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measurement

Estimating Forestland Area Change from Inventory Data

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Simple methods for estimating the proportion of land changing from forest to nonforest are developed. Variance estimators are derived to facilitate significance tests. A power analysis indicates that 400 inventory plots are required to reliably detect small changes in net or gross forest loss. This is an important result because forest certification programs may require additional precautions when wood from areas where forestland area loss is occurring is harvested or purchased. Net and gross forest area loss must be clearly differentiated to avoid confusion. Estimates of gross forest cover loss from satellite data should not be equated with net forest area loss, which can be better determined from remeasured forest inventory plots. Simultaneous tests of net and gross forest area loss should use multiple comparison procedures to ensure that overall error rates are correct. Examples of applications demonstrate how to properly perform these tests. A simulated example is used to verify that the variance estimators are reliable. An application to USDA Forest Service inventory data indicates that neither net nor gross forest loss at the state level was statistically significant for states that had sufficient remeasured plot data publicly available when this analysis was done.

Keywords: forest conservation, Forest Inventory and Analysis data, land use change, gross forest cover loss

The rate of forestland area change and conversion between forest and nonforest use is of interest for assessing sustainability, for carbon accounting, and for forest certification purposes. For example, forest products companies that use the Forest Stewardship Council (FSC) Controlled Wood Standard (FSC 2011) must consider the rate of forestland conversion in ecoregions from which they procure wood. If forest conversion rates exceed certain thresholds, users of this standard must take steps to ensure that their practices do not contribute to forest conversion.

To estimate forest conversion rates, practitioners may use remotely sensed data, such as National Land Cover Data (NLCD; Multi-Resolution Land Characteristic Consortium 2006), or data collected from ground plots such as those provided by the USDA Forest Service Forest Inventory and Analysis Program (FIA). With satellite data, it is not always possible to differentiate between pixels that have temporarily lost overstory trees due to fire or logging and pixels that have actually moved into a nonforest use (Reams et al. 2010). FIA data are gathered by ground crews who annually visit a subset of permanent field plots distributed across the nation (approximately 1 every 6,000 acres). FIA data probably provide an unbiased estimate of forestland area change, because FIA field crews are trained to differentiate sites where overstory trees have been harvested from those that have moved into a nonforest use. FIA defines forestland as land that is at least 10% stocked with trees of any size or that formerly had such tree cover and is not currently developed for a nonforest use. The minimum area for classification of forestland is 1 acre (USDA Forest Service 2004).

During the late 1990s, FIA began a new annual inventory system that includes the measurement of a fixed proportion of field plots in each state each year. Remeasured plot data are not yet available from Western states, which limits where forest conversion rates can be reliably estimated using FIA data. However, remeasured FIA data will become available for the entire United States and all ecoregions over the next few years, with Wyoming and New Mexico taking somewhat longer.

Methods for estimating a change in condition between two times from remeasured forest inventory plots have been discussed previously (Van Deusen and Roesch 2009, Roesch and Van Deusen 2012). Van Deusen and Roesch (2009) developed a maximum likelihood method for estimating the proportion of annual forest inventory plots that change from one state to another between remeasurements. An approximate estimator for standard errors (Van Deusen and Roesch 2009) was also provided. A sim-

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pler tabular approach for estimating conversion rates was presented (Roesch and Van Deusen 2012), but no method to estimate standard errors was provided. This is needed to perform *t*-tests to determine whether net loss estimates exceed zero.

We develop a variance estimator and demonstrate methods for determining type I and type II error rates for gross forest loss that can be applied to FIA or remotely sensed data. Gross forest loss ignores areas that gain forest but is important because it indicates something about forest disturbance. However, net forest loss must be evaluated to assess forestland area change. In some cases (FSC 2011), estimates of both net loss and gross loss may be required, which alters nominal type I error for a joint comparison. We suggest handling this with methods developed for multiple comparisons.

Gross and Net Loss

Forestland conversion and cover-change rates involve two land-use transition types: land going from forest to nonforest ($f2n$); and land going from nonforest to forest ($n2f$). *Gross loss* involves only the $f2n$ component, whereas *net loss* incorporates $f2n$ and $n2f$ as follows,

- Gross loss $= f2n$
- Net loss $= f2n - n2f$

Both gross loss and net loss are typically expressed as annual percentages. As formulated here in our analysis, a negative net loss indicates an increase in forest area or cover.

It is important to differentiate between forest cover loss and forestland change. Computation of *gross forest cover loss* from satellite data is a biased (Reams et al. 2010) estimate of forestland loss, because of the inability to consistently distinguish between temporary loss of overstory trees and actual land use change. Likewise, the $n2f$ component will contain pixels that were previously misclassified as nonforest, and the regenerating trees are now large enough to be identified from a satellite. The biases in the two net loss components, as computed from satellite data, may compensate for each other over time to result in a less biased estimate of forestland area change, but this hypothesis is untested.

Gross forest cover loss as computed from satellite data might provide information about disturbance, but it is not useful as an estimate of forestland loss. Net loss, also as computed from satellite data, is a more meaningful estimate of actual forestland change. NLCD is a valuable satellite-derived resource (Multi-Resolution Land Characteristic Consortium 2006), but studies have shown that forest cover estimates from NLCD products are significantly less than forest area estimates from aerial photos (Nowak and Greenfield 2010, Wickham et al. 2010).

Table 1. Possible forest and nonforest categories over 2 time periods.

Time 1	Time 2		
	Forest	Nonforest	Sum
Forest	75	5	80
Nonforest	12	8	20
Sum	87	13	100

Tabular Estimates of Forest Conversion Rates

A simple tabular approach can be used to obtain forest conversion rate estimates with both NLCD and forest inventory data. The following simple example can represent either pixel counts or forest inventory plot counts. The counts are summarized in a forest (f), nonforest (nf) table for times 1 and 2. Table 1 gives the number of pixels in each of four possible categories.

- $f2f = 75$ (forest at both times)
- $f2n = 5$ (gross loss: forest at time 1, nonforest at time 2)
- $n2f = 12$ (gross gain: nonforest at time 1, forest at time 2)
- $n2n = 8$ (nonforest at both times)
- Forest at time 1: $f1 = f2f + f2n = 75 + 5$
- Forest at time 2: $f2 = f2f + n2f = 75 + 12$
- net loss $= f1 - f2 = f2n - n2f = -7$

Suppose that Table 1 represents a sample of 100 pixels or plots from land that could be either forest or nonforest. Then the estimates of transition probabilities and net loss proportion from time 1 to time 2 would be as follows:

- $f2n = 5/100$
- $n2f = 12/100$
- Net loss $= 5/100 - 12/100 = -7/100$

The number of years between time 1 and time 2 can be used to annualize net loss by assuming a linear relationship over time, which justifies dividing the result by the number of years. In situations in which plots have different remeasurement periods, the average period can be used.

Variance Estimates

The variances of gross loss, gross gain, and net loss are derived in Appendix A. The derivations depend on p_1, p_{2f}, and p_{2n}, which are the proportion of forest at time 1, the probability of a plot remaining forested given that it was forested at time 1, and the probability of a plot changing to forest given that it was nonforest at time 1.

These probabilities are estimated from remeasured plot data or from consecutive satellite images. Their variance estimates follow from binomial random variable theory and are given in Appendix A. Substitute estimated variances for the actual variances in the true variance equations, as discussed in Appendix A.

The variance of gross loss (Equation A4) is derived in Appendix A as σ^2_{f2n}, the variance of gross gain (Equation A5) is σ^2_{n2f}, and the variance of net loss (Equation A7) is $\sigma^2_{f2n-n2f}$. The variance estimators have a number of uses. For example, the variance of net loss can be used to determine whether the confidence interval on the net loss estimate overlaps zero.

Type I and Type II Errors for Gross Loss

In some cases, it may be important to evaluate trends in gross loss of forest. Gross loss could be used as a surrogate for forest

Management and Policy Implications

Forest policy decisions at the state level depend on having information about growth, harvest rates, and land-use conversion. Forest monitoring systems can provide information on each of these items. Sustainable forest management implies that harvest will not exceed growth for an extended period of time. However, there is also an implication that the forestland base is stable. Decisions such as those related to locating new wood-using facilities and managing carbon stocks are informed by this information. Forest certification systems may also place additional restrictions on wood procured from areas where forestland is being converted. Thus, methods to reliably assess forestland area change are needed.

Table 2. Simulation results for 10,000 replications of a sample of size 200.

	Mean	Variance		Variance ratio
		Equation	Simulation	
Gross loss	0.091	0.000413	0.000416	1.01
Gross gain	0.06	0.000282	0.000285	1.01
Net loss	0.031	0.000750	0.000759	1.01

Samples are drawn from a simulated population that is 70% forested at time 1. Forested plots have an 87% chance of remaining forested at time 2. Nonforest plots have a 20% chance of being forested at time 2. The variance is presented as computed from the Appendix A equations and from the 10,000 simulation replications. The ratio of the simulation over the equation variance is also shown.

disturbance, and conclusions reached from some studies that have estimated gross forest cover loss from satellite imagery (e.g., Hansen et al. 2010) have led to concerns about forest sustainability in areas under active forest management, such as the southeastern United States. In addition, some practitioners have interpreted the FSC Controlled Wood Standard (FSC 2011) as requiring gross loss to be less than 0.5% per year. We demonstrate below that it is important to consider both type I and type II errors in the evaluation of gross loss to ensure that the sample size is large enough to have confidence in test results.

Type I error occurs if the null hypothesis (H_0) is rejected when it is true, and type II error occurs if the null hypothesis is not rejected when the alternative hypothesis (H_a) is true. For example, one might want to guard against failing to reject the null hypothesis that annual gross loss is less than 0.5%, when, in fact, there is a 1.0% annual gross loss. This requires setting an appropriate type I error and simultaneously controlling the type II error by having a sufficient sample size. Of course, this approach could also be applied to net loss. Derivation of type I and type II error is discussed in Appendix B for binomial random variables.

Multiple Comparisons

For scientific comparisons, the type I error is often set to reject if $P > 0.05$. This error rate applies to a single comparison and allows for the possibility that H_0 will be wrongly rejected 1 of 20 times (Curran-Everett 2000). If 20 comparisons are being made, there is a very large probability that at least one comparison will be rejected even if all are, in fact, true unless the P value is adjusted. Because P values are so well established in practice, we will not discuss arguments that they should be eschewed (Goodman 1999).

We will use the Bonferroni method (Holm 1979), which amounts to making each of the n comparisons using the error rate, $\alpha = \bar{\alpha}/n$ where $\bar{\alpha}$ is the desired family-wise error rate (FWER). There have been numerous modifications to the Bonferroni method (Dunnett 1955, Sidak 1967, Holm 1979, Hochberg 1988), but we are avoiding those for the purpose of simplicity. Furthermore, only two comparisons are involved here, i.e., testing H_1: net loss ≤ 0 and H_2: gross loss $\leq 0.5\%$. The Bonferroni method ensures that FWER $\leq \bar{\alpha}$. We demonstrate this approach in the simulated application below.

Simulated Application

We test the variance estimators (Appendix A) with a simulation. The simulation draws samples of size $n = 200$ from a forest where the proportion of forest at time 1 is $p_1 = 0.7$. The proportion of time 1 forest that remains forest at time 2 is $p_{2f} = 0.87$. The proportion of time 1 nonforest area that goes to forest at time 2 is $p_{2n} = 0.2$. The simulation is repeated 10,000 times. The results are presented in Table 2.

The actual variance found in the simulation is closely approximated by the equations in Appendix A (Table 2). In general, it would be useful to perform a t-test where the null hypothesis is H_0: net loss ≤ 0. This is an upper one-tailed test where the critical t value for 199 df and $\alpha = 0.05$ is 2.26. The test using the $\sqrt{variance}$ from Table 2 is $0.031/0.0276 = 1.12$, and we cannot reject the null hypothesis.

To test annual gross loss, it is important to know the remeasurement period (REM), i.e., the number of years between measurements. If we want gross loss to be less than 0.5% per year, then by the compound interest formula the null hypothesis should test that the total gross loss between remeasurements is less than $(1.005)^{\text{REM}} - 1$. For example, gross loss should be no more than 4.1% over an 8-year REM. The t-test for H_0: gross loss ≤ 0.041 also has a critical t value of 2.26. The test using the variance from Table 2 is $(0.091 - 0.041)/0.0204 = 2.47$, and we reject the gross loss null hypothesis. This is where the Bonferroni method becomes important. To maintain the FWER of $\bar{\alpha} = 0.05$, we should be using $\alpha = \bar{\alpha}/2 = 0.025$ for the individual hypothesis tests. Because these are one-sided tests we get a FWER critical t value of 2.52. Now the gross loss hypothesis cannot be rejected, although it is very close to the critical value.

Gross Loss Power Comparison

Gross forest cover loss as estimated from satellite data has been used to raise concerns about forest sustainability in areas under active forest management, such as the southeastern United States (Hansen 2010). When hypotheses about gross loss (e.g., H_0: gross loss $\leq 0.5\%$) are tested, it could be important to protect against an alternative hypothesis, H_a, by controlling the type II error.

Using the approach described in Appendix B, we need to select a critical value, n_c, for the number of plots that can change from forest at time 1 to nonforest at time 2. If n_c or more plots are converted, then the null hypothesis is rejected. The type I and type II errors and power for a range of critical values are shown (Table 3) for $n = 200$ and $n = 400$. The null hypothesis is H_0: $p_b = 0.025$, and the alternative for power computations is H_a: $p_b = 0.05$, where p_b is the binomial probability. The null value of $p_b = 0.025$ was selected to simulate the situation in which forest inventory plots are remeasured every 5 years. This would roughly correspond to an annual rate of 0.5%, because $(1.005)^5 - 1 = 0.025$. The alternative corresponds to a 1% annual conversion rate, which is protecting against failing to reject the null hypothesis when the conversion rate is actually twice the 0.5% desired maximum level.

Consider the columns in Table 3 for $n = 200$. The first critical value that has type I error $\alpha < 0.05$ is $n_c = 10$. Recall that n_c corresponds to the number of plots out of 200 that go from forest to nonforest. The expected number of converted plots under the null hypothesis would be $200 \times 0.025 = 5$, so it takes double that number with a small sample size to have a sufficiently small type I error. The power corresponding to $n_c = 10$ is only 0.5453. As discussed in Appendix B, the power column (Table 3) gives the probability of having less than n_c converted plots if the alternative hypothesis is true. This power result shows that there

Table 3. Binomial type I and type II errors for $n = 200$ and $n = 400$, where H_0: $P = 0.025$ and H_a: $P = 0.05$.

	$n = 200$			$n = 400$		
n_c	Type I	Type II	Power	Type I	Type II	Power
1.0000	0.9937	0.0000	1.0000	1.0000	0.0000	1.0000
2.0000	0.9613	0.0004	0.9996	0.9995	0.0000	1.0000
3.0000	0.8785	0.0023	0.9977	0.9975	0.0000	1.0000
4.0000	0.7385	0.0090	0.9910	0.9903	0.0000	1.0000
5.0000	0.5617	0.0264	0.9736	0.9722	0.0000	1.0000
6.0000	0.3840	0.0623	0.9377	0.9353	0.0001	0.9999
7.0000	0.2359	0.1237	0.8763	0.8730	0.0002	0.9998
8.0000	0.1307	0.2133	0.7867	0.7832	0.0006	0.9994
9.0000	0.0656	0.3270	0.6730	0.6700	0.0017	0.9983
10.0000	0.0300	0.4547	0.5453	0.5437	0.0042	0.9958
11.0000	0.0126	0.5831	0.4169	0.4170	0.0094	0.9906
12.0000	0.0048	0.6998	0.3002	0.3018	0.0190	0.9810
13.0000	0.0017	0.7965	0.2035	0.2060	0.0355	0.9645
14.0000	0.0006	0.8701	0.1299	0.1328	0.0614	0.9386
15.0000	0.0002	0.9219	0.0781	0.0808	0.0990	0.9010
16.0000	0.0001	0.9556	0.0444	0.0466	0.1499	0.8501
17.0000	0.0000	0.9762	0.0238	0.0254	0.2145	0.7855
18.0000	0.0000	0.9879	0.0121	0.0132	0.2912	0.7088
19.0000	0.0000	0.9942	0.0058	0.0065	0.3771	0.6229
20.0000	0.0000	0.9973	0.0027	0.0030	0.4680	0.5320

The type I and II error columns are derived from Equation B2 and Equation B3. The critical value, *nc*, is the number of plots going from forest to nonforest.

would be a good chance of failing to reject the null hypothesis when it is false with $n = 200$. We conclude that it is difficult to differentiate between forest conversion rates of 0.5 and 1.0% per year with sample sizes of 200 or less.

Now look at the columns for $n = 400$. The expected number of plots going from forest to nonforest under the null hypothesis would be $400 \times 0.025 = 10$. The first critical value in Table 3 for which $\alpha < 0.05$ is $n_c = 16$. In this case, the power is 0.8501, which is much higher than for $n = 200$. Thus, a sample size of 400 will usually lead to correctly rejecting the null hypothesis that annual gross loss is less than 0.5% when it is actually 1% or more, but a sample size of 200 or less would give unreliable results.

Forest Conversion Estimates for Selected States

We used the most recently available evaluation group for growth, removals, and mortality for FIA data in states that have

Table 4. Conversion statistics and significance tests by state.

ST	*f2f*	*f2n*	*n2f*	*n*	REM	net loss	gross loss	$t_{0.025}$	*t* net	*t* gross	signif
AL	3,382.19	62.26	86.47	4,916.20	5.5	−0.005	0.013	1.96	−2.02	−9.30	0
AR	2,860.71	46.85	117.77	5,273.18	5.2	−0.013	0.009	1.96	−5.62	−13.24	0
CT	193.19	1.87	5.61	354.71	5.1	−0.011	0.005	1.97	−1.38	−5.25	0
DE	40.48	1.25	0.75	146.43	6.2	0.003	0.009	1.98	0.35	−2.93	0
FL	976.82	29.90	76.42	2,065.56	9.3	−0.023	0.014	1.96	−4.63	−12.18	0
GA	3,874.78	94.61	71.50	5,869.46	5.5	0.004	0.016	1.96	1.82	−6.92	0
IL	649.35	19.74	49.56	5,755.39	5.1	−0.005	0.003	1.96	−3.60	−28.62	0
IN	722.17	7.28	28.15	3,722.55	5.2	−0.006	0.002	1.96	−3.52	−33.19	0
IA	412.77	21.17	29.62	5,900.63	5.2	−0.001	0.004	1.96	−1.19	−28.76	0
KS	278.21	15.22	81.73	8,626.59	5.2	−0.008	0.002	1.96	−6.79	−53.55	0
KY	1,875.37	52.79	89.81	4,057.01	6.0	−0.009	0.013	1.96	−3.16	−9.55	0
LA	580.97	10.37	49.12	1,180.33	10.8	−0.033	0.009	1.96	−5.15	−16.64	0
ME	2,905.63	11.62	22.39	3,217.48	5.0	−0.003	0.004	1.96	−1.85	−20.22	0
MD	139.71	2.54	5.78	368.52	6.4	−0.009	0.007	1.97	−1.13	−5.81	0
MA	333.12	5.80	11.05	564.82	5.1	−0.009	0.010	1.96	−1.30	−3.59	0
MI	4,267.25	39.81	146.13	7,967.55	4.9	−0.013	0.005	1.96	−7.89	−24.69	0
MN	4,814.00	60.72	361.01	16,245.15	5.1	−0.018	0.004	1.96	−14.82	−45.45	0
MS	1,339.46	30.84	28.01	2,108.50	8.6	0.001	0.015	1.96	0.37	−10.85	0
MO	2,365.47	57.03	109.97	7,110.93	5.0	−0.007	0.008	1.96	−4.15	−16.05	0
NH	576.79	4.73	7.16	685.06	5.9	−0.004	0.007	1.96	−0.71	−7.14	0
NJ	117.71	2.95	2.92	279.43	6.3	0.000	0.011	1.97	0.01	−3.42	0
NY	1,572.68	26.20	40.96	2,630.10	7.9	−0.006	0.010	1.96	−1.82	−15.25	0
NC	2,598.05	74.20	66.26	4,446.69	5.0	0.002	0.017	1.96	0.68	−4.33	0
OH	1,173.85	31.75	57.31	4,102.05	4.8	−0.006	0.008	1.96	−2.74	−11.88	0
OK	358.38	6.18	17.90	645.34	10.2	−0.018	0.010	1.96	−2.43	−10.80	0
PA	2,298.69	33.91	74.18	4,174.97	5.0	−0.010	0.008	1.96	−3.92	−12.15	0
RI	63.56	0.51	2.14	132.88	4.9	−0.012	0.004	1.98	−1.01	−3.84	0
SC	2,083.92	42.18	59.26	3,144.11	4.8	−0.005	0.013	1.96	−1.72	−5.16	0
TN	2,129.00	56.06	61.17	4,162.97	4.7	−0.001	0.013	1.96	−0.48	−5.62	0
TX	2,201.07	71.41	84.77	4,074.53	4.8	−0.003	0.018	1.96	−1.09	−3.15	0
VT	553.81	3.19	8.94	735.07	5.2	−0.008	0.004	1.96	−1.66	−8.93	0
VA	2,572.76	37.42	56.16	4,201.10	4.8	−0.004	0.009	1.96	−1.96	−10.41	0
WV	946.13	11.21	28.90	1,248.36	5.6	−0.014	0.009	1.96	−2.84	−7.12	0
WI	4,965.38	54.19	231.42	10,895.41	5.1	−0.016	0.005	1.96	−10.63	−30.45	0

The columns are as follows: ST, state abbreviation; *f2f*, number of plots that were forest at both times; *f2n*, number of plots that went from forest to nonforest; *n2f*, number of plots that went from nonforest to forest; *n*, total number of plots; REM, remeasurement period; $t_{0.025}$, one-sided *t* value; *t* net, *t* statistic for net loss test; *t* gross, *t* statistic for gross loss test; signif, 0 means joint *t*-test notsignificant. Net and gross loss are annual percentages. A negative net loss implies an increase in forest area.

good coverage with respect to remeasured plots. All FIA plots were included if they had a condition that was forested at either the current or previous measurement. We computed the total number of recently remeasured plots (n) for each state along with the number of plots that went from forest to forest ($f2f$) and nonforest to forest ($n2f$) between remeasurements. In addition, the average number of years between remeasurements (REM) is required to perform the necessary computations (Table 4). The condition mapping used by FIA can result in only a portion of a plot being forest, which explains the noninteger sample sizes. The results in Table 4 should not be viewed as official FIA estimates, because rigorous data screening was not attempted.

Net loss and gross loss were computed (Table 4) along with their estimated variances using the methods described in Appendix A. Net and gross loss one-sided t statistics (t net and t gross) were compared with the critical t value for one-sided 0.025 type I error. The signif column (Table 4) indicates that none of the states with sufficient FIA remeasured plots had annualized net loss > 0 or gross loss $> 0.5\%$. The net loss and gross loss columns (Table 4) were annualized by dividing the total loss for the remeasurement period by the average remeasurement period length (REM). The t value for a one-sided 0.025 level test results in a FWER of at most 0.05 as discussed above.

We did not compute the power = (1 − type II error) for each state, but states with fewer than 200 plots would have little power, i.e., Delaware, New Jersey, and Rhode Island.

Conclusions

There is considerable interest in general land-use change trends. Here, we focused on changes between forest and nonforest use. The methods we present can also be applied to forest cover loss, but it should be clear that forest cover change does not necessarily mean that the land is no longer in a forest use. In general, satellite imagery can provide data to assess forest cover trends, but forest inventory data should be preferred for assessing forestland-use trends.

The simulations and examples of applications presented here suggest that small changes in net or gross forest area loss require large sample sizes (perhaps 400 or more) to be reliably detected. A power analysis for binomial data was presented to support this contention. This implies that only fairly large areas could be reliably assessed for forest area change with FIA data, because there is one FIA plot for (approximately) 6,000 acres. It follows that areas less than $400 \times 6{,}000 = 2.4$ million acres should probably not be considered if the objective is to detect small changes in net or gross forest loss with FIA data.

These methods were applied to states with remeasured FIA plots, which allow for change assessment. Our analysis found no states with sufficient FIA remeasured plot data that had recently experienced statistically significant net forest area loss or annual gross forest area loss $> 0.5\%$. This does not preclude the possibility that there are zones that overlap state boundaries where significant forest area (net or gross) change is occurring.

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Appendix A: Computing the Variance of Gross Loss, Gross Gain, and Net Loss Estimates

Net loss is the difference in forest area or cover between times 1 and 2, which requires knowledge of the proportion of land going from forest to nonforest ($f2n$) and the proportion going from nonforest to forest ($n2f$). Therefore, net loss is $f_1 - f_2 = f2n - n2f$. The components of net loss, gross loss ($f2n$), and gross gain ($n2f$) are of stand alone interest as well. These estimates depend on recording the forest/nonforest status of each inventory plot or pixel at two times.

Suppose these data are recorded in vectors X_1 and X_2, where 0 indicates nonforest and 1 indicates forest. The proportion of forest at time 1 is estimated from $p_1 = \Sigma_{i=1}^{n} X_{1i/n}$ where n is the number of plots or pixels measured at both times. To estimate the components of net loss, split X_2 into two parts, X_{2f} and X_{2n}, where X_{2f} contains plots that were forested at time 1 and X_{2n} contains plots that were nonforested at time 1. The means of X_{2f} and X_{2n} are denoted as p_{2f} and p_{2n} and estimate the conditional probabilities of being forest at time 2 given the forest-land use status at time 1.

Net loss is the unconditional probability of change and is estimated from the following components:

$$\text{gross loss: } f2n = p_1 * (1 - p_{2f}) \quad \text{(A.1)}$$

$$\text{gross gain: } n2f = (1 - p_1) \cdot p_{2n} \quad \text{(A.2)}$$

The estimates of p_1, p_{2f}, and p_{2n} are independent, and they are all means of binomial random variables. Independence follows from the fact that p_{2f} and p_{2n} are

Table 5. Type I and type II error.

Decision	Status of H_0 True	False
Fail to reject	Correct	Type II
Reject	Type I	Correct

derived from distinct sets of plots. In addition, p_{2f} and p_{2n} are not correlated with p_1, because their time 1 measurements were either all 0s or all 1s; i.e., their time 1 measurements were constants. Their variance estimates follow from binomial random variable theory: $s_1^2 = p_1 \cdot (1 - p_1)/n$, $s_{2f}^2 = p_{2f} \cdot (1 - p_{2f})/n_1$, and $s_{2n}^2 = p_{2n} \cdot (1 - p_{2n})/n_0$, where n_1 is the number of 1s in X_1, n_0 is the number of 0s in X_1, and $n = n_0 + n_1$.

The variance of gross loss and gross gain estimates follows from the formula for the product of independent random variables (Goodman 1960), say u and v,

$$\sigma_{uv}^2 = \sigma_u^2\sigma_v^2 + \bar{v}^2\sigma_u^2 + \bar{u}^2\sigma_v^2 \qquad (A.3)$$

The variance of gross loss is then

$$\sigma_{f2n}^2 = \sigma_1^2\sigma_{2f}^2 + p_1^2\sigma_{2f}^2 + p_{2f}^2\sigma_1^2 + \sigma_1^2(1 - 2p_{2f}) \qquad (A.4)$$

where the last term is the variance of p_1 minus twice the covariance of p_1 and $p_1 \times p_{2f}$. Evaluate Equation A.4 by substituting estimates for the variances; e.g., substitute s_1^2 for σ_1^2. Likewise, the variance of gross gain is

$$\sigma_{n2f}^2 = \sigma_1^2\sigma_{2n}^2 + p_1^2\sigma_{2n}^2 + p_{2n}^2\sigma_1^2 + \sigma_{2n}^2(1 - 2p_1) \qquad (A.5)$$

The variance of net loss is easy to derive if we write it in a somewhat simpler form:

$$\text{net loss: } f2n - n2f = p_1 b - p_{2n} \qquad (A.6)$$

where $b = (1 - p_{2f} - p_{2n})$. Then the variance of net loss is written as

$$\sigma_{f2n-n2f}^2 = \sigma_1^2\sigma_b^2 + b^2\sigma_1^2 + p_1^2\sigma_b^2 + \sigma_{2n}^2(1 - 2_{p1}) \qquad (A.7)$$

where $\sigma_b^2 = \sigma_{2f}^2 + \sigma_{2n}^2$.

Appendix B: Controlling Type I and Type II Errors for Gross Loss Estimates

Gross forestland area loss not only is a component of net loss but also may be of interest in some forest certification standards such as the FSC Controlled Wood Standard (FSC 2011), which requires that there be no significant rate of loss (>0.5% per year). If loss is interpreted as gross loss, the FSC standard makes the null hypothesis H_0: $p_g \leq 0.025$ relevant for an inventory system where plots are remeasured every 5 years, because $p_g = 0.025$ roughly corresponds to a 0.5% annual gross loss. The relevant alternate hypothesis is H_1: p_g 0.025.

Consider a binomial vector, Z, where 1 indicates that the plot was forest at time 1 and nonforest at time 2; otherwise the plot gets a 0. Suppose the sample size is $n = 200$; then $E(Z) = np_g = 5$ when $p_g = 0.025$. For a particular sample, we determine the number of 1s in Z, say n_s, and decide if we should reject H_0. This decision should be based on consideration of type I and II errors. Table 5 shows the relationship between the two types of errors and correct decisions.

Type I Error

The binomial probability of getting n_s 1s from a sample of size n for a given binomial probability, p, is

$$P(n_s|n, p) = \binom{n}{n_s} p^{n_s}(1 - p)^{n-n_s} \qquad (B.1)$$

Suppose H_0 is rejected if $n_s \geq n_c$, and we want to select a critical value, n_c, that has a particular type I error. The formula for the type I error conditional on n and p_g is

$$\alpha = \sum_{ns=n_c}^{n} P(n_s|n, p_g) \qquad (B.2)$$

In practice, the critical value will be the first n_c where $\alpha \leq 0.05$ if the user preferred type I error rate is 0.05.

Type II Error

Typically, the type I error rate is referred to as α and the type II rate is β. Type II error protects against failing to reject H_0 when it is false, but it is necessary to specify the alternate hypothesis, H_a, that we want to protect against. In keeping with the FSC-motivated example, we might want to guard against $H_a \geq 0.05$, which is approximately twice the FSC allowed limit on gross loss for 5-year remeasurements.

The type II error conditional on n and p_a is

$$\beta = \sum_{ns=0}^{n_c-1} P(n_s|n, p_a) \qquad (B.3)$$

which could be written as $P(n_s \leq (n_c - 1)|p_a)$. Type II error can be reduced by increasing n, whereas type I error is selected by the user and is often set to 0.05.

The power of a test is the probability that H_0 will be rejected when H_a is true. It is easily computed as power $= 1 - \beta$. In fact, power is redundant, because power approaches 1 as β approaches 0.