Complying with the uncertainty requirements of the IPCC Good Practice Guidance for estimating land cover change

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Abstract

Tropical countries, often with remote and inaccessible forests, frequently rely on satellite image-based maps to estimate land cover change as a component of a greenhouse gas inventory. However, estimates obtained by simply aggregating map unit predictions are subject to classification error which induces bias into the estimation procedure. Further, overall map accuracy can be large and still induce bias into the process. The model-assisted estimator provides a mechanism for compensating for bias, simultaneously estimating uncertainty, and thereby complying with the IPCC good practice guidance. An example for Gabon is used for illustration purposes.

Keywords: Model-assisted estimator, bias correction, confidence interval.

1. Introduction

Greenhouse gas (GHG) inventories assess the scale of emissions from the forestry sector relative to other sectors. For countries without national forest inventories, the gain-loss approach is most commonly used to estimate emissions (Giardin, 2010). With this approach, the net balance of additions to and removals from a carbon pool is estimated as the product of the rate of land use area change, called activity data, and the responses of carbon stocks for particular land use changes, called emissions factors.

The IPCC definition of good practice requires that GHG inventories satisfy two criteria: (1) neither over- nor under-estimates so far as can be judged, and (2) uncertainties reduced as far as is practicable (Penman *et al*., 2003). For GHG purposes, activity data in the form of areas of forest cover and forest cover change are often estimated using satellite image-based maps. However, maps are only inaccurate depictions of the spatial distributions of attributes of interest. Further, estimates obtained by adding or averaging pixel classifications may deviate substantially from true values as a result of map classification error. Additionally, map accuracy indices provide no direct information on the accuracy or precision of estimates obtained from maps. Thus, satisfaction of the IPCC criteria requires compensation for classification errors and estimation of uncertainties using statistically rigorous methods. The primary means of estimating accuracies, compensating for classification error, and estimating uncertainty is via comparisons of map classifications and reference observations for an accuracy assessment sample.

Factors that affect satisfaction of the two criteria are the sampling design for the accuracy assessment sample, sample sizes, and map accuracy. For accuracy assessment and estimation to be valid for an area of interest using the familiar design- or probability-based framework (McRoberts and Walters, 2012), the accuracy assessment sample must be collected using a probability sampling design, regardless of how the training data are collected.

An example based on a study in Gabon for estimating area of deforestation is used to illustrate use of a design-based, model-assisted estimator for complying with the IPCC criteria. This estimator is particularly useful when the estimation unit is larger than a single satellite image pixel and when continuous auxiliary information can be used to improve estimation.

2. Data

A 100,000-km^2 region of Gabon was divided into 20-km x 20-km blocks with each block further subdivided into 2-km x 2-km segments. A 30-m x 30-m, forest/non-forest classification was constructed for the entire region for each of 1990, 2000, and 2010 using Landsat imagery and an unsupervised classification algorithm. For each time interval, the map predictions for the i^{th} segment consisted of the proportion of pixels, $\hat{y}_i$, whose classifications changed from forest to non-forest. For this example, the map data constituted the continuous auxiliary information.

The accuracy assessment data were acquired using a probability-based, two-stage sampling design for which the first-stage consisted of a random selection of blocks, and the second-stage consisted of a random selection of segments within blocks (Stehman, 2009). Reference observations for the accuracy assessment sample may be acquired from multiple sources, but their quality should be greater than the quality of the map data. Although ground data acquired by field crews that can be accurately co-registered to the map are generally regarded as the standard, finer resolution and/or more accurately classified remotely sensed data have also been used (Stehman, 2009, Section 5). For this study, reference data were acquired for each year by visually interpreting each pixel within each second-stage segment as forest or non-forest using independent Landsat data, aerial photography, and other spatial data. These reference data were assumed to be of greater quality than the map data, albeit of the same resolution. The sample of segments was denoted S, and for each time interval, the reference data for the i^{th} segment consisted of the proportion of pixels, y_i, within the segment whose visual interpretations changed from forest to non-forest.

3. Methods

The analyses used the model-assisted regression (MAR) estimator described by Särndal et al. (1992, Section 6.5). Although the term *regression* appears in the name of the estimator, it is commonly used with other prediction methods such as splines and non-parametric techniques. For each time interval, the map-based estimate of proportion deforestation area was calculated as,

$$\hat{p}_{map} = \frac{1}{M}\sum_{i=1}^{M}\hat{y}_i \qquad (1)$$

where M=25,000 was the total number of segments. However, the map estimates are subject to classification errors which induce bias into the estimation procedure. An estimate of this bias is,

$$\mathrm{B\hat{i}as}\left(\hat{p}_{map}\right)=\frac{1}{m}\sum_{i\varepsilon S}\left(\hat{y}_i-y_i\right) \tag{2}$$

where m=250 is the number of segments in the accuracy assessment sample. The MAR estimate is then the map estimate with the estimate of bias subtracted,

$$\hat{p}_{MAR}=\hat{p}_{map}-\mathrm{B\hat{i}as}\left(\hat{p}_{map}\right)=\frac{1}{M}\sum_{i=1}^{N}\hat{y}_i-\frac{1}{m}\sum_{i\varepsilon S}\left(\hat{y}_i-y_i\right). \tag{3}$$

The standard error (SE) of $\hat{p}_{MAR}$ is,

$$SE\left(\hat{p}_{MAR}\right)=\sqrt{\frac{1}{m(m-1)}\sum_{i\varepsilon S}\left(\varepsilon_i-\bar{\varepsilon}\right)^2} \tag{4}$$

where $\varepsilon_i=\left(\hat{y}_i-y_i\right)$ and $\bar{\varepsilon}=\frac{1}{m}\sum_{i\varepsilon S}\varepsilon_i$. In this manner, deforestation area was estimated for each time interval.

4. Results and discussion

Four results were particularly important. First, overall classification accuracies were all close to 0.98, and neither users' nor producers' accuracies were less than 0.90. Second, the bias estimates were uniformly small in absolute terms, but in relative terms were of approximately the same order of magnitude as the map-based estimates (Table 1). Third, the standard errors of the MAR estimates were of the same magnitude or smaller than the MAR estimates themselves. The estimate for 1990-2000 was statistically significantly different from zero, but such was not the case for the 2000-2010 estimate or the overall 1990-2010 estimate. The non-significance of the 2000-2010 estimate was attributed to creation of national parks and the implementation of forest concession management plans from 2000 onward. Fourth, the first three results taken together serve to emphasize the necessity of adjusting estimates for bias resulting from classification errors. Despite the very large overall accuracies, had there been no bias adjustment, the 1990-2000 estimate would not have been detected as statistically significantly different from zero.

Table 1. Estimates of deforestation area.

Interval	Proportion deforestation area				Confidence interval (km^2)[1]	
	$\hat{p}_{map}$	$\mathrm{B\hat{i}as}(\hat{p}_{map})$	$\hat{p}_{MAR}$	$SE(\hat{p}_{MAR})$	Lower limit	Upper limit
1990-2000	0.0017	0.0015	0.0033	0.0012	95	565
2000-2010	0.0003	0.0009	0.0011	0.0012	-125	345[2]
1990-2010	0.0020	0.0024	0.0044	0.0016	126	754

[1]Confidence interval limits are calculated as products of total study area and confidence interval limits for $\hat{p}_{MAR}$.

[2]Confidence intervals that include 0 indicate the estimate is not statistically significantly different from 0.

5. Conclusions

Three conclusions may be drawn from the study. First, as the study illustrated, large map accuracies cannot be construed to mean the absence of any detrimental effects of classification error. Thus, compliance with the IPCC good practice guidance requires statistically rigorous estimation of bias and uncertainty. Second, the two-stage sampling design is suitable for accuracy assessment of land cover maps and for this study represented a good compromise between ease and cost of data collection and good geographical distribution for the reference data. Third, the model-assisted regression estimator is simple, straight-forward, and may greatly increase the precision of estimates when the attribute of interest and the auxiliary information are highly correlated as was indicated for this study by the large overall accuracies. Of importance, the combination of two-stage sampling and the model-assisted regression estimation produced estimates of activity data that complied with the IPCC good practice guidance.

Additional details for the study are available in Sannier *et al*. (2014).

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