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Misclassification error in satellite imagery data: Implications for empirical land-use models

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ABSTRACT

Satellite-based land-use data sets are providing new opportunities for land-use research. However, care must be used when working with these datasets due to misclassification error, which causes inconsistent parameter estimates in typical land-use models. Results from satellite imagery data from the Northern Great Plains indicate that ignoring misclassification will lead to biased results. Even seemingly insignificant levels of misclassification error (*e.g.*, 1%) result in biased parameter estimates, which alter marginal effects enough to affect policy inference. At the levels of misclassification typical in current satellite imagery datasets (*e.g.*, 35%), ignoring misclassification can lead to systematically erroneous land-use policies.

1. Introduction

Land use research has focused on developing economic models of individual landowner's decisions within a spatially explicit framework (Irwin and Geoghegan, 2001; Lynch and Geoghegan, 2011). Resulting empirical models explain the effects of land-use on environmental resources (Lewis, 2010; Rashford et al., 2010; Rashford et al., 2011; Bhattacharya and Innes, 2013), forest resources (Deininger and Minten, 2002; Munroe et al., 2002; Lewis and Plantinga, 2007; Blackman et al., 2008), agricultural resources (Lynch and Liu, 2007; Butsic et al., 2011; Skevas et al., 2016), and urban and regional planning (Irwin and Bockstael 2002; Wu and Plantinga, 2003; Wu and Cho, 2007; Irwin and Bockstael 2007; Fragkias and Geoghegan, 2010). Natural resource managers, in particular, need this spatially explicit framework to effectively evaluate the social and environmental consequences of alternative land-use scenarios (Bockstael, 1996; Untenecker et al., 2016). The spatial configuration of land-use influences many important indicators of environmental quality, including bird populations (Askins, 2002; Faaborg, 2002), amphibian populations (deMaynadier and Hunter, 2000), health of riparian systems and estuaries (Gergel et al., 2002; Hale et al., 2004; Dempsey et al., 2017), human perceptions of scenic quality (Palmer, 2004), and the extent of urban sprawl (Carrión-Flores and Irwin, 2004).

Many studies use the US Department of Agriculture's (USDA) National Resources Inventory (NRI), which provides information on land-use choices for over 800,000 sample plots across the US from 1982 to 1997 (at five-year intervals) (*e.g.*, Tanaka and Wu, 2004; Lubowski et al., 2006; Lewis and Plantinga, 2007; Langpap and Wu, 2008; Lubowski et al., 2008; Lewis et al., 2009; Rashford et al., 2010; Langpap and Wu, 2011). The NRI, however, has issues of temporal consistency and availability.

Alternatively, researchers use aggregate data because of its availability, geographic coverage, and long temporal scale (*e.g.*, Plantinga and Irwin, 2006). Most commonly, aggregate data models estimate the proportion of an area in different land-uses as a function of exogenous variables expected to influence landowner utility or profits (*e.g.*, Alig 1986; Leitch, 1989; Stavins and Jaffe, 1990; Parks and Murray, 1994; Parks and Kramer, 1995; Wu and Brorsen, 1995; Wu and Segerson, 1995; Plantinga, 1996; Hardie and Parks, 1997; Plantinga et al., 1999; Parks et al., 2000; Hardie et al., 2000; Plantinga and Ahn, 2002; Munn et al., 2002). Since aggregate data models predict aggregate land-use proportions they are only useful for understanding phenomena that respond to aggregate-level land cover characteristics. Aggregate data models cannot predict the consequences of land-use for phenomena that are sensitive to the spatial pattern of the landscape (Lewis and Plantinga, 2007).

The increasing availability of land-use data derived from satellite imagery offers researchers a greater ability to model micro-level land-use (see Holloway et al., 2007). Several papers use early versions of satellite products to model land-use (many in developing countries where other data products are not available). These models examine a range of land-use issues, including agricultural dynamics (Thompson and Prokopy, 2009; Hendricks et al., 2014), ecosystem services (Polasky et al., 2008; Lawler et al., 2014), deforestation (Chomitz and

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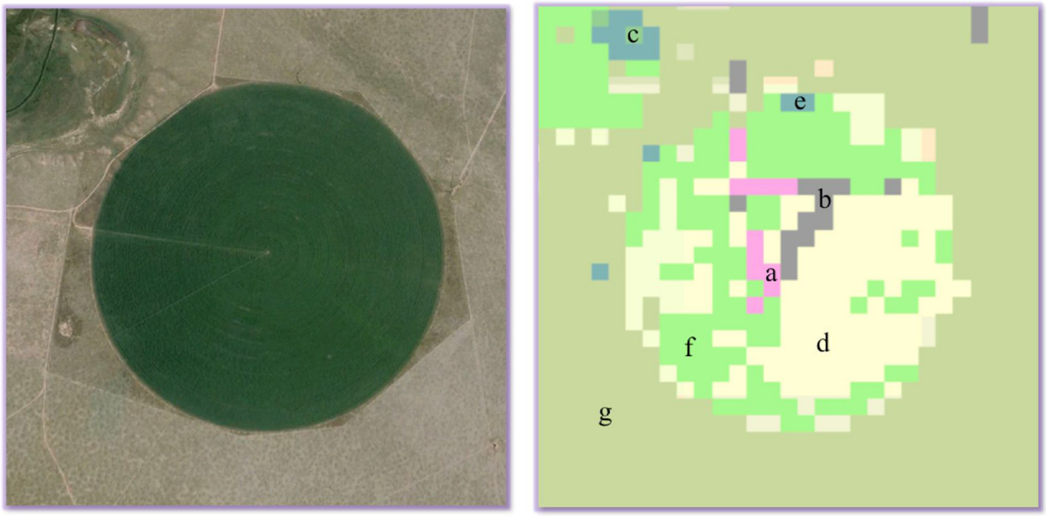

Fig. 1. National Agricultural Image Program aerial photo and corresponding Cropland Data Layer satellite rendered image showing the extent of misclassification error in an irrigation circle (approximately 41°14′21.0″N 105°39′07.7″W) (USDA, 2009a; USDA, 2009b). Each letter corresponds to a specific land cover classification; a: Alfalfa; b: Developed/Open Space; c: Evergreen Forest; d: Grass/Pasture; e: Herbaceous Wetlands; f: Non Alfalfa/Other Hay; g: Shrubland.

Gray, 1996; Nelson and Hellerstein, 1997; Mertens and Lambin, 2000; Cropper et al., 2001), wildlife habitat loss (Polasky et al., 2005; Shi et al., 2006), and climate change (Sohl et al., 2012). Recent availability of satellite-based land-use data sets (*i.e.*, raster datasets), with high resolution of contiguous spatial coverage over broad spatial extents, relatively long temporal coverage, and specific land cover classifications (*e.g.*, rye or winter wheat), are providing new opportunities for future research (Lark et al., 2017). The National Land Cover Database (NLCD) and Cropland Data Layer (CDL) in the US, for example, provide nationwide plot-level observation at high resolution (30 m × 30 m plots) classifying land into refined classifications from altered to natural land covers (*e.g.*, urban, corn, and herbaceous grassland).

Though satellite imagery data offers new opportunities for modeling land-use, it is not without drawbacks. Misclassification error – the phenomenon of observations of land-use being classified incorrectly (*e.g.*, Fig. 1) – can cause vagueness (*e.g.*, position of climatic zone boundaries), ambiguity (*e.g.*, a pixel with more than one class, called a mixel), positional inaccuracy (*i.e.*, data correspondence to true locations), logical inconsistency (*e.g.*, a pixel of tundra in an area of cropland), and incompleteness (*i.e.*, how well features in the data capture reality) in the data set (Bolstad, 2008).

Misclassification error does not have a single clear antecedent and is influenced by many factors. The source of error may stem from sample size, sample design, model misspecification, inference assumptions, positional uncertainty, scale misalignment, surrogate or restricted ground observations, and obfuscation of corrections, assumptions, and tolerances (Foody, 2002). Misclassification error causes mapped land-use to differ from true land-use, and although accuracy assessments attempt to disclose this disconnect often publications fail to even include this information (Olofsson et al., 2013). Our approach is distinct from remote sensing model assisted estimation techniques (*e.g.*, Foody et al., 1992; Canters, 1997; Stehman, 2009; McRoberts, 2011) due to its construction within an econometric framework and application for practitioners one step removed from the data generating process. Yet there are parallel themes that arise in deriving the conditional probabilities of land use consistently and in the fundamental understanding of the causes and effects of misclassification.

In the context of empirical land-use models, misclassification errors imply measurement error in the dependent variable of a discrete choice model. Unlike measurement error in the classic linear regression model (which only reduces the efficiency of parameter estimates), misclassification error leads to inconsistent and inefficient parameter estimates in discrete choice models (Hausman et al., 1998; Neuhaus, 1999; Hausman, 2001). Although its presence is well known and has long been considered in the epidemiology literature (Copeland et al., 1977; Magder and Hughes, 1997; Neuhaus, 1999; Lewis et al., 2012), misclassification error has largely been ignored in the land-use literature. Wright and Wimberly (2013), for example, acknowledge misclassification and use a raw data correction approach (*i.e.*, spatial smoothing) to calculate rates of land-use change using satellite imagery data. They do not, however, apply an empirical model and therefore do not consider how misclassification errors may propagate (see Kline et al., 2013).

We expand previous methods of accounting for misclassification error to make them directly applicable to empirical land-use modeling. This model specification is functionally equivalent to Hausman et al. (1998), however the interpretations of specific parameter are adapted to those commonly used in the land-use literature. We further expand this specification to account for multi-use land-use models in a more general model. This specification can allow for different misclassification levels across each land-use. We therefore expand the theory and estimation methods of Hausman et al. (1998) to account for this additional complexity. Our method is particularly applicable to studies that use satellite imagery as the basis for an econometric model of the probability of use in a cross-sectional setting. We demonstrate these developments using an application of land use in the US Northern Great Plains.

Our empirical results demonstrate that bias caused by ignoring misclassification can be substantially significant to affect policy decisions. These models are often used to derive the implications of alternative policies (*e.g.*, subsidies) or external shocks (*e.g.*, climate change). In our example we show that misclassification leads to errors in estimating the effects of alternative policies and external shocks by an order of magnitude larger than 350%. Simply put the errors constitute misconstruing areas larger than Yellowstone National Park in the United States over a total population study area only 13 times larger.

2. Theoretical modeling of land-use

Consider a landowner who faces a decision of what to do with their land. We will assume this landowner has a utility function and chooses the land-use that maximizes their utility (see Segerson et al., 2006). Specifically, the owner of plot i faces a choice among j land-use alternatives and receives varying amounts of utility (U_{ij}) from each land-use choice. Thus the landowner chooses land-use k if and only if $U_{ik} > U_{ij} \;\; \forall \; j \neq k$. Since landowner utility is unobservable, we assume utility is comprised of indirect utility (V_{ij}) and a random error component (ε_{ij}), specifically $U_{ij} = V_{ij} + \varepsilon_{ij}$. Furthermore, it is more tractable and useful for empirical analysis to assume that indirect utility is linear in parameters: $V_{ij} = \beta' x_{ij}$, where x_{ij} are observable attributes of landowner utility and β are parameters to be estimated.

Consider a latent variable specification of the multinomial response model. Let U_{ij} be the latent variable, such that the true response is given by:

$$y_{ik}^{*} = \mathrm{I}(U_{ik} > U_{ij} \;\; \forall \; j \neq k) \tag{1}$$

where $\mathrm{I}(\cdot)$ is the indicator function equal to 1 if true and 0 otherwise. Therefore, the probability that the owner of plot i chooses land-use k is given by:

$$\begin{aligned} P_{ik}^{*} &= \Pr(y_{ik}^{*} = 1) = \Pr(U_{ik} > U_{ij} \;\; \forall \; j \neq k) \\ &= \Pr(V_{ik} + \varepsilon_{ik} > V_{ij} + \varepsilon_{ij} \;\; \forall \; j \neq k). \end{aligned} \tag{2}$$

If we assume the random error component (ε_{ij}) is an i.i.d. error disturbance with a c.d.f. and p.d.f. of $F(\varepsilon_{ij})$ and $f(\varepsilon_{ij})$ respectively, then the probability can be further expressed as:

$$P_{ik}^{*} = \Pr(y_{ik}^{*} = 1) = \int \mathrm{I}(\varepsilon_{ij} - \varepsilon_{ik} < V_{ik} - V_{ij} \;\; \forall \; j \neq k) f(\varepsilon_i) d\varepsilon_i \tag{3}$$

For certain specifications of f, the probability can be expressed in closed form (*i.e.*, Fisher-Tippett Type I Extreme Value or Gumbel) (see Train, 2009).

However, what if y_{ik}^{*} is observed with error? Suppose the observed response is a function of the true response and misclassification error (*i.e.*, $y_{ik} = g(y_{ik}^{*}, \mu_{ik})$) therefore, $\Pr(y_{ik}^{*} = 1) \neq \Pr(y_{ik} = 1)$. The literature on misclassification offers a number of alternative empirical approaches. The alternative approaches depend on the assumptions of the nature of misclassification error.

By the law of total probability we can decompose the probability from the observed response as:

$$\begin{aligned} \Pr(y_{ik} = 1) &= \Pr(y_{ik} = 1 | y_{ik}^{*} = 1)\Pr(y_{ik}^{*} = 1) \\ &\quad + \Pr(y_{ik} = 1 | y_{ik}^{*} = 0)\Pr(y_{ik}^{*} = 0). \end{aligned} \tag{4}$$

Note that:

$$\begin{aligned} &\Pr(y_{ik} = 1 | y_{ik}^{*} = 0)\Pr(y_{ik}^{*} = 0) \\ &= \sum_{j \neq k} \Pr(y_{ik} = 1 \,\Big|\, y_{ij}^{*} = 1)\Pr(y_{ij}^{*} = 1). \end{aligned} \tag{5}$$

Furthermore, consistent with spatial analysis literature, we define the conditional probabilities as accuracies given by:

$$\alpha_k^k = \Pr(y_{ik} = 1 | y_{ik}^{*} = 1) \tag{6}$$

and,

$$\alpha_k^j = \Pr(y_{ik} = 1 \,\Big|\, y_{ij}^{*} = 1) \tag{7}$$

where the superscript holds the value of conditional probability space. The conditional probability α_k^k can be directly interpreted as accuracy of the use k observation. Whereas the conditional probability α_k^j is the proportion of use k observations that should be use j observations. Thus, $\sum_{j \neq k} \alpha_k^j$ can be interpreted as the total proportion of use k observations that should be observed as other uses – specifically the error that use k introduces to all other use observations. Thus we can restate the probability of observing land-use k in a way that accounts for potential misclassification errors as:

$$\begin{aligned} \Pr(y_{ik} = 1) &= \alpha_k^k \Pr(y_{ik}^{*} = 1) + \sum_{j \neq k} \alpha_k^j \Pr(y_{ij}^{*} = 1) \\ &\equiv \alpha_k^k P_{ik}^{*} + \sum_{j \neq k} \alpha_k^j P_{ij}^{*}. \end{aligned} \tag{8}$$

In the case of no misclassification, $\alpha_k^k = 1$ and $\alpha_k^j = 0 \;\; \forall \; j \neq k$, and the true response for the dependent variable is observed (*i.e.*, $\Pr(y_{ik}^{*} = 1) = \Pr(y_{ik} = 1)$).

Whether the conditional probabilities are known or unknown, the associated likelihood function has the same form. In a typical (naïve) estimation procedure the land-use probabilities are estimated along with the latent accuracy term, which results in attenuated marginal effects. If the conditional probabilities (accuracies) are robust and the researcher deems them appropriate for their specific model, they may be used to directly weight the likelihood function in a standard MLE. However, even if the conditional probabilities are correct, the weighted MLE will not necessarily produce consistent standard error estimates (Hausman and Scott-Morton, 1994). We focus on the MLE approach with exogenous conditional probabilities (*i.e.*, exogenous to each other). The likelihood function for a land-use model accounting for misclassification errors is given by:

$$L(\alpha_k^k, \alpha_k^j, \beta_k) = \prod_i \prod_k \left\{ \left(\alpha_k^k P_{ik}^{*} + \sum_{j \neq k} \alpha_k^j P_{ij}^{*} \right)^{y_{ik}} \right\}. \tag{9}$$

Note the accuracies are just parameters that are directly estimable. The model does require a monotonicity condition for identification, mainly $\sum_j (1 - \alpha_j^j) < 1$. This condition is intuitively appealing since its violation implies that the observed land-use data does no better (or systematically does worse) than chance in describing land-use. As Hausman et al. (1998) note, if this were the case "the project should probably be abandoned!"

3. Rhetoric and context of accuracy assessments

Spectroradiometers and their classification algorithms have yet to return data sets with perfect information. Even if they could classify land-use perfectly they are still limited by spatial, spectral, and temporal resolution. Even with the smallest available tolerances across all satellites there will be plots straddling land-use borders that change over time and have subtle within land-use distinctions. Therefore, satellite imagery datasets provide accuracy assessment matrices. These aptly named 'confusion matrices' provide probabilistic estimates of accuracy across each land-use classification. Unfortunately, there is no standard for measuring and reporting attribute accuracy (Foody, 2002). Accuracy is usually reported as the (expected) difference between database values and reality. In the remote sensing literature, attribute accuracy tables are reported per observation and not per transition.

To derive and interpret conditional probabilities from a confusion matrix, first consider an abstraction of satellite imagery data where there are two exclusive and exhaustive land uses, grass and crops. A typical confusion matrix may look like:

Where A, B, C, D are counts of land-use plots, and $A + B + C + D$ are the total number of plots on a landscape. Note that there are A plots observed to be in use 0 (*e.g.*, grass) that are truly in use 0 (*e.g.*, grass), there are B plots observed to be in use 0 (*e.g.*, grass) that are truly in use 1 (*e.g.*, crops), there are C plots observed to be in use 1 (*e.g.*, crops) that are truly in use 0 (*e.g.*, grass), and there are D plots observed to be in use 1 (*e.g.*, crops) that are truly in use 1 (*e.g.*, crops) (Table 1).

Therefore, of the $A + B$ plots observed to be in use 0, only A plots are correctly classified (*i.e.*, user's accuracy of land-use 0); and of the $C + D$ plots observed to be in use 1, only D plots are correctly classified (*i.e.*, user's accuracy of land-use 1). However, of the $A + C$ plots known to be in use 0, only A plots are correctly classified (*i.e.*, producer's accuracy of land-use 0); and of the $B + D$ plots known to be in use 1, only

Table 1
Attribute accuracy table.

		Truth		
		$Y_i^* = 0$	$Y_i^* = 1$	
Observed	$Y_i = 0$	A	B	$A + B$
	$Y_i = 1$	C	D	$C + D$
		$A + C$	$B + D$	$A + B + C + D$

D plots are correctly classified (*i.e.*, producer's accuracy of land-use 1). Attribute accuracy reports are notoriously confusing when trying to reconcile producer's accuracy and user's accuracy (*i.e.*, known truth versus truth to be known). To describe these accuracies intuitively can be difficult, however the real difference is illuminated through their mathematical construction. See Stehman and Czaplewski (1998) for further discussion of fundamental principle of accuracy and Olofsson et al. (2014) for best practice recommendations.

Overall accuracy: $\frac{A+D}{A+B+C+D}$

$$= P(Y_i^* = 0 \cap Y_i = 0) + P(Y_i^* = 1 \cap Y_i = 1)$$
$$= P(Y_i^* = 0 \mid Y_i = 0)P(Y_i = 0) + P(Y_i^* = 1 \mid Y_i = 1)P(Y_i = 1)$$
$$= P(Y_i = 0 \mid Y_i^* = 0)P(Y_i^* = 0) + P(Y_i = 1 \mid Y_i^* = 1)P(Y_i^* = 1)$$
$$= a_0^0 P_{i0}^* + a_1^1 P_{i1}^* \quad (10)$$

Producer's accuracy of land-use 0: $\frac{A}{A+C}$

$$= \frac{P(Y_i = 0 \cap Y_i^* = 0)}{P(Y_i^* = 0)} = P(Y_i = 0 \mid Y_i^* = 0) = a_0^0 \quad (11)$$

Producer's accuracy of land-use 1: $\frac{D}{B+D}$

$$= \frac{P(Y_i = 1 \cap Y_i^* = 1)}{P(Y_i^* = 1)} = P(Y_i = 1 \mid Y_i^* = 1) = a_1^1 \quad (12)$$

Omission error of land-use 0 (*i.e.*, 1 minus Producer's accuracy): $\frac{C}{A+C}$

$$= \frac{P(Y_i = 1 \cap Y_i^* = 0)}{P(Y_i^* = 0)} = P(Y_i = 1 \mid Y_i^* = 0) = a_1^0 \quad (13)$$

Omission error of land-use 1 (*i.e.*, 1 minus Producer's accuracy): $\frac{B}{B+D}$

$$= \frac{P(Y_i = 0 \cap Y_i^* = 1)}{P(Y_i^* = 1)} = P(Y_i = 0 \mid Y_i^* = 1) = a_0^1 \quad (14)$$

User's accuracy of land-use 0: $\frac{A}{A+B}$

$$= \frac{P(Y_i^* = 0 \cap Y_i = 0)}{P(Y_i = 0)} = P(Y_i^* = 0 \mid Y_i = 0) \quad (15)$$

User's accuracy of land-use 1: $\frac{D}{C+D}$

$$= \frac{P(Y_i^* = 1 \cap Y_i = 1)}{P(Y_i = 1)} = P(Y_i^* = 1 \mid Y_i = 1) \quad (16)$$

Commission error of land-use 0 (*i.e.*, 1 minus User's accuracy): $\frac{B}{A+B}$

$$= \frac{P(Y_i^* = 1 \cap Y_i = 0)}{P(Y_i = 0)} = P(Y_i^* = 1 \mid Y_i = 0) \quad (17)$$

Commission error of land-use 0 (*i.e.*, 1 minus User's accuracy): $\frac{C}{C+D}$

$$= \frac{P(Y_i^* = 0 \cap Y_i = 1)}{P(Y_i = 1)} = P(Y_i^* = 0 \mid Y_i = 1) \quad (18)$$

Not all data sets provide accuracy assessments, nor do they provide the particular level of classification that the researcher is interested in. Accuracy assessments are a static analysis and typically cannot be rerun post publication. Spatially heterogeneous errors are not represented (Foody, 2002). Furthermore, they are only themselves an estimate using sampling techniques and "ground truthing." This often means using existing satellite imagery data to "ground truth" the next generation of datasets (Wickham et al., 2013). Regardless of its source, reference data is just as susceptible to the errors of the sample data, and measuring the agreement of these two data sets does not necessarily measure what we want to measure: closeness to reality (Foody, 2002). Our accuracy breakdowns are intended to show more clearly what the accuracy alphas represent. And, yes, they can be used for MLE weights but only under specific circumstances (see Hausman and Scott-Morton, 1994). This section shows how the accuracy estimates could be double checked for consistency, and more to the point, to better define them in the context of economic land-use research and to develop a consistent rhetoric for these techniques.

4. Applying misclassification correction techniques

Loss of native land cover to intensive agricultural production is one of the primary global threats to ecosystem and biodiversity conservation (Rashford et al., 2013; Armsworth et al., 2004). Temperate grasslands, which have the highest ratio of converted to protected area of any major biome, are perceived to be most at risk (Hoekstra et al., 2005). Loss of native grasslands to cultivated croplands was historically extensive and continues worldwide today (*e.g.*, Liu et al., 2006; Rounsevell et al., 2005; Stephens et al., 2008). Grassland loss decreases biodiversity (Foley et al., 2005; Green et al., 2005), releases sequestered carbon (Foley et al., 2005), decreases water quality (Moss, 2008) and increases soil erosion (Montgomery, 2007).

Despite continuing efforts on the part of government programs (*e.g.*, Conservation Reserve Program) and private conservation agents, US temperate grasslands continue to face high loss rates (Wright and Wimberly, 2013; Rashford et al., 2010). The Northern Great Plains – one of the most diverse, contiguous grasslands left on the planet – provides habitat for many threatened or special conservation status species, such as the long-billed curlew, piping plover, mountain plover and greater sage-grouse. The region is also critical for North American waterfowl, which depend on the region's mix of grassland and pothole wetlands for breeding habitat. Much of this vast upland landscape of native grass has been plowed (Leitch, 1989), resulting in the loss and fragmentation of habitat, and altered hydrological networks (Bell and Irwin, 2002). Much of the remaining grassland, particularly in the Northern Great Plains, is privately owned and used for low-intensity agriculture (*e.g.*, pasture and rangeland), and is therefore subject to loss (Fischer et al., 2008).

Given the ecological importance of the Northern Great Plains, it is essential for policy-makers to understand the drivers of grassland loss. Empirically modeling grassland loss in the region, however, is challenging given the land-use data available. Standard datasets of agricultural land-use, such as the Census of Agriculture, only provide county-level aggregate data and do not explicitly categorize grassland. Thus, satellite imagery data, with its fine spatial resolution and explicit land-cover classifications, is the most widely and publically available source of data for monitoring and modeling grassland loss. Grassland land-covers in satellite imagery data, however, can suffer from high rates of misclassification. For example, the 2001 NLCD the pasture/hay class exhibits a 14% rate of omission error and a 24% rate of commission error and the grassland/herbaceous class exhibits a 37% rate of omission error and a 17% rate of commission error (Wickham et al., 2013). Grassland loss in the Northern Great Plains therefore provides an appropriate and important context for exploring the implications of misclassification error for empirical land-use modeling.

We develop a binary-use logit model to predict the probability of grassland and cropland in the North and South Dakota portion of the Northern Great Plains. We estimate both a naïve model and a corrected model that accounts for misclassification error. Because the data suffer from misclassification error, we cannot condition on starting use, the standard practice in previous land-use change modeling studies (Lubowski, 2002; Lewis, 2005).

Substituting [6] and [7] into [5] and simplifying with a binary use scenario of cropland and grassland generates a simple expression for the probability of land-use that accounts for potential misclassification errors:

$$\begin{aligned}\Pr(y_{ic}=1) &= \alpha_c^c P_{ic}^* + \alpha_c^g P_{ig}^* \\ &= \alpha_c^c P_{ic}^* + (1-\alpha_g^g)(1-P_{ic}^*) \\ &= 1-\alpha_g^g + (\alpha_c^c+\alpha_g^g-1)P_{ic}^* \end{aligned} \tag{19}$$

Progressing from previous land-use literature and established logit specifications (see Rashford et al., 2013; Train, 2009), we define the probability of observing cropland on plot i as:

$$P_{ic} = \left(\frac{1}{1+e^{-V_i}}\right) \tag{20}$$

where V_i is the indirect utility of land-use on plot i. Subsequently, $1-P_{ic}$ is the probability of observing grassland. However, if one suspects misclassification error, as we do in this application, the probability of observing cropland on plot i is:

$$P_{ic}^* = \left[1-\alpha_g^g + (\alpha_c^c+\alpha_g^g-1)\left(\frac{1}{1+e^{-V_i}}\right)\right] \tag{21}$$

where α_g^g and α_c^c are defined as above.

The coefficients for the naïve model are estimated using maximum likelihood with the following log likelihood function:

$$LL(\beta_0,\beta_1,\beta_2,\beta_3) = \sum_i \{y_{ic}\ln(P_{ic}) + (1-y_{ic})\ln(1-P_{ic})\}. \tag{22}$$

The corrected model estimates accuracies of land-use observations along with the parameters of indirect utility by maximizing the following log likelihood function:

$$LL\begin{pmatrix}\alpha_c^c,\alpha_g^g,\\ \beta_0,\beta_1,\beta_2,\beta_3\end{pmatrix} = \sum_i \begin{Bmatrix} y_{ic}\ln(1-\alpha_g^g+(\alpha_c^c+\alpha_g^g-1)P_{ic}) \\ +\ (1-y_{ic})\ln(\alpha_g^g+(1-\alpha_c^c-\alpha_g^g)P_{ic})\end{Bmatrix}. \tag{23}$$

We specify the indirect utility of choosing cropland as:

$$V_i = \beta_0 + \beta_1 CropRet_i + \beta_2 CropRet_i LCC58_i + \beta_3 Dry_i \tag{24}$$

where $CropRet_i$ is the net returns to cropland on plot i; $LCC58_i$ is a dummy variable indicating whether plot i is in land capability class 5–8; Dry_i is the dryness index on plot i; and the β' s are parameters to be estimated. Land capability classes are an index measure of the lands ability to support crop production; thus, interacting land capability class with returns allows returns to be scaled according to plot-level soil characteristics (Lubowski, 2002). Dryness captures plot-level climate characteristics. We do not explicitly measure the indirect utility of choosing grassland for two reasons. First, accurate data on grassland returns is not readily available (*i.e.*, since grassland is an input to livestock production) and proxies, such as pasture rental rates, are poorly measured. Second, grassland is a residual land-use – that is, grassland is 'chosen' when the land is not suitable for crop production. Thus, the decision to choose crops is expected to largely explain grassland.

We measure net returns to cropland with five-year lagged area-weighted average of returns less operating costs in real terms developed from survey base year 2005 by the Economic Research Service (USDA, 2010a). The dryness index, provided by the Rocky Mountain Research Station (Crookston and Rehfeldt, 2010), captures spatial variation in historical average weather conditions. It is calculated as the ratio of growing season degree days above 5 °C and growing season precipitation. This index has been used to explain crop production decisions in previous land-use models (see Rashford et al., 2013). Land capability class is a composite, plot-level index of soil productivity in agriculture, with LCC1 being most productive and LCC8 being the least (Kellogg, 1961).

We use observations of land-use from the 2009 and 2010 Cropland Data Layer (CDL) distributed by the National Agricultural Statistical Service (USDA, 2009b; USDA, 2010b). The CDL is currently the most comprehensive public dataset for observing land-use in the United States. This dataset provides a contiguous landscape of spatially referenced 30 m × 30 m plots. Plots may be classified as 1 of 135 different land-use categories. The strength and emphasis of the CDL is crop-specific categories. The CDL uses the NLCD 2001 for non-agricultural uses and internal validation. To focus on grassland conversion to cropland, we aggregate the CDL into two uses. Specifically, crop land-use categories (*e.g.*, corn, wheat, *etc.*) become one cropland category and *grass/pasture*, *shrubland*, *NLCD-shrubland*, and *NLCD-grassland herbaceous* become one grassland category. Any uses outside of these classifications are omitted. Finally, we draw a sample of 61,851 observations from plots in North and South Dakota.

Table 2
Parameter estimates from four land-use models.

	Naïve		Corrected	
Variable	2009	2010	2009	2010
Intercept	2.7377	1.1706	9.8307	22.4076
	(0.0840)	(0.0743)	(0.6427)	(2.8427)
Crop Returns	0.0034	0.0006	0.0282	0.0934
	(0.0005)	(0.0003)	(0.0035)	(0.0113)
Crop Returns × LCC58	−0.0082	−0.0046	−0.0259	−0.0639
	(0.0002)	(0.0001)	(0.0016)	(0.0068)
Dryness	−0.4757	−0.1212	−1.9935	−5.0467
	(0.0142)	(0.0143)	(0.1363)	(0.5797)
Accuracy of Crops			0.7012	0.6500
			(0.0047)	(0.0023)
Accuracy of Grass			0.7811	0.6129
			(0.0100)	(0.0072)

Note: All coefficient estimates in the four models are statistically significant except naïve crop returns 2010. All coefficient estimates across the two model specifications are statistically different from one another above the 99.99% level of significance.

We estimate four land-use models in total, a naïve and corrected specification for data from 2009 and 2010. All parameters are significant at the 99% level of confidence in both the naïve and corrected models unless noted otherwise (Table 2). The signs of the corrected estimates are consistent with economic theory and *a priori* expectations. The cropland returns parameter is positive, indicating that higher cropland returns increase the utility of cropland, and is less impactful on lower quality land (*i.e.*, $\beta_2 < 0$). The dryness index is negative, indicating that an increase in growing season degree-days above 5 °C, holding precipitation constant, decreases the utility of choosing cropland.

The accuracy estimates range from 0.61 to 0.78 for grassland and 0.65 to 0.70 for cropland, indicating that the data suffer from substantial misclassification error. Compared to the reported accuracies from the NLCD the parameter estimates are consistent with expected values. Specifically, we estimate an omission error for grassland of 21.89% in 2009 and 38.71% in 2010 whereas the NLCD reports an estimated 14% rate of omission error for pasture/hay and 37% rate of omission error for grassland/herbaceous (the two classes that comprise the grassland category). We estimate an omission error for cropland of 29.88% in 2009 and 35.00% in 2010 whereas the CDL reports an average area weighted omission error for cropland of 16.73% in 2009 and 16.22% in 2010.

To focus on the possible policy implications of ignoring misclassification error, we present the averages of the predicted probabilities obtained from each of the model specifications (Table 3). There are some stark and important differences between the two models. The naïve predicted probabilities are exactly the average frequency of each land-use observed in the data. Yet we know that these uses contain misclassification error. In the corrected method the predicted probabilities are free to adjust: they represent the true distribution of land-use. Because the predicted probabilities in each model must sum to one the absolute effect of misclassification on the predicted probabilities is not as clear. Even more relevant to policy decisions is the dispersion of

Table 3
Averages of the predicted probabilities.

	Naïve				Corrected			
Use	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Crops 2009	0.5918	0.1387	0.1965	0.8788	0.7732	0.2938	0.0085	0.9998
Crops 2010	0.6083	0.0749	0.4094	0.7214	0.8412	0.3253	0.0000	0.9999
Grass 2009	0.4082	0.1387	0.1212	0.8035	0.2268	0.2938	0.0002	0.9915
Grass 2010	0.3917	0.0749	0.2786	0.5906	0.1588	0.3253	0.0000	0.9999

Note: All average predicted probabilities across the two model specifications are statistically different from one another above the 99.99% level of significance.

coefficient estimates.

Because of the non-linear nature of the logit specification, direct interpretation of parameter estimates is difficult. However, the corrected estimates are always farther from zero than their naïve counterparts. To provide a more clear interpretation and comparison, we estimate the average of the marginal effects for each explanatory variable. The marginal effects demonstrate the consequences of ignoring misclassification. In the naïve model, for example, a $1 per acre increase in crop returns for 2009 increases the probability of cropland by 0.0003, whereas the corrected model suggests a 0.0014 increase in the probability of cropland (Table 4). Thus, accounting for misclassification implies a marginal effect that is 367% larger than what is obtained from using the inconsistent estimates from the naïve model.

Note that the 2010 crop returns marginal effect is negative. Thus, the results from the naïve specification are distorted so much that the marginal effect has the wrong sign. The trend continues for the marginal effect of dryness. In the naïve model, a one unit increase in the dryness index of 2009 decreases the probability of cropland by 0.1058, where as the corrected model suggests a 0.1776 decrease in the probability of cropland. Thus, accounting for misclassification implies a marginal effect that is 68% larger than what is obtained from using the inconsistent estimates from the naïve model. Finally, a one unit increase in the dryness index of 2010 decreases the probability of cropland by 0.0282 in the naïve model, whereas the corrected model suggests a 0.14 decrease in the probability of cropland, which is a 396% difference. However, the more meaningful comparison is between the predicted effects from the naïve model and the corrected model (Table 5).

By applying the accuracy assessments to the observed acreage we show that in total 4,315,563 acres are misclassified in expectation. Then using the observed and corrected acres from the two models we can predict the relative differences (consequences) between the two models. We first consider a $10 per acre increase (< 7%) in 2009 crop returns. There are many scenarios in which the relative returns to cropland increase and thus increase grassland loss in the Northern Great Plains. Federal polices, for example, continue to encourage biofuels as an alternative to traditional fossil fuels (Rashford et al., 2010). Biofuel production predominantly comes from corn ethanol, which is expected to bolster the recent high corn prices. Under the assumptions of the naïve model, we would expect 139,574 more acres of cropland given a $10/acre increase in crop returns. However, under the corrected model, we would expect 651,343 more acres of cropland, a difference of 511,769 acres in expectation.

Table 5
Misclassification realized on the landscape.

Treatment	Naïve	Corrected	Difference
Acres of Grass in 2009	35,188,505	30,872,942	4,315,563
Acres of Crops in 2009	11,336,014	15,651,577	4,315,563
Crop Returns increase by $10 - Cropland	+139,574	+651,343	511,769
Dryness increase by one unit - Cropland	−4,922,293	−8,262,755	3,340,462

Interpreting the magnitude of changes in dryness index is more difficult because it is a ratio variable. However the relative differences across the two model specifications is still enlightening. Consider a one-unit increase to the dryness index. This change equates to an on average increase of 30 growing season degree days, or approximately 0.3 °C increase in average temperature (300 growing season degree day tenths or 30 growing season degree days averaged over the growing season days > 5 °C (100 days) is equivalent to an average increase of 0.3 °C of each growing season degree day that year). Under the assumptions of the naïve model we would expect 4,922,293 less acres of cropland. However, under the corrected model we would expect 8,262,755 less acres of cropland, a difference of 3,340,462 acres. For perspective this difference is larger than the area Yellowstone National Park in the United States.

5. Conclusion

The increasing availability of satellite-based land-use datasets – including datasets with contiguous spatial coverage over large areas, relatively long temporal coverage, and detailed land cover classifications – is offering new opportunities for empirically modeling land-use. Data derived from satellite imagery offers a greater ability to model micro-level land-use, and thus to understand the drivers of, and predict, the fine-scale spatial configuration of both altered and natural landscapes. Though satellite imagery data offers new opportunities, it also poses new challenges for empirical modeling. Satellite-based land-use datasets all suffer from some level of misclassification error. Such misclassification implies that the dependent variable in a discrete choice land-use model may be misclassified. Although misclassification, and more generally measurement error, is found in many datasets, ignoring it in discrete choice models results in inconsistent parameter

Table 4
Marginal effects for probability of observing cropland.

	Naïve				Corrected			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Crop Returns 2009	0.0003	0.0008	−0.0012	0.0008	0.0014	0.0017	0.0000	0.0070
Crop Returns 2010	−0.0002	0.0005	−0.0010	0.0001	0.0011	0.0024	0.0000	0.0234
Dryness 2009	−0.1058	0.0085	−0.1189	−0.0507	−0.1776	0.1615	−0.4984	−0.0004
Dryness 2010	−0.0282	0.0012	−0.0303	−0.0244	−0.1400	0.3144	−1.2617	−0.0000

Note: Marginal effects across the two model specifications are statistically different from one another above the 99.99% level of significance.

estimates (Hausman et al., 1998). The consequences of, and corrections for, misclassification error are well addressed in the epidemiology literature (*e.g.*, in the context of health treatment effects); however, misclassification errors have not been considered in the context of empirical land-use modeling.

The application in the Northern Great Plains demonstrates the importance of correcting for misclassification errors. We use the Northern Great Plains for an application because temperate grasslands are at high risk of conversion to cropland, and such conversion threatens the habitat of many threatened or special conservation status species. Moreover, empirically modeling grassland in the region is challenging because commonly available datasets are too aggregated or do not explicitly categorize grassland; thus, satellite imagery is potentially the best source of data to monitor and model grassland. Grassland landcovers in satellite imagery data, however, suffer from high rates of misclassification. Our empirical results demonstrate that bias caused by ignoring misclassification can be substantial and thus could affect policy inference. Given that land-use models are often used to derive the implications of alternative policies (*e.g.*, subsidies) or external shocks (*e.g.*, climate change), our results suggest that ignoring misclassification could lead to incorrect inference.

Though this paper demonstrates applicable techniques that correct land-use models for misclassification, further research is needed. Our application uses a relatively simple land-use model (*i.e.*, two uses, one transition period, and a relatively simple specification of indirect utility). The complexity of the likelihood function that incorporates misclassification can pose convergence challenges and thus more complex models with multiple uses and many transition periods may not converge. Additionally, more thought is needed to interact these error correction techniques with techniques that rectify other issues of discrete choice land-use change models, such as spatial autocorrelation and computational complexity. A robust empirical study over many uses and time periods that attempts to explain and predict land-use change is needed. The results of our empirical research lack the full depth of scope to provide these results. Finally, the next step for this research is adapting techniques that account for endogenous misclassification error, relative to plots and across time. This step would relax the assumption that misclassification errors of land-use are independent of their geography and occur independently across time.

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