (1) detecting that changes have occurred, (2) identifying the nature of the change, (3) measuring the areal extent of the change, and (4) assessing the spatial pattern of the change (Brothers and Fish, 1978; Malila, 1985; Singh, 1986). Techniques to perform change detection with digital imagery have become numerous because of increasing versatility in manipulating digital data, better image analysis software, and increasing computing power. Change detection accuracy assessment is an important component of any change analysis project.

Assessing the accuracy of a single date or one point in time (OPIT) thematic map generated from remotely sensed data as presented in this book is a complex but attainable endeavor. In addition to the complexities associated with a single-date accuracy assessment of remotely sensed data, change detection presents even more difficult and challenging issues to consider. The very nature of change detection makes quantitative analysis of the accuracy difficult. For example, how does one obtain reference data for images that were taken in the past? How does one sample enough areas that will change in the future to have a statistically valid assessment? Which change detection technique will work best for a given change in the environment? Positional accuracy also plays a big role in change detection. It is critical to determine if an increase in size or shape of an area has actually occurred or if the apparent change is simply due to a positional error. Figure 11.1 is a modification of the sources of error figure for a single-date assessment presented early on in this book (Chapter 2, Figure 2.5) and shows how complicated the error sources get when performing a change detection. Most of the studies on change detection conducted up to now do not present quantitative results of their work, which makes it difficult to determine which method should be applied to a future project.

The following section presents the topics to be considered when preparing to perform a change detection accuracy assessment. There are three critical components

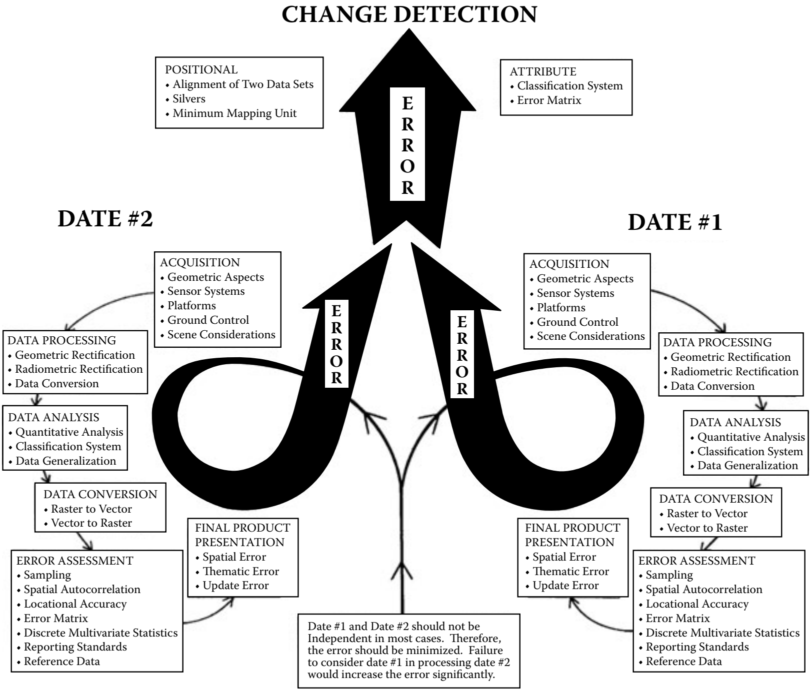

FIGURE 11.1 Sources of error in a change detection analysis from remotely sensed data. (Reproduced with permission from the American Society for Photogrammetry and Remote Sensing, from Congalton R.G. 1996. Accuracy assessment: A critical component of land cover mapping, in *Gap Analysis: A Landscape Approach to Biodiversity Planning*. A peer-reviewed proceedings of the ASPRS/GAP Symposium. Charlotte, NC, pp. 119–131.)

that must be considered in any change detection accuracy assessment. These are (1) reference data, (2) sampling, and (3) the change detection error matrix.

Reference Data

A collection of valid reference data is central to any accuracy assessment, whether it is a single-date assessment or for evaluating a change detection. Let us imagine conducting a change detection project in 2008 by comparing a vegetation/land cover map generated from 1998 Landsat Thematic Mapper (TM) imagery (call this time 1) with another map generated from 2008 TM imagery (call this time 2). Let us further suppose that the classification scheme used for both maps is the same because we created both maps. Reference data for evaluating the 2008 map could be collected on the ground in 2008 or even 2009 and still be considered valid. However, how can reference data for assessing the 1998 map and, therefore, the change detection, be obtained?

There are a few possible answers. The most probable answer is that there are no reference data available and really no way to assess the change. Second, there might be some aerial photography of the area that was acquired around the same time as the 1998 TM imagery. Of course, scale is an issue here. If the photos are of such small scale that sufficient detail cannot be accurately interpreted from them given the classification scheme used in the mapping project, then the photos cannot be used to provide reference data. Even if the scale is sufficient, photo interpretation is subject to error and the reference data may be flawed. Third, there may be some ground inventory of the area in question that can be used as reference data. This third possibility is extremely slim. Therefore, the lack of valid reference data is often a limiting factor when attempting to conduct a change detection accuracy assessment.

Sampling

There is one overriding issue that must be considered when sampling for change detection accuracy assessment that is beyond the sampling issues already presented in this book for a single-date assessment. Failure to consider this issue dooms the assessment to a wasted effort. It must be remembered that change is a rare event. Under normal circumstances, it would be unusual for more than 10% of a given area to change in a 5–10 year period. More likely, the change would be closer to 5%. In extreme cases, high change rates like 20% are possible. Of course, in certain catastrophic situations, change may be even higher.

Now consider sampling to find the change areas. Using a random sampling approach, even in a map with high change rates (20%), on average only 2 out of 10 samples will find any change. In the more usual case, it could take up to 20 samples before an area that has changed is found. Given the time and effort to collect samples for accuracy assessment, this sampling in the nonchange areas must be avoided. Stratification of the area to prioritize sampling in the change areas should be employed. However, exactly how to delineate these strata is not always obvious. If all the change areas were known, then no new map of change would be needed.

Fortunately, for many applications, logic or experience dictates the likely places for change to occur. For example, urban change occurs in areas around existing urban centers. It is extremely rare to find a new city built in the middle of nowhere. Sampling for urban change in a buffer zone around an urban center increases your chances of finding it when compared to a randomly placed sample. In this scenario, taking some portion of your sample in high-priority areas makes sense. Macleod and Congalton (1998) conducted a change detection accuracy assessment for monitoring eel grass change in Great Bay, New Hampshire. Because change is such a rare event, it was necessary to proportionally allocate more sampling effort to areas where change was more likely to happen. In this example, for mapping eel grass, we know that it is very unlikely that eel grass will grow in the channel (i.e., the deep water areas). Sampling should be limited in the channel. On the other hand, the eel grass is more likely to expand around existing eel grass beds and in shallow areas where no eel grass currently grows. The sampling effort should be increased in these areas. Therefore, we modified our sampling efforts in the following ways: (1) Only 10% of our sampling effort occurred in the deep water areas, (2) 40% of our sampling effort was dedicated to a buffer area within one sample grid (i.e., pixel) of existing eel grass, and (3) 50% of our sampling effort was dedicated to shallow areas where new eel grass seedlings could occur. In this way, the sampling was designed to find the change areas (Congalton and Brennan, 1998).

There are many other factors to consider when sampling for change detection accuracy assessment. However, failure to note that change is a rare event influences all these other factors and must be considered first.

Change Detection Error Matrix

In order to apply established accuracy assessment techniques to change detection, the standard single-date classification error matrix needs to be adapted to a change detection error matrix as proposed by Congalton and Macleod (1994) and Macleod and Congalton (1998). This new matrix has the same characteristics of the single-date classification error matrix, but also assesses errors in changes between two time periods (between time 1 and time 2) and not simply a single classification.

Table 11.1 reviews a single-date error matrix and the associated descriptive statistics: overall, producer's, and user's accuracies that have already been presented in this book. This single-date error matrix is for three vegetation/land cover categories (F = Forest, U = Urban, and W = Water). The matrix is of dimension 3 × 3. The *y*-axis of the error matrix represents the three vegetation/land cover categories as derived from the remotely sensed classification (i.e., the map) and the *x*-axis shows the three categories identified in the reference data.

The major diagonal of this matrix is highlighted and indicates correct classification. In other words, when the classification indicates the category was F and the reference data agrees that it is F, then the [F, F] cell in the matrix is tallied. The same logic follows for the other categories: U and W. Off-diagonal elements in the matrix indicate the different types of confusion (called omission and commission errors)

TABLE 11.1
An Example of a Single-Date (One Point in Time) Error Matrix Showing Overall, User's, and Producer's Accuracies

Classified Data	Reference Data F	U	W	Row Total
F	40	9	8	57
U	1	15	5	21
W	1	1	20	22
Column Total	42	25	33	100

Land Cover Categories

F = Forest
U = Urban
W = Water

OVERALL ACCURACY
= 40 + 15 + 20
= 75/100 = 75%

PRODUCER'S ACCURACY

F = 40/42 = 95%
U = 15/25 = 60%
W = 20/33 = 61%

USER'S ACCURACY

F = 40/57 = 70%
U = 15/21 = 71%
W = 20/22 = 91%

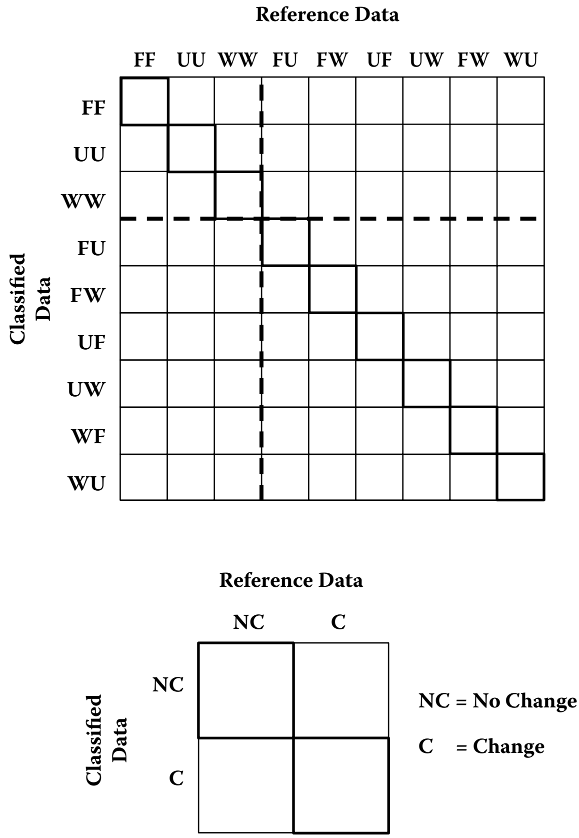

FIGURE 11.2 A change error matrix for the same three map categories (Forest, Urban, Water) as the single-date matrix and the collapsed no change/change matrix. (Reproduced with permission from the American Society for Photogrammetry and Remote Sensing, from Congalton R.G. 1996. Accuracy assessment: A critical component of land cover mapping, in *Gap Analysis: A Landscape Approach to Biodiversity Planning*. A peer-reviewed proceedings of the ASPRS/GAP Symposium. Charlotte, NC, pp. 119–131.)

that exist in the classification. Omission error occurs when an area is omitted from the correct category. Commission error occurs when an area is placed in the wrong category. This information is helpful in guiding the user to where the major problems exist in the classification.

The top part of Figure 11.2 shows a change detection error matrix generated for the same three vegetation/land cover categories (F, U, and W). Note, however, that the matrix is no longer of dimension 3×3, but rather 9×9. This is because we are no longer looking at a single classification, but rather a change between two different maps generated at different times. Remember, in a typical error matrix, there is one row and column for each map category. However, in assessing change detection, the error matrix is: the size of the number of categories squared. Therefore, the question of interest is: What category was this area at time 1 and what is it at time 2? The answer has 9 possible outcomes for each axis of the matrix (F at time 1 and F at time 2, U at time 1 and U at time 2, W at time 1 and W at time 2, F at time 1 and U at time 2, F at time 1 and W at time 2, U at time 1 and F at time 2, U at time 1 and W at time 2, W at time 1 and F at time 2, or W at time 1 and U at time 2), all of which are indicated along the rows and columns of the error matrix. It is then important to note what the remotely sensed data said about the change and compare it to what the reference data indicates. This comparison uses precisely the same logic as for the single classification error matrix; it is just complicated by the two time periods (i.e., the change). Again, the major diagonal indicates correct classification, while the off-diagonal elements indicate the errors or confusion. The descriptive statistics (i.e., overall, user's, and producer's accuracies) can also be computed.

It is important to note that the change detection error matrix can also be simplified or collapsed into a 2 × 2 no change/change error matrix (bottom of Figure 11.2). The no change/change error matrix can be generated by summing the appropriate cells in the four sections of the complete change detection error matrix partitioned by the dotted lines. For example, to get the number of areas for which both the classification and reference data determined that no change had occurred between the two dates, you would simply sum all nine cells in the upper left box (the areas that did not change in either the classification or reference data). To summarize or collapse the cells in which change occurred in both the classification and reference data, you would sum the 36 cells in the lower right box. The other two cells in the no change/change matrix would be determined in a similar manner. From this no change/change error matrix, the analysts can easily determine if a low accuracy was due to a poor change detection technique, misclassification, or both.

It should be obvious to the reader that performing a change detection accuracy assessment is a very complex undertaking. By simply scaling the single-date assessment methodology, the size of the error matrix increases, as does the number of samples required for the assessment. In the example error matrix for a single-date, three-class map (Chapter 10, Table 10.1), 150 samples (3 classes × 50 samples/class) are required. By adding a second time period, the number of samples grows to 450 (9 change classes × 50 samples/class). If a single-date mapping project had 10 classes, the required sample size would be 5000 (10 × 10 × 50 samples per class) samples. Since not all changes are logical within a given period of time (e.g., one would not expect water to become forest in 5 years), that number would likely be smaller, but the number of required samples is still much greater than for a single-date accuracy assessment and probably not feasible under most time and budget conditions.

Therefore, while it may not be possible to perform a complete change detection accuracy assessment and generate a change detection error matrix for every change detection project, it is still relevant to try to answer the following two questions: (1) How accurate have the areas that have changed between time 1 and time 2 been mapped? and (2) How well was the change captured? To answer these questions, the change detection accuracy assessment process can be divided into two steps instead of using a single assessment and the change detection error matrix approach.

Two-Step Approach to Change Detection Accuracy Assessment

If it is not possible to use the change detection error matrix approach to perform your change detection accuracy assessment, then you may wish to use this two-step approach. This method does not allow you to obtain the accuracy of all the change classes (e.g., the map was forest in time 1 and is now residential in time 2; from forest to residential), but it does provide for assessing the accuracy of the areas that changed in time 2 and to assess how well the overall changes were captured.

The first step in this process is to assess the accuracy of just the areas that changed between the two time periods in question. In other words, conduct a single-date accuracy assessment only on the areas that changed between time 1 and time 2. The sampling procedure is similar to that of a traditional single-date accuracy assessment with the requisite number of samples per land cover class selected using a chosen sampling strategy from the map area. However, in this case, only areas classified as change (i.e., the map class is different in time 2 than it was in time 1) are used to select the samples. The accuracy assessment only needs to be conducted for the change areas for time 2 because the rest of the map has the same accuracy as the map did in time 1 for all the areas that did not change.

The second step in this process is simply a change/no change validation. This step is similar to collapsing the change detection error matrix to the change/no change (2×2) matrix presented at the bottom of Figure 11.2. The difference here is that instead of having to sample to fill in the entire change detection error matrix, the sampling is performed to only assess the change/no change. Treating the map as a binary or two-class scheme (change/no change) requires a simpler sampling technique than the multinomial situation of a complete change detection error matrix. Since we are working with a two-case situation where we only wish to know whether the classification is change or no change, we can use the binomial distribution to calculate the sample size. Ginevan (1979) introduced this sampling method to the remote sensing community and concluded that:

- The method should have a low probability of accepting a map of low accuracy.
- It should have a high probability of accepting a map of high accuracy.
- It should require a minimum number of samples.

Computing the sample size for the binomial approach requires the use of a look-up table that presents the required sample size for a given minimum error and a desired level of confidence. For example, a map with a chosen accuracy of 90% (10% error) and using a 95% confidence level (at 95%, we run the risk of a 1 in 20 chance that we reject a map that is actually correct), the minimum number of samples required for the assessment is 298. Given this sample size, the map is rejected as inaccurate if more than 21 samples are misclassified.

Therefore, this two-step approach is quite effective. While not producing a complete change detection error matrix or assessing the accuracy of each change (to–from) class, it does provide a means of assessing the accuracy of the labeling (thematic accuracy) of the areas that changed between the two time frames. In addition, an assessment of whether or not the change is accurately captured can be generated using the binomial change/no change approach. These two steps are considerably easier and require significantly less time, money, and resources than using the change detection error matrix approach. However, if the required resources are available, the change detection error matrix provides the most information about the change analysis and is the recommended approach to use.

Case Study

This case study details the change detection accuracy assessment for the Kentucky Landscape Census (KLC), National Land Cover Dataset (NLCD) update from 2001 to 2005. Appendix 11.1 presents a list of the land cover classes and a brief description of each. It was not possible in this project, due to limited time and resources, to collect enough data to generate a change detection error matrix. Instead, the goal for this change analysis was to assess the accuracy of the change classification (the areas that were changed between 2001 and 2005) and to determine how well change, in general, was captured between the two dates.

To accomplish this task, the accuracy assessment was completed in two steps. First, the 2005 change areas were assessed as a single-date land cover map. Validation samples were collected by interpreting high-resolution imagery collected within a year of the 2005 Landsat imagery (NLCD classification). Generating an error matrix with at least 30 samples per class, the overall map accuracy was computed as well as the omission and commission error rates for each individual thematic class within the map. Second, a change mask was assessed as a binary change/no change map. Samples were collected using a stratified random selection approach within Kentucky. To limit the selection area to areas of likely change, various strata layers were created to prioritize the selection of the samples. By conducting the assessment in these two separate steps, the following questions were answered: How accurate is the 2005 change map and how well was land cover change captured?

Step 1: Accuracy of the Change Areas

The first step in the change detection accuracy assessment was to assess the accuracy of the areas that changed as a separate, single-date map. The sampling procedure is similar to that of any traditional accuracy assessment with between 30 and 50 samples per land cover class randomly selected from the mapping area. However, in this case, only areas classified as change between 2001 and 2005 were used to draw samples, and only the 2005 classification was assessed. The reference data for this time period was 1 m color imagery from the National Agricultural Imagery Program (NAIP). Complete coverage for all of Kentucky was available from NAIP.

The results of the accuracy assessment of the 2005 change areas are presented in error matrix form in Table 11.2. Inspection of the error matrix shows that not all classes were assessed for accuracy and included in the error matrix. While all classes in the USGS classification scheme (Appendix 11.1) were classified, the bulk of the change occurred in only some of the land cover classes. Changes to cover types such as wetland features or forest regrowth classes did not occur in sufficient amounts and, therefore, too few samples were available with which to assess the accuracy of these classes.

TABLE 11.2
Error Matrix Shows the Accuracy of the 2005 Change Areas

	REFERENCE								*User's Accuracies*			
LABELS	Water	Developed Open Space	Developed Low Intensity	Developed Medium Intensity	Developed High Intensity	Bare Land	Shrub	Grassland	Deterministic Totals	Deterministic Accuracies	Fuzzy Totals	Fuzzy Accuracies
MAP Water	15	0,0	0,0	0,0	0,0	0,4	0,0	0,0	15/19	78.9%	15/19	78.9%
Developed Open Space	0,0	9	21,1	4,0	0,0	2,5	0,0	1,2	9/45	20.0%	37/45	82.2%
Developed Low Intensity	0,0	4,0	24	3,0	1,1	1,3	0,0	0,1	24/38	63.2%	33/38	86.8%
Developed Medium Intensity	0,0	0,0	4,0	5	1,0	0,3	0,0	0,0	5/13	38.5%	10/13	76.9%
Developed High Intensity	0,0	0,0	2,0	0,0	11	0,0	0,0	0,0	11/13	84.6%	13/13	100.0%
Bare Land	0,0	0,0	1,2	0,1	0,0	49	0,0	1,0	49/54	90.7%	51/54	94.4%
Shrub	0,0	0,1	0,1	0,0	0,0	0,6	31,0	19,12	31/61	50.8%	50/61	82.0%
Grassland	0,0	1,0	0,0	0,0	0,0	9,18	0,2	40,0	40/70	57.1%	50/70	71.4%
Producer's Accuracies												
Deterministic Totals	15/15	9/15	24/56	5/13	11/14	49/100	31/33	40/76				
Deterministic Accuracies	100.0%	60.0%	42.9%	38.5%	78.6%	49.0%	91.7%	52.6%				
Fuzzy Totals	15/15	14/15	52/56	12/13	13/14	61/100	31/33	61/76				
Fuzzy Accuracies	100.0%	93.3%	92.9%	92.3%	92.9%	61.0%	91.7%	80.3%				

Overall Accuracies

Deterministic		**Fuzzy**	
184/313	58.8%	250/313	79.9%

The overall deterministic accuracy for the 2005 change areas is 58.8%, and the fuzzy accuracy is 79.9%. The 21.1% difference between deterministic and fuzzy accuracies can be attributed to two similar effects. Much of the increases in fuzzy accuracy are related to class confusion within the developed classes and a separate but similar confusion between grassland and shrub land. The four developed classes are defined by the percentage of impervious surface in each class:

- Developed, Open: 0–25%
- Developed, Low Intensity: 26–50%
- Developed, Medium Intensity: 51–75%
- Developed, High Intensity: 76–100%

While this division results in well-defined class boundaries, there is a degree of uncertainty associated with the percent impervious map that translates to the final classification. As the pixels in the percent impervious map are assigned through a statistical regression analysis technique, a degree of error is associated with each estimated value, generally ±10%. This results in pixels within less than 10% of the class boundaries potentially being in two developed categories. For example, a pixel with a value of 55% would be categorized as "Developed, Medium Intensity"; however, by factoring in the degree of uncertainty with the estimate, it could also be categorized as "Developed, Low Intensity." For the purposes of this accuracy assessment, a developed accuracy point was given a fuzzy interpretation if, by factoring in the degree of uncertainty, it satisfied the categorization criteria for more than one developed class. The predominance of the developed categories in the final map and their inherent uncertainty contribute to the variance between the deterministic and fuzzy estimates.

Similar confusion between grass and shrub is the second major contributor to the difference between the deterministic and fuzzy accuracies. These classes are rarely found naturally in Kentucky. Instead, the two classes more often represent a transition or succession of vegetation growth after a disturbance related to forestry or mining. Determining the amount of shrub to grass vegetation based on the hard class breaks leads to fuzziness in some accuracy calls.

Step 2: Change/No Change Assessment

Treating the map as a binary scheme (change/no change) requires a simpler sampling technique than generating a complete change detection error matrix with all the "from" and "to" classes. We can use a binomial distribution to calculate the sample size (Ginevan, 1979). A simple look-up table can be used to determine the required sample size for a given minimum error and a desired level of confidence. For a map accuracy of 90% and using a 95% confidence level (at 95%, we run the risk of a 1 in 20 chance that we reject a map that is actually correct), the minimum number of samples required is 298, with the map being rejected as not meeting the accuracy standard if more than 21 are misclassified.

In order to compensate for the rarity of change within the landscape, an approach was designed that employed five strata layers to increase the sampling to areas of likely change. The first stratum is called the change mask and incorporates all the

TABLE 11.3
Sampling Breakdown Based on Strata Layer

Strata Layer	Percentage of Total Samples	Number of Samples
Change mask	30	88
Distance from change mask	25	75
Spectral magnitude	25	75
Probability of change	10	30
Remaining unsampled area	10	30

areas indicated to have changed by the image analysis change methodology used in this project. Thirty percent of the sampling was performed within the change mask. The second area sampled was a buffer surrounding the change mask. It is expected that change will occur near change, so it follows that sampling should occur around the change areas. Twenty-five percent of the samples were taken in this buffer area around the change mask. A third stratum used for another 25% of the sampling included those areas indicated by spectral analysis of the two images as changed. Fourth, 10% of the samples were allocated to those map classes that had the highest amounts of change. In other words, sampling was increased for those map categories for which significant change occurred between 2001 and 2005. Finally, the last 10% of the sampling was allocated to the rest of the map. Table 11.3 presents a summary of the sampling allocation by strata along with the number of samples taken in each stratum.

The overall accuracy for the change/no change assessment was 96% (Table 11.4). Seven samples were labeled "change" on the map, but were not "change" on the

TABLE 11.4
Final Change/No Change Matrix

		REFERENCE		*Producer's Accuracies*	
		Change	No Change	**Totals**	**Accuracies**
MAP	Change	75	7	75/82	92%
MAP	No Change	6	210	210/216	97%
	User's Accuracies			***Overall Accuracy***	
	Totals	75/81	210/217		
	Accuracies	93%	97%	285/298	96.0%

reference data whereas 6 samples were labeled "no change" on the map but actually did change. Only 13 total errors were found. Given the binomial sampling selected with a desired map accuracy of 90% and a 95% confidence level, 21 errors were permitted. Therefore, this map was accurate at the 90% level, and the error matrix shows the true accuracy to be 96%.

Determining the accuracy of the KLC change map was a critical component of this project. The process demonstrated by this case study was designed to assess the accuracy of the change areas on the 2005 map and evaluate how well change was captured between 2001 and 2005. It was not possible, in this project, to conduct a full change detection accuracy assessment and generate a change detection error matrix. This two-step approach is an effective compromise when the available time and resources do not permit a full assessment. These results show that change was captured with a success rate of 96%.

While the deterministic accuracy assessment is low at 58.8%, the fuzzy assessment of the classification shows a favorable overall classification accuracy of 79.9%.

MULTILAYER ASSESSMENTS

Everything that has been presented in the book up to this point, with the exception of the last section on change detection, has dealt with the accuracy of a single map layer. However, it is important to at least mention multilayer assessments. Figure 11.3

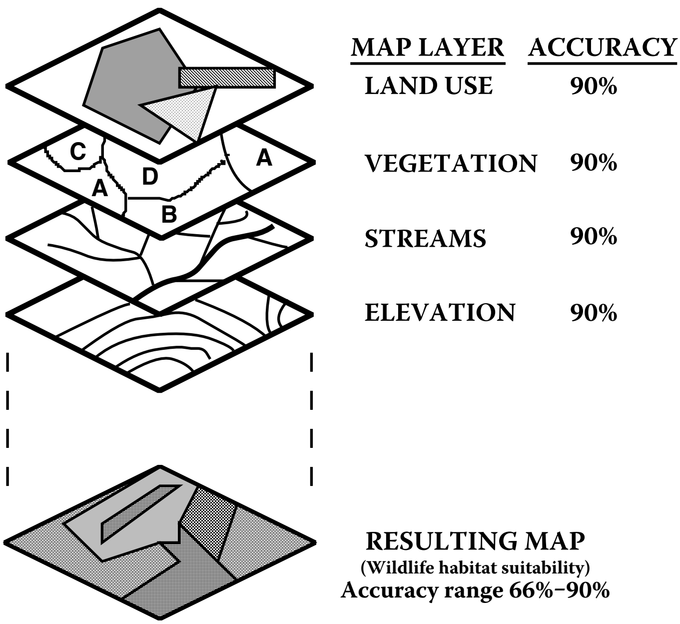

FIGURE 11.3 The range of accuracies for a decision made from combining multiple layers of spatial data.

demonstrates a scenario in which four different map layers are combined to produce a map of wildlife habitat suitability. In this scenario, accuracy assessments have been performed on each of the map layers; each layer is 90% accurate. The question is, how accurate is the wildlife suitability map?

If the four map layers are independent (i.e., the errors in each map are not correlated), then probability tells us that the accuracy would be computed by multiplying the accuracies of the layers together. Therefore, the accuracy of the final map is 90% × 90% × 90% × 90% = 66%. However, if the four map layers are not independent but completely correlated with one another (i.e., the errors are in the exact same place in all four layers), then the accuracy of the final map is 90%. In reality, neither of these cases is very likely. There is usually some correlation between the map layers. For instance, vegetation is certainly related to proximity to a stream and also to elevation. Therefore, the actual accuracy of the final map could only be determined by performing another accuracy assessment on this layer. We do know that this accuracy will be between 66 and 90%, and will probably be closer to 90% than to 66%.

One final observation should be mentioned here. It is quite an eye-opener that using four map layers, all with very high accuracies, could result in a final map of only 66%. On the other hand, we have been using these types of maps for a long time without any knowledge of their accuracy. Certainly, this knowledge can only help us to improve our ability to effectively use spatial data.

APPENDIX 11.1

Class Descriptions of the 2005 NLCD Land Cover

Task	Duration
Open Water	All areas of open water, generally with less than 25% cover of vegetation or soil.
Developed, Open Space	Includes areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.
Developed, Low Intensity	Includes areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20–49% of total cover. These areas most commonly include single-family housing units.
Developed, Medium Intensity	Includes areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50–79% of the total cover. These areas most commonly include single-family housing units.
Developed, High Intensity	Includes highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses, and commercial/industrial. Impervious surfaces account for 80 to 100% of the total cover.

Bare Land	Barren areas of bedrock, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits, and other accumulations of earthen material. Generally, vegetation accounts for less than 15% of total cover.
Deciduous Forest	Areas dominated by trees generally more than 5 m tall, and greater than 20% of total vegetation cover. More than 75% of the tree species shed foliage simultaneously in response to seasonal change.
Evergreen Forest	Areas dominated by trees generally more than 5 m tall, and greater than 20% of total vegetation cover. More than 75% of the tree species maintain their leaves all year. Canopy is never without green foliage.
Mixed Forest	Areas dominated by trees generally more than 5 m tall, and greater than 20% of total vegetation cover. Neither deciduous nor evergreen species are greater than 75% of total tree cover.
Scrub Shrub	Areas dominated by shrubs less than 5 m tall with shrub canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage, or trees stunted from environmental conditions.
Grassland Herbaceous	Areas dominated by Grammanoid or herbaceous vegetation, generally greater than 80% of total vegetation. These areas are not subject to intensive management such as tilling, but can be utilized for grazing.
Pasture Hay	Areas of grasses, legumes, or grass–legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20% of total vegetation.
Cultivated Crop	Areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial woody crops such as orchards and vineyards. Crop vegetation accounts for greater than 20% of total vegetation. This class also includes all land being actively tilled.
Woody Wetland	Areas where forest or shrubland vegetation accounts for 25–100% of the cover and the soil or substrate is periodically saturated with or covered with water.
Emergent Herbaceous Wetland	Areas where perennial herbaceous vegetation accounts for 75–100% of the cover and the soil or substrate is periodically saturated with or covered with water.