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USDA Forest Service Rocky Mountain Region Forest Health Aerial Survey Accuracy Assessment 2005 Report

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USDA Forest Service Rocky Mountain Region Forest Health Aerial Survey Accuracy Assessment 2005: *a Pilot Project*

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Introduction

Aerial sketchmapping is a remote sensing technique for observing forest damage caused by insects, disease or other damaging agents from an aircraft and documenting them manually onto a map. Forested areas exhibiting damaged or dying foliage are delineated by points or polygons onto a paper map or computer touch screen. When feasible, the numbers of affected trees per point or polygon are estimated. In the western U.S., aerial surveys have been performed annually to locate areas of forest pest activity. Recently, aerial surveys have been used to monitor and report on the health of forest ecosystems as part of the national Forest Health Monitoring (FHM) program. The relative accuracy of aerial sketchmap data is therefore of interest in a least two regards.

Classification error is a term used in remote sensing when a pixel, determined by ground observation to be in one category, is assigned to another category during the classification process (Campbell 2002). It is a means of measuring the accuracy of a map by comparing it to reference data. Contrasting observed versus expected classification of pixels provides a statistical basis for accuracy assessment.

In the 2005 field season, a pilot study was initiated in the Rocky Mountain Region to assess the accuracy of aerial survey data using the *error or contingency matrix* approach. Levels of aerial survey accuracies, once derived, could then be incorporated into the aerial survey metadata to assist with data interpretation and use. Metadata describes a data set and often includes information on data definitions and data accuracies. While the application of error matrices to asses the accuracy of aerial survey data is new to the United States, this approach has been used in southern Brazil to successfully calculate aerial survey accuracies (de Oliviera et al. 2004).

The goal of this project was to determine the spatial and classification accuracies of select categories of aerial survey observations. No attempt was made to assess the accuracies of the mortality level estimates commonly attributed during aerial surveys.

Materials and Methods

Geographic Area

The 2005 aerial detection survey encompassed much of the forested lands within the USDA Forest Service's Rocky Mountain Region except the state of Kansas and the Gunnison National Forest and Sopris Ranger District in central Colorado (Fig. 1). In 2005 in the Rocky Mountain Region, approximately 42.8 million acres were surveyed resulting in 26,735 mapped observations.

Sample Design

We set a goal to visit between 20 and 30 ground points per national forest during the 2005 field season. As 15 of the region's 16 national forests were scheduled to be surveyed, we anticipated that ground information would be obtained from between 300 and 450 sites.

The following eight categories of commonly mapped forest pests/ pest complexes included in the accuracy assessment:

Douglas-fir beetle in Douglas-fir (DFB)
Spruce beetle in Engelmann spruce (SB)
Mountain pine beetle in Ponderosa pine (MPB-PP)
Mountain pine beetle in lodgepole pine (MPB-LPP)
Mountain pine beetle in limber and/or whitebark pine (MPB-WP)
Subalpine fir mortality, principally a combination of western balsam bark beetles and *Armillaria* sp. root disease (SAF)
Ips sp. beetles in Ponderosa and jack pines (IPS)
No damage (NO DAM).

A two-pronged approach was used to generate sample points in order to eliminate bias by field crew personnel, some of whom also performed the aerial surveys. First, area-weighted-probability random sample points were generated within the aerial survey damage polygons. These points were constrained as follows: points had to fall within the defined damage polygons equaling or exceeding aerial estimates of 1 faded tree-per-acre; points had to fall within damage polygons having only one causal agent attribute per polygon; points had to fall on land administered by the USDA Forest Service; and points had to fall within 1.5 miles of a primary or secondary road. Next, an equal number of secondary points were generated in areas mapped as having "no damage". These points were constrained as follows: points had to fall within vegetation polygons corresponding to the damage categories being assessed; points must fall on land administered by the USDA Forest Service; and points had to fall within 1.5 miles of a primary or secondary road. With this design, there would be a 50% chance that any generated point would be contained within an aerial survey polygon. Field crew personnel had no advance knowledge of the status of these generated points.

Field Sample

The selected points were visited by field personnel using Garmin *etrex* GPS units. Since one acre represents the defined minimum mapping unit of the aerial forest health survey, each GPS-identified point was considered to represent the southwest corner of a square acre on the ground. Field personnel counted and recorded all overstory trees exhibiting discolored or "fading" foliage contained in the square acre. For every faded tree, the species and associated damage causing agents were recorded. It was also noted if the fading was recent or old. The following supplementary items were also recorded:

Presence of green infested trees
Overstory species composition
Understory species composition.

The crews also noted the presence of fading trees outside of the acre plot, recorded their species, and estimated their distance from the plot boundary.

Additional Data

To increase the sample size and demonstrate the feasibility of incorporating auxiliary data into the error matrix, a total of 24 additional data points were added to the sample. The data points, which were collected for the Dillon Ranger District's *Lower Blue* and *Dillon Reservoir Analysis Areas* as part of a salvage/ sanitation program to reduce tree losses to the mountain pine beetle, were derived randomly and consisted of georeferenced variable radius plots with information on currently infested and year-old mountain pine beetle-killed trees. Plots with positive values for year-old mountain pine beetle-killed trees were selected for a site specific comparison with the aerial survey data. In effect, these plots were added to the damage point pool that was generated as described in the "Sample Design" section above. For this additional data, ground plots were located and measured independently of and then compared with aerial survey data for that area.

Error Matrix

Data was input into a Microsoft Excel spreadsheet formatted into three columns; one containing the pest category from the ground plot, one containing the pest category from the corresponding aerial survey map, and a count of each categorical combination of the values in columns 1 and 2. This file was imported into a Microsoft Access database to produce a cross tabulated matrix which we used as the error matrix.

The error matrix containing rows, columns, row marginals, column marginals, and diagonals was used to calculate the following statistics: percentage correct or overall accuracy, commission error (EC), omission error (EO), and the κ (kappa) statistic. Errors of commission occurred when an aerial survey observation was mapped and classified into a category that differs from the category found on the ground. Errors of omission occurred when a category other than "no damage" was found on the ground but no observation was placed on the aerial survey map.

Producer accuracies (PA) and consumer accuracies (CA), which were also calculated, will only be briefly discussed within this paper as they are terms expressly related to map production. Producer and consumer accuracies are basically the reciprocals of omission and commission error. For further information on producer's and consumer's accuracies refer to Campbell (2002).

The overall accuracy was calculated by dividing the total number of correct classifications, obtained by summing the diagonal cell values, by the total number of records. CA was calculated by dividing the diagonal by its corresponding column marginal. PA was calculated by dividing the diagonal by its corresponding row marginal. EO was calculated by subtracting the PA from 1. EC was calculated by subtracting the diagonal from the column marginal divided by the row marginal (Campbell 2002). CA, PA, EO, and EC were all expressed as percentages.

The κ (kappa) statistic was used to quantitatively assess the error matrix by determining the degree of association between the two set of observations. Specifically, κ measures the difference between the agreement of the ground and aerial survey observations with what would have been attained by a chance assignment of randomly drawn polygons to randomly selected pest categories. The following equation was used to calculate κ (Campbell 2002):

$$\kappa = \frac{\text{observed - expected}}{\text{1 - expected}}$$

After statistics were calculated for the original data, error matrices were recalculated using tolerances of 50 meters and 500 meters. Relaxing the spatial tolerance for aerial survey observations acknowledges the spatial error inherent in the process of sketchmapping and allows a more complete consideration of the sketchmapper's intent. For example, if a faded tree was noted to be within 50 meters of an acre plot void of damage, that acre plot would change categories from "no damage" to the appropriate damage category represented by that nearby faded tree. Similarly, if faded trees were found within a ground plot originally classified as having no damage from the aerial survey, but these faded trees were within 50 meters of an aerial survey damage polygon, that ground plot's damage category would be changed from "no damage" to the nearby aerial survey polygon's category in the relaxed tolerance error matrix.

Results

Between July 26 and November 10, 2005 a total of 233 plots were measured by field crews across the Rocky Mountain Region (Fig. 1). Due to time and staffing constraints, random points were only collected on 10 of the intended 15 National Forests. Of the 233 random plots visited, 145 were classified by the aerial survey as having no damage and 88 were categorized as exhibiting tree mortality (Fig. 2). The 24 auxiliary plots were incorporated into the error matrix to bring the total number of plots used to 257.

Figure 1. Map of accuracy assessment plot location within the USDA Forest Service's Rocky Mountain Region.

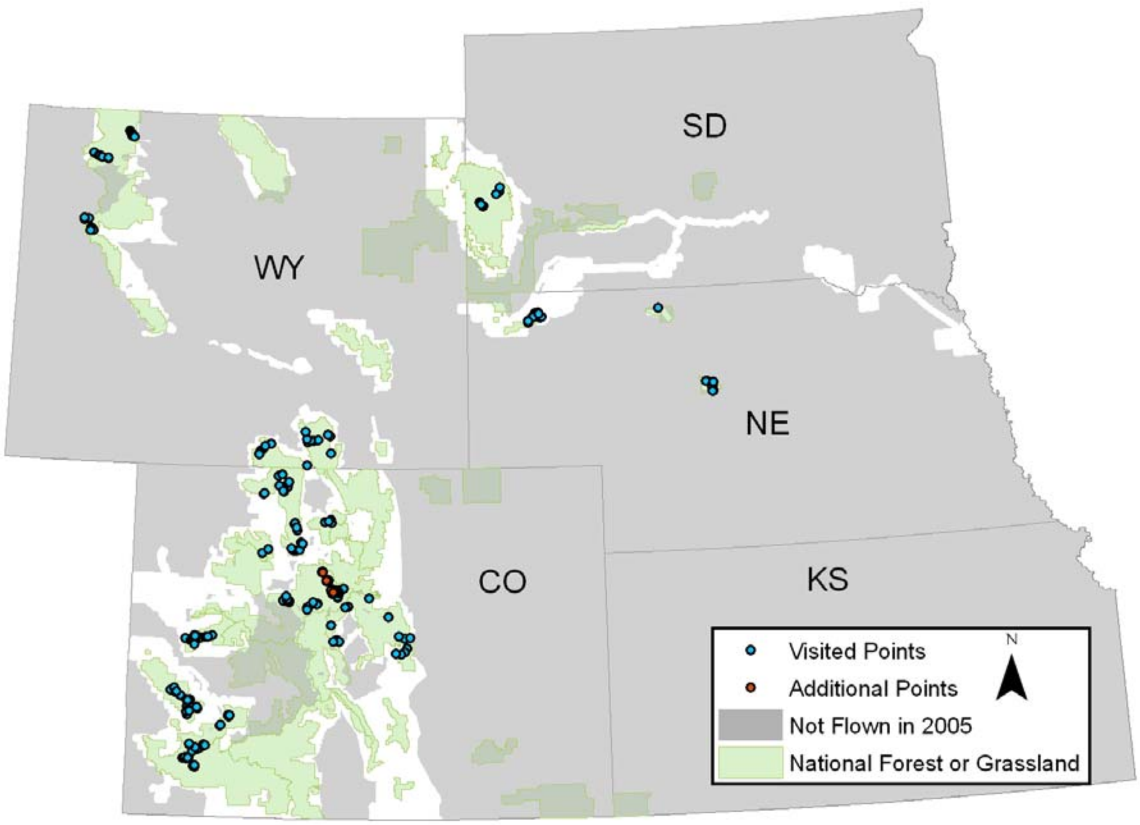
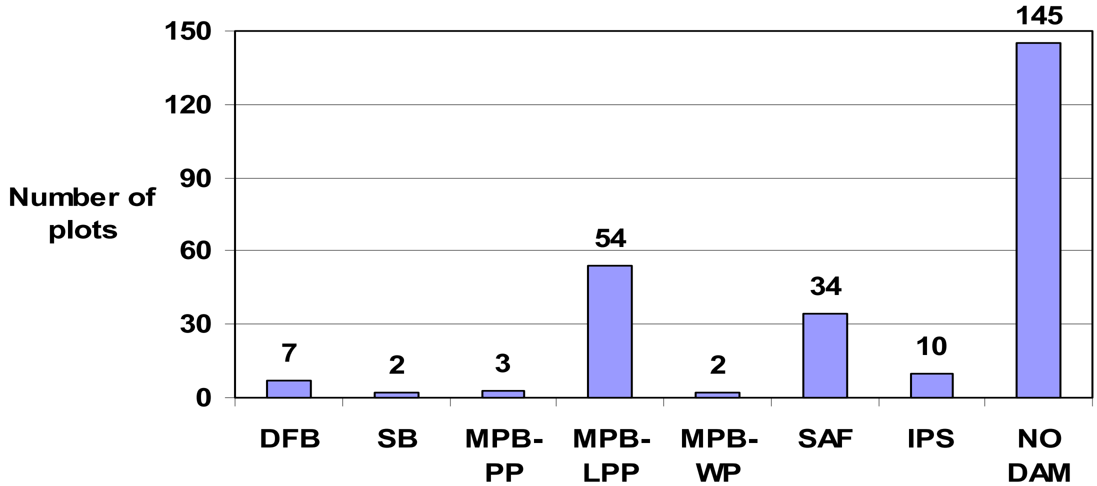


Figure 2. Histogram of visited ground survey plots by non-damage and damage causal agents as determined by field sampling of randomly selected aerial survey observations (N = 257).



Results of the accuracy assessment are shown in tables 1-4. Accuracy statistics improved with increasing spatial tolerance. The overall aerial survey accuracy when no spatial tolerances were allowed was 61.1%. When a spatial tolerance of 50 meters and 500 meters was allowed, the aerial survey accuracy improved to 67.7% and 78.6%, respectively. Overall κ values for the three error matrices indicate the aerial survey achieved an accuracy that was between 37.2% and 69.3% better than what would be expected from the chance assignment of randomly drawn polygons to randomly selected pest categories (Table 1). κ analysis (Bishop et al. 1975) confirmed that the three error matrices were statistically different from each other.

Table 1. Summary of statistics for three error matrices used for accuracy assessment of the 2005 Rocky Mountain Region's forest health aerial survey.

Tolerance	Observed accuracy (%)	Expected accuracy due to chance (%)	κ	Variance of κ	Z (κ)*
0	61.09	38.06	0.3718	0.0024	7.6336
50 meters	67.70	34.95	0.5035	0.0020	11.2274
500 meters	78.60	30.20	0.6933	0.0013	19.0499

*a z value ≥ 1.96 indicates that the observed agreement is significantly better than chance agreement at the 95% confidence level (Ciesla 2000).

Categorical Results – Error Matrix with no Spatial Tolerance
With no spatial tolerances allowed, the NO DAM category had the lowest omission error (32.4%). The lowest commission error (14.3%) belonged to the DFB category. The SB and the MPB-WP categories both had highest omission errors (100%). The highest commission error belonged to the SB category (250%).

Categorical Results – Error Matrix with a 50 meter Spatial Tolerance
When a 50 meter spatial tolerance was allowed, the MPB-PP category had the lowest omission error (20%). The lowest commission error (14.3%) once again belonged to the DFB category. The SB and the MPB-WP categories once again had the highest omission errors (100%). The highest commission error once more belonged to the SB category (300%).

Categorical Results – Error Matrix with a 500 meter Spatial Tolerance
When a 500 meter spatial tolerance was allowed, the MPB-PP category once again had the lowest omission error (0%). The MPB-LPP category had the lowest commission error (13.1%). The SB and the MPB-WP omission errors improved to 50%. The highest commission error again belonged to the SB category (400%).

Table 2. Error matrix comparison of aerial survey results to ground reference results without spatial tolerances. DFB = Douglas-fir beetle in Douglas-fir, SB = spruce beetle in Engelmann spruce, MPB-PP = mountain pine beetle in Ponderosa pine, MPB-LPP = mountain pine beetle in lodgepole pine, MPB-WP = mountain pine beetle in limber pine, SAF - subalpine fir mortality (principally western balsam bark beetle and/or *Armillaria* sp. Root disease), IPS = *Ips* sp. bark beetle in Ponderosa or jack pines, NO DAM = no damage. CA = consumer's accuracy, PA = producer's accuracy, EO = errors of omission, EC = errors of commission.

Error Matrix - No Tolerance

		Aerial Survey											
		DFB	SB	MPB-PP	MPB-LPP	MPB-WP	SAF	IPS	NO DAM	Totals	PA	EO	EC
Ground Data	DFB	**2**							5	7	28.6%	71.4%	14.3%
	SB								2	2	0.0%	100.0%	250.0%
	MPB-PP			**2**					1	3	66.7%	33.3%	133.3%
	MPB-LPP				**35**				19	54	64.8%	35.2%	27.8%
	MPB-WP								2	2	0.0%	100.0%	50.0%
	SAF		1		2	1	**15**		15	34	44.1%	55.9%	32.4%
	IPS							**5**	5	10	50.0%	50.0%	140.0%
	NO DAM	1	4	4	13		11	14	**98**	145	67.6%	32.4%	33.8%
	Totals	3	5	6	50	1	26	19	147	257			
	CA:	66.7%	0.0%	33.3%	70.0%	0.0%	57.7%	26.3%	66.7%				

Overall Classification Accuracy: 61.1%
Overall Kappa Statistic: 0.372

Table 3. Error matrix comparison of aerial survey results to ground reference results with a spatial tolerance of 50 meters. DFB = Douglas-fir beetle in Douglas-fir, SB = spruce beetle in Engelmann spruce, MPB-PP = mountain pine beetle in Ponderosa pine, MPB-LPP = mountain pine beetle in lodgepole pine, MPB-WP = mountain pine beetle in limber pine, SAF - subalpine fir mortality (principally western balsam bark beetle and/or *Armillaria* sp. Root disease), IPS = *Ips* sp. bark beetle in Ponderosa or jack pines, NO DAM = no damage. CA = consumer's accuracy, PA = producer's accuracy, EO = errors of omission, EC = errors of commission.

Error Matrix - 50 meter Tolerance

		Aerial Survey											
		DFB	SB	MPB-PP	MPB-LPP	MPB-WP	SAF	IPS	NO DAM	Totals	PA	EO	EC
Ground Data	DFB	**2**							5	7	28.6%	71.4%	14.3%
	SB								2	2	0.0%	100.0%	300.0%
	MPB-PP			**4**					1	5	80.0%	20.0%	40.0%
	MPB-LPP				**43**				15	58	74.1%	25.9%	19.0%
	MPB-WP								2	2	0.0%	100.0%	50.0%
	SAF		2		2	1	**17**		13	35	48.6%	51.4%	31.4%
	IPS						1	**10**	4	15	66.7%	33.3%	60.0%
	NO DAM	1	4	2	9		10	9	**98**	133	73.7%	26.3%	31.6%
	Totals	3	6	6	54	1	28	19	140	257			
	CA:	66.7%	0.0%	66.7%	79.6%	0.0%	60.7%	52.6%	70.0%				

Overall Classification Accuracy: 67.7%
Overall Kappa Statistic: 0.504

Table 4. Error matrix comparison of aerial survey results to ground reference results with a spatial tolerance of 500 meters. DFB = Douglas-fir beetle in Douglas-fir, SB = spruce beetle in Engelmann spruce, MPB-PP = mountain pine beetle in Ponderosa pine, MPB-LPP = mountain pine beetle in lodgepole pine, MPB-WP = mountain pine beetle in limber pine, SAF - subalpine fir mortality (principally western balsam bark beetle and/or *Armillaria* sp. Root disease), IPS = *Ips* sp. bark beetle in Ponderosa or jack pines, NO DAM = no damage. CA = consumer's accuracy, PA = producer's accuracy, EO = errors of omission, EC = errors of commission.

Error Matrix - 500 meter Tolerance

		Aerial Survey											
		DFB	SB	MPB-PP	MPB-LPP	MPB-WP	SAF	IPS	NO DAM	Totals	PA	EO	EC
Ground Data	DFB	**5**							2	7	71.4%	28.6%	14.3%
	SB		**1**						1	2	50.0%	50.0%	400.0%
	MPB-PP			**5**						5	100.0%	0.0%	40.0%
	MPB-LPP				**53**	2	1		5	61	86.9%	13.1%	13.1%
	MPB-WP					**1**			1	2	50.0%	50.0%	150.0%
	SAF		4		1	1	**24**		9	39	61.5%	38.5%	17.9%
	IPS						1	**15**	3	19	78.9%	21.1%	26.3%
	NO DAM	1	4	2	7		5	5	**98**	122	80.3%	19.7%	17.2%
	Totals	6	9	7	61	4	31	20	119	257			
	CA:	83.3%	11.1%	71.4%	86.9%	25.0%	77.4%	75.0%	82.4%				

Overall Classification Accuracy: 78.6%
Overall Kappa Statistic: 0.694

Discussion

By inspecting the error matrices, inferences can be made as to how well the aerial survey represented truth on the ground. Diagonal values display the agreement between the expected classifications from aerial survey and the observed classifications from field-sampling, while off-diagonal values represent disagreement. Row marginals represent the number of points (acres) by category from the field samples. Column marginals represent the number of points (acres) assigned to each class as defined by the aerial survey. For example, looking at the error matrix in Table 4 reveals that of the 61 points (acres) determined as MPB-LPP from the ground sample (row 4 column 9), 53 of those points (acres) were correctly classified by the aerial survey (row 4 column 4). Reading successive values along this row shows the field sampling results *that differed from the aerial survey classification* (2, 1, and 5 points belonging to the MPB-WP, SAF, and NO DAM ground categories respectively). These numbers are used to calculate errors of omission. Reading successive values down the column from this diagonal reveals the values classified by the aerial survey *that differed from the field sample* (1 and 7 points belonging to the aerial survey categories SAF and NO DAM respectively). These numbers are used to calculate errors of commission.

Due to the small number of sample points collected in the DFB, SB, MPB-PP, and MPB-WP classes, their true accuracies remain uncertain. These categories accounted for some of the highest sources of error which may be due to the small sample size as well as other factors such as difficulty discerning pest signatures from the air and/ or a high variability of within-polygon mortality distribution. For example, Douglas-fir trees killed by DFB tend to occur in aggregated spatial patterns. Often, when the sketchmapper is faced with delineating these areas as quickly as possible while flying at over 100 miles-per-hour, the aggregations of mortality are "lumped" into larger polygons. Large portions of the resulting polygons will contain areas not affected by the insect which in turn diminishes the spatial accuracy of the classification. Other signatures, such as spruce beetle mortality, are difficult to map due to subtle color changes and a narrow biological window for detection. Faded needles on a dead spruce tree will only remain for several weeks, whereas pine needles remain on a dead pine for at least two years.

A general target for accuracy assessments found in remote sensing literature is an overall accuracy of >85% where all of the classes have relatively even accuracy levels, *but it need be stressed that these target accuracies are seldom attained* (Foody, 2002). While digital image classification is regarded to be quantitative in nature, aerial sketchmapping is not. It is commonly considered as much an art as it is a science (McConnell et. al 2000). If quantitative methods recurrently fall below the 85% mark then we suggest that aerial sketchmapping, a qualitative method, have an appreciably lower target accuracy of 70%.

The following is an interpretation for κ values is given by Landis and Koch (1977):

Strong Agreement = $\kappa > 0.80$
Moderate Agreement = $\kappa \geq 0.40$ and ≤ 0.80
Poor Agreement = $\kappa < 0.40$

The κ value for the error matrix with no spatial tolerance was 0.372 which, according to Landis and Koch (1977), would be a *poor agreement,* although close to the *moderate agreement's* lower limit. κ values for the 50 and 500 meter error matrices were 0.504 and 0.694 respectively, both falling within Landis and Koch's (1977) *moderate agreement* range.

Because only the MPB-LPP, SAF, IPS, and NO DAM categories had sufficient sample sizes to infer class accuracies, we will limit the discussion to these classes:

For the error matrix comparison of aerial survey results to ground reference results without spatial tolerances (Table 2), the omission errors for the MPB-LPP, SAF, IPS, and NO DAM classes were 35.2%, 55.9%, 50.0%, and 32.4% respectively. Commission errors for the MPB-LPP, SAF, IPS, and NO DAM classes were 27.8%, 32.4%, 140.0%, and 32.8% respectively. Accuracies (refer to the CA and PA results in Table 2) for the MPB-LPP and NO DAM classifications met or came near our target accuracy of 70%.

High SAF omission and commission errors can be attributed to a tactic known to sketchmappers and aerial photo-interpreters as "lumping". Subalpine fir mortality is pervasive throughout its cover type and the many, often scattered, spots of SAF mortality are commonly "lumped" by sketchmappers into very large polygons (2005 mean polygon size = 77.42 acres). It is also sometimes ignored by sketchmappers when tree species that are considered by land managers to be more important are dying in adjacent areas (low mapping priority). This explains why omission errors are much higher than commission errors in the SAF class.

The IPS classification had an omission error of 50.0% and a commission error of 140.0%. Because the majority of mortality caused by *Ips* spp. within the region is found within small, isolated pockets (2005 mean polygon size = 3.54 acres), the high commission error is likely caused by difficulties in precisely delineating these small areas onto the frequently used 1:100,000 scale base map during a sketchmap survey, resulting in the spatial displacement of these polygons. Pin-pointing these smaller infestations would be made easier by using a finer scale base map, such as 1:24,000 scale, or one providing more detail, such as digital ortho quads (DOQs), satellite imagery, or scanned aerial photography.

When a spatial tolerance of 50 meters was allowed (i.e., the one acre minimum map unit was buffered by an additional 50 meters), the omission error improved to 25.9%, 51.4%, 33.3%, and 26.3% for the MPB-LPP, SAF, IPS, and NO DAM classes respectively (Table 3). Commission errors improved to 19.0%, 31.4%, 60.0%, and

31.6% for the MPB-LPP, SAF, IPS, and NO DAM classes respectively. By allowing a spatial tolerance of 50 meters, accuracies (refer to the CA and PA results in Table 3) for the MPB-LPP and NO DAM categories exceeded our 70% target accuracy mark and the SAF and IPS classes were significantly improved, moving closer to our target mark. The high commission error of the IPS class caused by polygonal displacement was improved by allowing a spatial tolerance of 50 meters.

Accuracies (refer to the CA and PA results in Table 4) again markedly improved when the spatial tolerance was increased to 500 meters. Accuracies for the MPB-LPP and NO DAM classes exceeded 80%. Accuracies for the IPS class exceeded 70% and the SAF class nearly missed our target of 70%. The SAF class's omission error remained high (38.5%) which was again due to its lower mapping priority.

One goal of this pilot study was to integrate aerial survey accuracy assessment results into the metadata. The three error matrices will now be incorporated into the metadata to give users a better understanding of the strengths and limitations of using aerial survey data. Aerial survey data is reliable when used and viewed at course scales (78.6% accurate ±500 meters) and moderately acceptable when used and viewed at intermediate scales (67.7% accurate ±50 meters). When site specific analyses are required, aerial survey data may not be the best option with an accuracy rate of only 61.1%.

It needs to be stressed that this study assessed the accuracy of the broad annual "overview" aerial survey where much ground is covered within a narrow time frame (42.8 million acres were covered by aerial surveyors between July 7 and September 30, 2005). A "special" aerial survey, where helicopters may be used along with fine scale maps to pinpoint infestations within project sized areas (< 100,000 acres), would probably produce results sufficiently acceptable for site specific analyses.

Another goal of our pilot project was to determine the feasibility of implementing an annual program to measure accuracies for each year's data set. The methodology we applied, along with some sampling refinements suggested later, would be a functional solution for assessing the aerial survey data's site-specific categorical accuracies. Field personnel spent approximately 650 person-hours collecting the reference data over the course of three months. Additionally, our GIS specialist spent approximately 300 person-hours generating the sample points and creating maps for the field crews. The feasibility of incorporating auxiliary data into the error matrix from other sources was also demonstrated which would reduce sampling costs. It is again worth reiterating that this approach only estimates categorical accuracies and does not infer accuracies associated with mortality estimates – addressing this question would prove more costly as it would require using satellite imagery, aerial photography and/or a massive effort on the ground.

Improving the Sampling Design

Our sample was stratified into two classes: damage and no damage. In essence, the damage categories were proportionally stratified by the areal extent of each class included in the accuracy assessment. Because the areal extent of damage from subalpine fir decline and mountain pine beetle in lodgepole pine is greatest within the region, these classes were over represented by the field sample leaving other classes, such as Douglas-fir beetle and spruce beetle, underrepresented. For future assessments, we advocate stratifying the damage class equally to ensure equal class representation. The total number of points to be sampled (N) can be calculated using probability theory (Scheaffer et. al. 1996):

$$N=\frac{z^2(p)(q)}{E^2}$$

where: p= expected accuracy, q= 100-p, E=allowable error, z= 2 (95% 2 sided-confidence level). With an expected accuracy of 70% and a 5% allowable error, 336 points would need to be sampled. One-half of these points (168) should be generated from the no damage category to ensure minimal sampling bias. The other half should be equally allocated to each damage class; in our case equaling 24 points per class for each of our 7 damage classes. This improvement to the sampling design would ensure that each class would have sufficient samples to infer class accuracies.

Conclusion

The error matrix traditionally used for assessing remote sensing classifications can also be applied to the assessment of aerial survey class accuracies. Supplemental data can also be incorporated into the error matrix to further reduce costs. A simple improvement to the sampling design was suggested to prevent under-representing classes having lesser areal extents.

Aerial survey accuracy results ranged from an estimated 61.1% accurate based on site-specific comparisons to an estimated 78.6% accurate when a 500 meter spatial tolerance was allowed. Results of the accuracy assessment will be incorporated into the aerial survey's metadata in order to give users a better understanding of its limitations and value.

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