Predicting land use change: comparison of models based on landowner surveys and historical land cover trends

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Abstract

To make informed planning decisions, community leaders, elected officials, scientists, and natural resource managers must be able to evaluate potential effects of policies on land use change. Many land use change models use remotely-sensed images to make predictions based on historical trends. One alternative is a survey-based approach in which landowners' stated intentions are modeled. The objectives of our research were to: 1) develop a survey-based landowner decision model (SBM) to simulate future land use changes, 2) compare projections from the SBM with those from a trend-based model (TBM), and 3) demonstrate how two alternative policy scenarios can be incorporated into the SBM and compared. We modeled relationships between land management decisions, collected from a mail survey of private landowners, and the landscape, using remotely-sensed imagery and ownership parcel data. We found that SBM projections were within the range of TBM projections and that the SBM was less affected by errors in image classification. Our analysis of alternative policies demonstrates the importance of understanding potential effects of targeted land use policies. While policies oriented toward increasing enrollment in the Conservation Reserve Program (CRP) resulted in a large (11-13%) increase in CRP lands, policies targeting increased forest thinning on private non-industrial lands increased low-density forest projections by only 1%. The SBM approach is particularly appropriate for landscapes including many landowners, because it reflects the decision-making of the landowners whose individual actions will result in collective landscape change.

Introduction

Changing land use practices can have substantial effects on social, economic, and ecological systems and have created conflict over traditional land management practices, property subdivision, and the preservation of open space in the western United States (Greider and Garkovich 1994, Smith and Krannich 2000). Land use change and exurban development can directly reduce native species' habitat and biodiversity (Theobald and Hobbs 2002, Maestas et al. 2003) and create low quality habitat that may act as a population sink (where reproductive success is below the replacement rate) (Hansen and Rotella 2002, Schlaepfer et al. 2002). Additionally, increased exurban development in fire-prone areas increases the potential for property loss from wildland fires (Cohen 2000, Dellasala et al. 2004). Predicting and evaluating potential land use patterns through modeling can assist community leaders, elected officials, scientists, and natural resource managers to make more informed project- to landscape-level planning decisions. Efforts to predict land use change have expanded greatly in recent years, with many different approaches being applied (Lambin and Geist 2006).

Many land use change modeling studies use an historical series of remotely-sensed imagery to empirically derive transition parameters across landscapes (Theobald and Hobbs 1998, Wear and Bolstad 1998, Conway and Lathrop 2005). The underpinning assumption of this trend-based modeling (TBM) method is that future trends will resemble recent historical trends (Theobald and Hobbs 1998). Models based on projections arising from decision-making of individuals reduce the influence of this assumption. In this study, we present a survey-based model (SBM) in which individual landowners predict their land use decisions, which are influenced by and affect the landscape. This SBM approach is an alternative to agent-based modeling (ABM), in which individuals interact and react to their environment and may make strategic optimization decisions (Parker et al. 2003). ABMs have been widely used to represent individual and household decision-making (Parker et al. 2003, An et al. 2005, Brown and Robinson 2006, Brown and Xie 2006). Our SBM differs from this method in that it models the projected change resulting from landowner survey responses to parcels directly, and not the behavior of the agents themselves or their social environment (Verburg et al. 2006). Because they focus on the decision-making process, both ABMs and SBMs are well-suited for evaluating how individuals will react to alternative policy scenarios. Decision-based models have been used to project landscape conditions under alternative policies in forested and agricultural landscapes of

Oregon (Spies et al. 2002, Baker et al. 2004) and agricultural regions of Iowa (Santelmann et al. 2004), Minnesota (Boody et al. 2005), and Texas (Musacchio and Grant 2002). In these studies, local experts and lay groups made predictions about the decisions major stakeholders and land managers would make. In contrast, our SBM approach uses statistical models derived from a stratified random sample of individual landowners to predict future land use patterns and effects of alternative policy scenarios.

The objectives of our research were: 1) to develop a spatially-explicit SBM representing landowner decisions to simulate future land use changes in two counties of northern Idaho, 2) to compare the results of the SBM to a Markov chain TBM that used pairs of remotely-sensed images, and 3) to demonstrate how this SBM can be used to compare the outcomes of two policy scenarios. Our study is unique for modeling land use change under current conditions and alternative policy scenarios based on self-reported probabilities of landowner actions instead of historical trajectories, economic or ecological models, or expert opinion. This research is part of a larger project examining the social and ecological implications of land use change in northern Idaho.

Methods

Study area

The study area consists of Latah and Benewah counties, Idaho, U.S.A. (4794 km^2; Figure 1). This area has undergone significant land use changes during the past 150 years. Nearly all native grassland vegetation and some forests were converted to agriculture by Euro-American settlers during the late 1870's; wheat has been the dominant crop in the region since the early 1900's (Black et al. 1998). Other crops include peas, lentils, and bluegrass seed. In 1985, the U.S. government initiated the Conservation Reserve Program (CRP), which provides payments to landowners who plant perennial vegetation cover on highly erodible agricultural lands. Since this time, a large amount of highly erodible, marginal agricultural land has been removed from production and enrolled in the CRP. Beginning in the 20th century, the region's forests experienced high-grade logging. By the 1960s, when most easily accessible trees had been removed, the forest industry switched to clearcutting practices. Forest structure and composition has become more homogeneous than it was historically, and the landscape contains few old forests (Hessburg and Agee 2003).

Latah and Benewah counties are predominantly rural and privately owned, with the largest populations in the cities of Moscow (~22,000) and St. Maries (~2,500; U.S. Census Bureau 2005). The remaining population (~20,000) lives in dispersed rural communities and developments. Like many non-metropolitan counties in the western U.S.A., this area has recently experienced population growth above the national average (Shumway and Otterstrom 2001), resulting in increased rural residential development, transitioning demographics, and changing agricultural and forestry practices. The two counties are located in the transition zone between the grassland-dominated Palouse Prairie and forest-dominated Bitterroot Mountain ecoregions. The ecological and economic diversity of this ecotone combined with the dominance of private land ownership creates the potential for a diversity of land use changes and policies that could have a large influence on the landscape.

Map creation

We created a current land ownership map and current land use/land cover (LU/LC) map (Figure 1a) using ArcGIS (Environmental Systems Research Institute, Redlands, CA) and ENVI 4.2 (Research Systems Inc., Boulder, CO). The land ownership map was classified from 2005 GIS layers of property tax parcels. We used owner names to classify parcels as federal (14%), state (8%), industrial (25%), and private non-industrial (53%).

The current LU/LC map was created using Landsat 7 ETM+ data acquired in August 2002 and converted to at-sensor radiance and at-sensor reflectance (NASA 2005). Gram-Schmidt Spectral Sharpening was used to fuse the 15-m panchromatic and 30-m multispectral bands, resulting in a 15-m multispectral image (Li et al. 2004). The image was geo-referenced to 2004 National Agriculture Imagery Program (NAIP) digital orthorectified 1-m resolution imagery, resulting in spatial accuracy of 5.6 m. We used a maximum likelihood algorithm with no probability threshold for supervised image classification. The spectral reflectance characteristics of development were not separable from that of some other classes. Therefore, development training points were initially classified as barren and redefined in a secondary step. Ground reference data consisted of 360 data points, classified and geolocated by global positioning system (GPS; 1-m accuracy) in 2003 and 2004, of which two-thirds were used for training and the remainder for accuracy assessment. Additional barren and water points were generated using the 2004 NAIP imagery. Ground reference points were buffered in ArcGIS to create plots with a radius of 20 m that were verified against the NAIP and Landsat imagery. Only the 327 plots accurate for the 2002-2004 time frame were used. The classification was sieved and clumped to incorporate isolated pixels into neighboring classes. We calculated overall classification accuracy, the Kappa statistic, and producer's and user's accuracy for each LU/LC class (Table 1).

Following this classification, we added development (rural residential and urban) and CRP classes. The development class was created using a 2005 GIS layer of built structures obtained for Latah County and the 2004 NAIP imagery. Data on CRP grassland locations were not publicly available, so we modeled potential CRP grasslands based on program enrollment criteria. CRP enrollment typically occurs by land areas referred to as common land units (CLUs), which are the agriculture land management units for U.S. government programs. We obtained a map of CLUs from the USDA Farm Service Agency Aerial Photography Field Office (http://www.apfo.usda.gov/). For parcels that were included in the mail survey of private landowners, we matched the landowner-reported CRP acreage with the land cover in the CLUs most likely to be in the CRP (grassland or stand initiation/shrub). We modeled the remaining acreage reported for each county in CRP grasslands (Jim Knecht and Tami Gauthier, Farm Service Agency, pers. comm., March 2006) by randomly selecting CLUs with a majority of pixels identified as grassland and classified as highly erodible by the USDA Natural Resources Conservation Service. Because the 2002 image was updated with more recent auxiliary data sources, hereafter we refer to the map produced through these methods as the *current* map. Forest is the dominant land class (51%), followed by stand initiation/shrub and grasslands (28%), agriculture (20%), and development (1%; Figure 1a).

We also created maps of historical LU/LC using 30-m multispectral resolution Landsat TM imagery acquired in mid-July to mid-August in 1985, 1992, 2000, and 2003 (Beck and Gessler, In Press). The images were converted to at-sensor reflectance (after Markham and Barker 1986) and a maximum likelihood algorithm was used for classification. The training and accuracy datasets were the same as those used for the current map. Ground reference points that had changed land use since the historical image date were discarded. We were unable to separate the two forest classes, so a single forest class was used. As with the current landscape map, development was classified in a two-step process. Well locations (Idaho Department of Water Resources 2006) were overlaid on the built structures locations to estimate the date of construction for rural residential development. The footprints of town boundaries, where development is typically tied to a municipal water supply, were digitized from each Landsat image. Overall accuracy ranged from 81% for the 1985 image to 91% for 1992 (Table 1).

Calculating SBM transition probabilities

We collected data on LU/LC transition probabilities for the SBM on private non-industrial lands using a mail survey about current and future plans for land use and management strategies. We selected a stratified random sample of non-industrial, privately owned land parcels greater than 0.8 ha (2 ac). We stratified by parcel size to ensure that the sample was not biased towards small parcels. We received responses from owners of 442 parcels (54% of eligible respondents). A non-response bias test, based on phone interviews of willing non-respondents, suggested a slight bias towards response from property owners with a higher level of education.

Questions regarding future land use plans employed a continuous scale from 0 to 100 in which respondents were asked to rate the likelihood that they would employ given strategies within a 10-year time frame. Questions focused on land use plans and management strategies for four land uses: 1) agricultural lands, 2) CRP lands, 3) forests, and 4) residential developments. These questions were statements that respondents rated, for example, "I plan to plant trees on at least some of my CRP land," or "I plan to subdivide and sell some land for residential development."

To extrapolate transition probabilities to every parcel within the study area, we used 37 spatially explicit explanatory variables that we expected to relate to land use change, including development density, land cover, land ownership, parcel characteristics, population centers, topography, and transportation (Table 2). Our objective was to obtain the most predictive combination of explanatory variables and statistical model structure for our survey data given the mappable explanatory data. Therefore, we chose an inductive pattern-based approach to identify correlates of land use change rather than attempting to identify drivers of land use change using a deductive hypothesis-driven approach.

For each transition, we used two variable selection approaches to identify 8 of the 37 variables to use in the predictive statistical model. We used random forests regression trees (Breiman 2001) in program R (Liaw and Wiener 2002, R Development Core Team 2006) to identify four variables associated with the largest increases in predictive model accuracy. Another four variables were selected that had the highest Pearson correlation coefficient (r) with the transition probabilities. Predictor variables exhibiting multicollinearity ($r > 0.7$) were not used in the same models; the lower-ranked variable was excluded.

To obtain the best predictive statistical model for each of the 14 transitions included in the mail survey (Table 2), we selected the model with the best fit from the following four regression approaches: 1) generalized linear models (GLM) with Poisson, zero-inflated Poisson, negative binomial, inverse Gaussian, and gamma response distributions, 2) censored GLM (Tobit models), 3) ordinal logistic regression, and 4) geographically weighted regression (GWR) with Gaussian and Poisson distributions. Ordinal logistic models were created by binning the response probabilities, and using the bins as ordinal responses. Models were fit using R or SAS 9.1.3 (SAS Institute, Cary, North Carolina). Statistical models were selected based on three criteria. First, we assessed predictive ability of each model based on the R^2 of the predicted versus observed values in the sampled data (Table 2), using k-fold cross-validation for the GWR models. Two models with $R^2<0.05$ were eliminated. Second, we tested whether the remaining 12 models explained more variation than random ($p<0.10$) by performing Monte Carlo simulations with 1000 permutations for each model (Table 2). Third, we compared the distributions of observed and predicted transition probabilities for each transition over all parcels to ensure that the predicted distribution sufficiently reflected the shape of the observed distribution.

We applied the 12 selected statistical models of landowner-reported transition probabilities to all private non-industrial parcels in the study area. For the two transition models that did not meet the above criteria (Table 2), we used semi-variograms to evaluate whether transition probabilities could be interpolated to all parcels based on spatial covariation in the sample data. In the data reflecting the decision to expand residential development for personal use, we found insufficient spatial covariation. Therefore, we applied the sampled data distribution randomly across all parcels. The final transition dataset (no forest management) exhibited spatial covariation, which we kriged on a 50-m grid and used the kriged value nearest to the parcel centroid to spatially interpolate the data to all parcels.

Finally, to apply the landowner-decision model on public and industrial lands, we gathered data on management practices from published reports and interviews with representatives from US Forest Service, US Bureau of Land Management, Idaho Department of Lands, University of Idaho Experimental Forest, and large industrial forest owners. The majority of these lands are forested, and interviews indicated that potential for development on these lands in this time frame was unlikely. Data on forest harvest rotation lengths, the number of acres harvested per year, average treatment size, and the ratio of forest thinning to clearcutting were used to enact forestry transitions on public and industrial land.

Two alternative future scenarios were generated based on the mail survey data that queried possible landowner responses to technical assistance and incentive programs. The scenarios reflect how changes in natural resource policy may affect land use and management practices on private non-industrial lands. The technical assistance scenario was designed to demonstrate how private non-industrial landowners would respond to increased resource management education and planning assistance. The incentive scenario was designed to show response to fiscal and management enticements for specific types of resource management. The scenarios were operationalized by asking survey questions about barriers and enablers to two specific land use practices: 1) enrollment of agricultural land in the CRP and 2) forest thinning. Respondents were asked why they had not in the past (barriers) and what might cause them in the future (enablers) to apply for the CRP or thin their forests. For example, respondents rated the following statements: "I would thin my forest if I had more resources to help me plan and implement," or "I would apply for CRP enrollment if the annual payment were higher." Responses were recorded on a five point Likert-type scale (strongly agree (2) to strongly disagree (-2) with the midpoint being labeled neutral).

We conducted factor analysis on each scenario’s set of survey questions, resulting in a single factor explaining 80% or more of the variance in each scenario’s set of survey questions. A scale score was computed as the average of the responses for each scenario’s set of survey questions (Table 3). Scale scores were used to adjust the transition probabilities for forest thinning and the conversion of agriculture to CRP. Scale scores below zero were censored to zero so that agreement with the barrier and enabler items could be used to apply an upward adjustment on a transition probability, while disagreement with the policy would not reduce the original transition probability.

To adjust the baseline transition probabilities, we began by bootstrapping the scenario scale distributions to the population of private non-industrial parcels. We then used the scale scores for each parcel to adjust the respective unscaled transition probabilities. To calculate the adjusted transition probability, TP_{ij}, we derived the following formula:

$$TP_{ij} = TP_i + \left(10^{\sqrt{\text{ScenarioScore}_{ij}}} - 1\right) \qquad \text{for all i,} \qquad (1)$$

where TP_i equals the original unscaled transition probability for transition i, and $ScenarioScore_{ij}$ equals the scenario scale score for transition i given scenario j. For example, if the incentive scenario score for the transition from agriculture to CRP equaled 2, then the original transition probability would be increased by 25%. The derivation of Equation 1 was aimed at limiting adjustments to transition probabilities due to policies to a maximum of 25%, which we assume represents a conservative response to changes in policy.

LU/LC transition models

For the SBM, we developed a stochastic transition model to project changes from current classes of land use to other classes (Figure 2). The model had one time step representing 10 years and modeled land use change at the scale of LU/LC patch within an ownership parcel. To implement the model we imposed two rules. First, we restricted the model to allow only one transition per LU/LC patch per parcel to occur in each model run. We determined that one transition per LU/LC patch was appropriate because, on average, respondents treated options for a given land cover as exclusive (e.g., respondents were likely to thin or develop forested portions of their land, but not both). Second, we scaled the transition probabilities for each LU/LC within a parcel so that the sum of all transition probabilities equaled one for all scenarios. This was necessary because each LU/LC within a parcel could transition to one of multiple alternative LU/LC classes, and the transition probability for each was estimated independently. The exception to this method was for development, where the probability of no development was calculated as the difference between one and the sum of the probabilities for the two development options (subdivide and expand). If the two development probabilities summed to more than one, they were scaled to equal one.

We programmed the SBM using Arc Macro Language (AML) in the ArcInfo Workstation 9 ArcGrid module, using grids representing LU/LC, parcels and ownership, transition probabilities for 12 transitions, and expert-generated data for transition sizes (Table 4). Each LU/LC class was engaged separately, and units considered for transition were individual land use patches within each ownership parcel. The scaled transition probabilities for all possible transitions within the LU/LC patch were compared to a random number selected from a uniform distribution between zero and one to determine which transition, if any, would occur during each simulation. When a transition to an alternate LU/LC was selected, the AML program located a random pixel within the original LU/LC class and expanded to the expert-generated transition size specific to that LU/LC class, within parcel boundaries or tenure classes (Table 4). Each transition generated a new LU/LC that was written over the original LU/LC map. We ran the AML program 100 times, each run simulating a different realization of future LU/LC. At 100 runs the variance in selected metrics had stabilized. To realize alternative futures with the two scenarios, the model was rerun incorporating the respective adjusted transition probabilities, producing 100 additional simulations for each scenario.

The exception to the patch-based transition procedure was for development, where units considered for transition were whole ownership parcels. Transitions were of two types: subdivision and expansion. For subdivision, we used survey data to determine the LU/LC class within the parcel that was most likely to be developed. If any of the modeled transition probabilities from forest, agriculture, or CRP lands to development was <0.50, then development was modeled to occur randomly within that LU/LC class. If none of the probabilities met this criterion, then the simulated development was located randomly within the parcel. Rules governing the number of residential developments placed on the parcel were based on current subdivision ordinances for each county (Table 4).

For the TBM, we used the four historical LU/LC maps to generate five landscape projections for 2015, using IDRISI Andes software (Clark Labs, Worcester, MA). A Markov transition matrix was created to identify the likelihood that a given LU/LC class in two historical maps would transition to another class (Pontius and Malanson 2005). Five separate Markov chain transition models were created using different sets of image dates: 1985 to 2000, 1985 to 2003, 1992 to 2000, 1992 to 2003, and 2000 to 2003. Each transition model was run on single year time steps to 2015. The assumptions, data requirements and outputs of this modeling approach differed from the SBM approach in several ways, including by operating at the pixel scale (Table 5).

Statistical analysis and model verification

We measured the amount of land area in each LU/LC class and the number of rural housing units added for each model simulation. We tested for differences in mean areas of CRP and low-density forest classes among baseline and alternative policy scenarios using a one-way ANOVA and subsequent Tukey-Kramer tests.

We validated the historically-based approach by projecting landscape changes to 2003 using two sets of image dates, 1985 to 2000 and 1992 to 2000, and comparing the outcomes with the realized LU/LC map for 2003.

Because we lacked a reference map for 2015 or previous landowner-reported transition probabilities from which to quantify the predictive accuracy of the SBM model (Pontius et al. 2004), we instead developed a spatially explicit measure of stochastic certainty as recommended by Brown et al. (2005b). We developed a location-based method to evaluate the stochastic certainty of our model using a common landscape metric that measures the degree of dominance, D, of a particular LU/LC given a maximum possible diversity of LU/LC for a patch within a parcel (O'Neill et al. 1988):

$$D_{ijk} = \left(\frac{H_{max,k} + \sum_{i=1}^{m} \left(P_{ijk} * \ln P_{ijk}\right)}{H_{max,k}} \right) \quad \text{for all k} \qquad (2)$$

where m is the number of possible LU/LC types in patch k and j is the total number of simulated landscapes. P_{ijk} is the proportion of j simulated landscapes where patch k is equal to LU/LC type i and $H_{max,k} = \ln(m)$ for patch k, or the diversity value when each LU/LC type i occurs in equal proportions of j simulations in patch k. Transitions occur at the patch level in our model, and each patch has several associated transition probabilities reflecting the ability for a patch in LU/LC i to transition into several other LU/LCs. Therefore, values of D_{ijk} approaching one indicate patches in which one transition probability is predominant, leading to a dominant predicted transition.

Results

LU/LC projections

The land areas in each LU/LC class in the TBM 2003 validation maps were within 50% of the original 2003 map, with the exception of the forest SI/shrub class, which was over predicted by 200%. Residentially developed area was under-predicted by 1 to 2% (Figure 3). Class area projections for 2015 from the TBMs differed depending on the pair of images used, reflecting differences in patterns of change during those time periods (Figure 4). The TBMs consistently projected increases in rural housing units (23-56%) and decreases in forest (18-27%) and agriculture (7-22%), while grassland projections were inconsistent. Forest SI/shrub projections are not presented because of poor validation results for this class (Figure 3).

SBM projections were generally consistent with those from the TBM (Figure 4). Both models projected substantial increases in rural housing units, with a mean increase of 28%

projected by the SBM. The SBM predicted a smaller decrease in forest (mean 11%) than the TBM (Figure 4), consistent with the under prediction of forest area in the TBM validation. Forest thinning was projected to increase by a mean of 20%. Agriculture was projected to decrease by a mean of 7%, a smaller decrease than projected by three of the TBMs (Figure 4). The SBM projected a small increase in overall grassland area (mean 4%), with CRP area projected to increase by 12%.

Projections from the SBM exhibited high stochastic certainty (Figure 4). Of the land use classes in the transition model, certainty was greatest on agricultural land (D_{ijk}=0.36; dominant transition occurred approximately 73% of the time), followed by high-density forest (0.32), CRP grassland (0.29), and low-density forest (0.26; Figure 1b).

Alternative policy scenarios

Policy scenarios directed at providing increased technical assistance and incentives increased both the amount of agricultural land predicted to be enrolled in CRP and forest land predicted to be thinned (p<0.0001). CRP lands were increased by 11 to 13% relative to the baseline projection (Figure 5), with the incentives scenario resulting in a 2% greater increase than the technical assistance scenario (p<0.05). Both technical assistance and incentive policies had less effect on the amount of forest land that was thinned, with increases of 1% in the mean area of low-density forest (p<0.05; Figure 5). The amount of low-density forest did not differ between the two policy scenarios. The area of forest SI/shrub was significantly lower under both policy scenarios than in the baseline scenario, reflecting that the scenarios affected a decision-making tradeoff between clearcut logging and selective harvesting.

Discussion

LU/LC projections

The increasing rate of development projected by both the survey- and trend-based models reflects findings that non-metropolitan growth rates in the U.S.A. have been increasing since the late 1980's (Johnson and Beale 1994, Shumway and Otterstrom 2001, Brown et al. 2005a, Theobald 2005). The past and predicted rates of exurban development are further indication of the increasing importance of amenity-driven migration and economic mobility experienced by many Americans (Beyers and Nelson 2000). One limitation for projections from both models is that neither directly incorporates variation in the real estate market, which could influence the pace of new residential development in either direction depending on broader economic factors.

The decrease in projected mature forest area using both models can be attributed to increases in forest harvesting (transition to forest SI/shrub from other forest covers) and residential development. A similar trend has been observed in the Oregon coast range, where early successional forests have been projected to remain the dominant forest cover on privately owned lands (Spies et al. 2002). While some of the decrease in forest area projected by the SBM can be attributed to the model structure (i.e., harvesting of forests was allowed but stand initiation forests did not mature during the 10-year period), results were consistent with the TBM projections and general trends towards increased timber harvesting on private lands due to harvest constraints on public land (Haynes 2002).

The projected decrease in agricultural land over the next 10 years is consistent with a national trend; agricultural land area decreased by 11% from 1950 to 2000 (Brown et al. 2005a). In our study, the reduction of agricultural land can be attributed mostly to conversion of agriculture to CRP and residential development. Federal funding currently limits CRP enrollment in our study area, while the SBM allows unlimited transition from agriculture to the CRP. Therefore, if current federal policies persist, real increases in grassland may be smaller than projected as some agricultural producers choose to remain in agriculture or develop their land as an alternative to enrolling in the CRP (Johnson and Maxwell 2001).

Comparison of SBM and TBM approaches

Image classification errors had a larger impact on the TBM because the calculation of transition probabilities from changes between the two images magnified the impact of errors in each. Overall image classification accuracies were high, but forest SI/shrub and grassland class accuracies were low for all images. The 200% over prediction of forest SI/shrub area in the TBM validation can be explained by this image misclassification. Other researchers have also had difficulty spectrally distinguishing similar shrub and grassland classes when creating LU/LC maps (Scott et al. 2002, Brown de Colstoun et al. 2003). Systematic classification error may have had significant influence on projections from the TBMs (Fang et al. 2006). This issue appears to be a particular problem for the grassland class. Grassland classification errors in the 2000 image resulted in significantly different grassland projections for those projections including the 2000 versus 2003 image (Figure 4). Other changes over time can also influence projections from the

TBM. For example, water was over predicted by 50% in the TBM validation, which can be explained by the construction of a large reservoir between the 1996 and 2000 image dates.

Validation of spatially-explicit land use change models is challenging, especially for models that are not informed by historical trends (Brown et al. 2005b). Although we are currently unable to determine the predictive accuracy of our SBM, measurement of stochastic certainty allowed us to verify that the model was functioning in the manner that we had expected. For all transitioning LU/LC classes in the SBM, each land cover unit was predicted to the same class in the majority of the simulated landscapes.

There are strengths and limitations associated with both survey- and trend-based modeling approaches. The TBM is based on the assumption that past patterns of landscape change will persist and is highly sensitive to classification errors. The SBM relies upon individual landowners to project land use changes under the assumption that landowners' survey responses are a reasonable indication of their plans for the future and that they will follow through with them. Economic studies using contingent valuation methods demonstrate that this assumption is overly stringent and that stated behavioral intentions and realized actions are often different (e.g., Loomis et al. 1996). Furthermore, explanatory power of our SBM is limited by the challenge of using mapped environmental and property ownership data to model human decision-making. Clearly human decision-making is greatly influenced by other social and economic factors (Gustafson et al. 2005). Nonetheless, the SBM reflects general trends in decision making and the process by which land use change occurs on privately owned lands. This approach can empower local stakeholders through the visualization of their combined decision-making.

While we believe that the above considerations should drive the choice of methodology, constraints on availability of data and expertise may also be important factors. The TBM requires multiple historical images and remote sensing expertise, while the SBM requires a current parcel map and land cover map as well as social science, statistical modeling, and programming expertise. Where LU/LC trends can be expected to continue, the TBM approach may be more efficient. The SBM method is more appropriate when this cannot be comfortably assumed. Finally, our implementation of both modeling approaches used inductive logic, limiting the temporal and spatial generalizability of the models.

Alternative policy scenarios

Although the acreage of the CRP program is currently constrained by federal funding, our models demonstrate that the CRP is a land use option that is in demand. An increase in CRP may provide additional wildlife habitat (Dunn et al. 1993, Ryan et al. 1998) and reduce the rate of rural residential development (Johnson and Maxwell 2001). The two policy scenarios differ in the amount of land converted to CRP (with incentives producing more CRP lands than technical assistance). Both scenarios increase CRP grassland to nearly 25% more than what exists in the current landscape and over 10% more than the increase in the baseline projection. However, it should be pointed out that the amount of land affected by these changes is only about 1% of the privately owned landscape. These figures should be interpreted within the context of the assumption that policy changes in the SBM could only increase transition probabilities up to a maximum of 25%. The relative effects of the alternative policies are independent of this assumption.

Forest thinning decisions showed little response to changes in policies. This finding may reflect the current focus upon and funding for reducing fire hazards around rural communities as a result of recent large and severe fires in Idaho and the western U.S.A. The lack of meaningful difference in the level of forest thinning between the scenario and baseline projections may indicate that property owners who are considering forest thinning have already decided to act in response to perceived fire risk. Our findings suggest that hazard communication and public education coming from current policies such as the National Fire Plan may already be successfully shifting landowner attitudes about fire hazard management, and that new policy changes to induce greater levels of forest thinning on private non-industrial lands may not have a meaningful effect on the landscape.

Conclusions

In alternative futures modeling, potential outcomes of policies have been translated into landscape changes through a variety of approaches. Some studies have applied alternatives that are formulated as regulations that directly influence landscape change (White et al. 1997, Theobald and Hobbs 2002, Conway and Lathrop 2005, Jepsen et al. 2005). Other studies have focused on policies where the effect of alternative scenarios on the landscape is derived from expert opinion (Musacchio and Grant 2002, Baker et al. 2004, Santelmann et al. 2004, Boody et al. 2005), while additional applications have been based on ecological (Hansen et al. 1993, Spies et al. 2002) and microeconomic (Irwin et al. 2003) modeling. While our approach is most similar to the stakeholder-driven scenarios employed by Baker and colleagues (e.g., Baker et al. 2004), it differs in that our scenarios result from incorporating changes in policy mechanisms into landowner decision models rather than envisioning normative outcomes. Whether our landowner decision approach or one based on expert opinion is more accurate is unknown, but our survey-based approach may be most useful for cases where trends observed in the past are losing relevance due to changing conditions and demographics, and where the responses of private landowners to policies are difficult to predict.

We found that a SBM of land use change based on landowner decision-making resulted in projected landscapes that were compositionally within range of those derived from a TBM approach, indicating that trends predicted from landowner-reported plans were within the range of what would be expected under the assumption that historical trends will continue. The SBM appeared to be less affected by errors in image classification, due to the use of only one classified image, and had high stochastic certainty. We demonstrated that the landowner decision-based modeling approach is useful for understanding the landscape-scale impacts of potential land management policies. Our analyses show that policies designed to attract enrollment into the CRP could be very successful in the study area, especially those focused on financial and management incentives. In contrast, we found that policies directed towards increasing forest thinning would have a smaller effect on landscape changes, primarily because landowners reported that plans to thin forests were already in place. Our findings demonstrate that SBM approaches can provide insights on the landscape-scale effects of individual private landowner decision-making. These insights may be especially valuable to local land managers, planners, and extension agents.

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Table 1. Maximum likelihood classification percent accuracy and Kappa coefficients for each image date.

	1985		1992		2000		2003		Current	
Overall accuracy	81		92		88		91		87	
Kappa[c]	0.73		0.87		0.81		0.86		0.83	
LU/LC class	Prod.[a]	User[b]	Prod.	User	Prod.	User	Prod.	User	Prod.	User
Agriculture	98	94	99	93	95	95	98	99	99	100
Grassland	52	46	100	84	57	50	89	79	82	98
Developed	100	78	100	96	95	87	100	77	100	99
Barren	67	33	100	100	67	33	67	100	95	100
Water	83	100	100	100	100	100	100	100	12	100
Forest SI/Shrub	11	11	29	33	48	48	26	54	99	62
Forest	74	85	87	98	88	93	90	86	-	-
Low-density	-	-	-	-	-	-	-	-	61	86
High-density	-	-	-	-	-	-	-	-	95	73

[a]Producer's accuracy is the probability that the ground truth or reference pixels are mapped correctly (errors of omission). [b]User's accuracy is the probability that a pixel is not in the correct class (errors of commission). [c]The Kappa coefficient is a measure of whether classification results are better than that arrived at by chance, where a value greater than 0.80 represents strong agreement between the image classification and the reference data (Congalton and Green 1999).

Table 2. Methods used to apply each transition probability across all parcels in the study area, including regression model fits and predictor variables. R^2 is based on models of observed versus predicted probabilities, and the MC p-value represents whether the model R^2 was higher than that obtained in 1000 Monte Carlo simulations with randomly allocated transition probabilities.

Transition	Method	Model type[a]	R^2	MC p-value	Regression predictor variables (*significant α=0.05)[b]
AG to AG	Regression	Ordinal logistic	0.09	<0.001	Grass(+), Barren(+*),Elev.mean(+*), N.Dev(-), N.Open(-*), Town.dist(-), Parcel.size(+), HU.Parcel(-)
AG to DEV	Regression	Zero-inflated (log link)	0.21	<0.001	HU.Buffer(-*), HU.1km(+*), Slope.mean(+*), N.Dev(-*), OwnerCount(-*), N.Barren(+*), Barren(+*), Inso.mean(+*)
AG to FOR-SI	Regression	Gamma (inverse link)	0.14	<0.001	Ag(+*), Grass(-), Xer.hi(-), N.Xer.hi(-), N.Mes.lo(+), Forest(+), Xer.lo(-)
AG to CRP	Regression	Zero-inflated (log link)	0.17	<0.001	Ag(+*), Grass(+*), Xer.hi(+*), N.Xer.hi(+*), N.Mes.lo(-*), Forest(-*), Xer.lo(+*)
CRP to CRP	Regression	Logistic (logit link)	0.27	<0.001	Hwy.dist(-*), N.Ag(+*), N.Mes.lo(-*), Xer.hi(+*), Elev.SD(-), HU.Buffer(+)
CRP to AG	Regression	Zero-inflated (log link)	0.25	0.05	HU.Buffer(+*), HU.1km(-*), N.Mes.hi(-*), OwnerCount(+), Dev(-), Northing(+*), Xer.hi(+). Open(-)
CRP to DEV	Regression	Zero-inflated (log link)	0.48	<0.001	HU.Parcel(-*), N.Xer.lo(-*), Grass(+*), N.Open(+*), N.Dev(-*), Inso.mean(-*)
CRP to FOR-SI	Regression	Logistic (logit link)	0.16	0.10	Dev(+), Barren(+), N.Mes.lo(-), N.Xer.hi(+), N.Forest(+), Elev.mean(+)
FOR to FOR-SI	Regression	Zero-inflated (log link)	0.14	<0.001	OwnerCount(+*), N.Xer.lo(+*), HU.Parcel(+*), Xer.lo(-*), N.Xer.hi(+*), Forest(+*), Xer.hi(-*), HU.Buffer(-*)
FOR-HI to FOR-LO	Regression	Ordinal logistic	0.10	0.09	Xer.hi(+), Xer.lo(+), Grass(-), Elev.mean(+), N.Forest(-), Mes.hi(+), N.Xer.hi(-*), N.Xer.lo(+)
FOR to DEV	Regression	Zero-inflated (log link)	0.13	<0.001	N.Barren(-*), Barren(+*), Dev(-*), Xer.lo(+*), OwnerCount(+*), N.Xer.lo(+*), HU.Buffer(-*), N.Mes.lo(+*)
FOR to FOR	Kriging	Semi-variogram	-	-	Semivariogram model: nugget = 845 m^2 , spherical model with scale = 184 m^2 and length = 13,500 m.
DEV subdivide	Regression	Gamma (inverse link)	0.15	<0.001	HU.Buffer(+), HU.1KM(-), Town.dist(+), Open(-), OwnerCount(-*), N.Ag(+), N.Xer.hi (+), Elev.SD (+)
DEV expand	Bootstrapping	-	-	-	-

[a] For two-part zero-inflated models (zero-inflated/logit and Poisson/count), only results from the Poisson portion of the model are presented.

[b] Land cover types are proportions within a parcel (Grass=grassland, Ag=agriculture, Dev=development, Mes.lo=low-density mesic forest, Mes.hi=high-density mesic forest, Xer.lo=low-density xeric forest, Xer.hi=high-density xeric forest, Forest=all forest, Open=agriculture, barren, grassland); land covers preceded by N are proportion within parcels 75m from original parcel; HU=housing units within parcel, 1km total, or 1km buffer (not including parcel); Town.dist=road distance to nearest urban center, Hwy.dist =straight-line distance to nearest highway; OwnerCount=number of parcels owned by landowner in study area; Northing=north-south geographic coordinate, Elev=elevation, Inso=total annual solar insolation; SD=standard deviation

Table 3. Alternative policy scenarios scale data reflecting responses to questions about barriers and enablers to application for the CRP and forest thinning. Responses ranged from strongly agree (2) to strongly disagree (-2).

Policy scenario	Mean	S.D.
Technical assistance for CRP enrollment	0.77	1.09
Incentives for CRP enrollment	0.88	1.04
Technical assistance for forest thinning	0.54	1.01
Incentives for forest thinning	0.24	1.10

Table 4. Rules for land use/land cover transition sizes and parcel subdivision on private non-industrial lands

Transition	Transition size or subdivision rule	Data source
AG to FOR-SI, CRP to FOR-SI	Mean transition size = 10 ha; range = 1 to 26 ha Based on mean sizes of Conservation Reserve Program tree plantings	Farm Service Agency, CRP Active Contract Reports, Latah and Benewah counties, 1997-2006 http://www.fsa.usda.gov/dafp/cepd/crp_reports.htm
AG to CRP	Based on sampled distribution mean transition size = 19 ha; range = 8 to 200 ha	Confirmed CRP fields from surveyed landowners
CRP to AG	Entire patch within a parcel transitions	
FOR to FOR-SI, FOR to FOR-LO	If forest in parcel <= 32 ha, harvest = 1.2 ha If forest in parcel = 32 to 65 ha, harvest = 3.6 ha If forest in parcel = 65 to 162 ha, harvest = 10 ha If forest in parcel > 162 ha, harvest = 24 ha FOR to FOR-LO used area within parcel of high-density forest only	University of Idaho and Latah and Benewah County Extension foresters
DEV expand	Current development was expanded by 1 pixel, resulting in a 0.6 ha development. For parcels having no current development, one new residential development (0.2 ha) was added.	Approximated from examination of aerial photograph
DEV subdivide Latah County	Existing parcels with at least 10 but less than 40 ac. of less productive soil types are eligible for 1 new residential development (RD). Parcels with 40 ac. or more of less productive soil types are eligible for 2 new RDs. Existing parcels of at least 160 ac., regardless of soil type are eligible for one new RD for each 160 ac. portion of the parcel.	Latah County Subdivision Ordinance and productive lands spatial data layer
DEV subdivide Benewah County	If parcel size < 5 ac., 1 RD added If parcel size < 10 ac., 2 RDs added If parcel size < 15 ac., 3 RDs added If parcel size >= 20 ac., RDs equal parcel size divided by 20, plus 4 Number of subdivisions/RDs per parcel was capped at 30	The Benewah County Subdivision Ordinance was used as a guide. It could not be followed exactly because of reliance on a non-digital 1972 map and because it applied very few constraints.

Table 5. Characteristics of the survey-based and trend-based models compared in this study

	Survey-based model	Trend-based model
Assumptions	Assumes landowners know their future plans and their actions match those plans. Assumes that landowner decisions can be statistically modeled based on landscape data	Assumes that past rates of LU/LC change will persist
Required data	Transition probabilities, ownership parcel GIS layer, current LU/LC map	Current and historical LU/LC maps
Transition probabilities	Reported by landowners; extrapolated using regression	Generated using Markov chain models
Model type	Stochastic	Deterministic
Spatial output	Multiple simulated spatially-explicit outputs	One aspatial output
Transition unit	LU/LC patch within an ownership parcel	LU/LC pixel
Time step	One, 10 years	Multiple, 1 year
Validation/ Verification	Verification: Assessment of variance among stochastic outputs	Validation: Comparison of projection with existing LU/LC image classification

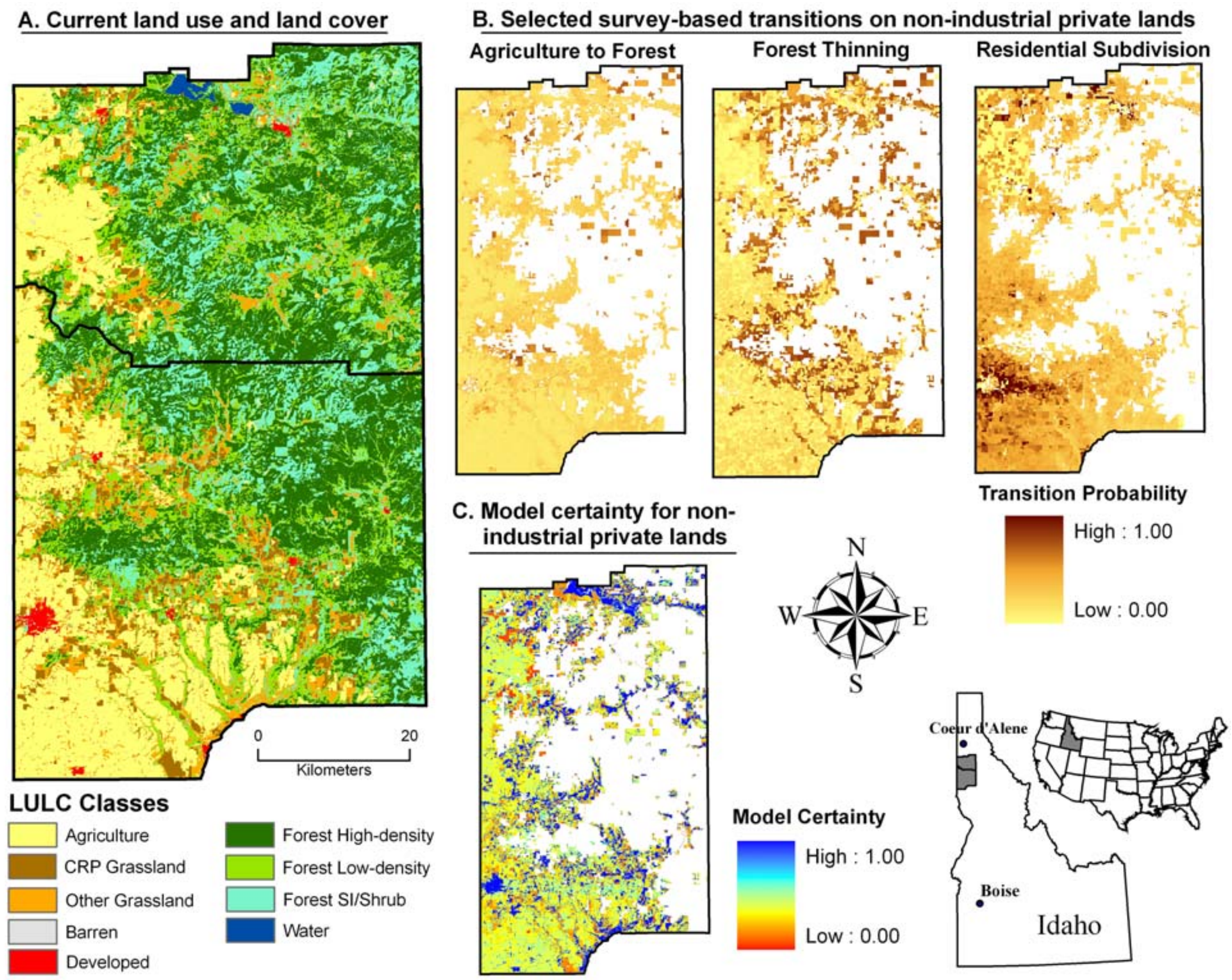

Figure 1. A) Current land use and land cover for Benewah (top) and Latah (bottom) counties. B) Selected transition probability maps for non-industrial private lands. C) Model certainty for non-industrial private lands.

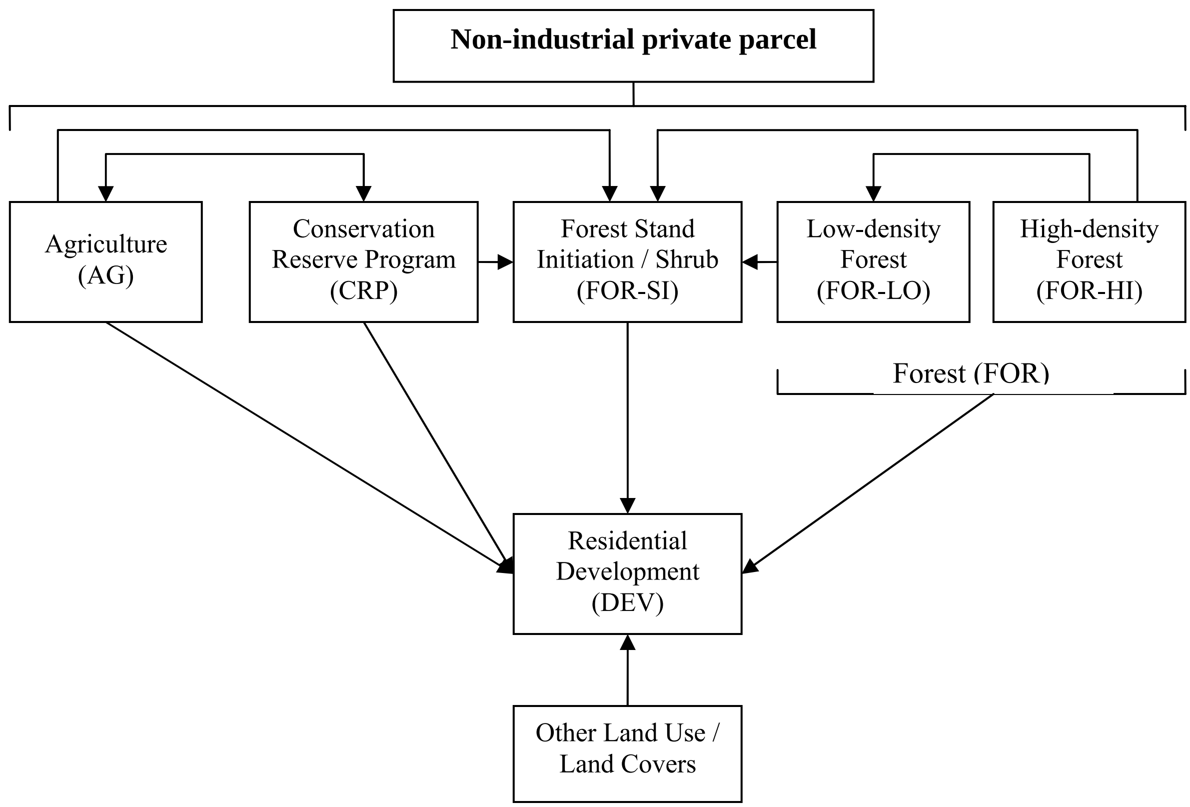

Figure 2. Land cover/land use transition model. Rectangles indicate land use classes in the model; arrowheads represent potential future transitions.

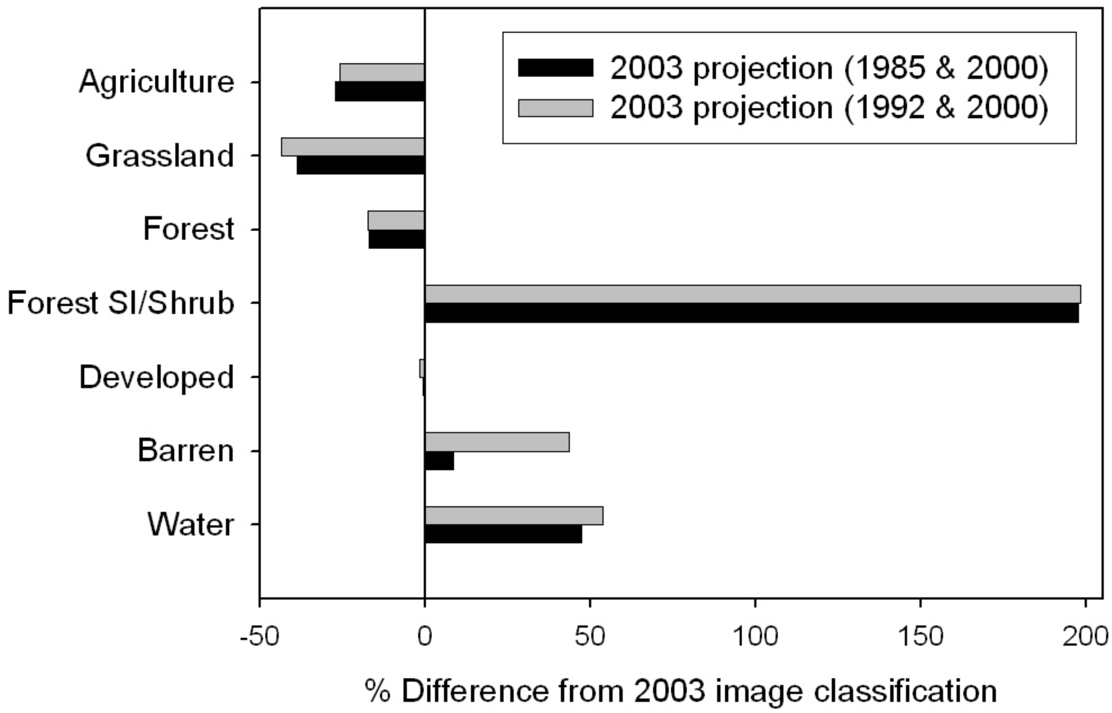

Figure 3. Historically-based model validation. Percent difference in the area (ha) of each LU/LC class between the 2003 reference image classification and projected 2003 landscapes, based on two pairs of images.

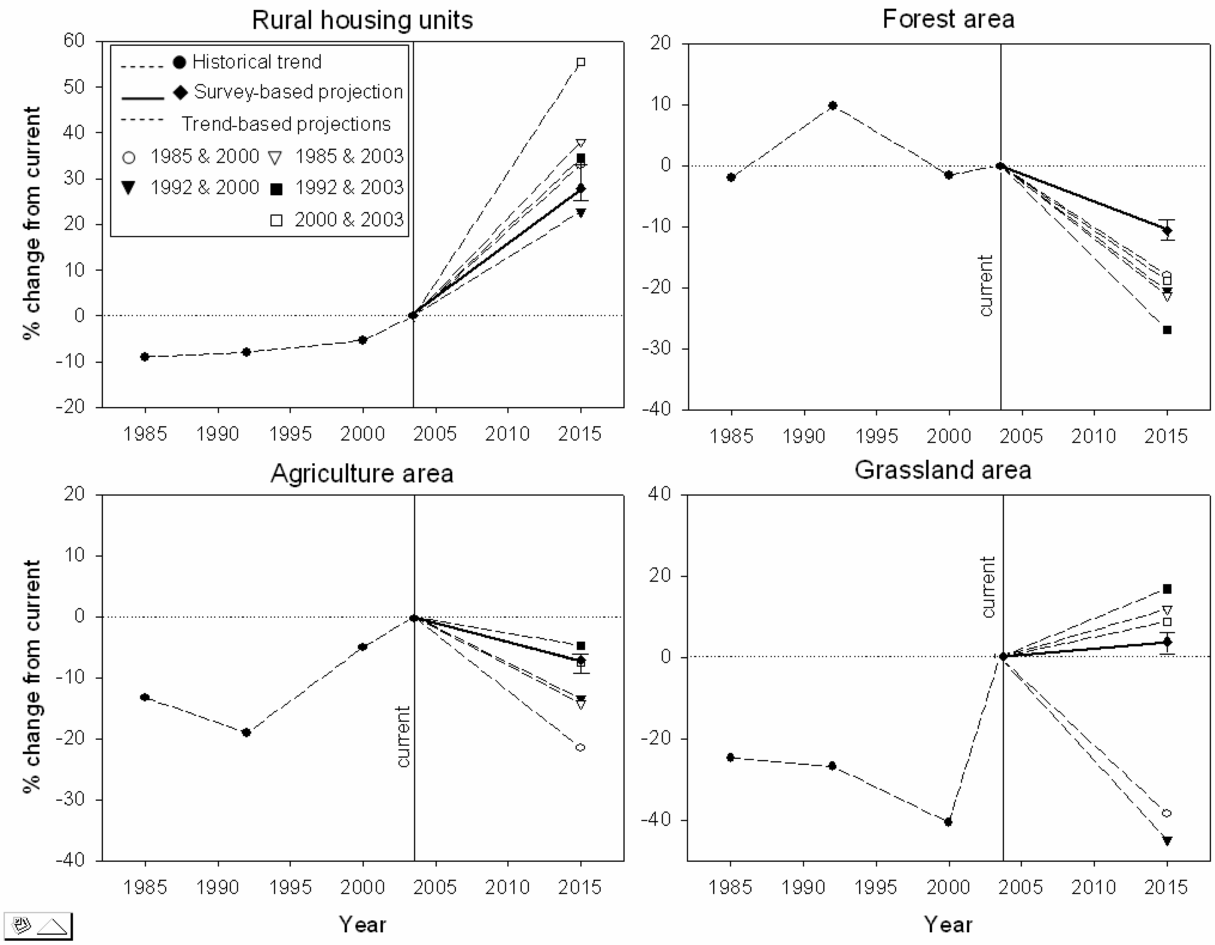

Figure 4. Percent change in class area (ha) and rural housing unit numbers relative to current LU/LC maps, as projected using trend-based and survey-based models. Error bars around survey-based projection represent the minimum and maximum.

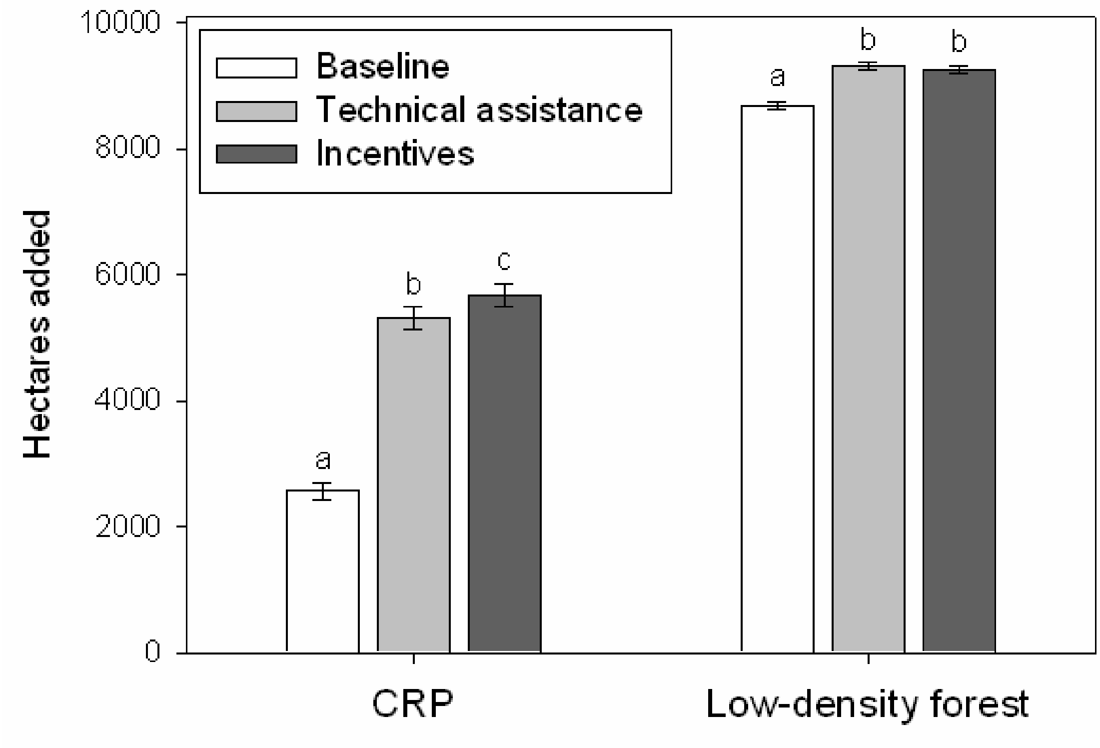

Figure 5. Increase in the number of hectares of non-industrial private land enrolled in the Conservation Reserve Program (CRP) or thinned to become low-density forest. Error bars represent the 95% confidence interval around the mean. Different letters indicate statistically significant differences within each LU/LC class among scenarios at α= 0.05.