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Estimation of Forest Stand Structure Attributes from Aerial Photographs

Abstract

Awareness of potential inaccuracies in stand structure data derived from remotely sensed imagery is important in landscape-level analyses. Attributes of forest stand structure were estimated from aerial photographs using standardized photointerpretation procedures and accuracy assessments were conducted using error matrices by comparing the estimates to plot data. Over 500 stands were photo-interpreted by a single interpreter (1:15,840 nominal scale, normal color) for six forest structure attributes (canopy cover, stand height, DBH, cover type, crown diameter, and canopy layers). Percentage accuracy adjusted for chance agreement ranged from 29 percent to 59 percent; percentage accuracy varied according to the techniques used to evaluate individual attributes. Potential means for correcting biases and rating landscape analyses are discussed.

Keywords: aerial photo interpretation, remote sensing, accuracy assessment, forest stand structure, landscape analysis.

Introduction

Defining relatively homogeneous patches (stands) across forested landscapes is crucial in assessing wildlife habitat, fire risk, forest health, and resource outputs for project planning. Ground-based survey methods for defining forest stand structure are prohibitive in time and cost for large landscapes. Efficient and accurate patch characterization from remotely sensed images is critical to landscape-level studies. Of equal importance is the accuracy of data collected from these images.

Our primary objectives in this study were: 1) to determine the accuracy of obtaining forest stand structure attributes from 1:15,840 nominal scale color aerial photographs, and 2) to compare two measures of accuracy used for data derived from remotely sensed images.

Photointerpreted data have been used in wildlife habitat models (Short 1988), old growth surveys (Rutledge and Hejl, 1990), and large-scale landscape assessments (Kalkhan *et al.* 1995; Allen 1994, Gonzales 1994; Lehmkuhl *et al.* 1994, Green *et al.* 1993, Deegan and Befort 1990). In these types of studies it is necessary to be aware of the potential inaccuracy of photointerpreted data and the effect this inaccuracy may have upon the results. Deegan and Befort (1990) showed that inaccurate photointerpretation can have a substantial effect on forest cover type acreage estimations. Some researchers have used aerial photo data as "ground truth" reference data for maps constructed from satellite digital images (Green *et al.* 1993, Hudson 1987). However, errors in the reference data

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may affect quality of digital image classifications as well as efforts to assess their accuracy (Congalton, 1991).

Data obtained from aerial photographs continue to be important in natural resource management because of widespread accessibility, cost effectiveness, and relative ease in developing interpretation skills. Like all remotely-sensed data, however, the accuracy of the data should be assessed and incorporated appropriately into the analysis.

Previous investigations into the accuracy of estimating stand structure attributes from aerial photographs have been conducted at the plot or single tree level (Spurr 1960, Worley and Meyer 1955, Worley and Landis 1954); few studies have examined this issue at the stand or landscape scale (Deegan and Befort 1990). Our study explores accuracy at the landscape scale using structure attributes interpreted at the stand level.

Methods

Study area

The Finley Creek management area is located on the Flathead Indian Reservation, north of Missoula, Montana. The area ranges in elevation from 3,800 ft to 6,000 ft (1,158 m to 1,829 m) and is generally west-facing. A wide range of cover types are present in the 11,200 acre (4,532 ha) management area; the drier, lower elevation slopes contain ponderosa pine (*Pinus ponderosa*)/ Douglas-fir (*Pseudotsuga menziesii*) forest cover types, whereas the highest portions of the area are dominated by whitebark pine (*Pinus albicaulis*) and subalpine fir (*Abies lasiocarpa*) cover types.

The lower elevation western part of the Finley Creek area has been extensively managed using both even- and uneven-aged silvicultural methods, while the eastern portion of the area has no history of silvicultural activity with the exception of fire suppression activities. The eastern part of the management area is characterized by steep, rocky slopes, high-elevation lakes and meadows.

Photo interpretation

Confederated Salish/Kootenai Tribal Forestry personnel provided stand boundaries in the form of an ARC/INFO file. We transcribed these boundaries on acetate sheets overlaying the aerial photos using even-aged cutting units, roads, lakes and talus slopes to reference the maps provided by the Tribe. Stand structure attributes were photo-interpreted in July 1995, using techniques described in Lillesand and Keifer (1994) and in Paine (1981). Photointerpreted stand structure attributes included DBH (diameter 4.5 ft above ground), crown diameter, height of the dominant and co-dominant trees, canopy layers, canopy cover, and cover type. A single investigator conducted the photointerpretation and field work to eliminate any bias between observers.

The aerial photographs (1:15,840 nominal scale, 9" x 9", normal color, date of exposure 8/90) were scaled and effective areas delineated. We measured height, canopy cover, and crown diameter with standard photointerpretation tools such as estimation templates (transparencies), parallax bar, a Bausch and Lomb zoom stereoscope (6-10 X power), and 10-power hand lens.

Cover type and stand canopy layers were estimated based on the texture, tone, and pattern visible on the image. We identified four cover-type classes based on the majority overstory species: DF (Douglas-fir), WL (western larch [*Larix occidentalis*]), LP (lodgepole pine [*Pinus contorta*]), and PP (ponderosa pine). We interpreted each stand as having one, two, or three layers; stands lacking distinct layers were assigned to class four. Canopy layers were required to have at least 20% canopy cover. We determined stand cover type and canopy layers by visually estimating the conditions seen throughout the stand; no formal photo interpretation plots were measured within each stand. The DBH was visually estimated to the nearest inch from the aerial photos.

Sampling design

Following photointerpretation, we selected 51 stands randomly, approximately a 10 percent sample intensity, for field inventory. Simple random sampling was selected as the sampling scheme because the Kappa analysis technique (see below) assumes a multinomial sampling model (Congalton 1991).

We systematically located five 1/5 acre (0.05 ha) plots in each of the 51 sample stands on maps plotted from the ARC/INFO files.

Field methods

Within each plot, we selected three representative dominant or co-dominant trees that best represented the stand conditions within the plot. We then recorded the DBH, height, crown diameter, and species of each tree. Tree measurements were taken using standard forest mensuration tools (diameter tape, logger's tape, clinometer). For each plot we estimated the number of canopy layers; each layer was required to have at least 20% canopy cover. Canopy cover within each plot was estimated considering only tree vegetation ten feet in height or greater because trees smaller than ten feet could not be distinguished from brush on the aerial photographs.

Data compilation and analysis

We calculated the mean plot value for DBH, height, crown diameter, and canopy cover; the mean of these values for all five field plots located within each stand was calculated to produce the stand value for each attribute. We determined stand cover type and canopy layers by using the majority of the five plots. For example, if a stand had 3 plots with a cover type of Douglas fir, then the stand would be recorded as Douglas fir. In cases where a majority could not be determined, we selected a cover type and/or canopy layer class based on observations made while traveling between plots within the stand.

The two data sets (field and photo) were compared to develop an accuracy assessment for the photo interpretation work. The five-plot data set will hereafter be referred to as reference (ground) data.

We used two different methods, error matrices and a Chi-square test, to assess accuracy in the analysis of the data. When conducting these assessments, we assumed for all attributes that the 'true' values are the field inventory values from the reference data set.

<u>Error matrix tables (Story and Congalton 1986).</u> — Two-way error-matrix tables were constructed for all attributes. In addition to estimating errors of commission, errors of omission, and overall accuracy, the error matrix tables displayed classes that were misinterpreted and for the interval attributes, which were inaccurately estimated.

Of the two types of accuracy that can be determined from error matrices, we determined that errors of commission, or user's accuracies, were of greater importance in this study. The user's accuracy is the number of stands correctly classified divided by the total number of stands placed into that class (row total). User's accuracy is considered a measure of reliability of a map in depicting ground conditions; it is the probability that what is shown on the map is actually representative of what is on the ground (Story and Congalton 1986). Errors of omission, or producer's accuracies, are described as the probability that a particular stand is correctly represented on the map and may be useful in some circumstances. However, they do not represent the accuracy of the map in depicting ground conditions, which is a concern in applied use of maps and images by land managers. The producer's accuracy is calculated by taking the number of stands correctly classified and dividing by the total number of stands in that class in the reference data (column total). Interval attributes including DBH, height, crown diameter, and canopy cover, were collapsed into error matrix classes (Table 1).

Using the error matrix table comparing the photo-interpreted estimates of stand DBH to ground values (Table 2), we show how the tables were analyzed. Stands were placed in cells in the table based on the estimated value of the attribute (row) and the ground value of the attribute (column). The shaded cells indicate the number of stands that were correctly classified (Table 2). The sum of the stands in the major diagonal divided by the total number of sample stands is the overall accuracy.

Stands in cells to the right of the major diagonal were placed in a class lower than the reference data; these stands were underestimated. Likewise, stands in cells to the left of the major diagonal were overestimated. If the number of underestimated stands equals the number of overestimated stands, then the photo-interpreted estimate is not biased.

Analysis of producer's accuracy provides information on classes where stands were consistently omitted from the correct class. User's accuracies can be explored in a similar way by examining the rows of the table and identifying those stands that were placed in the wrong class by the estimating technique.

Three accuracy coefficients, Kappa (K), Tau (T_e), and overall accuracy (P_o), were calculated from the error matrices using methods described in Ma and Redmond (1995). The Kappa and Tau coefficients represent adjustments to overall accuracy to account for chance agreement.

To simplify the analysis, we focused on just one of the error matrix coefficients. We selected the Tau coefficient because of its ability to compensate for chance agreement. P_o does not account for the chance placement of a stand into the correct cell in the matrix and therefore tends to overestimate accuracy (Ma and Redmond 1995, Congalton and Mead 1983). Foody (1992) demonstrated that the Kappa (K) coefficient overcompensates for chance agreement and thus under-represents classification accuracy. When the three coefficients are calculated from the same matrix, K tends to be the highest value, P_o the lowest, and T_e falling somewhere in between (Ma and Redmond 1995). T_e is an improvement over K because it compensates for random chance agreement and for actual correct classification (Foody 1992, Ma and Redmond 1995).

<u>Chi-square test of a hypothesized variance (Freese 1960).</u> — This test compares the estimates of an interval attribute to the true values so that the accuracy of an estimating technique can be determined. We used the chi-square test to calculate the probability, P(Z), that the estimate is within the user-specified allowable error of the ground value (Table 3) and to determine if there is any consistent difference between the estimated values and the true values. An example of a source of bias would be an improperly calibrated instrument used in the estimating technique or perhaps using an incorrect constant in a formula. The chi-square test allows for the detection of bias and subsequent calculation of P(Z) assuming the source of bias was eliminated. We removed bias if it resulted in an increase of 0.05 or greater in the P(Z) value. The allowable error values (Table 3) are consistent

Table 1. *Classes for error matrix tables. The interval attributes were collapsed into these classes for the error matrix analysis.*

DBH (inches)	Height (ft)	Canopy closure	Crown diameter (ft)
1. < 5 (12.7 cm)	1. < 20 (6.1 m)	1. < 25%	1. < 5 (1.3 dm)
2. 5 - 8.9 (22.8 cm)	2. 20 - 39 (11.9 m)	2. 26 - 59%	2. 5 - 8.9 (2.3 dm)
3. 9 - 14.9 (38.1 cm)	3. 40 - 59 (17.9 m)	3. > 60%	3. 9 - 14.9 (3.8 dm)
4. 15 - 20.9 (53.3 cm)	4. 60 - 70 (21.3 m)		4. 15 - 20.9 (5.3 dm)
5. > 21 (53.3 cm)	5. 71 - 99 (30.2 m)		5. > 21 (5.3 dm)
	6. > 99 (30.2 m)		

Table 2. *Error matrix table of the aerial photo estimates of stand DBH. Shaded cells indicate stands that were correctly classified. Accuracy values for the table are overall accuracy (P_0) = 0.53, Tau (T_e) = 0.41, and Kappa (K) = 0.27.*

	Reference (ground) data							
	Class	1	2	3	4	5	User's Accuracy (%)	Row total
Photo-interpreted data	1			1			-	1
	2	1	2	2	1		33	6
	3		1	14	5	1	67	21
	4			8	10	2	50	20
	5				2	1	33	3
	Producer's Accuracy (%)	-	67	56	56	25		
	Column total	1	3	25	18	4		51

Table 3. *Allowable error for chi-square test. These values were used in the chi-square test of a hypothesized variance (Freese, 1960) for the interval attributes.*

Attribute	Allowable error
DBH	+/- 3" (7.62 cm)
Height	+/- 10' (3.05 m)
Crown diameter	+/- 4' (1.2 m)
Canopy closure	+/- 10%

with errors reported for images of this scale in the literature (Worley and Landis 1954, Worley and Meyer 1955, Spurr 1960). We rearranged the basic equations presented by Freese (1960) algebraically so the probability the estimate is within the allowable error of the ground value could be easily determined. The chi-square technique assumes a normal distribution of the data. Normal probability plots were examined to test this assumption.

The Tau coefficient (T_e) and the Z probability corresponding to the chi-square test of a hypothesized variance were the accuracy measures used to evaluate the estimation techniques.

Results

Photointerpretation error matrices

Table 4 summarizes the stands that were accurately interpreted and those that were mis-estimated for the interval attributes.

DBH. — The User's accuracy figures indicate we were best able to interpret DBH in classes 3 and 4. Over 80% of the stands were in these two classes (Table 2).

Height. — Estimates of stand height from the photos were generally underestimated, such that stands were frequently placed in lower classes by the photo-interpreter (Table 4). The User's accuracies for stand height classes 3 and 4 were greater than 50 percent, and 86 percent of the stands were in these two classes.

Crown diameter. — Photo estimates of average crown diameter tended to be low. Thirteen stands were underestimated while 7 were overestimated (Table 4). Like the estimates of DBH and height, the User's accuracies were high in the classes that contained the majority of the stands (classes 3 and 4).

Canopy cover. — Estimates of canopy cover did not appear to be biased (Table 4). All of the stands were either in class 2 or 3. Most of the underestimated stands were in class 3, whereas all of the overestimated stands were in class 2; thus interpreters were unable to distinguish classes 2 and 3. Accuracy is low considering that there were just three classes.

Canopy layers. — Most of the sample stands were single-layered (class 1) and there was substantial misclassification between one-and-two layered stands. Fifteen stands were classified as one-layered when they were actually two-layered, indicating that it was difficult to detect the second layer of stand canopy.

Cover type. — Over half of the sample stands were of the Douglas-fir cover type (27 out of 51); User's accuracy for Douglas-fir was high (74 percent). User's accuracy for subalpine fir was also high (75 percent). Five stands were incorrectly classified as Douglas-fir; conversely six Douglas-fir stands were erroneously classified as other cover types.

Error matrix coefficients calculated for each attribute show a similar trend as reported by Ma and Redmond (1995), with K coefficient values being the lowest, T_e values in the middle, and P_o values the highest (Table 5).

Chi-square test of a hypothesized variance

The P(Z) values were substantially higher than the corresponding Tau coefficient values (Table 6) for each attribute. The chi-square analysis was not applicable to the nominal attributes (canopy layers, cover type). Bias was detected in DBH, height, and crown diameter attributes; the P(Z) values (Table 6) were calculated with bias removed.

Table 4. *Summary of error matrix results for ordinal attributes. Each cell represents the number of stands.*

Attribute	Underestimated by > 1 class	Underestimated by 1 class	Accurately classified	Overestimated by 1 class	Overestimated by > 1 class	Sample size (stands)
DBH	3	9	27	12		51
Height	4	13	25	8	1	51
Crown Diameter	5	8	31	7		51
Canopy Cover		13	27	11		51
Canopy Layers		15	33		3	51

Table 5. *Error matrix accuracy coefficient values. The same error matrix for each attribute was used to calculate each coefficient.*

Variable	Kappa	Tau	P_o
DBH	0.27	0.41	0.53
Height	0.14	0.29	0.49
Crown diameter	0.42	0.51	0.65
Canopy cover	0.13	0.29	0.53
Canopy layers	0.18	0.50	0.63
Cover type	0.47	0.59	0.64

Table 6. *Summary table of the Tau and P(Z) accuracy measures for each attribute.*

Variable	Tau	P(Z)
DBH	0.41	0.69
Height	0.29	0.55
Crown diameter	0.51	0.84
Canopy cover	0.29	0.52
Canopy layers	0.50	N/A
Cover type	0.59	N/A

Discussion

Spurr (1960) reported on the tendency to underestimate crown diameter which agreed with our findings. He stated that thin branches cannot be resolved on the photos causing an underestimation of crown diameter. This may be one factor explaining the significant bias detected in the chi-square equation for this attribute. However, the quality of film and lenses has increased tremendously since the 1960s and low resolution may not be the cause of this underestimation.

The steep topography in parts of the study area resulted in shadows and changes in resolution that may have resulted in the overestimation of canopy cover. The detected error in our comparison might result from the tendency to underestimate canopy cover from the ground (Spurr, 1960). Estimates of canopy cover from aerial photographs may be more accurate than estimations from the ground. We found that the percentage of ground obscured by overstory canopy for the entire stand was easier to visualize from an aerial perspective than from a series of ground plots. This discrepancy may be partially responsible for the low reported accuracy for this attribute.

Estimating canopy layers from the photos was difficult and we often depended more on the site characteristics, topography, elevation, and aspect of the stand rather than the texture, tone or patterns seen on the photograph (Paine 1981, Spurr 1960). Site characteristics were obtained from topographic stand maps. Our knowledge of the plant ecological relationships to physical site characteristics played an important role in the interpretation. The reported accuracy ($T_e = 0.50$) was fairly high considering the difficulties described above. Perhaps greater familiarity with the vegetation conditions and how they relate to the physical characteristics of the stands would have resulted in an increase in accuracy for this attribute.

Over half of the stands were in the Douglas-fir cover type; the remaining six cover types had six or fewer stands in each cover type class. The high reported User's accuracy for subalpine fir may be because this species tends to have a distinctly pointed crown compared to the other species and therefore was easier to distinguish on the photos. We chose single species cover types because of the large variety of species mixes that occur in the study area. We felt that it would be easier to identify the major species on the photos rather than try to define species mixes by canopy cover composition. Like the stand layers attribute, the site characteristics of the stand were often critical in making cover type judgments from the photos. Accuracy ($T_e = 0.59$) is high when the difficulty of determining the dominant cover type species from the many mixed species stands is considered; the accuracy reported for cover type is not significantly different from that reported by Deegan and Befort (1990), who analyzed data from 1:15,840 scale black and white infrared photos and ground plots in northern Minnesota ($T_e = 0.54$).

We detected significant bias in the chi-square calculations for DBH, height, and crown diameter; this may be partially due to the growth of the trees since the time the photos were taken. The photos were taken in August 1990 and the field inventory was conducted in August - September 1995, which would have allowed growth to occur.

For all of the attributes, the majority of stands were classified into one or two classes, with a few stands scattered among the remaining classes. In many of the under-represented classes, small sample sizes allowed for greater errors. For example, the DBH class 2 producer's accuracy would be reduced from 67 percent to 33 percent if just one of the correctly classified stands had been misclassified (Table 2). A larger number of sample stands would presumably add stands to the under-represented classes and increase reliability of the producer's and user's accuracy figures. The User's accuracies for the classes where most of the stands were placed by the reference data were relatively high for most of the attributes, suggesting that our photo-estimating techniques may be more accurate than the error matrix coefficients indicated.

Congalton (1991) points out that traditional statistical methods for determining sample size are not appropriate for error matrix tables and that a minimum of 50 samples per error matrix category is recommended. Adhering to this recommendation would mean field sampling 250 stands (half the stands in the study area) to populate an error matrix with five categories. We sampled 51 stands for practical reasons (field time, expense). We intended to sample 50 stands, one extra stand was accidentally sampled.

Selection of class breaks and the number of classes can have a significant effect on error matrix accuracy coefficients. We selected these error matrix classes based upon their utility to Salish/Kootenai forestry personnel and because the class boundaries seemed logical for this region. The same data aggregated into a different number of classes may result in different accuracy coefficient values (Openshaw 1987). It is interesting to speculate on whether collecting data in an ordinal form would have any effect on error matrix accuracy. Biging *et al.* (1991) interpreted stands into broad classes using methods and imagery similar to this study; reported accuracies are somewhat higher. This may be because their classes were much broader than ours. Placing stands directly into categories seems to be popular (Lehmkuhl *et al.* 1994), probably because of the relative ease and speed with which stands are interpreted. In short, manipulating the number and width of classes and the class breaks can have a significant impact on accuracy and should be considered prior to data collection or aggregation into classes.

The observed tendency for the P(Z) values to be higher than the corresponding Tau values is because the two methods measure accuracy in different ways. The P(Z) value is the probability that the estimate is within the allowable error of the ground estimate. Thus, with a reported P(Z) value of 0.68, in 68 out of 100 stands we would expect the estimate to be within the allowable error of the ground value. Error matrix values (T_e) indicate the percent chance that a stand is in the correct class. They can also be interpreted as the percent improvement over a random placement of stands into cells in the error matrix table. It seems that the two measures should be closer than the results (Table 6) indicate; the higher P(Z) values reported may be because this technique considers the difference between each attribute pair (estimated - observed) whereas the error matrix technique lumps the interval attribute pairs into categories. In directly comparing the predicted versus estimated values, the effects of gross estimation errors in any one stand may be smoothed over by other, more accurately interpreted stands.

The obvious difference between the two measures is that one measures interval scale data (chi-square) and the other measures categorical data. Collecting interval scale data allowed us to collapse the data using many different classifications. Thus, if a particular model or analysis requires different class breaks, we could collapse the interval data into the appropriate categories. This freedom is lost if the data were collected in categories.

Although direct comparison of the two accuracy assessment techniques is not possible, the success of the estimating techniques in predicting the ground values of the interval attributes may be higher than the Tau coefficients indicate because of the problem of low sample sizes in many of the classes. The sample sizes recommended by Congalton (1991) are certainly reasonable for satellite images where the population consists of thousands pixels, but they are impractical when the experimental unit is the stand, not the pixel. We recommend using the chi-square test when few ground plots are available.

A question that a land manager must ask when faced with the need for landscape-level data is whether the increased accuracy of a ground-based inventory method justifies the extra expense. Photointerpretation is a cost-efficient method of obtaining data, especially if imagery does not have to be purchased. Project objectives are critical to this discussion of efficiency versus accuracy. Resource managers may accept a higher level of error when the goal is estimation of the areal extent and arrangement of various structure and cover types in broad classes across a large landscape. When a smaller landscape is being assessed for management planning, the level of acceptable error may be lower, perhaps to the point of justifying a ground survey of all stands. The objectives may involve collapsing attribute data into a stand type classification based on two or more of the attributes. In this case, the accuracies of each of the attributes used in the classification would be multiplied for the estimated accuracy of the stand classification. For example, if a stand type classification is based on diameter class and cover type and the Tau coefficients for these two attributes are 0.75 and 0.80, then the accuracy coefficient of the classification would be (0.75)(0.80) = 0.60.

A reasonable approach to landscape assessment would be to combine remotely-sensed data, existing ground data (stand exams), and field survey data into the landscape assessment, as in Morrison (1994). Ground data could be used to conduct an assessment of the photo-interpreted stands provided that the inventory methods were compatible, or to train photo-interpreters before data collection from the photos.

Conclusions

As more is learned about landscape-level processes, there will be a greater need for efficient methods of collecting data across landscapes. Satellite image technology is progressing, but accurate classification of some forest structure attributes has not been attained (Spies 1994, Cohen 1994). When compared to digital image processing, photointerpretation is a relatively low cost method that is within the means of most land management agencies. A multi-stage approach is probably best; satellite images may be used for data collection in broad classes across large areas, and aerial photographs for more specific data on mid-scale landscapes. For detailed, site-specific data field inventory will be necessary.

In this study, we used photointerpretation methods similar to those used by most land management agencies. Other methods of collecting information from aerial photographs (Martin and Gerlach 1981, Teuber 1983) are certainly valid, but the methods used in this study seem to be commonly used in operational landscape assessments (Lehmkuhl *et al.* 1994).

Accuracy assessments should be conducted on all projects where data from remotely sensed images are used. The accuracy assessment methods we describe could easily be implemented on most data sets. The number of field plots or sample stands may be restricted by expense, but as few as 50 plots (stands) provide insight into errors and misclassifications. Existing stand inventory data may be used in assessing the accuracy of remotely sensed or modeled data; this would minimize the amount of new field data needed. Knowledge of the accuracy of remotely sensed data will give increased confidence in decisions based upon the data and also provide feedback to improve future interpretation and classification projects.

Forest structure attributes frequently are the defining characteristics for landscape elements such as the patch, matrix and corridor (Forman 1995). Landscape models have been developed to meet the challenge of implementing ecosystem management; some examples include SIMPPLE (Chew 1995), FIRE-BGC (Keane *et al.* 1996), and FRAGSTATS (McGarigal and Marks 1995) These models frequently utilize remotely sensed data of these forest landscape elements. The accuracy of these input data and the effect of errors on model output are frequently overlooked (Hess 1994). The application of some models may be pointless and misleading if the input data are not accurate to a certain extent. Land cover weighting schemes, which are often used in wildlife habitat models, can be adjusted based on observed classification error (Prisley and Smith 1987). Further research into the effect of errors in spatial data on landscape models, and methods to adjust models based on these errors, is needed.

Often land managers have data from several different sources at their disposal when making resource decisions. They need a method to weight these different data sets; an accuracy assessment provides a good basis for weighing the value of remotely sensed data (McCloy 1995). Resource professionals will continue to look to remote sensing technology as a cost-effective way to obtain data as they assess forest resource patterns and processes across larger landscapes. Awareness of the limitations of this technology and of potential inaccuracies in these data are critical factors to consider when decisions are to be made based on a landscape-scale analysis.

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