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A model for the propagation of uncertainty from continuous estimates of tree cover to categorical forest cover and change

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ABSTRACT

Rigorous monitoring of Earth's terrestrial surface requires mapping estimates of land cover and of their errors in space and time. Estimation of error in land-cover change detection currently relies heavily on external, post hoc validation—i.e., comparison of estimated cover to independent values that are assumed to be true. However, reference data are themselves uncertain, and acquiring observations coincident with historical data is often impossible. Complementarily, modeling the transmission, or propagation, of error through the processes of classification and change detection provides an internal means to estimate classification and change-detection error at the scale of pixels. Modeling uncertainty around the estimate of fractional, "continuous-field" cover as a standard Normal distribution in each pixel at each of two times, we derive a method for propagating this uncertainty to categorical land cover-classification and change detection. We demonstrate the approach for mapping forest-cover change and its uncertainty based on bi-temporal estimates of percent-tree cover and their associated root-mean-square errors (RMSE). The method described here propagates only the imprecision component of error and not bias, so neither the resulting categorical estimates of cover nor the detection of change (e.g., forest loss) are affected by the transmission of uncertainty. However, propagating the RMSE of input estimates into probabilities of forest cover and change enables mapping and visualization of the spatial distribution of the imprecision resulting from model-based estimation of tree cover and from selection of the threshold of tree cover to define "forest". When compared to reference data with a fixed definition of forest (e.g., ≥30% tree cover) the threshold effect is an importance source of apparent error in forest-cover and -change estimates. The approach described here provides a useful description of classification and change-detection certainty and can accommodate any definition of forest based on tree cover—an especially important consideration given the variety of institutional definitions of forest cover based on remotely sensible structural characteristics.

1. Introduction

1.1. Background

Sustaining the welfare of a growing human population in a changing environment is dependent on regular and reliable ecosystem monitoring (Sexton, Urban, Donohue, & Song, 2013; Townshend & Brady, 2006). To this end, a growing number of remotely sensed datasets representing Earth's land cover now span multiple observations over time. However, error accompanies all inferences, and so rigorous land-cover monitoring must be based on maps of land cover and change accompanied by estimates of their errors (Congalton & Green, 2009; Foody, 2002; Heuvelink, Burrough, & Stein, 1989; Stehman, 2000).

Consistent with the Inter-governmental Panel on Climate Change IPCC (2006), we define *error* as the inverse of *truth*, or the degree to which a set of values differs from reality. We further partition the concept of error into systematic, i.e., *inaccuracy* or *bias*, and unsystematic, or random, error—i.e., *imprecision* (Willmott, 1982); we treat uncertainty as synonymous with imprecision. To date, error estimation in land-cover mapping and change detection has employed predominantly *validation*—i.e., post hoc comparison of estimates to external sources of reference (Congalton & Green, 2009). When based on a rigorous sampling design, remote sensing validation falls within the general statistical framework of design-based inference (Foody, 2002; Gregoire 1998; Stehman, 2000). Given a lack of error in the reference data themselves, validation can provide estimates of both accuracy and precision

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(Willmott, 1982). However, the acquisition of accurate reference observations is an expensive—and itself often uncertain—endeavor (Berger, Gschwantner, McRoberts, & Schadauer, 2014; Breidenbach, Antón-Fernández, Petersson, McRoberts, & Astrup, 2014; Foody, 2002), and the necessarily sparse samples it yields often support only broadly aggregated, regional summaries of error (Fisher, Hurtt, Thomas, & Chambers, 2008; Foody, 2002).

Errors in remotely sensed data vary in space and time, and so description of these errors must likewise strive to reflect this complexity (Steele, Winne, & Redmond, 1998). The proper scale at which to infer error in land-cover estimates is thus equivalent to that of cover itself—i.e., at pixel resolution and extent. As an alternative to *design*-based inference, *model*-based inference (Gregoire 1998) has been used to map the estimated certainty of static land-cover categories (e.g., Liu, Gopal, & Woodcock, 2004; McRoberts, 2006; Steele et al., 1998) and of their changes over time (e.g., McRoberts & Walters, 2012). Further, the development of multi-temporal datasets representing continuous biophysical attributes (DeFries, Field, Fung, & Justice, 1995, DiMiceli et al., 2011, Hansen et al., 2011; Sexton, Song, Feng, et al., 2013; Sexton, Song, Huang, et al., 2013) and their increasing use for mapping and change detection (e.g., Hansen et al., 2013; Hansen, Stehman, & Potapov, 2010; Huang et al., 2010; Kennedy, Yang, & Cohen, 2010) prompt the development of a rigorous approach to categorical change detection based on multi-temporal continuous fields.

Errors arise both from models and from data, including: (1) the specification and parameterization of models and (2) the spatial and temporal registration, sampling, and measurement of data (Berger et al., 2014; Burnham & Anderson, 2002; Clark, 2007; Heuvelink et al., 1989). Ideally, the effects of all pertinent error sources should be communicated alongside model inferences, including estimates of model parameters and "predicted" cover values. For various components of the total error budget, this is typically accomplished in any of three ways: by sample-based methods (Stahl et al., 2014); by error propagation (Berger et al., 2014; IPCC, 2003; Stahl et al. 2014); and by Monte-Carlo—i.e., "parametric bootstrap"—methods (Breidenbach et al., 2014; Gertner & Dzialowy, 1984; Metropolis & Ulam, 1949).

Error propagation is practiced commonly in allometric estimation of tree and forest attributes and occasionally in land-cover mapping and change detection. Berger et al. (2014) incorporated imprecision from model specification and measurement of covariates into the variance of allometrically estimated tree stem volume. Breidenbach et al. (2014) used Monte-Carlo simulation to quantify model-related variability in biomass stock and change estimates. Based on a logistic regression relating binary forest cover to top-of-atmosphere reflectance, McRoberts (2006) incorporated estimation uncertainty—including spatial autocorrelation in the training data—into the uncertainty of regional forest-area estimates. McRoberts and Walters (2012) used a validation error matrix to illustrate the construction of confidence intervals for net forest-cover loss estimated from maps of forest-probability at two times.

1.2. Objectives

In this paper we derive a model for the propagation of error from fractional, "continuous-field" estimates of cover, through classification of discrete land-cover categories, to post-classification change detection in each pixel. We demonstrate the approach by application to forest-cover change detection in a region of active clearing and regrowth, using tree cover and corresponding uncertainty estimates from a previously published global, Landsat based tree-cover dataset (Sexton, Song, Feng, et al., 2013). Although the method is applicable to any continuous, bi-temporal representation of biophysical attributes (e.g., canopy height or biomass) or land cover (e.g., impervious surface), this development is especially pertinent to mapping forest changes across the wide variety of definitions of "forest" based on remotely sensible characteristics.

Although the method is general, several specific data sources are used here to illustrate our approach, using model-based inference to propagate uncertainty from input estimates of tree cover and using design-based inference to validate the resulting maps of forest cover and change. Input rasters of estimated tree cover and error were taken from a global, percent-tree cover dataset produced at 30-m resolution for circa-2000 and -2005 (Sexton, Song, Feng, et al., 2013). These estimates were produced by an empirical regression-tree model trained on an ensemble of land-cover datasets as the response variable and Landsat-based surface reflectance as covariates. Their errors were estimated in each pixel by propagating the uncertainty from training data relative to lidar-based reference measurements of tree cover. Using design-based inference, an independent reference dataset of visually interpreted observations of binary forest/non-forest cover was used to validate the resulting forest-cover and –change maps.

2. Methods

2.1. Theory

2.1.1. Defining forest cover in terms of tree cover

Define "forest" as a class of land cover wherein tree cover, c, exceeds a predefined threshold value, c^*. The probability of belonging to "forest", $p(F)$, is therefore the probability of c exceeding the threshold c^* (Fig. 1)—i.e., the integral of the probability density function of c above c^*:

$$p(F) \stackrel{\text{def}}{=} p(c > c^*) = \int_{c*}^{100} p(c)dc. \tag{1}$$

Complementarily, the probability of membership in non-forest is simply $1 - p(F)$.

In any location i, tree cover c_i is commonly estimated by a model f of remotely sensed covariates $\boldsymbol{X}$ (Hansen et al., 2003; Homer, Huang, Yang, Wylie, & Coan, 2004; Sexton, Song, Feng, et al., 2013):

$$c_i = f(\boldsymbol{X}; \beta) + \varepsilon_i, \tag{2}$$

where β is a set of parameters, which are estimated empirically, and ε is residual error.

Given a joint sample of locations $i = [1,2,\ldots n]$ with coincident true and estimated values of a continuous variable such as tree cover $(c_i, \hat{c}_i)$, error may be quantified as the root-mean-square error (RMSE), which for large samples approximates the standard deviation of estimates of the true value of cover:

$$\sigma_\varepsilon = \sqrt{\frac{\sum_i (c_i - \hat{c}_i)^2}{n-1}}. \tag{3}$$

Thus, given c_i, and an estimator (e.g., linear regression) producing estimate $\hat{c}_i$ and root-mean-square error $\sigma_i = \sigma$, a Normal probability distribution of possible values of c_i may be assumed (Clark, 2007; Hastie, Tibshirani, & Friedman, 2001; Snedecor & Cochran, 1989):

$$p(c_i) \stackrel{\text{def}}{=} N\left(\hat{c}_i, \sigma^2\right) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(c_i - \hat{c}_i)^2}{2\sigma^2}}. \tag{4}$$

Given paired estimates of cover and its RMSE, this model provides a probability density function of tree cover $p(c)$ (Eq. (1)) and therefore the probability of identifying forest for each pixel i.

2.1.2. Change detection based on bi-temporal class-probabilities

Given the probability of detecting forest in a location $i = (x,y)$ at each of two times t, four dynamic classes (D) are possible: stable forest (FF), stable non-forest (NN), forest gain (NF), and forest loss (FN).