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Abstract	<i>Context:</i> Evaluation of Land cover change (LCC) is commonly done at the pixel level; however, the model's purpose may be relevant at a different grain size. Thus, the same model may be good for one purpose but inappropriate for another. For conservation applications, it is crucial to assess land change simulations' at the grain relevant for the assessment of biodiversity impacts. <i>Objectives:</i> Evaluate land cover change scenarios in Bolivia, at the pixel-level and grain relevant to biodiversity, to inform LCC models for biodiversity assessments. <i>Methods:</i> We created six deforestation simulations that varied deforestation allocation based on forest management units (national, province, and municipality), ecoregions, and carbon stocks. We evaluated the simulations at the pixel level, and the objective's relevant grain size through stratified error decomposition. We assessed biodiversity impacts by comparing the quantity of reference and simulated deforestation within species ranges. <i>Results:</i> The spatial distribution of deforestation differed across simulations; however, their pixel-level error was similar. The province and municipality land change simulations had the lowest allocation errors at the relevant grain despite their large pixel-level errors, and they showed the lowest biodiversity errors. The province simulation provided the best balance identifying both affected species composition and the area of impact. <i>Conclusions:</i> This work presents evidence of the importance of incorporating information regarding the purpose of the simulation during model evaluation and selection. Error decomposition allowed ignoring irrelevant errors, translating into meaningful assessments of biodiversity impacts. As opposed to pixel-level metrics, stratified errors identified models that characterized biodiversity impacts best.	
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Linking land change model evaluation to model objective for the assessment of land cover change impacts on biodiversity

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Abstract

Context Evaluation of Land cover change (LCC) is commonly done at the pixel level; however, the model's purpose may be relevant at a different grain size. Thus, the same model may be good for one purpose but inappropriate for another. For conservation applications, it is crucial to assess land change simulations' at the grain relevant for the assessment of biodiversity impacts.

Objectives Evaluate land cover change scenarios in Bolivia, at the pixel-level and grain relevant to biodiversity, to inform LCC models for biodiversity assessments.

Methods We created six deforestation simulations that varied deforestation allocation based on forest management units (national, province, and municipality), ecoregions, and carbon stocks. We evaluated the simulations at the pixel level, and the objective's relevant grain size through stratified error

decomposition. We assessed biodiversity impacts by comparing the quantity of reference and simulated deforestation within species ranges.

Results The spatial distribution of deforestation differed across simulations; however, their pixel-level error was similar. The province and municipality land change simulations had the lowest allocation errors at the relevant grain despite their large pixel-level errors, and they showed the lowest biodiversity errors. The province simulation provided the best balance identifying both affected species composition and the area of impact.

Conclusions This work presents evidence of the importance of incorporating information regarding the purpose of the simulation during model evaluation and selection. Error decomposition allowed ignoring irrelevant errors, translating into meaningful assessments of biodiversity impacts. As opposed to pixel-level metrics, stratified errors identified models that characterized biodiversity impacts best.

Keywords Land change modeling · Biodiversity · Bolivia · Deforestation · Model evaluation

Introduction

Human-induced landscape changes, such as deforestation, are the leading cause of worldwide

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biodiversity extinctions (Brondizio et al. 2019; Sala et al. 2000). Dirzo et al. (2014) suggested an estimate of 11,000 to 58,000 species lost per year (Dirzo et al. 2014). The study of land use and land cover change predictions and impacts was identified as one of the top 10 key research areas in landscape ecology (Wu 2013). Deforestation affects biodiversity by modifying habitat quantity, quality, connectivity, and metapopulation dynamics (Ferraz et al. 2007). The relationship between habitat quantity and biodiversity has been well studied, where larger habitats support more biodiversity, lower extinction rates, and an overall lower impact of disturbances. Moreover, deforestation from human activities, such as agricultural development or urbanization, creates a matrix habitat (Ricketts 2001) that can have negative (Debinski and Holt 2000) or positive effects (Norton et al. 2000), depending on species adaptiveness to that matrix. Deforestation processes impact landscape structure by increasing edges, reducing patch area, modifying the matrix, and isolating forest patches. These structural changes in habitat can double the impact of deforestation on biodiversity, compared to the effects caused by direct habitat loss alone (Barlow et al. 2016; Pfeifer et al. 2017). With the rapid increase in global deforestation, there is an increased interest in applying land cover change models to predict deforestation scenarios and their impacts.

Assessment of the impacts of land cover change on biodiversity and ecosystem services relies on the evaluation and extrapolation of historical changes through simulation models (Armenteras et al. 2019; Liang and Liu 2017; Pérez-Vega et al. 2012; Pickard et al. 2017b; Reidsma et al. 2006; Sangermano et al. 2012; Sharma et al. 2018). As varying landscape patterns may result in different biodiversity implications, models must be evaluated for their capacity to identify impacts before creating future deforestation scenarios. This evaluation is, however, rarely done.

Model evaluation is a critical component of land change modeling, as it allows assessing the quality of the simulation and inform possible model improvements. Notwithstanding, a meta-analysis of land cover change publications (van Vliet et al. 2016) found that 31% of published manuscripts did not report the model evaluation. Even though the spatial pattern of land cover changes may be more critical than pixel-level accuracy when studying environmental and biodiversity impacts (Prestele et al. 2016), few studies (23%

according to van Vliet et al. (2016)) incorporate the assessment of deforestation pattern as complementary to pixel-level assessments. Still, pixel-level metrics are the most commonly reported means of model evaluation in land change model assessments.

Lack of alignment between the objective of a simulation and the evaluation method can cause scientists to focus on results that are not relevant to the research question or the model's intended application. For conservation applications, pixel-level accuracy is not as important as evaluating the model's capacity to simulate impacts, as multiple deforestation scenarios with different pixel-level accuracy may result in a similar reduction in species habitat. Moreover, a model selected based on pixel-level metrics is not guaranteed to simulate impacts correctly.

This work assesses six business-as-usual land cover change scenarios for Bolivia that varied the regionalization of demand-for-land and allocation model components. The work's main objective was to identify the impact of the evaluation gain on selecting land change modeling simulations developed to assess biodiversity impacts, as well as to and inform land change simulation improvements. We evaluated the six different scenarios through quantity and allocation error decomposition, error assessment at the pixel level, error stratification at the grain appropriate for the evaluation of biodiversity impacts, and errors on the assessment of biodiversity impacts.

Methods

Study area

The study region (Fig. 1) encompasses forested areas within the country of Bolivia. This country was chosen as a case study as it presents the second-highest rate of deforestation in Latin America (Killeen et al. 2007; Sangermano et al. 2012). The country is subdivided into four administrative levels: departments, provinces, municipalities, and cantons. Deforestation in Bolivia presents regional differences (Steininger et al. 2001), and it is related to economic growth, expansion of mechanized agriculture, and cattle ranching (Killeen et al. 2008). Under Evo Morales' presidency, land reform policies emphasize the principle of social and economic function of the land. This principle requires



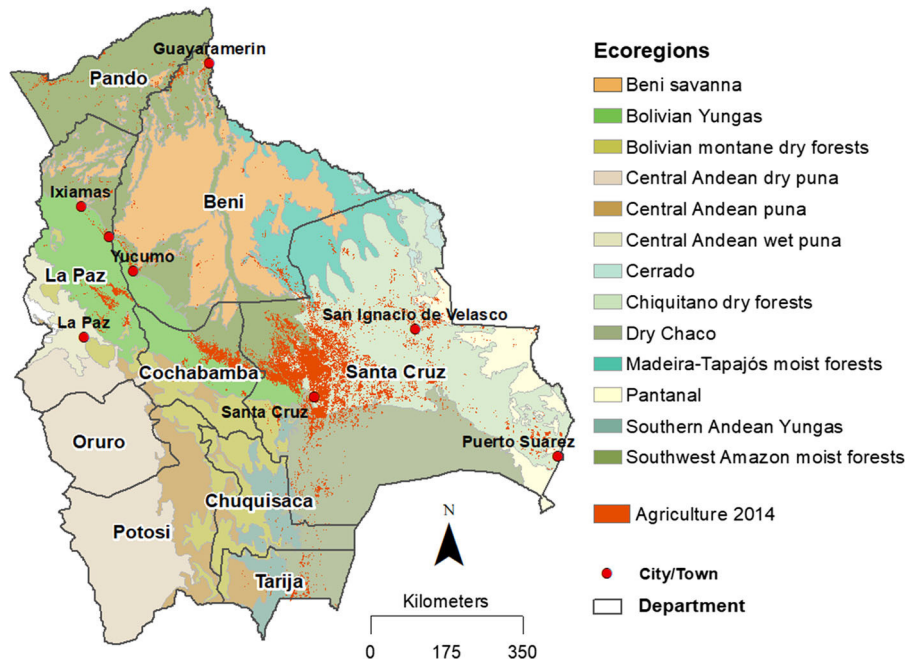


Fig. 1 Study area map showing the distribution of deforestation across ecoregions and departments

owners to demonstrate that their property is socially and economically productive and not abandoned to preserve their ownership rights (Bottazzi and Dao 2013; Redo et al. 2011). Under fear of land expropriation, owners seek to demonstrate land use, leading to an increase in deforestation in the region (Redo et al. 2011). Bolivia has decentralized its management of natural resources, giving regional autonomous units power to execute conservation policies. This decentralization is complex and spatially discordant since natural resources are managed at the national, departmental, municipality, and regional levels. As such, this decentralization affects the distribution of deforestation within the country.

Land change modeling overview

Empirical models of land cover change identify historical changes, relate those changes with a set of predictors of change, and use those relationships to extrapolate future deforestation simulations. Land change modeling usually consists of five steps (Fig. 2). Step one consists of identifying land changes between a land cover map in an initial time (T1) and a land cover map in a subsequent (T2) time. In step two, the land suitability to change is established through a

model that relates those land changes and predictor variables. Step three consists of calculating the quantity of change expected on an evaluation date, while step four focuses on the spatial allocation of that quantity, generating a simulated land cover (T3s). Finally, in step five, the simulated land cover (T3s) is evaluated through a comparison to a reference land cover (T3r). The method used to establish the land suitability to change is called the transition potential model. The calculation of the future quantity of deforestation is called the demand-for-land model, and the method used to allocate that amount of change spatially is called the allocation model. Together, these three models define the simulated pattern of deforestation.

Historical deforestation and drivers of change

A land cover map for Bolivia for the year 2001 at 30 m resolution was obtained from Killeen et al. (2007). This land cover map was updated with deforestation information from the Global Forest Change 2000–2014 data product version 1.2 (Hansen et al. 2013), to produce land cover maps for the years 2005, 2010, and 2014. If an area was deforested before 2001, it was assumed to remain deforested until 2014, thus

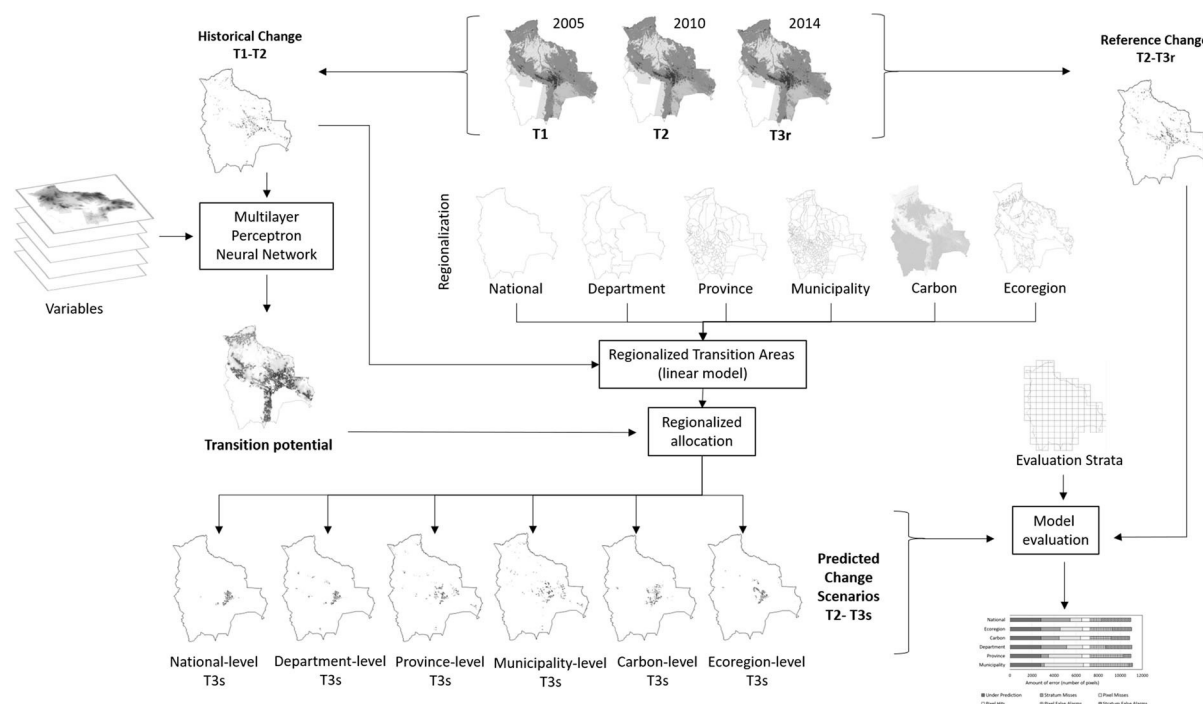


Fig. 2 Manuscript workflow scheme. T1: land cover 2005, T2: land cover 2010, T3r: reference land cover 2014, T3s: 2014 simulated change

ignoring reforestation or regeneration. The final land cover maps were upscaled to 990 m and projected to UTM-20s following Sangermano et al. (2012) (Online Resource Fig. S1).

Deforestation predictors included variables previously identified to be associated with deforestation in Bolivia (Sangermano et al. 2012). These variables encompassed: cost distance to populated places, cost distance to the city of Santa Cruz, precipitation seasonality, euclidean distance to roads, and euclidean distance to previously deforested areas. The variable cost distance to the city of Santa Cruz was considered independently from populated places, as being the central hub for the National Railroad System is a proxy for access to export markets, and deforestation is mostly related to large scale mechanized agriculture for soy production (Müller et al. 2012). On the other hand, the distance to populated places reflects access to local markets. A global map of accessibility (Nelson 2008) was used as a friction layer to calculate cost distances. Distance to already deforested areas was considered a dynamic variable (Sangermano et al. 2012).

Transition potential modeling

Land cover maps for 2005 (T1) and 2010 (T2) were used to identify the historical deforestation used to train the transition potential and demand-for-land models. The land cover map for the year 2014 (T3r) was used as a reference to evaluate the simulated land cover maps.

We simulated the transition potential based on a single algorithm, the Multi-Layer Perceptron Neural Network (MLP), as it has demonstrated to be successful in simulations of land change across multiple study areas (e Silva et al. 2020; Kim 2010; Mirici et al. 2017; Sangermano et al. 2012). The MLP network consisted of a hidden layer with three nodes. Following Sangermano et al. (2012), MLP was trained using a starting learning rate of 0.001 and an ending learning rate of 0.0001. The use of a dynamic learning rate allowed to decrease fluctuations in the adjustments of network weights. Activation layers were standardized to a 0 to 1 range using a sigmoidal function (sigmoid constant $a = 1$). The output of the MLP transition potential model is an image with values ranging from 0 to 1 representing the suitability

of the land to experience change. The transition potential model was developed using TerrSet software (Eastman 2016).

Demand for land and allocation models

Land change models are commonly developed based on the calculation of constant demand-for-land for each transition; however, spatial differences in deforestation rates may exist due to regional policy changes and deforestation practices. We generated six deforestation scenarios for 2014 that differ on the regions used to define the demand-for-land and allocation (Table 1). In the national-level land change scenario allocation of deforestation is performed at the country level and assumes a uniform demand-for-land to transition from forest to non-forest across the study area; this is the most common demand for land and allocation model used in the land change modeling literature. We regionalized the demand-for-land and allocation models on administrative units, generating the department-level, province-level, and municipality-level scenarios. These scenarios represent the scale of Bolivia's natural resource management practices.

To represent differences in demand-for-land across forest with different carbon content, we regionalized the demand-for-land and allocation models using a carbon density map (Saatchi et al. 2011) classified into ten equal-intervals bins. Finally, a regionalization based on ecoregions (Olson et al. 2001) was done to represent differences in demand-for-land across forest with different environmental characteristics and ecological dynamics.

The regional demand-for-land models use the annual rate of deforestation between 2005 and 2010 to predict the quantity of deforestation in the year 2014 for each region defined above (national-level, department-level, province-level, municipality-level, carbon-level, and ecoregion-level). The predicted amount of deforestation between 2010 and 2014 for each region (d) was calculated as $(A_{T2d} - A_{T1d}) / (t_{T2-T1}) \times (t_{T3-T2})$, where $A_{T2d} - A_{T1d}$ is the area deforested between 2005 and 2010 for region d , t_{T2-T1} is the reference period (5 years), and t_{T3-T2} is the prediction period (4 years) rounded to the nearest integer since the allocation of less than a pixel is not possible. This linear demand-for-land model assumes stationary rates of change. A common practice in land change

Table 1 Description of each of the six land change scenarios developed by changing the regionalization of the demand-for-land and allocation models

Scenario name	Demand-for-land model $DFL_d = \frac{A_{T2d} - A_{T1d}}{t_{T2-T1}} * t_{T3-T2}$	Rationale	Allocation model
National-level	Regionalization d defined by national boundaries	Standard approach in land change modeling. Assumes demand-for-land is uniform across the study area	Pixels with the highest transition potential at the country level are allocated to deforestation
Department-level	Regionalization d defined by departmental boundaries	Assumes demand-for-land varies across departments due to different management practices	Deforestation is allocated to the highest transition potential within each department
Province-level	Regionalization d defined by province boundaries	Assumes demand-for-land varies across provinces due to different management practices	Deforestation is allocated to the highest transition potential within each province
Municipality-level	Stratum d defined by municipality boundaries	Assumes demand-for-land varies across municipality due to different management practices	Deforestation is allocated to the highest transition potential within each municipality
Carbon-level	Regionalization d defined by carbon stocks	Assumes a non-homogeneous forest, with demand-for-land varying depending on forest productivity	Deforestation is allocated to the highest transition potential within each forest carbon class
Ecoregion-level	Regionalization d defined by ecoregion boundaries	Assumes a non-homogeneous forest with demand-for-land varying with the ecoregion where the forest is present	Deforestation is allocated to the highest transition potential within each ecoregion

DFL_d is the demand for land calculated for each region d , A_{T1d} is the area deforested in 2005 within the region d , A_{T2d} is the area deforested in 2010 within the region d , t_{T2-T1} is the reference period (5 years), and t_{T3-T2} is the prediction period (4 years)

modeling is to avoid modeling demand for land by using the reference quantity of deforestation. However, this practice only allows evaluating the transition potential model, and thus, assessment of the demand-for-land model is ignored. Modeling demand for land using a simple linear model allows assessing if deforestation rates vary over time and their implications on future deforestation projections.

Deforestation scenarios (T3s) were created by allocating the predicted quantity of deforestation for 2014 in each region using a top-rank approach. In this approach, after ranking the transition potentials independently for each region, deforestation is allocated to the pixels with the highest transition potential (Eastman et al. 2005).

Model evaluation

The change between 2010 (T2) and the land cover in 2014 (T3r) was used as a reference to evaluate the transition potentials and regional allocation models. We evaluated the transition potentials using the area under the total operating characteristics curve (TOC-AUC, (Pontius and Si 2014)). TOC-AUC identifies the relationship between ranked deforestation suitability and the reference deforestation between 2010 (T2) and 2014 (T3r). High TOC-AUC values indicate that areas deemed highly suitable for deforestation were deforested in the reference, while areas that did not experience deforestation occur in locations of low deforestation suitability. TOC-AUC ranges from zero to one, where values above 0.5 represent better than random predictions.

Using the Figure of Merit (FOM) metric (Chen and Pontius 2011; Pontius et al. 2007, 2008a, 2018), we compared the deforestation between T2 and T3r, called herein the reference change, with the deforestation between T2 and T3s, called herein the simulated change. FOM is widely used for validation of land change models and is the recommended evaluation metric for Verified Carbon Standards methodology for avoided unplanned deforestation (VCS 2012). FOM is computed by identifying hits, misses, and false alarms at the pixel level. Hits are pixels correctly predicted to change, false alarms are pixels predicted to change that remained unchanged in the reference, and misses are pixels incorrectly predicted to remain unchanged. FOM is the ratio of hits to the sum of misses, hits, and false alarms

(Pontius et al. 2008a), and provides a value ranging from zero to one that summarizes the simulation performance at the pixel level. Here, we will call the FOM, the Pixel-level Figure of Merit (PFOM), to acknowledge the grain at which the evaluation is done.

Land change models can have errors of two types: quantity and allocation. Quantity errors relate to the demand-for-land model, indicating if the model overestimates or underestimates the amount of deforestation. In contrast, allocation errors refer to misspecification of the actual change locations and are related to the transition potential and allocation models. PFOM incorporates both misses and false alarms into a single index; therefore, PFOM fails to reveal whether errors derive from the model of deforestation quantity or allocation. Distinguishing between these types of errors is essential for the interpretation and comparison of simulations. If a simulation predominantly has quantity error, then the modeler may want to assess the demand-for-land model. If a simulation mostly has allocation error, then the modeler may wish to evaluate the parameterization of the transition potential model (e.g., the variables used or model fit), or the allocation model.

Pixel-level metrics used for assessing land change models, such as the PFOM, cannot identify the appropriateness of a model for a particular purpose, as it only provides information at an artificially defined unit. Pixel level metrics can identify a simulation as completely erroneous if, for example, the predicted deforested pixel is neighboring the reference location of deforestation. The error in such simulation may not be meaningful for a particular objective, such as identifying species intersecting deforestation and could still be useful for biodiversity assessments. Thus, errors happening within the objective's relevant grain size are considered irrelevant for that objective, while errors happening beyond the objective's grain size are deemed meaningful.

To overcome the limitations of pixel-level metrics, we implemented a stratified evaluation method, allowing the assessment of the six land change simulation models (national-level, department-level, province-level, municipality-level, carbon-level, and ecoregion-level) at the grain size appropriate for the objective of assessing biodiversity impacts. Given that biodiversity impacts were evaluated using IUCN species range polygons (explained in the section below), we defined the evaluation strata (ES) as a



100 km × 100 km grid, which is the grain size that balances accuracy and detail in the IUCN biodiversity data (Hurlbert and Jetz 2007; Kreft and Jetz 2010). This evaluation grain size is conservative as larger errors in the IUCN species range database have been reported reaching 2.78 decimal degrees for south American anurans (Hughes 2019).

For each land change simulation, we report correctly predicted deforestation (hits, Eq. 1) as well as the presence of quantity errors (Eqs. 2, 3, 4), stratum errors (Eqs. 5, 6, 7), and pixel-level errors (Eqs. 8, 9, 10).

Hits are calculated as:

$$\text{Pixel Hits} = \sum_{d=1}^D H_d, \quad (1)$$

where H_d is the number of pixel Hits in stratum d , D is the number of strata. Hits are calculated at the pixel level and indicate the model's capacity to correctly classify change at the resolution of the simulation (990 m in this case).

Quantity errors indicate the ability of the demand-for-land model to estimate the amount of deforestation. Quantity error is calculated as:

$$\text{Quantity Error} = \text{Underprediction} + \text{Overprediction}, \quad (2)$$

where:

$$\text{Under Prediction} = \text{MAXIMUM} \left[0, \sum_{d=1}^D (M_d - F_d) \right], \quad (3)$$

$$\text{Over Prediction} = \text{MAXIMUM} \left[0, \sum_{d=1}^D (F_d - M_d) \right], \quad (4)$$

and where F_d is the number of False Alarm pixels in stratum d , and M_d is the number of Misses in stratum d . If misses are larger than false alarms, the demand-for-land model is underpredicting deforestation. If false alarms are larger than misses, the demand-for-land model is overpredicting deforestation. As defined, underprediction and overprediction of quantity apply to the totality of the study area extent; therefore, a model cannot underpredict and overpredict quantity at the same time.

The Stratum Allocation Error represents allocation errors among the evaluation strata, which was defined in this work as the effective resolution of the IUCN species range data. Stratum Allocation Error is calculated as:

$$\text{Stratum Allocation Error} = \text{Stratum Misses} + \text{Stratum False Alarms}, \quad (5)$$

$$\text{Stratum False Alarms} = \text{Stratum Misses}, \quad (6)$$

$$\text{Stratum Misses} = \text{MINIMUM} \left(\sum_{d=1}^D M_d, \sum_{d=1}^D F_d \right) - \sum_{d=1}^D \text{MINIMUM}(M_d, F_d). \quad (7)$$

Stratum Allocation Error is positive when misses and false alarms are not equal within each stratum, meaning that at least one stratum has more misses than false alarms, while at least one other stratum has fewer misses than false alarms. Thus, Stratum Allocation Errors are those occurring beyond the objective's grain size, and therefore are considered meaningful.

Pixel Allocation Error refers to total pixel-level error within the evaluation strata, and is calculated as:

$$\text{Pixel Allocation Error} = \text{Pixel Misses} + \text{Pixel False Alarms}, \quad (8)$$

$$\text{Pixel Misses} = \sum_{d=1}^D \text{MINIMUM}(M_d, F_d), \quad (9)$$

$$\text{Pixel False Alarms} = \text{Pixel Misses}. \quad (10)$$

Pixel Allocation Errors indicate that although the model allocated deforestation at the incorrect pixel, it did it within the correct stratum. Pixel Allocation Errors are positive when misses and false alarms exist within any single stratum. As pixel allocation errors are those that happen within the relevant grain size of the objective, they can be considered irrelevant for the modeling purpose.

The above components of errors allow the interpretation of sources of errors within the simulated map, and can be summarized into single metrics. PFOM (Pontius et al. 2008a, 2018) can be calculated from the components as:



$$\text{PixelFOM} = \frac{\text{Pixel Hits}}{\text{Under Prediction} + \text{Stratum Allocation Error} + \text{Pixel Allocation Error} + \text{Pixel Hits} + \text{Over Prediction}} \quad (11)$$

The Stratum Figure of Merit (SFOM), ignore the irrelevant pixel allocation errors within the evaluation strata and can be calculated from the previously defined error components as:

(JSI). The Jaccard similarity index is calculated as the number of species in common within the reference and simulated change, divided by the total species in the reference and simulated change areas. A Jaccard

$$\text{Stratum FOM} = \frac{\text{Pixel Allocation Error} + \text{Pixel Hits}}{\text{Under Prediction} + \text{Stratum Allocation Error} + \text{Pixel Allocation Error} + \text{Pixel Hits} + \text{Over Prediction}} \quad (12)$$

Two models may produce the same PFOM regardless of the spatial distribution of allocation errors; therefore, PFOM does not allow for the discrimination of a model with meaningful allocation errors (those across the evaluation strata) versus irrelevant allocation errors (those within the evaluation strata). More details on the interpretation of these figures can be found in the online supporting information.

Evaluation of biodiversity impacts

Each simulation's expected biodiversity impacts were assessed by intersecting the reference and simulated change maps with the IUCN species ranges of mammals, amphibians, and birds endemic to Bolivia (IUCN 2018), which were rasterized to the resolution of the land change simulations (990 m). From all IUCN species ranges endemic to Bolivia, a total of 93 species (fourteen mammals, nine birds, and seventy amphibians) intersected the reference and simulated change. A forest specialist species may be negatively affected by deforestation, while a generalist species may be affected positively by the presence of agriculture. In this work, we focused on the models' capacity to identify the species affected by deforestation and their area without evaluating the direction of the impact (positive or negative). To assess the capacity of each of the six land change simulations to detect the species affected by deforestation, we compared the species composition overlapping the simulated and reference change through the Jaccard similarity index

similarity of 1 indicates that species composition in areas simulated to change is the same as the species composition in the reference change areas. The lower the Jaccard similarity index, the lower the species shared between the simulated and reference deforestation areas. To assess the simulation ability to capture the area of species ranges affected by deforestation, we calculated each species' area range that was deforested in the simulated and the reference change maps. The amount of deforestation between 2012 and 2014 within each IUCN species range was extracted for the reference and land change simulations. The Mean Absolute Error (MAE, Eq. 13) and its quantity and allocation components (Pontius et al. 2008b) were calculated. MAE is the sum of the allocation disagreement component and quantity disagreement component. The Allocation Disagreement component of MAE (AE, Eq. 14), represents deforestation simulated in an incorrect species range and is calculated as the MAE minus the quantity disagreement. The quantity disagreement component of MAE (QE, Eq. 15) is the absolute value of the mean error (ME, Eq. 16) and represents the average quantity of error across all species ranges. MAE and its components are calculated as:

$$\text{MAE} = \frac{\sum_{i=1}^n |y_i - x_i|}{n} \quad (13)$$

$$\text{AE} = \text{MAE} - \text{QE} \quad (14)$$



$$QE = \left| \frac{\sum_{i=1}^n y_i - x_i}{n} \right|, \quad (15)$$

$$ME = \frac{\sum_{i=1}^n y_i - x_i}{n}, \quad (16)$$

where y_i is the area of simulated change within the species range i , and x_i is the area of reference change within the species range i , and n is the total number of species considered in the evaluation.

Results

An area of 16,230 Km² was deforested in Bolivia in the period 2005 to 2014. This deforestation was distributed particularly surrounding the city of Santa Cruz, along the Yungas, and in the department of Pando bordering Peru (Fig. S1).

Evaluation of regional-level simulations at pixel and stratum level

The transition potential generated by the MLP model was good, with a goodness of fit of 79.34%, and TOC-AUC of 0.86 (Fig. S3). Partitioning of errors into components (Fig. 3) revealed an underprediction of the quantity of deforestation across all regional simulations (Table 2), comprising about 25% of all errors. The remaining errors were divided into pixel and stratum allocation error components. Aggregated

allocation errors (pixel allocation error plus stratum allocation errors) were similar across all six land change scenarios.

The spatial distribution of deforestation was different across simulations, as can be seen in the spatial distribution of hits and false alarms (Fig. 4). A high proportion of misses in Fig. 4 are a reflection of the underprediction of deforestation. Despite this, the pixel-level Figure of Merit (Table 2) showed low variability across models, with values ranging from 5.5 to 8%. These similarities in PFOM values were due to the similar numbers of hits, reference change, and simulated change across all regional simulations. The province-level and municipality-level simulations presented the most substantial pixel-level allocation errors, indicating that the model failed to simulate the actual locations of deforestation within the evaluation stratum. The stratified error allowed identifying misses and false alarms happening across the 10,000 km² evaluation scale. At this grain size, province-level and municipality-level simulations presented the lowest stratum errors, resulting from a distribution of misses and false alarms more balanced within the evaluation strata, when compared to the other regional simulations. This can be seen in Fig. 4 where the spatial distribution of false alarms is similar to that of the misses for the province-level and municipality-level land change simulations.

The stratified evaluation results indicate that for the province-level and municipality-level simulations, pixel-level errors were within the spatial resolution

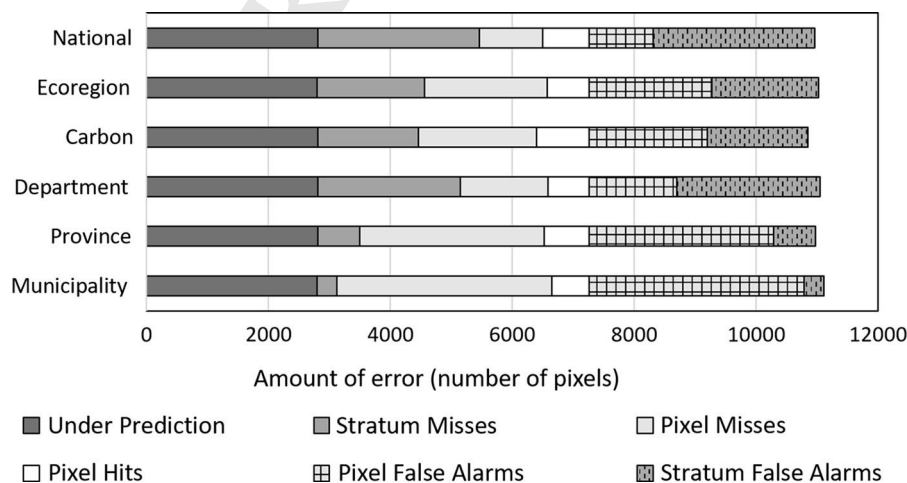


Fig. 3 Partition of errors across regional simulations. Underprediction + Stratum Misses + Pixel Misses represent the Total Misses; Pixel False Alarms + Stratum False Alarms (+ Overprediction, which is null in this case) represent the Total False Alarms

Table 2 Tabulation of errors

Regional simulation	Reference change	Simulated change	Quantity ERRORS	Pixel alloc. error	Stratum alloc. errors	PFOM (%)	SFOM (%)
National	7261	4457	2804	2094	5304	6.9	18.2
Ecoregion	7261	4458	2803	4030	3504	6.3	30.0
Carbon	7261	4457	2804	3878	3304	8.0	31.5
Department	7261	4457	2804	2876	4700	6.1	21.9
Province	7261	4456	2805	6044	1392	6.7	47.3
Municipality	7261	4461	2800	7044	650	5.5	54.5

Reference change equals *Under Prediction + Stratum Misses + Pixel Misses + Pixel Hits*; Simulated change equals *Pixel Hits + Pixel False Alarms + Stratum False Alarms + Over Prediction* (which is null in this case); Pixel Allocation errors are *Pixel Misses + Pixel False Alarms*; Stratum Allocation Errors are *Stratum Misses + Stratum False Alarms*. Pixel Figure of Merit (PFOM) equals $Hits / (Under Prediction + Stratum Allocation Error + Pixel Allocation Error + Pixel Hits + Over Prediction)$; Stratum Allocation Errors are $(Hits + Pixel Allocation Error) / (Under Prediction + Stratum Allocation Error + Pixel Allocation Error + Pixel Hits + Over Prediction)$

of biodiversity data and thus could be ignored when evaluating biodiversity impacts. On the other hand, the national-level simulation presented the most substantial stratum allocation error, representing a high unbalance of misses and false alarms within the evaluation strata (Fig. 4), and indicating that, after removing the effect of quantity, misses and false alarms occurred in different strata. These errors act beyond the valid grain size of the biodiversity data and could affect the assessment of impacts. The carbon-level land change simulation had the highest hits; however, stratum allocation errors were also high, indicating that although this land change simulation was the best identifying pixels that correctly changed with a stratum, misses and false alarms happened beyond the grain relevant for the objective, thus, presenting the highest meaningful errors for the purpose of the land change model. The ecoregion-level land change simulation presented an intermediate performance across all evaluation metrics. Province-level and municipality-level simulations showed the highest SFOM at the grain size relevant for the analysis of biodiversity, meaning that a large proportion of pixel-level errors could be ignored for this objective.

Simulation impact evaluation

From all the species included in the study, thirteen birds, eight mammals, and nineteen amphibians intersected the reference or the simulated change maps (see

online resources for a comprehensive list of species and areas of change within these ranges). The municipality-level simulation resulted in an impact on species composition most similar to the reference (JSI = 0.44), capturing 80% of the species intersecting the reference deforestation. The second best simulation was the province-level, with the second-highest JSI (JSI = 0.38) and capturing 70% of the species intersecting the reference deforestation.

All simulations underpredicted the amount of species ranges affected by deforestation, indicated by the negative sign of the mean error (ME, Table 3). As all land change simulations underestimated the total quantity of deforestation, this result was expected. The absolute of the ME indicates the quantity error. The carbon-level land change simulation had the smallest quantity error but presented the highest allocation error component (AE), indicating that deforestation was allocated to the incorrect species range. When removing the species *Akodon dayi* (Fig. 5), which has the most extensive overlap with the study region, the carbon-level land change simulation presented the second smallest quantity error after the municipality-level. After removing *A. dayi* from the analysis, the carbon-level simulation remained the worst simulation based on deforestation allocation to the correct species range (highest AE, Online resource Fig. S4).

The municipality-level simulation presented the lowest mean absolute error (MAE), followed by the province-level simulation (Table 3, Fig. 5). The



Fig. 4 Spatial distribution of Hits (first column), Total Misses (Second Column), and Total False Alarms (third column) per evaluation strata. Values range from 0 to 1 and indicate the proportion in relation to Hits + Total Misses + Total False Alarms. The higher proportion of Misses indicates the underestimation of quantity across all simulations

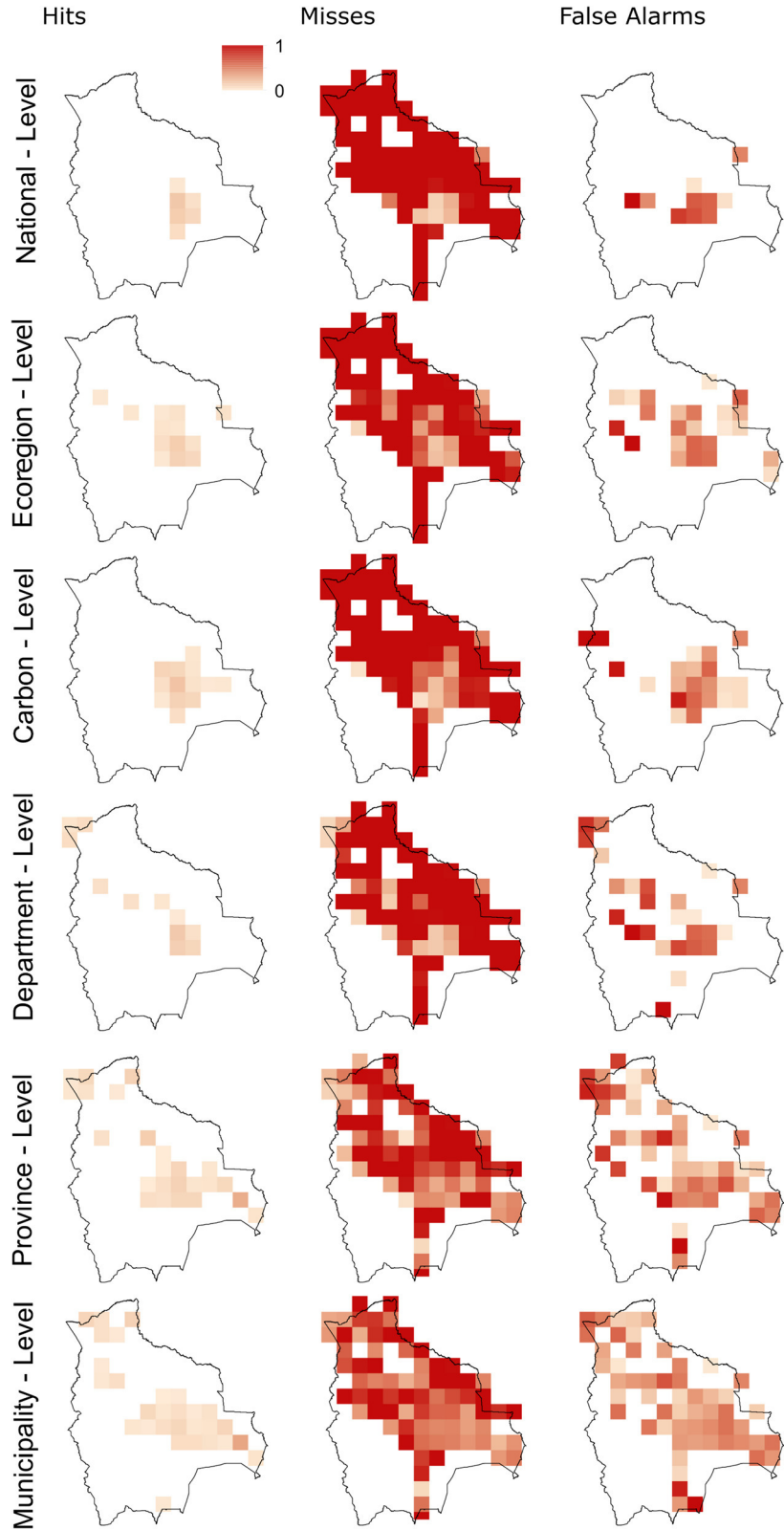


Table 3 Assessment of deforestation impacts

Regional simulation	JSI	% Species agreement	MAE	ME	AE
National	0.20	26.7	134.9	– 95.0	39.0
Ecoregion	0.26	36.7	114.9	– 93.2	21.7
Carbon	0.33	56.7	119	– 72.6	46.4
Department	0.35	63.3	129.5	– 84.7	44.8
Province	0.38	70.0	109.5	– 96.7	12.8
Municipality	0.44	80.0	105.3	– 90.4	14.9

JSI Jaccard similarity index (higher is better), % species in agreement (higher better), MAE mean absolute error (lower is better), ME mean error (lower is better), AE allocation error (lower is better)

province-level simulation had a smaller AE than the municipality-level simulation, indicating that, even though it underpredicted the amount of deforestation affecting species ranges, it was the model that best described the distribution of deforestation across species ranges. These relationships did not change by excluding *Akodon dayi* (Online resource Fig. S4). Thus, the province-level simulation reflects a right balance between recognizing the species composition affected by deforestation and the area of impact within those species.

Discussion

PFOM allows assessing simulations at the pixel-level; however, some errors are more critical when evaluating impacts than others. By identifying error components, we could discern between quantity errors, and irrelevant and meaningful allocation errors.

In this study, allocation errors not relevant for assessing biodiversity impacts are pixel-level errors happening within the biodiversity data's valid grain. On the other hand, meaningful allocation errors are those occurring beyond the proper grain size of the biodiversity data ($100 \times 100 \text{ km}^2$ in this study) and are identified through the stratum allocation errors. The presence of stratum allocation errors could indicate the transition potential model's misspecification, for example, through variables not being weighted properly within each region. In this work, the spatial distribution of transition potentials was dominated by the influence of the variable "Distance to Santa Cruz", as most of the change during the training period (2005–2010) happened around this

city. However, this variable is expected to be less relevant for other provinces, for example, in northern Bolivia. Models could potentially be improved by developing independent transition potential models for each region (e.g., for each province), accounting for spatial non-stationarity of the relationships between deforestation and factors of change (Mas 2016).

Temporal non-stationarity includes both deforestation rates and temporal variations in the importance of drivers of change (Mas et al. 2004). In this study, quantity errors uncovered that the linear extrapolation of demand-for-land underestimated the total change. The amount of expected change in 2014 was estimated using a linear function based on the rate of deforestation between 2005 and 2010, thus assuming a constant rate of change. However, the rate of deforestation between 2010 and 2014 was higher than in the reference period, indicating that linear extrapolation is not representative of future demand-for-land for this case study. As Bolivia presents volatility of year-to-year deforestation rates that are strongly linked to National policy changes, these high quantity errors are expected. The constitutional reform of Morales administration in 2006, contributed to the increasing deforestation, as the conversion of forest to agriculture became the most compelling justification to demonstrate the economic and social function of the land needed to avoid land redistribution (Müller et al. 2014). In 2013 the Morales administration announced pardons for illegal deforestation, which fomented speculation and encouraged ranchers and settlers to encroach illegally into the forest to achieve legalization during the regularization process (Müller et al. 2014). Legal deforestation has also increased with the

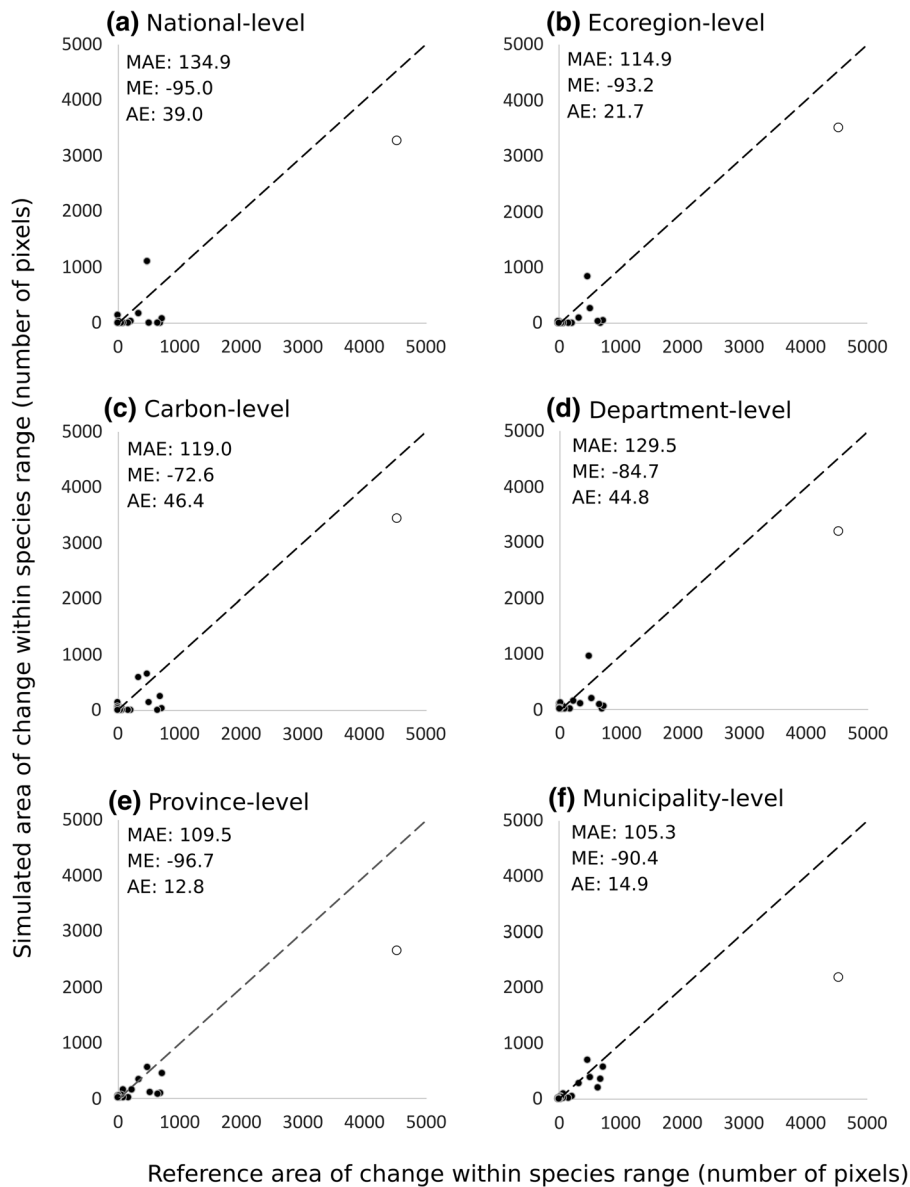


Fig. 5 Scatterplots of reference area of change within species range (x) vs. simulated area of change within species range (y), for each model: **a** national-level, **b** ecoregion-level, **c** carbon-level, **d** department-level, **e** province-level, **f** municipality-level. Province and municipality-level simulations show closer alignment to the 1:1 identity line, resulting in lower MAE

values. The lower allocation error for the province-level simulation is reflected by points residing mostly on one side of the identity line. White marker corresponds to the species *Akodon dayi*. Figures and statistics excluding this observation are provided in the online materials (Fig. S4)

increase in permits given by the Forest and Land Authority of Bolivia that almost doubled from 2010 to 2014. Deforestation rates are expected to increase even further. In July 2019 Morales administration amended a Decree (Supreme Decree 26075) that foments the expansion of the agricultural frontier in

Santa Cruz Beni's provinces by authorizing land-use changes relating to farming and controlled burning.

Results from the quantity error components uncover the presence of varying deforestation rates in Bolivia that depend on changes in policies. Thus, it reveals uncertainties in the demand-for-land model

that can affect future projections of deforestation. Future projections of deforestation can incorporate the uncertainty related to the difficulties of modeling deforestation quantity, by creating multiple deforestation scenarios based on varying development trajectories (Sangermano et al. 2012). Some land change modeling practices ignore quantity errors by setting the predicted quantity to the reference quantity. Model evaluation in those cases can only assess the transition potential model, missing the demand-for-land model component. By partitioning model errors, we can acknowledge both quantity and allocation model errors that uncover, and allow to account for, uncertainty in applying the land change model to predict future deforestation.

The assessment of simulations was profoundly affected by the evaluation metric used. Land cover change models are commonly evaluated at the pixel level (van Vliet et al. 2016). In this case study, a pixel-level assessment would have led to selecting the carbon-level land change simulation as the best representation of deforestation. This simulation, however, presented the highest errors in the evaluation of biodiversity impacts. On the other hand, the municipality-level land change simulation, even though it showed high pixel-level errors, resulted in a small proportion of stratum errors. Thus, even though the municipality-level simulation did not identify precisely where pixels were going to change, misses and false alarms fell within the grain relevant for the study of biodiversity. This relationship is also reflected in the assessment of biodiversity impacts.

In Bolivia, biodiversity impacts vary with the spatial distribution of deforestation due to differences in species composition between the humid forest and the dry Chiquitano forest ecoregion (Fig. 1). The national-level simulation allocated most of the deforestation within the Chiquitano Dry Forest. In contrast, the municipality-level and provincial-level simulations were more similar to the reference, identifying higher amounts of deforestation in humid forest ecoregions, thus better-representing biodiversity impacts. Sangermano et al. (2012) predicted deforestation to the year 2050 to evaluate biodiversity impacts based on a national-level allocation. This work indicates that their biodiversity assessment could be inaccurate due to a mismatch between pixel-level evaluation and the objective's relevant grain. The stratified evaluation approach, together with the

evaluation of impacts, uncovered that deforestation simulations to analyze biodiversity in Bolivia should be developed at the province-level. Moreover, simulations of future deforestation could be improved by modeling transition potentials independently for each province and creating different deforestation quantity scenarios.

Sensitivity analysis of land change simulation models is rarely done, with only 12% of the models evaluated by Van Vliet et al. (2016) assessing model sensitivity. This work demonstrates the importance of sensitivity analysis when developing land change models, by modifying the type of demand for land and allocation model, we found substantial variability in deforestation's spatial distribution and resulting impacts. Developing and evaluating multiple models allowed identifying the best demand-for-land and allocation model to assess land cover change impact on biodiversity in Bolivia.

The literature of land change modeling distinguishes between near and far errors (Chen and Pontius 2010; Pontius et al. 2008a, 2011) calculated through multiresolution analysis, and where far errors are considered more important than near ones. However, the determination of error importance depends on the purpose of the simulation. It is crucial to evaluate land change models with a method fit for the model purpose. Although multiresolution evaluation of errors allows identifying the grain size at which a simulation could be applied, it is not directly linked to the simulation objective. In this work, the evaluation strata was a regularly sized grid signifying the valid grain of the IUCN species range data used in biodiversity assessments; however, for other modeling purposes, this evaluation strata could take irregular shapes. For example, for applications of land change models for Reduced Emissions from Deforestation and Forest Degradation (REDD), the deforestation model could be assessed using carbon stock strata. In that example, misses and false alarms balanced within the same carbon stock could be ignored, as they will produce the same carbon emission impacts. On the other hand, stratum errors, happening when misses and false alarms are not balanced within the carbon stock, would be relevant for REDD, as they could potentially overestimate or underestimate the amount of modeled carbon emissions.

Some land cover change applications (23%, Van Vliet et al. 2016), have incorporated pattern analysis as



a means for linking model evaluation to the model purpose. A limitation of configuration based evaluation approaches is that they rely on choosing pattern metrics, and more work is needed to identify the ones more relevant for assessing landscape configuration (Pickard and Meentemeyer 2019). Similar to the findings in this study, the increased interest in developing pattern-based evaluation metrics of land change models recognizes the need to move beyond pixel-level assessments (Chen et al. 2014; Pickard et al. 2017a, b; Pickard and Meentemeyer 2019).

Conclusions

Land cover change models are increasingly used to evaluate biodiversity and ecosystem impacts. However, for those assessments to be meaningful, careful model evaluation is needed. This work presents evidence of the importance of incorporating information regarding the simulation's purpose during model evaluation and selection. By decomposing errors, it is possible to assess their sources, allowing ignoring irrelevant ones. The distinction of quantity errors, pixel allocation errors, and stratum allocation errors allows identifying patterns not evident when using pixel-level metrics alone. This information permits making better-informed decisions on model selection, translating into meaningful assessments of model impacts.

To increase transparency and allow more robust applications of land change models to assess biodiversity and ecosystem impacts, we urge scientists to (1) link the evaluation method to the model purpose, (2) decompose errors to inform model assessment and improvement, and (3) perform a sensitivity analysis, to select the simulations more appropriate for the identified model objective.

We conclude that a pixel-level assessment of errors fails to represent our models' accuracy for their intended purpose. Moreover, selecting models based on pixel-level assessment metrics leads to the incorrect characterization of impacts. On the other hand, stratified evaluation metrics, with strata related to the purpose of the land change simulation, allowed for identifying the model that represented biodiversity impacts best.

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Author contributions FS Developed concept, performed impact analysis and validation, analyzed results and wrote the manuscript. RGP developed the stratified evaluation metrics and edited manuscript. AM and JC run the land change simulation models.

Data availability The datasets generated during the current study are available from the corresponding author on reasonable request. The authors do not have the right to re-distribute the species range polygons. These data can be obtained from the IUCN Red List (mammals and amphibians) and Birdlife International (birds). The Python plug-in tool to perform the regional allocation in TerrSet is available from the corresponding author upon request.

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