LAND COVER CHANGE UNDER FUTURE SCENARIOS OF ZERO-DEFORESTATION COMMITMENT IMPLEMENTATION IN SOUTH AMERICA

A THESIS SUBMITTED TO THE GRADUATE DIVISION OF THE
UNIVERSIY OF HAWAIʻI AT MĀNOA IN PARTIAL FULFILMENT OF THE
REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

IN

NATURAL RESOURCE AND ENVIRONMENTAL MANAGEMENT

SEPTEMBER 2019

By

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Keywords: land use and land cover change, tropical agricultural expansion, soy, spatially-explicit simulation model

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1 Abstract

Public alarm over deforestation from tropical commodity crop expansion has led many corporations that handle such commodities to adopt zero-deforestation commitments (ZDCs), which are pledges to stop sourcing products produced on recently deforested or currently forested lands. Most ZDCs have yet to be implemented and vary in their implementation details including forest clearance cut-off date and off-limit land covers. Moreover, region- or supply-chain specific ZDCs may simply displace deforestation to areas not covered by commitments through market or activity leakage. My research aims to investigate the effect of ZDCs on tropical land cover by addressing the following questions: 1) How might ZDC implementation affect geospatial patterns of soy expansion? 2) How do changes in soy expansion patterns alter locations and patterns of non-soy land cover change? 3) How does ZDC implementation date affect these outcomes? To answer these questions, I built a land cover change model that simulates corporate ZDC implementation in soy producing regions in South America from 2014-2030. I evaluated land cover outcomes under several future scenarios, including no ZDC implementation, fulfillment of currently pledged ZDCs, earlier implementation of these current pledges, and a moratorium on soy expansion into natural land covers the Cerrado and Gran Chaco ecoregions. In contrast to a future with no ZDCs, the 2025 ZDC scenario reduced natural land cover conversion by 3.2% while maintaining projected soy area growth, despite some displacement of natural land conversion from the Cerrado and Chaco to the Brazilian Amazon and Argentinian Pampas. Compared to the 2025 ZDC scenario, early implementation of ZDC pledges (by 2020) resulted in conservation of an additional 357,000 ha (6.7%) of natural land cover in BBAP by 2030, while the Cerrado and Gran Chaco moratorium generated just 35,000 ha (0.6%) of additional conservation. These findings suggest that ZDCs may generate net preservation of natural land cover despite intra-country displacement. Earlier ZDC implementation appears to be far more effective at conserving natural land cover than increasing ZDC market share in later years.

2 Introduction

Demand for agricultural commodities has increased in recent years as a result of population growth and greater consumption of meat, oils, fruits, and vegetables driven by increases in wealth (Popkin, 1993). In tropical regions, most recent deforestation is associated with the production of agricultural commodities including edible oils (Gibbs et al., 2010; Henders, Persson, & Kastner, 2015), which has increased sharply since 1990. This expansion of agricultural lands at the cost of forested areas generates negative environmental and social impacts including the loss of biodiversity, increased rural income inequality, hydrological changes, greenhouse gas emissions, and land conflicts (Carlson et al., 2013; Carlson & Garrett, 2018; Fearnside, 2016; Rachael D. Garrett & Rausch, 2016).

Soy (Glycine max) harvested area increased by almost 400% from 1970 to 2017 (FAO, 2019), and by 2014 More than one million km^2 of soy was harvested worldwide (FAO, 2019). The crop has a 20% oil content, making it useful for cooking oil, and a 40% protein content, making it high quality livestock feed, one of the primary uses of soy (Peine, 2013). Increased consumption of chicken and pork in domestic and international markets has been identified as a major driver of increased soy production in Brazil (Peine, 2013; Rausch & Gibbs, 2016). While United States was historically the leader in soy production, since 1950s, production has increased especially in tropical regions. In 2017, Brazil, Bolivia, Argentina, and Paraguay had a combined soy production of around 178 million metric tons, almost half of the world's soy production (World Agricultural Production, 2018). Since the start of the 2000s, these areas have incurred substantial loss of natural ecosystems (le Polain de Waroux et al., 2018; Rausch & Gibbs, 2016; Strassburg et al., 2017). Such clearing has been driven largely by increased agricultural production, particularly conversion to pastureland for cattle production and cropland for soy or corn (Graesser, Aide, Grau, & Ramankutty, 2015).

2.1 Zero-deforestation Commitments

To address these negative outcomes, many companies that trade tropical commodities have adopted Zero-Deforestation Commitments (ZDCs) to reduce or eliminate deforestation "embodied" within their supply chains (Lambin et al., 2018). In 2006, the first set of commitments, called the Soy Moratorium, was established by soy trading companies operating in Brazil to reduce deforestation associated with soy production in the Amazon (Gibbs et al., 2015). This "Soy Moratorium" was signed by traders in the Brazilian Association of Vegetable Oil Industries and the Association of Cereal Exporters in Brazil, which at the time purchased around 90% of all soy grown in the Brazilian Amazon (Brannstrom, Rausch, Brown, de Andrade, & Miccolis, 2012). The Soy Moratorium resulted from public pressure associated with a Greenpeace campaign against major soy trader Cargill that labeled Cargill as a key driver of deforestation because of its involvement in the soy trade (Greenpeace, 2006). Since its inception, the soy moratorium has been continuously renewed until 2016, when the Soy Moratorium was extended indefinitely (Kastens, Brown, Coutinho, Bishop, & Esquerdo, 2017).

Since this benchmark agreement, more sustainability commitments have been made by commodity producers such as beef, palm oil, and soy, with more than 750 agreements between more than 400 entities in 2017 (Supply-Change.org, 2018) and some have been effective at reducing deforestation (Carlson et al., 2018; Gibbs et al., 2016, 2015; Macedo et al., 2012a; Nepstad et al., 2014). Companies are now being pressured to extend the Soy Moratorium to Brazil's Cerrado ecosystem, which has experienced substantial natural ecosystem loss from soy expansion (Prager, 2019; Soterroni et al., 2019; World Wildlife Fund, 2018). Several soy traders with pledges to implement ZDCs in the 2020s have significant market shares across South America's soy producing regions (Ermgassen et al., 2019; trase.earth, 2019).

Recent research on ZDCs suggests that they can reduce deforestation within committed supply chains (Carlson et al., 2018; Gibbs et al., 2016, 2015; Macedo et al., 2012b; Nepstad et al., 2014). However, ZDCs differ in their characteristics and implementation details. Many commitments have a "cut-off" date after which deforestation is prohibited and differences may affect the success of the commitment (Potts, Lynch, Huppe, Cunningham, & Voora, 2014; Romijn et al., 2013). If the selected cut-off date is in the future, producers may increase clearing before the target date, creating temporal leakage of deforestation (Carlson et al., 2018). Definitions of "forest" and "deforestation" determine the geographic coverage of a commitment and delineate which lands are off limits, which differ between commitments (Romijn et al., 2013).

Implementation of ZDCs is also hypothesized to result in spillover effects, including 'leakage', where deforestation is displaced to different regions, commodities, or actors (Alix-Garcia & Gibbs, 2017). Studies that focus on areas protected by public policies or private agreements have reported varying levels of leakage, with some finding a significant increase in deforestation outside of protected boundaries (Alix-Garcia & Gibbs, 2017; Meyfroidt & Lambin, 2009; Robalino, Pfaff, & Villalobos, 2017) but others not detecting leakage (Heilmayr & Lambin, 2016). Thus, when considering the success of ZDCs at preventing deforestation, leakage is an important consideration (Aukland, Costa, & Brown, 2003).

However, the variations ZDCs characteristics on their success, as well as the degree to which ZDCs lead to leakage, is not well understood (R.D. Garrett et al., 2019; Lambin et al., 2018). In part, this is because many commitments have yet to be implemented (Ermgassen et al., 2019; R.D. Garrett et al., 2019). To overcome these issues, a simulation tool can be used to compare how different future scenarios of ZDC implementation may alter land cover.

2.2 Modeling the Effects of Zero-Deforestation Commitments on Land Cover

Economic theory suggests that decisions made by individuals regarding land use are governed by economic factors, particularly the profits obtained from land use (Walker & Solecki, 2004). Changes in technology, infrastructure, policy, and markets incentivize individuals to employ land to generate profits (Barbier, 2012). Relationships between agricultural land use and the associated profits confirm that agricultural land rents guide human decisions about land use le Polain de Waroux et al. (2018). The rents depend on biophysical conditions, transport infrastructure, and market dynamics, among other factors (Rachael D. Garrett, Lambin, & Naylor, 2013). Because rents help drive agricultural land use decisions, accurately representing decision-making in a region where ZDCs are being implemented in a spatially explicit model would ideally include the influence of ZDCs on land rents. Indeed, in recent studies, the use of agricultural rents has been favored as the spatial variable for representing economic decisions, as it provides a more complete representation of economic factors that lead to decisions (Mann et al., 2010, 2014; Walker et al., 2009; Walker & Solecki, 2004).

A simulation model capable of accurately representing the driving forces and proximate causes that affect land cover and land use is a valuable tool for scientists looking to understand how policy changes will affect the landscape (Veldkamp & Lambin, 2001).Researchers focused on trade analysis tend to use sector-based economics models (e.g., the General Trade Analysis Project (GTAP) Model) (Burniaux & Truong, 2002; Hertel & Tsigas, 1997; Siriwardana & Yang, 2008) to simulate changes in commodity fluxes between regions. Such a model has been applied to study soy expansion in the Brazilian Cerrado under various conservation scenarios (Soterroni et al., 2019). This model simulated soy expansion in the biome while and considering spillover effects to global markets. However, the model was limited by a 250x250 km spatial resolution and considered temporal changes in five-year time steps. Thus, the model was limited in the level of detail that observations could have. Simulation of land cover changes due to ZDC implementation within and across regions requires high resolution information on land cover and land cover change, explicit consideration of farmer profits, and a smaller simulation time scale for proper analysis.

Several software packages are available for developing such spatially-explicit models (Camacho Olmedo, Pontius, Paegelow, & Mas, 2015). One of these is Dinamica EGO, which was first released in the early 2000s and was developed with the intention of modeling land use and land cover changes in the Amazon (B. S. Soares-Filho, Cerqueira, & Pennachin, 2002). Since its inception, the platform has been improved to increase its computational capacity. Dinamica has been used to simulate deforestation in Brazil with a focus on the Amazon and Cerrado biomes (Carvalho Lima, Carvalho Ribeiro, & Soares-Filho, 2018; Gibbs et al., 2015), and has also been applied in other regions and contexts, including simulation of oil palm plantation expansion in Indonesia (Carlson et al., 2013; Thapa, Shimada, Watanabe, Motohka, & Shiraishi, 2013) and deforestation associated with resource extraction in the Congo (Galford, Soares-Filho, Sonter, & Laporte, 2015).

3 Research Objective and Questions

Adoption of ZDCs by soy trading companies is likely to affect corporate sourcing behavior, and in turn may alter spatial patterns of soy expansion. Yet, outcomes due to ZDC adoption are difficult to study empirically since many have not been implemented due to future commitment dates and the difficulty of isolating the effects of ZDC implementation from other influences on land cover change. Given the potential future importance of ZDC adoption in soy supply chains for tropical land cover, and the difficulty of observing ZDCs effects empirically, the goal of this study is to investigate the effect of ZDCs on tropical land cover using a land use change simulation model. Here, I address the following questions:

1. How might ZDC implementation affect geospatial patterns of soy expansion, given a fixed trajectory of soy area?

2. How do these alterations in soy expansion patterns change the locations and patterns of non-soy land cover change?

3. Given that ZDCs vary in their implementation timelines, how does ZDC implementation date affect geospatial patterns of soy expansion and resulting changes in land cover?

To answer these questions, I compared land cover change under several scenarios of ZDC adoption by soy traders across four countries in South America from 2015-2030 in a spatially explicit land cover simulation model. The model, built using Dinamica EGO, simulates ZDC implementation in soy producing regions of South America. These regions are particularly suitable to address my research questions because they have experienced substantial loss of natural vegetation due to soy expansion and are the focus of significant planned implementation of ZDCs by soy traders. I compared two scenarios of ZDC implementation to a baseline case in which no commitments were implemented. Results prove a better understanding of how differences in implementation of ZDCs affect land cover, including forest conservation.

4 Methods

4.1 Study Area

This research focuses on the countries of Bolivia, Brazil, Argentina, and Paraguay (BBAP) in South America, which have a combined surface area of around 1,270 million hectares (Graesser et al., 2015). In 2014, around 4.5% of BBAP land area was under soy production (World Agricultural Production, 2018) and in 2017, soy production in BBAP totaled around 178 million metric tons, or almost half of global soy production (FAO, 2019). Major soy producing regions in BBAP include the Amazon, Gran Chaco, and Cerrado regions, which have unique land cover change histories as described in the following paragraphs (Figure 1).

The Amazon region (2,038 thousand km^2) lost 9% of its forest cover to development related to agriculture and resource extraction from 2000 to 2017 ("Global Forest Watch," 2018). From 2000 to 2006, soy area expanded by about 10,000 km^2 and was an important contributor to deforestation. However, since the 2006 a combination of the Soy Moratorium, market dynamics, and public policies that discouraged deforestation led to substantially reduced soy expansion into forests (Macedo et al., 2012b; Morton et al., 2006). Recent deforestation is primarily due to pasture expansion for beef cattle (Alix-Garcia & Gibbs, 2017), while continued soy expansion has focused on non-forest land covers such as pasture (Graesser et al., 2015).

The Cerrado region (4,154 thousand km^2) neighbors the Amazon region on the east and has also recently experienced landscape changes caused by colonization efforts and agricultural expansion. The Cerrado is a savanna ecosystem and covers almost 25% of Brazil's land area (The Nature Conservancy, 2018). It is a global biodiversity hotspot with more than 4,800 endemic plant and vertebrate species, yet land cover changes have endangered many of these species (Myers, Mittermeier, Mittermeier, Da Fonseca, & Kent, 2000). The Cerrado experienced deforestation rates twice as high as the Amazon region from 2002 to 2011 (Strassburg et al., 2017). By 2012, around 50% of the region's original vegetation had been cleared, and less than 20% remained intact (Ferreira et al., 2012). Remaining intact areas are suitable for more agricultural expansion, and while the region is not currently covered by the Soy Moratorium, food corporations have recently reached agreements that could protect forests from being cleared (Strassburg et al., 2017; World Wildlife Fund, 2018)

The Gran Chaco, also known as the Dry Chaco, is a dry woodland region in South America which extends over 70 million hectares including parts of Argentina, Bolivia, and Paraguay. Since 1985, the forest clearing in the Gran Chaco has converted 20% of the region's forest to other land cover (Baumann, Piquer-Rodríguez, Fehlenberg, Gavier Pizarro, & Kuemmerle, 2016). This deforestation threatens a large number of species in the region including 145 mammal and over 400 bird species (Torres, Gasparri, Blendinger, & Grau, 2014). In recent years, however, deforestation rates have decreased as a result of public policies that inhibit more expansion into forested areas (C. Nolte et al., 2018).

4.2 Land Cover Change Model

To simulate the effects of ZDC implementation on land cover, I developed a land cover simulation model using the software Dinamica EGO (B. S. Soares-Filho et al., 2002). The model was trained or "calibrated" with observed land cover dynamics and other inputs (e.g., elevation, soy prices) for 2012-2013 and validated by simulating change and then comparing simulated to actual change in 2013-2014. Then, this model was used to simulate future land cover change across the study region from 2015-2030. Quantities of future land cover change were set based on observed past land cover transitions (for non-soy changes) and on future demand (for soy changes).

4.2.1 Land Cover Inputs

To train the land change model and develop an understanding of past changes in land cover, I used a 2001-2014 annual timeseries of 250 m resolution classified land cover maps (Figure 2) derived from MODIS satellite data for all of South America (Graesser et al., 2015). To reduce the number of classes for input into the land change model, these nine land cover types were re-categorized into five classes. The original plantation category in this dataset included citrus fruits, grapes, and coffee, which are products that government organizations, such as Argentina's Ministry of Production and Employment (Ministerio de Agricultura, Ganaderia y Pesca, 2019) and Brazil's IBGE (Sistema IBGE de Recuperação Automática, 2019), include in their cropland statistics. For this reason, I combined the plantation category with croplands. The plantation trees category covers non-crop trees such as pines and palms, not included in government organizations statistics. Thus, I combined original water, bare and built-up, and plantation tree categories into a new "other" category following the approach of Graesser et al., (2015) (Table 1). Out of these 5 categories, I considered forests and shrubs to be natural landcover areas, while the other 3 (cropland, pastureland, and other) as not, this decision was guided by the definitions from Graesser et al., (2015).

In Brazil's Cerrado biome, these reclassified maps resulted in low average cattle stocking rates. In 2006, estimates suggest that Cerrado stocking rates ranged from 0.67-1.11 cattle heads per hectare (Strassburg et al., 2017). Based on Cerrado Biome pasture area from Graesser et al. (2015),and cattle heads data reported by le Polain de Waroux et al. (2017),I estimated stocking rates of just 0.21 cattle heads per ha The potential cause of this discrepancy is an overestimate in Cerrado pasture area due to misclassification of shrublands as pasture. To address this issue, I updated the reclassified maps with data from MAPBIOMAS (Brazilian Annual Land Use and Land Cover Mapping Project) in the Cerrado biome in Brazil (Mapbiomas, 2019). I chose the MAPBIOMAS dataset because it is specific to Brazil and is available annually from 1985-2018. I first resampled the MAPBIOMAS dataset to 250x250 meters. In the Cerrado, I set all pixels identified as pasture by MapBiomas as pasture, and set all pixels identified as pasture by Graesser et al. (2015)but not as pasture in MAPBIOMAS as shrub. The merged map has average stocking densities of 1.31 in year 2006, which is closer to previous estimates.

4.2.2 Spatial Propagation of Change

I determined the locations of change from probability maps generated using the Weights of Evidence (WOE) method, which is readily available in Dinamica EGO. The WOE method assesses the influence that spatial variables, such as elevation, have on the likelihood of change for a particular land cover transition such as forest to pasture (Agterberg, Bonham-Carter, & Wright, 1990; Goodacre, Bonham-Carter, Agterberg, & Wright, 1993). In Dinamica, changes are allocated according to probability maps using patcher and expander functions. These functions operate according to parameters that determine the size and shape of land cover transitions, which can be adjacent to other areas of the same type (expander) or where no previous area of the same type is present (patcher). Parameters used in the patcher and expander functions were calculated at the state level during the 2011-2014 time period.

4.2.3 Spatial Variables

I used both categorical (e.g., ecoregions and protected areas) and continuous variables (e.g., distance to deforestation) to generate probability maps using the WOE method (Table 1**:** Original Land Cover Types, Description, and Reclassification. The reclassification is similar to the one done by Graesser et al. (2015).

). I chose variables based on my understanding of the system and prior research that indicates that they are likely to influence the spatial pattern of land cover change (Carlson et al., 2013; Galford et al., 2015). Some of these variables are dynamic (e.g., distance to deforestation), while others are static (e.g., distance to town) across time and scenarios. The WOE method requires that continuous variables be converted to categorical variables before running the procedure. All variables were re-sampled to 250 m resolution in ArcGIS Pro (ESRI, 2019) so that they had the same resolution as the land cover maps.

Dinamica allows the user to measure similarity between spatial variables and test the assumption that they are independent of one another. To support such assessment, the program produces several coefficients calculated in the Weights of Evidence process. These include Crammer's coefficient (Goodacre et al., 1993) which indicates correlation between spatial variables, ranging from 0 (full independence) to 1 (full association). Retaining variables with high association may produce results overly influenced by those variables. I calculated Crammer's coefficient at the country level per land cover transition, and removed variables with a coefficient higher than 0.45 (Table 3,Table 4,Table 5, and Table 6). Galford et al. (2015) also removed variables with a coefficient above 0.45 and the variable with the least independence from the entire set was be removed.

Spatial variables might have a different influence on land cover across space. For example, distance to roads could be very influential in determining areas that are likely to experience forest loss in some states, while in other states variables such as distance to rivers or to towns might play a bigger role. Thus, WOEs were estimated at the first administrative level (e.g., for each state) to account for the variable influence that different variables might have across regions.

4.2.4 Crop Area, Yield, and Price Data

Annual timeseries of harvested area and yields for soy and other crops were gathered from agricultural institutions and associations from each country in BBAP. In Argentina, data were downloaded from their Ministry of Production and Employment (Ministerio de Agricultura, Ganaderia y Pesca, 2019) and were available annually from 1970 to 2017 at the municipality level. In Brazil, data were downloaded from SIDRA (Sistema IBGE de Recuperação Automática, 2019), and were available on an annual basis from 1970 to 2017 at the municipality level. For Bolivia these data were available at the municipality level from ANAPO (Asociación de Productores de Oleaginosas y Trigo, 2019), the Association of Producers of Oilseeds and Wheat. For the years 2010 to 2017 the data was available from their website, and for the years 1988 to 2009 the data were synthesized from ANAPO reports by le Polain de Waroux et al. (2017) For Paraguay, data were sourced from production reports from INBIO (Instituto de Biotechnologia Agricola, 2019), the Institute of Agricultural Biotechnology ,(at the provincial level from 2010 to 2015.

For soy prices (USD/ha), I used annual country-level 2001-2014 data provided by le Polain de Waroux et al. (2017) synthesized from various data sources including NGOs and government institutions in the four countries.

4.3 Supply Chain Data

To model soy commodity flows handled by actors with ZDCs, I used data from the online platform Trase (trase.earth, 2019). For all BBAP countries, for exported soy, Trase provides annual data including quantity of soy produced (tons), the names of traders handling soy, export destination (country), and port of export. These data are available for the years 2003-2017 at the municipality level in Brazil, for 2013-2017 at the department level in Paraguay, and country level in Argentina (2013-2017) and Bolivia (2015-2018). Trase also provides this information for soy consumed domestically for Brazil and Paraguay. To estimate annual domestic soy consumption from 2016-2018 in Argentina and 2014-2015 in Bolivia, I used reports from the USDA Foreign Agricultural Service (Meador & Sandoval, 2018; G. E. Nolte, 2015). This information was used to calculate transaction costs associated with ZDCs as part of the soy rent model, and to simulate future ZDC implementation by company.

In some cases, Trase did not report which port received soy for a municipality in Brazil and Paraguay. In these municipalities, I used information from neighboring municipalities (i.e., municipalities that share a border with the municipality without port data) to estimate sourcing patterns, as follows:

1) $$P_{i,j} = \frac{\sum_{e=1}^{n} \frac{V_{e,j}}{V_e}}{n}$$

Here, P is the proportion of total soy volume exported via port j from municipality i with no port data, V is the volume of soy produced in neighboring municipality e and the volume exported to port j, and n is the number of neighboring municipalities with port data.

4.3.1 Soy Yields

To predict soy yields in areas where soy was not grown in the past, I developed a model of potential soy yields. For Brazil and Argentina (Figure 3), in regions where yields were not available, I modeled soy yields at the municipality level using a linear model with multiple biophysical variables associated with soy agriculture. These consist of soil type (Hengl et al., 2017), precipitation in mm (Fick & Hijmans, 2017), temperature in °C (Fick & Hijmans, 2017), and direct normal irradiation in kWh/m (Global Solar Atlas, 2017). To factor in potential differences between states, such as technology or fertilizer use, my model incorporated a categorical variable representing the first administrative level (i.e., state).. This model was also used to predict future yields.

2) $$Y_i = \beta_0 + \beta_1 ST_i + \beta_2 PP_i + \beta_3 TP_i + \beta_4 DI_i + \beta_5 AD_i$$

Here Y is the yield for municipality i, ST is the mode soil type, PP is the mean yearly precipitation, TP is the mean yearly temperature, DI is the mean direct normal irradiation, and AD is the administrative area (state) the municipality is in.

Some Brazilian and Argentinian states reported no soy yields. In Argentina, these states produce no other agricultural crops (Viglizzo et al., 2011) and are likely too dry to expect production in the near-term (Aramburu Merlos et al., 2015), so I assumed that no soy could be grown here in the future and did not predict yields in these areas. In Brazil, these states were in the same climate regions and biomes as others that produce soy, so to predict potential yields in these states, I first calculated the average yield in neighboring states (i.e., states that share a border with the state of interest) and then calculated the potential yield in the state with no soy production as follows:

3) $$Y_i = \frac{\sum_{e=1}^{n} Y_{e,i}}{n}$$

Here, Y indicates soy yield (kg/ha) for state i, n is the number of states with soy yield data, and e is each neighboring state.

For Bolivia and Paraguay (Figure 4), limited time series data prevented development of a robust linear model Thus, in these countries I used the average national soy yield, and soy yields for these countries did not change over time. Soy yield was used to calculate soy rent, one of the spatial variables used in the WOE method. Yields were also used to calculate annual changes in soy production based on simulated changes in soy area.

4.4 Validation

The simulated land cover was compared to actual land cover using a fuzzy comparison method, also known as fuzzy similarity test (Hagen, 2003; Power, Simms, & White, 2001). This approach compares maps of simulated and observed changes within windows of varying sizes surrounding the center cell of interest. A matching cell found within a window takes a value of 1, while non-matching cells take a value of 0, then overall map similarity is calculated by averaging the similarity scored of all map cells. I compared the simulated map to the observed map and vice versa, and then chose the lower score from the two comparisons.

For cropland expansion, the model produced a 56% fit within a 1.75 km window (7 x 7 cells), which improved to a 69% fit with a 2.75 km window (11 x 11 cells) (Figure 11). The similarity between other landcover changes varied between 40% and 80% (Table 9). This is in line with other recent studies simulating land change with Dinamica EGO, Galford et al. (2015) reached a 78% fit within a 3.5 km search radius (7 x 7 cell window) and 90% fit within a 5.5 km search radius (11 x 11 cell window), while Silvestrini et al. (2011) reached a fit between 60-70% within a 22 km search radius (11 x 11 cell window).

4.5 Agricultural Rents

All prices were adjusted for inflation and converted to 2015 US dollars (USD), which is the amount used for every monetary value used in this project. Potential agricultural rents from soy production (R, USD), composed of gross farm-gate revenue (U, USD) minus operation (O, USD), transaction (T, USD), and travel (TR, USD) cost, were calculated at for each pixel p, time t, land cover m, and municipality i as follows:

4) $$R_{p,t} = \left(U_{i,t} - O_{i,t} - T_{i,t}\right) \times TR$$

Gross farm-gate soy revenue was estimated for each municipality by multiplying annual soy yield (Y, tons/ha) by soy price (P, USD/ton) and pixel area (PA, hectares):

5) $$U_{i,t} = Y_{i,t} \times P_t \times PA$$

While soy agriculture incurs several costs including the cost of labor, machinery, and fertilizers, information on all relevant costs was not available across BBAP. Thus, I use fertilizer cost as a proxy for operational costs. Fertilizer use (FP, kg/ha) was available at the regional level (similar to Biome) for Brazil for the year 2006 (FAO, 2006), and country level for Argentina, Bolivia, and Paraguay for the year 2010 (Rosas, 2012). Fertilizer price (FU, USD/mt) data was sourced from the World Bank Commodity Price Data Index (World Bank, 2019) at the global level, for the years 2000-2018 .Past the year 2018 I continued using 2018 prices. Operational costs at the pixel level were calculated as follows:

6) $$O_{i,t} = FU_i \times FP_t \times PA$$

I hypothesize that ZDCs generate transaction costs, the cost of compliance or non-compliance with a ZDC. Such costs may include licensing fees, payments to third-party auditors, and/or costs of protecting forests (R.D. Garrett et al., 2019). I assume that these costs depend on the degree of ZDC adoption within a region, with higher costs in regions with more committed soy volumes such that transaction cost is a function of proportion of soy production (V, tons) covered by a ZDC (committed) relative to total soy production:

The relationship between ZDC adoption and effects on forest land rent may be non-linear such that ZDC adoption might not have a substantial effect on soy rents until the volume traded under ZDCs is relatively high (R.D. Garrett et al., 2019). To reflect this hypothesized relationship between the fraction of soy production under ZDCs to total soy production, I used the following logistic relationship:

7) $$TR = \frac{100}{\left(1 + e^{-100\left(\frac{V_{committed}}{V_{total}} - 0.5\right)}\right)}$$

To reflect the desirability of different land cover types, in natural vegetation areas (forests and shrubs) I multiplied rent by this transaction cost (TR), and for areas not in this category I multiplied rent by 1/TR.

4.6 Travel Cost

I calculated soy travel cost from each pixel in BBAP to port (for exports) or location of domestic consumption. First, I developed a friction map that represents the cost of moving soy through each pixel. To generate this cost estimate, roads (paved and unpaved) sourced from OpenStreetMap (“OpenStreetMap,” 2018), and water bodies (rivers and lakes) from Global

Surface Water (Pekel, Cottam, Gorelick, & Belward, 2016), were overlaid on the land cover map. Then, each class including roads and water bodies was assigned a friction value representing the cost (USD) of transporting soy one kilometer through each class. These values are adapted from (Vera-Diaz et al., 2008) (Table 7). Travel cost from each pixel to each port was then calculated with Dinamica's "Calculate Cost Map" tool, which calculates the least cost pathway to reach a port, using the friction map as the landscape and port and domestic consumption locations as destinations. In Brazil, soy destined for domestic consumption was routed to Rio de Janeiro, given the large population in this city as well as soy's known use for chicken feed, which is concentrated in the south (Smaling, Roscoe, Lesschen, Bouwman, & Comunello, 2008). For Paraguay, Bolivia, and Argentina, domestic consumption was routed to national capitals.

Next, to account for cases where soy from a single pixel is sent to several ports, the weighted average travel cost to all ports per pixel (C, USD/ton) was calculated from the proportion of total soy volume (V, tons) produced in each administrative unit i exported from that administrative unit to each port (j), as well as the travel cost (T, USD/ton) from the pixel (k) to the port:

8) $$C_k \sum_{j=1}^{n} T_{k,j} \times \frac{V_{i,j}}{V_i}$$

Finally, I converted these per ton costs to total travel cost (Z, USD) based on soybean yield (Y, tons/ha) and area (PA, ha) for each pixel k:

9) $$Z_k = C_k \times Y_k \times PA$$

4.7 Quantity of Land Cover Change

For future scenarios, the methods chosen to predict the quantity of change between land cover categories depends on the research question. The amount of land to be converted could be derived from future goals (Carlson et al., 2013), from a linear regression using historical data (Galford et al., 2015), or simply past observed changes (Gibbs et al., 2015).

In future simulations, the quantity of soy expansion or contraction was simulated according to observed changes in area (for 2015-2017) or projections (2018-2030) at the country level. Non-soy land cover transitions were based on the average of the last three years of available land cover data (2011-2014) at the state or province level (Figure 8). I chose these years because they were the representative years available for all other land cover change. Specifically, transition matrices describing the gross rates of change (i.e., the number of pixels per year) were calculated at the state or province level and were then used to drive future change within those administrative regions.

4.7.1 Cropland Areas and Double Cropping

In parts of BBAP, soy is double cropped with other crops such as maize (Zalles et al., 2019). Because my model requires crop area without double cropped crops, I calculated this "true" crop area by removing double cropped area from the total crop area, the sum of all crop harvested area regardless of double cropping. For Bolivia and Paraguay, reports from each country differentiated between the first crop ("zafra") and second crop ("zafrina"), and thus I only used the first crop ("zafra") in my model. For Brazil, I used an approach similar to Zalles et al. (2019) who focused on beans, maize, and wheat as they are the main crops known to be double cropped in Brazil. SIDRA has data available for double cropped beans and maize available, which I then subtracted from total area for each municipality. I also subtracted all wheat from the total area, as most wheat in Brazil tends to be a winter crop and is grown with a summer crop (Zalles et al., 2019). In Argentina, all barley and wheat are double cropped with either soy or another crop (G. Therisold, personal communication, April 2019). Thus, for Argentina I subtracted these two from total soy area for each municipality. A comparison of this new area calculated from government sources, and total cropland area from land use maps show an agreement for both Brazil (Figure 6) and Argentina (Figure 7).

4.7.2 Soy and Non-Soy Crop Transitions

Soy expansion in the model is driven by changes in soy area, yet the land cover maps did not differentiate between non-soy crops and soy. To estimate past changes in soy and non-soy crops from 2007 to 2014, I quantified the annual gross expansion or contraction (A, hectares) of soy (S) and all croplands including soy (C), accounting for double cropped area (D, hectares) at the country level from government-reported (G) sub-national (i) cropping information as follows:

10) $$\Delta A_{S,G} = \sum_{i=1}^{n} \Delta A_{S,G,i}$$

11) $$\Delta A_{C,G} = \sum_{i=1}^{n} \Delta A_{C,G,i} - D$$

Then, I calculated the annual proportion of total government-reported expansion or contraction attributed to soy, and multiplied this by annual gross cropland expansion or contraction observed in the land cover dataset (LC) to estimate cropland area change for soy and non-soy (NS) crops:

12) $$\Delta \mathrm{A}_{\mathrm{S,LC}} = \Delta \mathrm{A}_{\mathrm{C,LC}} \times \frac{\Delta \mathrm{A}_{\mathrm{S,G}}}{\Delta \mathrm{A}_{\mathrm{C,G}}}$$

13) $$\Delta \mathrm{A}_{\mathrm{NS,LC}} = \Delta \mathrm{A}_{\mathrm{C,LC}} - \Delta \mathrm{A}_{\mathrm{S,LC}}$$

For future simulations, I used observed country-level soy area from 2014 to 2017 (FAO, 2019), and global soy area projections from 2018 until 2028 (OECD & FAO, 2018) (Figure 9). I used the annual mean global soy expansion rate from 2018 to 2028 to estimate soy area in 2029 and 2030. Then, to calculate annual soy area (A) for each country (i) in BBAP for each year t from 2018 to 2030 from global (g) soy area, I scaled global production based on the fraction of global production from each BBAP country in 2017, the last year of soy data available from FAO:

14) $$A_{i,t} = A_{g,t} \times \frac{A_{i,2017}}{A_{g,2017}}$$

These annual country-level soy areas were then converted to change in area for use in the model.

One important limitation on future simulations is the lack of expansion for soy areas into non-cropland soy areas. Given that the original land cover maps do not reflect these differences by categories, this process was not calibrated in the model. Soy contraction was also not permitted in the model unless specified in the area harvested expected for that year, to ensure model met expected demand.

4.7.3 ZDC Sourcing Behavior Groups

To model future soy expansion under ZDCs, I first grouped soy area added demand into domestic and export. Then, exported soy area was further divided into supply chains with an implemented ZDC and those with no implemented ZDC, using company market share (trase.earth, 2019) and information regarding ZDC adoption (Ermgassen et al., 2019), (Table 8). For companies with ZDCs, commitments vary in terms of coverage areas, land cover classes protected, commitment start dates, and cutoff date for deforestation (Table 8). To account for these differences in commitments, I grouped companies by these commitment characteristics into what I have tentatively called "sourcing behavior groups". The group that a company belongs to can change over time if the commitment characteristics change.

4.8 Future ZDC Implementation Framework

Two approaches were applied to implement ZDCs in the model. The first ("soy rent modification") alters the soy agricultural rents in accordance with the assumption that compliance or non-compliance with ZDCs alters landholder profits through mechanisms including market exclusion, costs of certification, monitoring costs, and credit availability (see section Agricultural Rents). This method does not guarantee full compliance from these actors, given that agricultural rents are just one of many variables used to create soy expansion probability maps. Since this method depends on subnational trader-specific soy sourcing data to allow subnational variation in rent maps, it was applied only in Brazil and Paraguay.

The second method is a "probability map modification" that manipulates the probability maps such that soy expansion driven by demand in a ZDC supply chain is not developed in landcovers that are off-limits according to ZDC rules (i.e., natural land covers such as forest or shrublands, including those converted after the ZDC implementation date). This method assumes full compliance by traders in such areas and thus does not permit any expansion of ZDC soy into off-limits areas. This method was implemented throughout BBAP.

Because the Brazil's Soy Moratorium was already being implemented during the model calibration period, its influence on land cover change should already be incorporated into probability maps in the Amazon. All companies with future ZDCs are already party to the Soy Moratorium. Therefore, my model does not alter probabilities or land rents in the Brazilian Amazon.

4.8.1 Future Scenarios

I developed five future scenarios of ZDC implementation across BBAP from 2014-2030. Scenario development was based on an assessment of current company commitments as well as an understanding of realistic future trajectories developed from recent literature and supply chain developments. All scenarios assume the same annual soy supply at the national level (Crop Area, Yield, and Price Data). Future projections extend to 2030 because projections of future soy demand extend to 2028 (OECD & FAO, 2018), commitments (29%) have a target implementation date of 2025 and beyond, and five years should be sufficient time to analyze their effects on land cover (R.D. Garrett et al., 2019). I assumed that all commitments were implemented as a "zero-gross" deforestation because they were either specified as zero-gross by the commitment, or no information was provided about this aspect of the commitment. For all scenarios, company market share remains fixed at levels in 2017 year at the country level, but a company may shift its sourcing locations freely within a country. Finally, forests and shrublands were considered as protected by commitments for all ZDCs in all scenarios because many global commitments refer to protecting natural vegetation areas beyond forests (Table 8). Scenarios differ in ZDC implementation date, regional coverage (e.g., the Cerrado or the Amazon), the number of companies adopting a ZDC, and the method for implementing the ZDC. Each scenario is described briefly below.

4.8.1.1 No ZDCs

This scenario represents the future without any company commitment implementation and serves as a baseline to understand the potential benefits of 2025 ZDCs. No ZDC mechanism is implemented.

4.8.1.2 ZDCs – 2025 – Probability Map

This scenario represents a future in which companies implement their pledges by 2025. The only companies that have a stated target implementation date are Bunge (2025), Cargill (halving deforestation by 2025), and Denofa (2030). Denofa was not in Trase's database. Here, ZDCs are implemented using probability map modifications.

4.8.1.3 ZDCs – 2025 - Rent Changes

This scenario is equivalent to the 2025 Probability Map scenario, except that ZDC implementation occurs by only affecting only soy agricultural rents. It is limited to Brazil and Paraguay as they are these only countries with subnational soy sourcing data that allow variation in rents across different levels of ZDC implementation.

4.8.1.4 ZDCs – Early implementation

This scenario is the same as the "2025 – Probability Map" scenario, except it implements all commitments in 2020. I developed this model to understand the effect that earlier ZDC implementation may have on regional land cover change.

4.8.1.5 ZDCs – 2025 Probablity Map + Cerrado and Gran Chaco Moratorium

This optimistic scenario represents a future that combines the 2025 Probability Map scenario with a moratorium on soy expansion into natural land cover in the Cerrado and Gran Chaco ecoregions starting in 2022 (i.e., a cutoff date of 2022). A Cerrado moratorium is of interest (Soterroni et al., 2019), and recent supply chain initiatives reduce deforestation caused by their operations in the region (Prager, 2019). While there are no specific ZDCs for the Gran Chaco, the idea of implementing a soy moratorium in both regions has been proposed in the past (Rainforest Action Network, 2008), and public pressure to reduce deforestation associated with soy in the region is mounting (Gonzales, 2018).

5 Results

5.1 Land Cover Change 2001-2014

From 2001 to 2014, net natural land cover area in BBAP declined at a rate of -0.29% yr^{-1}, while agricultural land expanded by +0.53% yr^{-1} (Figure 10). However, these net rates mask variable trends across time and land covers. Forest area declined throughout the study period (-0.52% yr^{-1}). Croplands expanded rapidly from 2001 to 2008 (+4.75% yr^{-1}) but changed little from 2009 to 2014 (+0.35% yr-1). Pastureland area increased from 2001 to 2005 (+0.64% yr^{-1}) then declined slightly from 2006 to 2014 (-0.03% yr^{-1}). Shrubland area declined from 2001 to 2009 (-0.95% yr^{-1}) and increased by +3.19% yr^{-1} from 2010 to 2014. The 'other' category expanded by +0.08% yr^{-1} from 2001 to 2014. By 2014, the study region was 46% forest, 14% shrubland, 28% pasture, 7% cropland, and 5% other.

From 2011-2014, forest loss was largely attributed to pasture expansion (62% of total forest loss), shrub expansion (26%), and crop expansion (8%, Figure 8). Shrublands regrew to forest (58%) or were converted to pasture (33%). Pasture regrew to forest (38%) and shrubs (28%), while loss of cropland areas was typically due to pasture expansion (61%), forest regrowth (21%) and shrubland expansion (16%).

5.2 ZDC Implementation Method Comparison

Comparison of ZDC implementation methods indicated relatively small inter-method differences in the locations of soy expansion and rates of land cover conversions. In Paraguay, compared to the soy rent modification, the probability map approach generated 2% and 0.75% more soy expansion into the Wet Chaco and Atlantic Forest ecoregions, respectively, and a reduction of soy expansion in the Gran Chaco. In Brazil, compared to soy rent modification, the probability map model led to a 0.4% increase in soy expansion into the Cerrado ecoregion, and 1.7% less soy expansion into the Amazon ecoregion.

Compared to the soy rent modification, the probability map modification, method resulted in 0.2% less soy expansion into natural land cover areas across Brazil and Paraguay (Figure 15). Specifically, altering agricultural rents rather than changing probabilities increased soy expansion into shrub areas by 0.7% and decreased expansion into pastureland and forests by 0.1% and 0.2%, respectively. The largest relative increases in soy expansion were 0.7% additional expansion into shrubland in Brazil, and 1.4% more expansion into pastureland in Paraguay. The greatest relative decreases were a 0.05% decline of soy expansion into forests in Brazil and a 1.7% decrease into forests in Paraguay. Because of these relatively small differences between ZDC implementation methods, the remainder of the results presents only the 2025 ZDC scenario using the probability map modification.

5.3 Spatio-temporal patterns of soy expansion

Under the No ZDC scenario total soy expansion across BBAP from 2015-2030 was 12,075,819 ha (Figure 16). Soy expansion was stable across all scenarios, just 0.0013% less under the 2025 ZDC scenario and 0.0017% less under the Gran Chaco and Cerrado Moratorium scenarios (Figure 18).

Regions with high ZDCs implementation rates, including the Cerrado and Gran Chaco, tended to experience reduced soy expansion (Figure 13). In Brazil's Cerrado ecoregion, soy expanded by 3,993,000 ha under the No ZDC Scenario, with relative expansion declines of 2.22% and 3.16% in the 2025 ZDC and Gran Chaco and Cerrado moratorium scenarios, respectively. This soy expansion was displaced to other Brazilian biomes. When compared to the No ZDC scenario, in other scenarios soy expansion increased in the Amazon by 3.35% (2025 ZDC) and 4.89% (Gran Chaco and Cerrado moratorium) and in the Atlantic forest by 0.50% (2025 ZDC) and 0.88% (Gran Chaco and Cerrado moratorium).

In Argentina's Gran Chaco, soy expanded by 841,000 ha in the No ZDC scenario but decreased by 0.71% in the 2025 ZDC scenario and by 2.62% in the Gran Chaco and Cerrado moratorium scenario. In the Paraguayan Gran Chaco, the No ZDC scenario generated 19,000 ha of soy expansion, with 8.39% and 16.19% less soy expansion in the 2025 ZDC and Gran Chaco and Cerrado moratorium scenarios, respectively. In Bolivia's Gran Chaco region, soy expanded by only 5,000 ha in the No ZDC scenario and increased by 3.02% in the 2025 ZDC scenario and decreased by 1.39% in the Gran Chaco and Cerrado moratorium scenario.

5.4 Land use conversion for soy expansion

Across BBAP, in the No ZDC scenario, about 5,515,000 ha of natural vegetation (i.e., forest and shrubland) was converted for soy expansion. The 2025 ZDC scenario reduced natural vegetation clearing, with 2.6% less forest conversion and 4.1% less shrubs conversion, while the Gran Chaco and Cerrado Moratorium Scenario led to a 2.9% less forest conversion and 5.2% less shrubs conversion (Figure 12).

The 2025 ZDC scenario, in comparison with no ZDCs, predicted that soy would expand by an additional 2.5% into pastureland and 10% into other, with reduced expansion into forest (-2.6%) and shrubland (-4.1%). These general trends held across all countries in BBAP. In Brazil, large relative changes included increased expansion into pastureland (+3.3%) and reduced clearance of forests (-2.0%) and shrubland (-4.0%). In Argentina and Paraguay, expansion into pastureland increased (+1.4% and +3.8%, respectively), and forest conversion to soy decreased (-4.7% and -4.0%, respectively). Bolivia had the least projected future soy expansion among BBAP countries and has smallest market share of ZDC commitments in BBAP (Figure 5). Thus, Bolivia experienced small relative changes across scenarios (+0.48% expansion into pastureland, -2.04% expansion into forests).

Under the Gran Chaco and Cerrado moratorium, compared to the no ZDC scenario, soy expanded by an additional 3.2% into pastureland and 3.6% into other, with reduced expansion into forest (-2.9%) and shrubland (-5.2%, Figure 12). These changes mainly occurred in Brazil's Cerrado region, where expansion increased into pastureland (+4.5%), and decreased into forests (-4.8%) and shrubland (-5.5%). In the other three countries, this scenario produced results similar to those of the 2025 ZDC scenario, with overall changes in in soy expansion into any land cover totaling <1,000 ha per country from 2014 to 2030. This is due to the relatively small projected soy expansion into the Gran Chaco ecoregion, as well as the relatively small cropland area in the Gran Chaco compared to total agricultural areas in Argentina, Paraguay, and Bolivia.

5.5 Changes with an earlier implementation date

Implementing global commitments in 2020 instead of 2025 would have led to a substantial decrease in soybean expansion into the Cerrado and Gran Chao regions (Figure 12). Compared to the 2025 ZDC scenario, the Earlier ZDC scenario reduced soy expansion into Brazil's Cerrado ecoregion by 3.5%, and into Argentina's Gran Chaco by 1.1%. In Brazil, there was a 1.6% increase in soy expansion into the Amazon when comparing the same two scenarios.

Earlier implementation also reduced conversion of natural land cover areas by about 6.7% compared to 2025 implementation, instead pushing soy expansion into already-cleared areas (Figure 12). In Brazil, earlier implementation produced substantial changes in soybean expansion into pastureland (+8.3% compared to 2025 scenario), forests (-6.3%), and shrubland (-6.8%). In Argentina and Paraguay, soy expansion into pastureland increased (+0.8% and +6.5%, respectively), and expansion into forests decreased (-3.3% and -7.6%, respectively). For Bolivia, soy expansion into forests decreased (-5.16%) while expansion into the 'other' land cover class increased (+3.06%).

5.6 Natural Landcover Conservation

Relative to the no commitment scenario, by 2030 the 2025 ZDC scenario produced 0.04% more remaining forest (242,606 ha), and the Cerrado and Gran Chaco moratorium scenarios resulted in 0.03% more forest (153,825 ha, Table 10). Changes in shrublands followed a similar pattern, with 0.06% more shrublands remaining under the 2025 ZDC scenario (133,288 ha additional shrublands), and 0.05% more shrublands under the Gran Chaco and Cerrado moratorium scenario (113,781 ha). While these results seem unusual, inherent randomness in the model as well as the multiple land cover changes simulated that aren't soy (Figure 8) could account for this result. A future recommendation for further projects would be to run simulations multiple times to obtain means and standard deviations, to account for inherent model randomness.

This natural land cover conservation was distributed across all major ecoregions. In the Amazon ecoregion, compared to the No ZDC Scenario, the 2025 ZDC scenario generated 0.04% (126,137 ha) more forest and the Gran Chaco and Cerrado Moratorium scenario led to 0.03% (87,168 ha) additional forest (Table 10). The Cerrado had a 0.16% (187,262 ha) increase in natural land cover in the 2025 ZDC scenario, and a 0.12% (91,093 ha) increase in the Gran Chaco and Cerrado moratorium scenario compared to the No ZDC scenario. Finally, the Gran Chaco had a 0.05% (17,575 ha) increase in natural land cover in the 2025 ZDC scenario, and a 0.09% percent (32,500 ha) increase in the Gran Chaco and Cerrado moratorium scenario, compared to the No ZDC scenario.

6 Discussion

By developing a land change model with a mechanism for simulating the implementation of corporate zero-deforestation commitments in the South American soy sector, I investigated how ZDCs may affect soy expansion and natural land cover areas. My results indicate that ZDC implementation reduces net loss of natural land cover, despite displacement of soy expansion from regions where ZDCs are implemented to other areas with less protection. These model-based results support findings from previous empirical studies that suggest ZDC implementation does lead to reduced natural land cover conversion (Gibbs et al., 2015), and also provide suggestions of where intra-country leakage may occur.

My results suggest soy expansion patterns similar to a recent study that also implemented ZDCs in a spatial modeling framework. Soterroni et al. (2019) investigated the effects of a potential soy moratorium in the Cerrrado and found that such a moratorium would result in reduced regional natural land cover loss (Soterroni et al., 2019). Their results indicated soy expansion in the Cerrado would decrease by 10% (0.34% yr^{-1}) under a 2020 to 2050 Cerrado moratorium scenario when compared to the baseline. My Gran Chaco and Cerrado scenario indicates a 3% (0.19% yr^{-1}) decrease in the Cerrado by the year 2030. Compared to my results that indicated more relative leakage of forest clearing for soy into the Amazon biome, Soterroni et al. (2019) reported more leakage into other Brazilian biomes, such as the Atlantic Forest biome. This difference might be the result of not incorporating Amazon Soy Moratorium ZDCs into my model (section 4.8). To better account for the Amazon Soy Moratorium, future model versions should include these commitments in the model calibration process.

By creating different scenarios differing only in ZDC implementation details, I was able to produce model-based results that indicate how these differences may alter soy expansion into diverse land covers. Other variables remained constant throughout the scenarios, including the total annual soy expansion area, which was simulated at the country level. While earlier implementation dates are expected to reduce natural land cover conversion (R.D. Garrett et al., 2019), my approach was able to measure not only the effect of such accelerated timelines, but also compare these outcomes with alternate regional moratorium scenarios. My results indicate that earlier ZDC implementation resulted in more conservation of natural land cover than regional moratoriums in the Cerrado and Chaco. While this is not a perfect comparison, because the earlier ZDCs were implemented in 2020 and the moratoriums were put in place in 2022, they do illustrate a previously unexplored comparison of what implementation characteristics have a bigger impact. Future comparisons not included in this study could revolve around the number of global ZDCs adopted by companies, which in my study remained unaltered.

My model was designed to allocate annual soy expansion at the country level, which allowed intra-country leakage (see section Crop Area, Yield, and Price Data). While leakage was forced by the model's design, the distance over which soy expansion 'leaked' was substantial. My model only limits conversion of natural land cover areas. While I expected some expansion to be displaced, I expected most of it would remain within the same region where ZDCs were implemented, given no biophysical scarcity of already cleared areas in these regions (e.g., the Cerrado). Instead, soy expansion was displaced to locales distant from ZDC implementation (e.g., the Amazon).

My research builds upon findings from major previous investigations of the effects of ZDC implementation on deforestation, as well as spatially explicit models focused on policy interventions attempting to control deforestation. When compared other recent work focusing on ZDC implementation (Soterroni et al., 2019), my model had both a smaller spatial (250 meter) and temporal (1 year) resolution (compared to 50km and 5 years), as well as larger geographical extent which covered four countries. This increases the frequency of observations that can be made, by being yearly, and the detail of these, as my model has a 40,000 times finer resolution. By covering a larger geographical region, my model also has increased flexibility of scenarios, as they can be altered at the country level. While the use of agricultural rents has been a previous feature (le Polain de Waroux et al., 2018; M. del C. Vera-Diaz, Kaufmann, Nepstad, & Schlesinger, 2008; Walker & Solecki, 2004), the way I used rents to model ZDCs is novel. To my knowledge, my model is the first to include the idea of "transaction costs" specific to the type of land cover, to reflect the potential for conservation efforts to make development of already cleared land more profitable and natural areas less profitable. Furthermore, while other works have used yield models to estimate potential soy revenues across space (M. del C. Vera-Diaz et al., 2008), using the Trase dataset to create a rent map from observed soy sourcing patterns created more realistic transport cost estimates that accounted for the variability observed in soy export patterns across time in model calibration, and the fact that soy was often exported via distant rather than nearby ports.

The results of my research indicate the potential for current global ZDCs, if implemented, to reduced soy expansion into natural land cover areas. While I did not conduct a per company analysis, implementation of commitments from six companies by 2025 resulted in 2% (110,000 ha) less natural land cover conversion for soy in the BBAP region. This information could be used by companies to showcase the positive effect their adoption of ZDCs will have not only in their supply chains, but in the soy sector. Critically, I found that the implementation date of these commitments may be more important than their spatial coverage, which suggests that civil society should not only campaign for more companies to adopt ZDCs, but also focus on advocating already committed companies to accelerate implementation.

7 Limitations

The results presented here are limited in several ways. First, while the model was able to endogenously simulate intra-country leakage by allocating annual soy expansion areas at the country level, I was unable to incorporate inter-country leakage. Potentially, increased domestic ZDC implementation could reduce soy supply from that country by limiting areas suitable for soy expansion. This may lower market prices which could alter patterns of soybean expansion elsewhere (Morton et al., 2006). Because I did not incorporate these market effects into my model, the model likely overestimates domestic soy expansion at the country level and does not consider international leakage. Coupling the regional Dinamica EGO model with a global economic model could allow for such international leakage (Soterroni et al., 2019).

Second, because my research questions focused on the effects of ZDC implementation in the soy sector, my model is driven by future projected changes in soy area. Rates of land cover change for other croplands and land covers were derived from the observed changes from 2011-2014. As the past is not always a good predictor of the future, incorporating future projections for these other land covers could provide a more realistic future outcome.

Third, the land cover maps I used did not differentiate between different types of crops and simply has a broad "cropland" category. This lack of differentiation prevented analysis of past locations of soybean expansion and contraction. As a result, I was unable to calibrate the model to realistically simulate the spatial pattern of soy vs other crop land use change, which may have resulted in lower accuracy of future maps if these patterns were significantly different. Moreover, I was forced to estimate soy (and non-soy crop) expansion and contraction rates and locations for model calibration and validation process. To address this problem, I used sub-national crop areas reported by institutional and government sources to differentiate between soy and other crops (See section Soy and Non-Soy Crop Transitions). This approach resulted in agreement between remotely sensed and reported area (Figure 6 & Figure 7), suggesting that these data sources are appropriate to determine soy and non-soy cropland expansion and contraction. Satellite-derived products that differentiate between different crop types may be one way to overcome this problem in the future.

Finally, soy trading company commitments lack specificity in their details (e.g., forest definition, cut-off date of deforestation). Few companies provided the start date of the commitment, or what land cover type would be protected under their commitment (Table 8). Because of this I had to make assumptions about the implementation details, and thus my results might not reflect actual impacts. Actual impacts on the region will depend on the level of ZDC implementation, as well as the implementation details. This type of information critical for civil society campaigns to hold companies accountable to their promises (R.D. Garrett et al., 2019). For instance, recent actions by Cargill indicate a lack of intention to implement their commitments (Yaffe-Bellany, 2019), and cause worry of when these ZDCs will be implemented globally if at all. My model assumes 100% compliance, as well as no changes in company market share in the soy market for the region and the same export patterns (such as ports used) that have been observed in the past. Global commitment market share and export patterns could change in the future, and while a mechanism for simulating changes in these could be created, the intricacies of simulating decision making by such companies is outside of the scope of my project.

8 Conclusions

My results suggest that implementation of ZDCs by soy supply chain actors will result in less soy expansion into natural land cover, even if leakage of soy expansion to other domestic regions takes place. This indicates ZDC implementation by companies may not only reduce the "embodied" conversion of natural landcover in their supply chain but is also likely to have a net benefit for environmental protection overall. Furthermore, different scenarios indicated that while regional moratoriums in endangered ecoregions further reduced the conversion of natural landcover areas beyond what is expected if current company pledges are implemented, earlier implementation dates of these company pledges had a bigger effect on natural land conservation. These findings, as well as observations on the lack of specificity of commitments, indicate that companies should be encouraged to specify implementation dates in the near future and then act to implement those pledges well before these public deadlines.

9 Acknowledgements

My research could have not been possible without the help from many people who helped and guided me along the way. My advisor Kimberly Carlson and committee members Rachael Garrett and Linda J. Cox have been of great help and guidance throughout this project. Hermann Rodrigues was also integral in me learning Dinamica EGO, which was used to creating this simulation model. Other collaborators that helped me include Sam Levy, Florian Gollnow, Nelson Villoria, Yann Le Polain de Waroux, and Jordan Graesser. Fellow students at the University of Hawaii, including Tanya Torres, Charlotte Smith, Sita Ekaputri, Cole Hendrickson, Patrica Laporte, Bradley Weiss and Hi'ilei Casco, also provided invaluable support. This work was supported by the National Socio-Environmental Synthesis Center (SESYNC) under funding received from the National Science Foundation DBI-1052875, and by the National Science Foundation Geography and Spatial Sciences Program (Award #1739253).

10 Figures and Tables

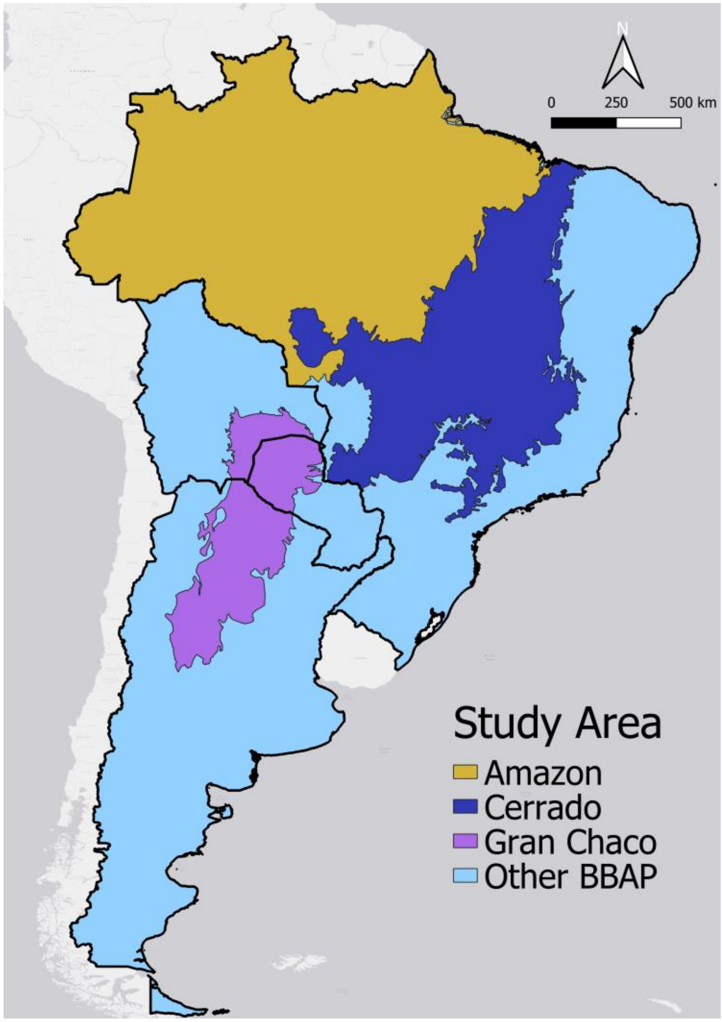

Figure 1: Brazilian Amazon, Gran Chaco, and Cerrado regions in the countries of Brazil, Bolivia, Argentina and Paraguay. These three are of importance because of their ecological value and have experienced loss of natural areas in recent years. Source: ("The Nature Conservancy," 2018)

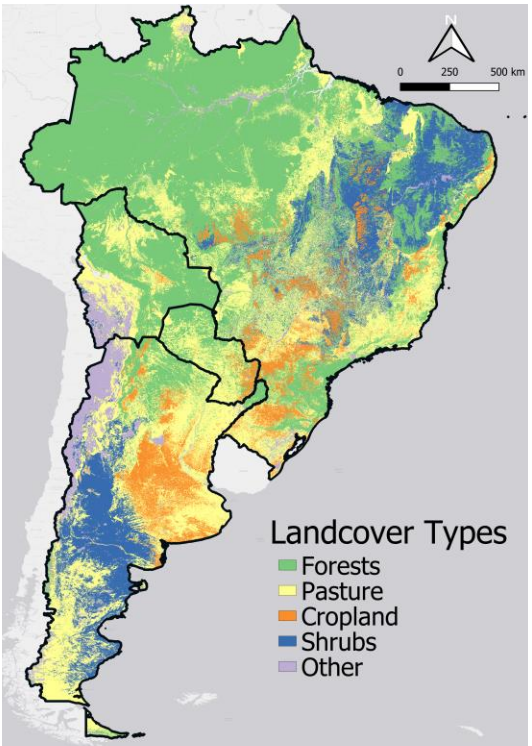

Figure 2: 2014 Land cover map for the region of Brazil, Bolivia, Argentina, and Paraguay (BBAP). The map was recategorized from nine original categories to five. Source: (Graesser et al., 2015)

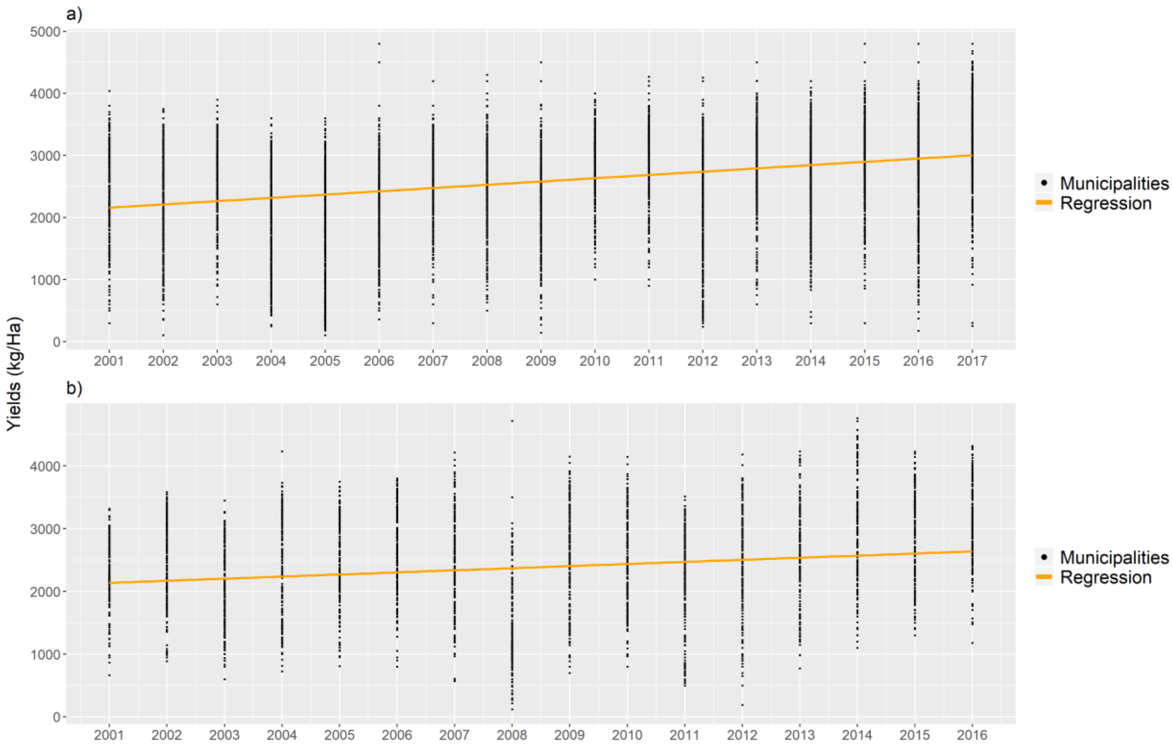

Figure 3: a) Past Brazil soy yields per municipality. Each dot represents a record of soy yield for the given year, and line representing linear regression. Source: (Sistema IBGE de Recuperação Automática, 2019) b) Past Argentina soy yields per municipality. Each dot represents a record of soy yield for the given year, and line representing linear regression. Source: (Ministerio de Agricultura, Ganaderia y Pesca, 2019)

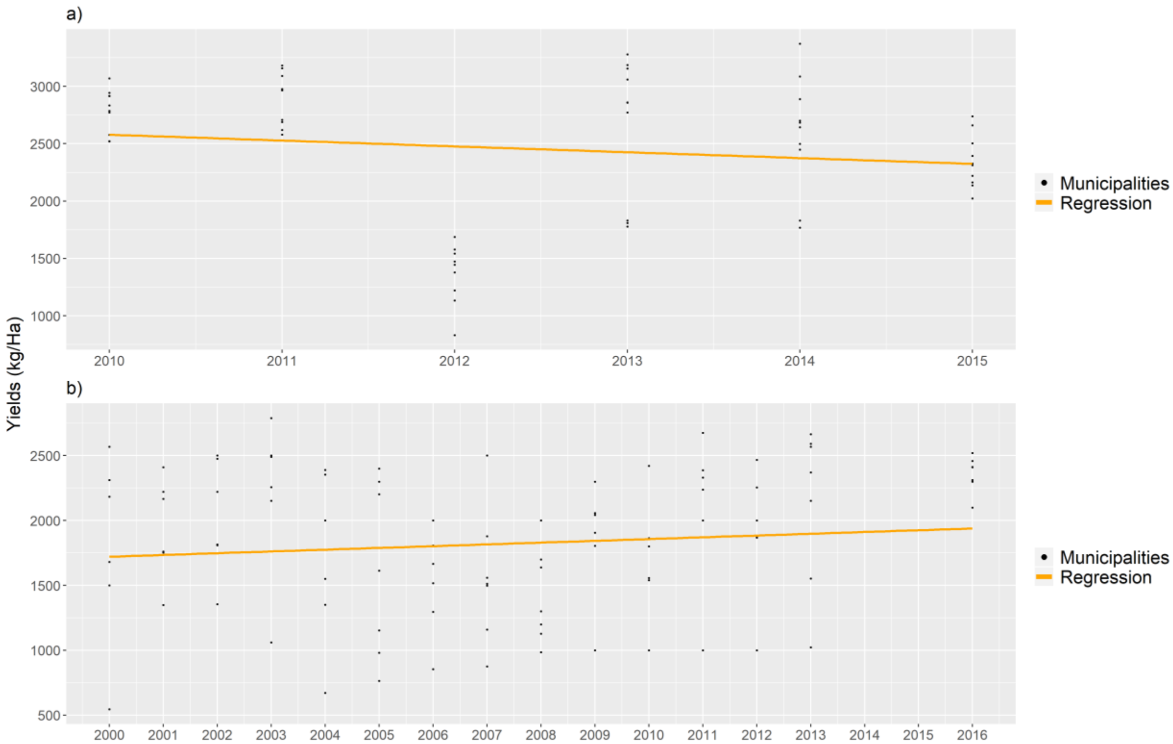

Figure 4: a) Past Paraguay soy yields per municipality. Each dot represents a record of soy yield for the given year, and line representing linear regression. Source: (Asociación de Productores de Oleaginosas y Trigo, 2019) b) Past Bolivia soy yields per municipality. Each dot represents a record of soy yield for the given year, and line representing linear regression. Source: (Instituto de Biotechnologia Agricola, 2019)

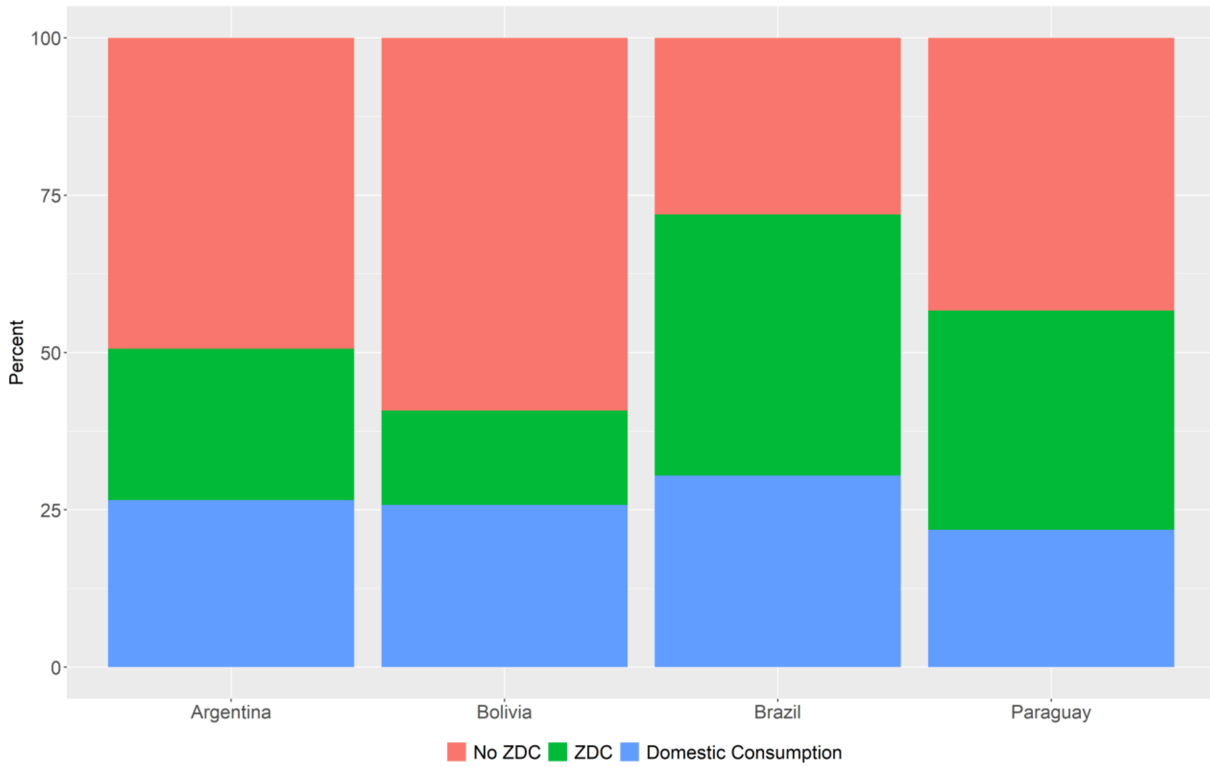

Figure 5: Percent of Zero Deforestation Commitment market share in Brazil, Bolivia, Argentina, and Paraguay (BBAP) by countries. Source: (Ermgassen et al., 2019; NYDF Global Platform, 2018; trase.earth, 2019) Note: Excludes Amazon Soy Moratorium

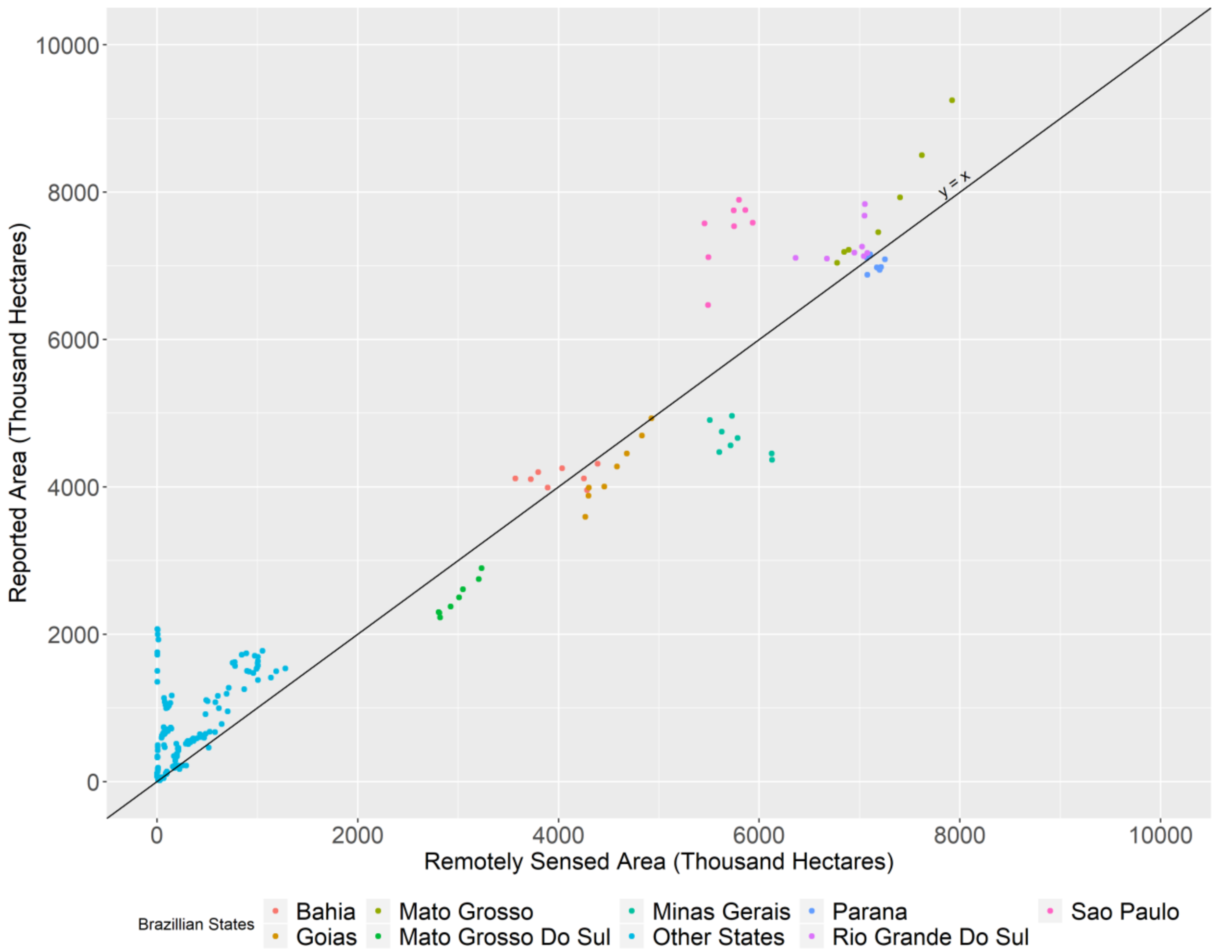

Figure 6: Brazil Cropland Areas By State (2007-2014). Each dot represents a state during a given year. Both datasets are in agreement on area. Source: Remotely sensed area:(Graesser et al., 2015; Mapbiomas, 2019) Reported area: (Sistema IBGE de Recuperação Automática, 2019)

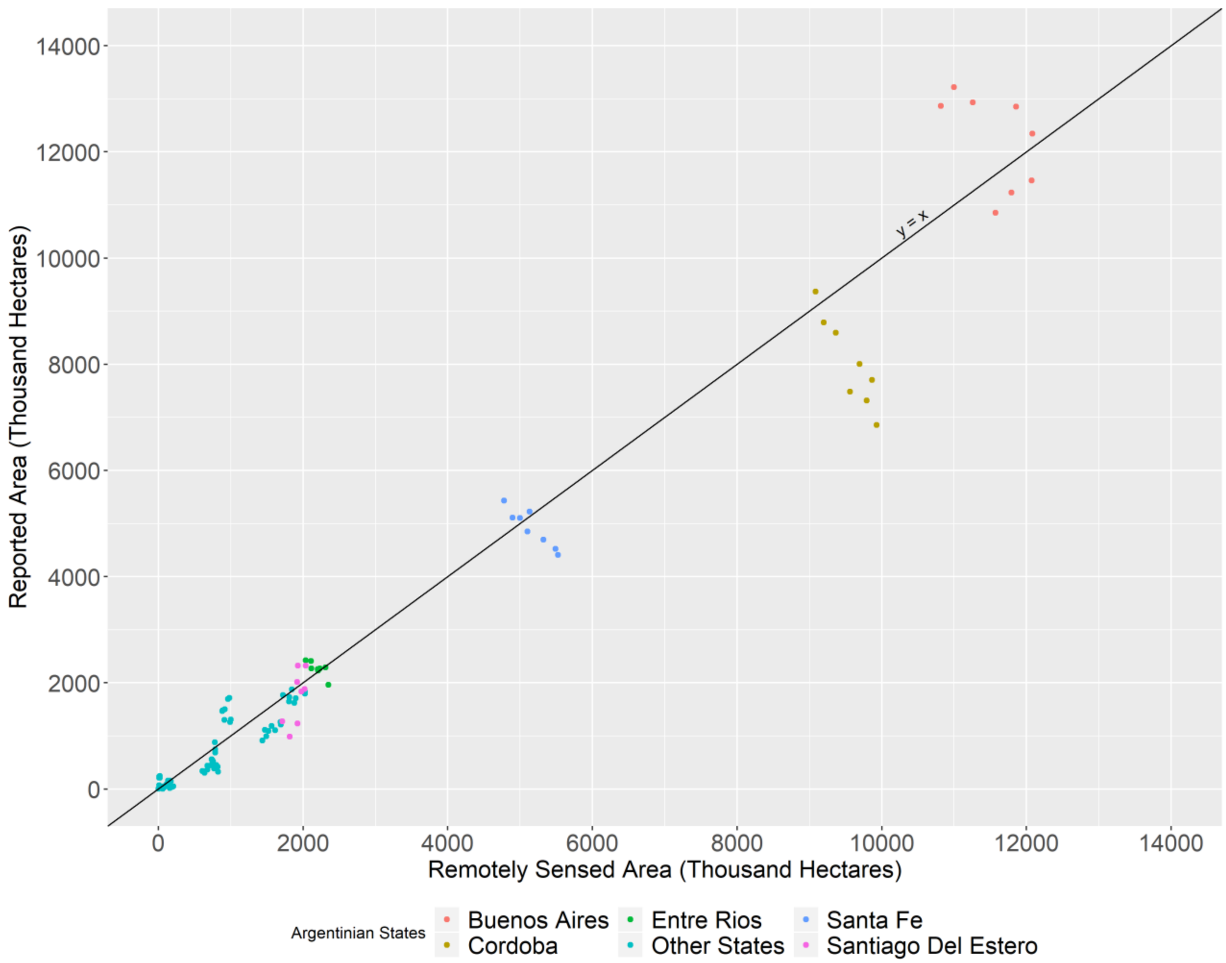

Figure 7: Argentina Cropland Areas By State (2007-2014). Each dot represents a state during a given year. Both datasets are in agreement on area Source: Remotely sensed area:(Graesser et al., 2015) Reported area: (Ministerio de Agricultura, Ganaderia y Pesca, 2019)

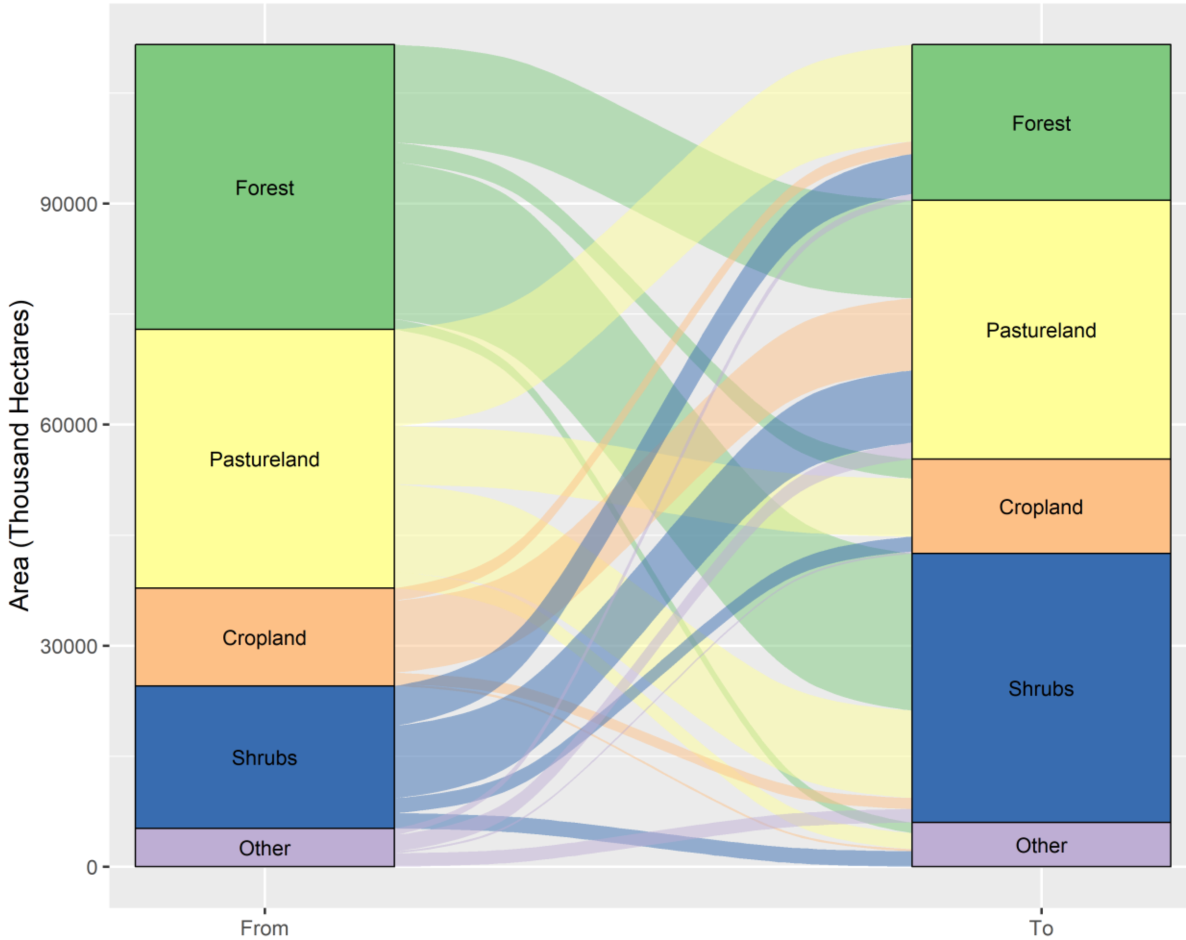

Figure 8: Land cover changes between categories in Brazil, Bolivia, Argentina, and Paraguay (BBAP). (2011-2014). Significant changes not including cropland involve forest to shrubs changes, as well as pastureland to forests and vice versa. Source: (Graesser et al., 2015; Mapbiomas, 2019).

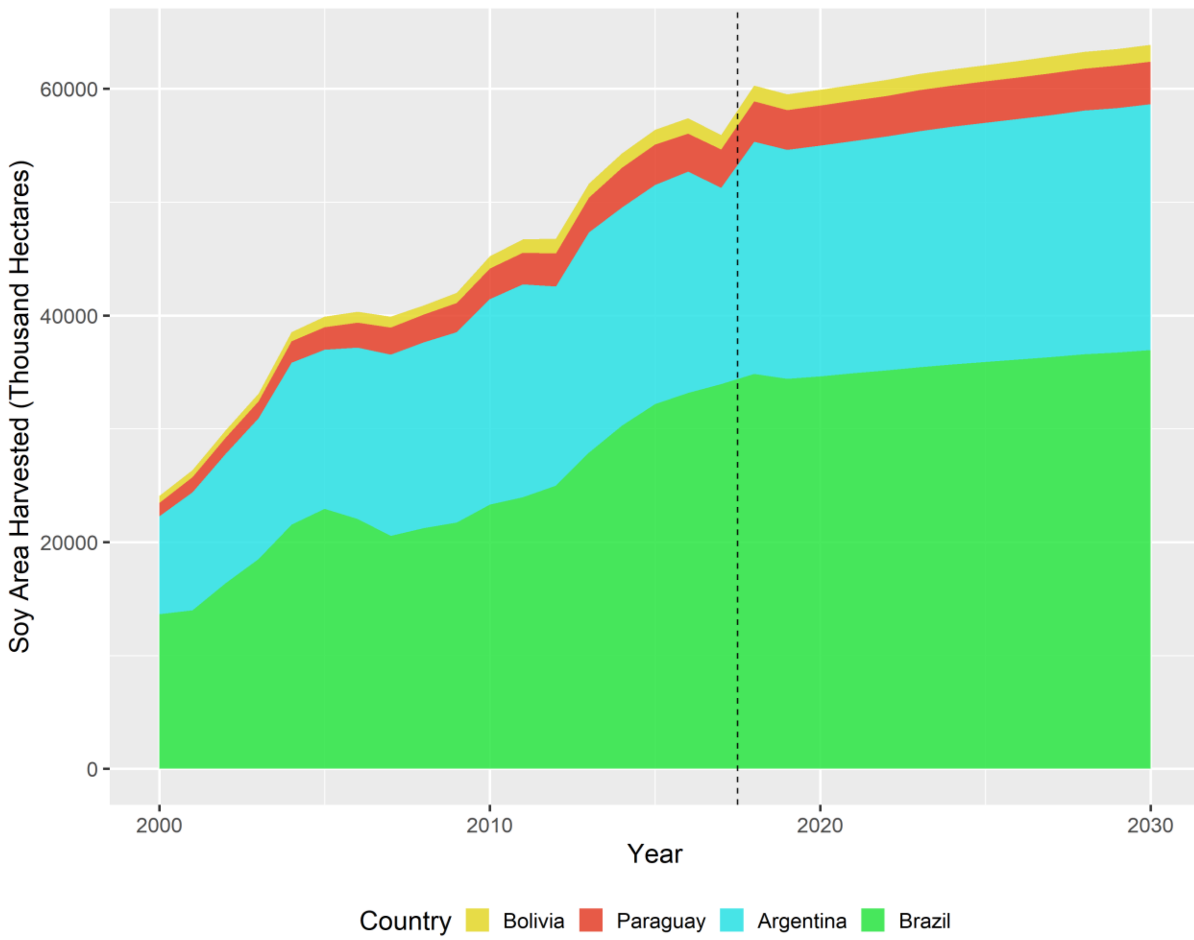

Figure 9: Soy Area Harvested in Brazil, Bolivia, Argentina, and Paraguay (BBAP) during 2000-2030. Areas past the year 2018 are projected. Source: (FAO, 2019; OECD & FAO, 2018)

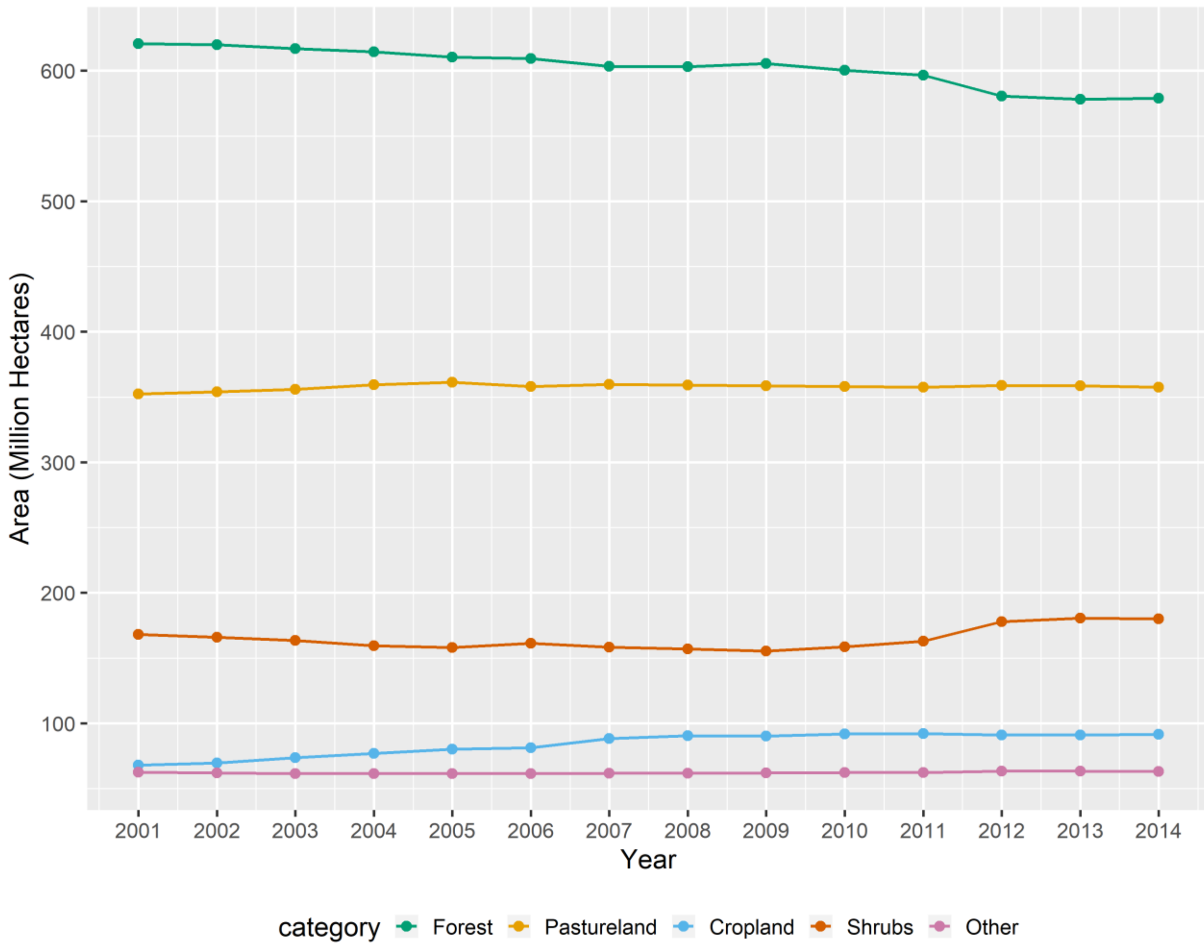

Figure 10: Areas in Brazil, Bolivia, Argentina, and Paraguay (BBAP) combined by land use type between 2001-2014. Trends indicate forest reduction, while an increase in Shrubs and Cropland. Source: (Graesser et al., 2015; Mapbiomas, 2019)

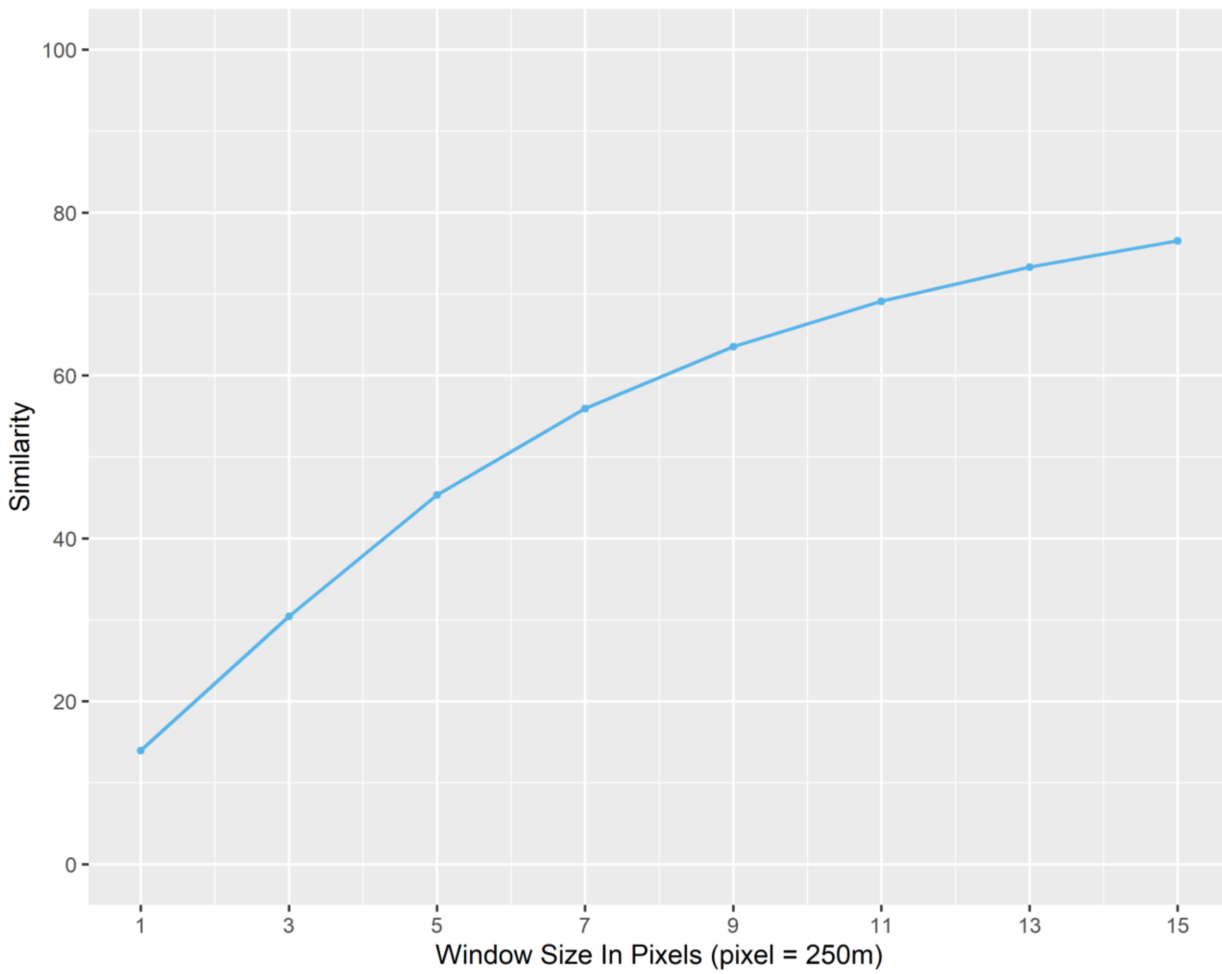

Figure 11: Cropland expansion similarity at multiple window sizes. For cropland expansion, the model produced a 56% fit within a 1.75 km window (7 x 7 cells), which improved to a 69% fit with a 2.75 km window (11 x 11 cells). This is in line with other recent studies simulating land change with Dinamica EGO, see section: Validation.

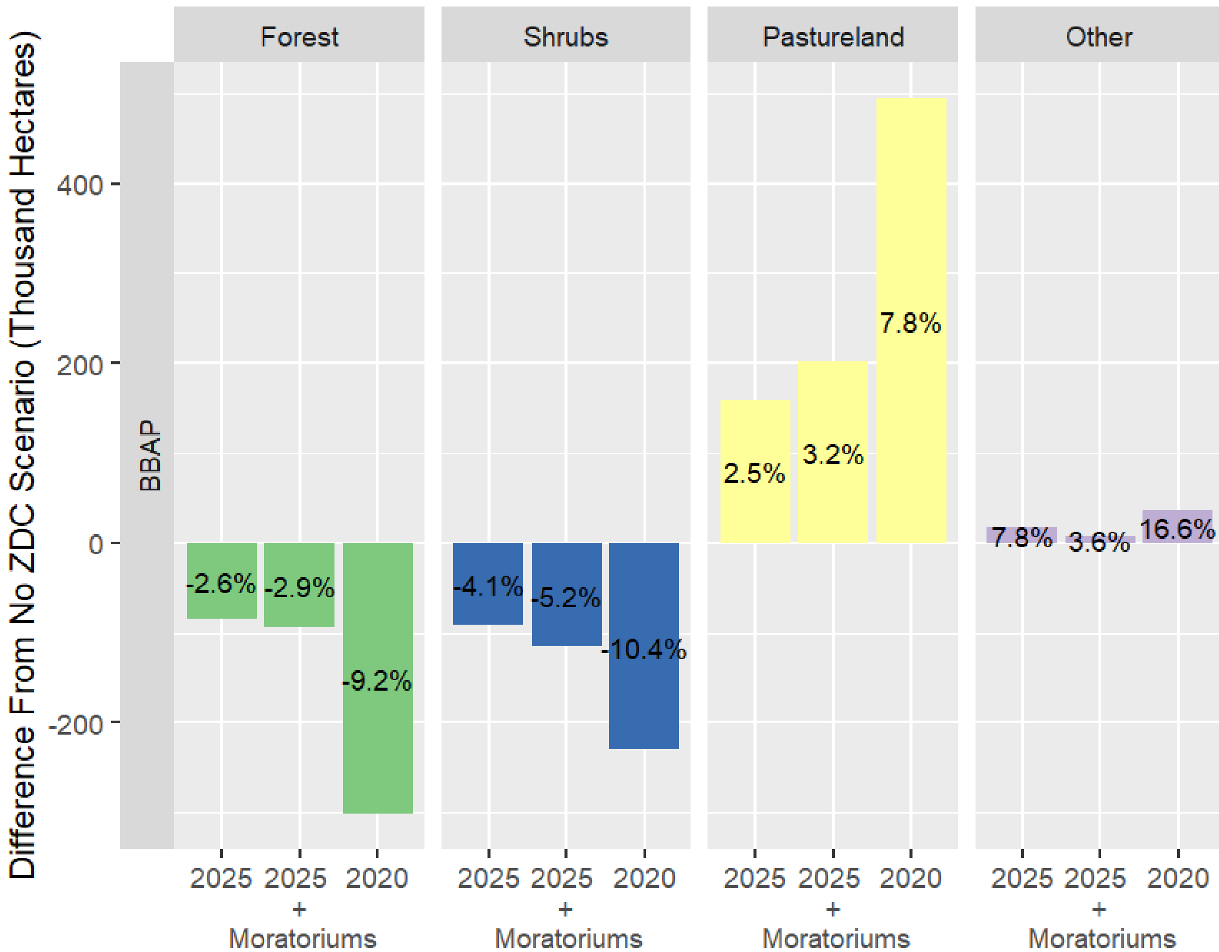

Figure 12: Relative Difference in Landcover Converted Soybean Expansion Between 2015 and 2030 in Brazil, Bolivia, Argentina, and Paraguay (BBAP) by Scenario. All scenarios indicated a reduction of forests and shrubs, and an increase in pastureland conversion, for soy expansion.

Figure 13: Difference in Regions of Soybean Agricultural Expansion Between 2015 and 2030 in Brazil, Bolivia, Argentina, and Paraguay (BBAP). Reduced expansion was observed in the Cerrado and Gran Chaco across all scenarios.

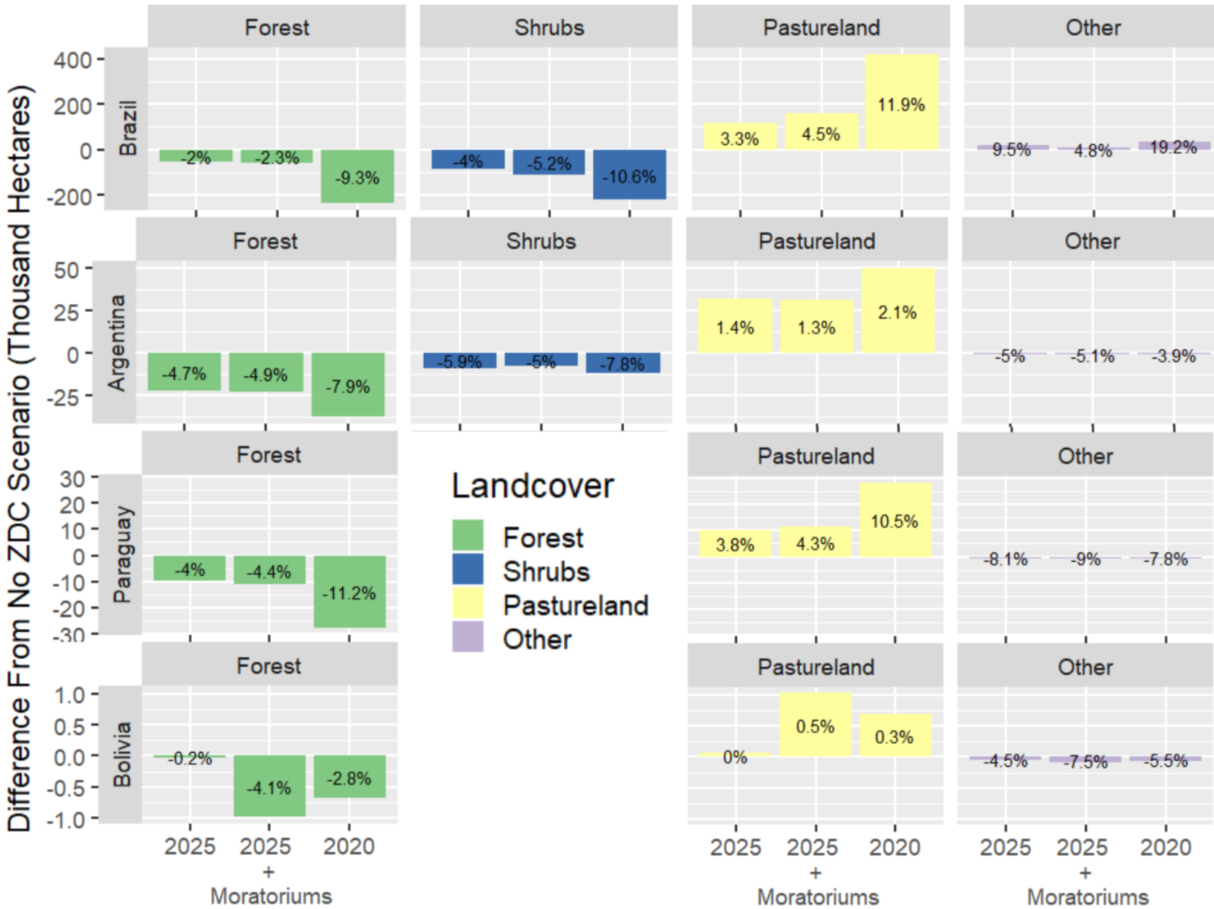

Figure 14: Difference in Landcover Converted Soybean Expansion Between 2015 and 2030 in Brazil, Bolivia, Argentina, and Paraguay (BBAP) by country. All countries experienced a reduction of forests and shrubs (if present), and an increase in pastureland conversion, for soy expansion.

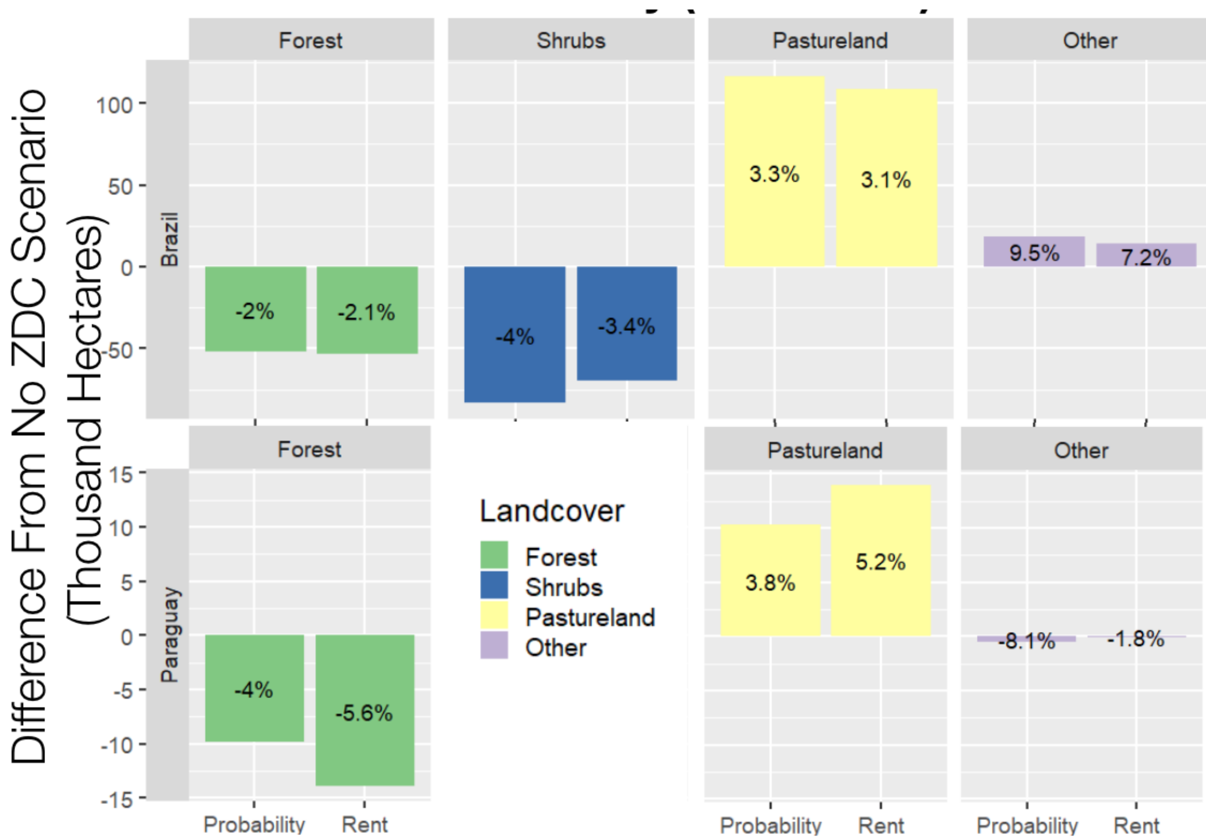

Figure 15: Comparison relative difference of land cover converted for soy expansion between "probability map" and "rent" methods to simulate ZDC adoption. Similarity between results indicate both methods are appropriate.

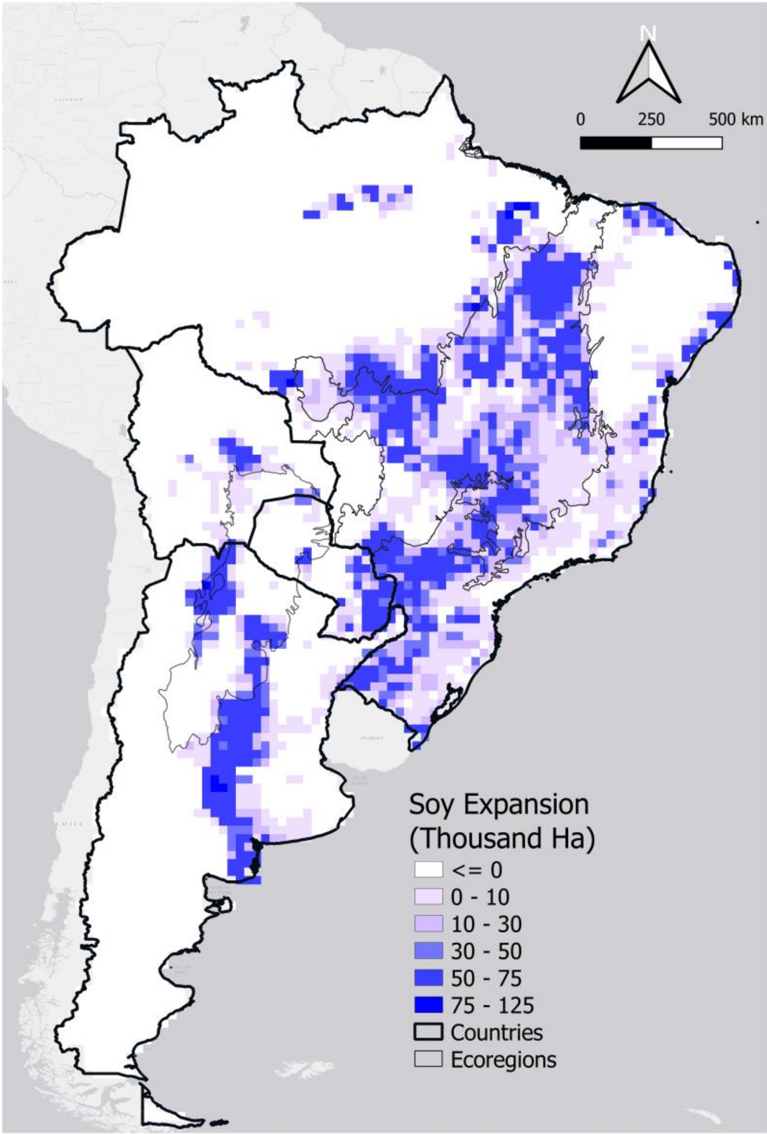

Figure 16: Soy Expansion (2015-2030) in the No ZDC Scenario. Regions of significant expansion include the Cerrado and Atlantic forest ecoregions, as well as the Argentinian portion of the Gran Chaco and the Argentinian Pampas.

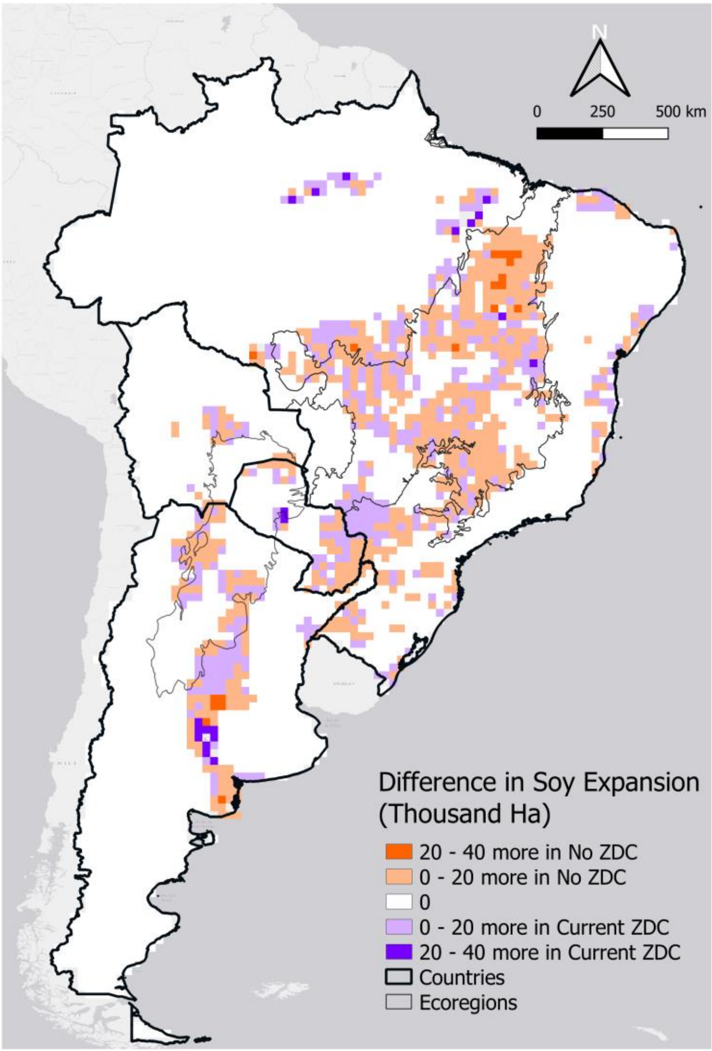

Figure 17: Difference in Soy Expansion (2015-2030) Between No ZDC Scenario and 2025 ZDC Scenario. Regions of significant difference match those of large expansion in the No ZDC scenario, the Cerrado and Atlantic forest ecoregions, as well as the Argentinian portion of the Gran Chaco and the Argentinian Pampas.

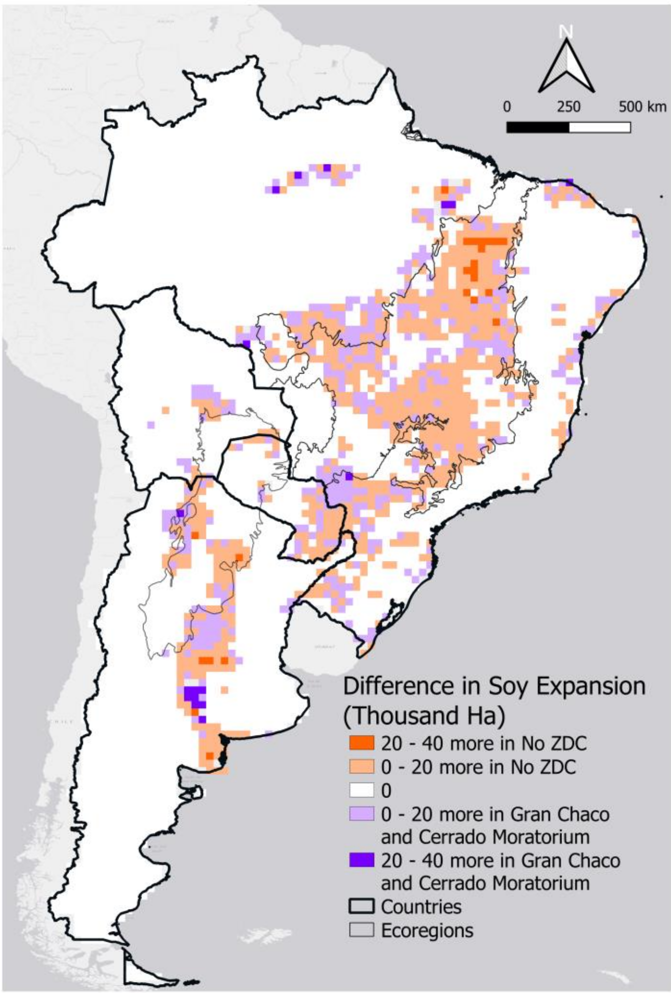

Figure 18: Difference in Soy Expansion (2015-2030) Between No ZDC Scenario and Grand Gran Chaco and Cerrado Moratorium Scenario. Regions of significant difference match those of large expansion in the No ZDC scenario, the Cerrado and Atlantic forest ecoregions, as well as the Argentinian portion of the Gran Chaco and the Argentinian Pampas.

Original Land Cover Class	Description	Reclassified Land Cover
Built-Up	Structures	Other
Cropland	Row crop agriculture (e.g., maize, soy, wheat, sugarcane)	Cropland
Shrubs	Sparse vegetation <2 meters, typically in dry habitats	Shrubs
Trees	Natural tree cover	Forest
Pastureland	Grazing land or natural grassland	Pasture
Bare	Bare soil, ice, snow, rock, sand dunes.	Other
Plantation	Citrus, vineyard, coffee, etc.	Other
Water	Water Bodies	Other
Plantation Trees	Tree plantations (e.g., pine, eucalyptus, banana, citrus, olives, palms)	Other

Table 1: Original Land Cover Types, Description, and Reclassification. The reclassification is similar to the one done by Graesser et al. (2015).

Spatial Variable	Type	Source	Categorical (yes/no)
Distance to deforestation	Dynamic	Calculated from input land cover maps (Grasser et al. 2014). Calculated from previous year's land cover map, defined as areas where forest was converted to different land cover type.	no
Distance to lost cropland	Dynamic	Calculated from input land cover map (Grasser et al. 2014). Calculated from previous year's land cover map, defined as areas where cropland was lost.	no
Distance to lost shrubland	Dynamic	Calculated from input land cover map (Grasser et al. 2014). Calculated from previous year's land cover map, defined as areas where shrubland was lost.	no
Distance to lost other	Dynamic	Calculated from input land cover map (Grasser et al. 2014). Calculated from previous year's land cover map, defined as areas where other was lost.	no
Distance to lost pastureland	Dynamic	Calculated from input land cover map (Grasser et al. 2014). Calculated from previous year's land cover map, defined as areas where pastureland was lost.	no
Distance to new cropland	Dynamic	Calculated from input land cover map (Grasser et al. 2014). Calculated from previous year's land cover map, defined as areas where cropland was added.	no
Distance to new shrubland	Dynamic	Calculated from input land cover map (Grasser et al. 2014). Calculated from previous year's land cover map, defined as areas where shrubland was added.	no
Distance to new forest	Dynamic	Calculated from input land cover map (Grasser et al. 2014). Calculated from previous year's land cover map, defined as areas where forest was added.	no
Distance to new other	Dynamic	Calculated from input land cover map (Grasser et al. 2014). Calculated from previous year's land cover map, defined as areas where other was added.	no
Distance to new pastureland	Dynamic	Calculated from input land cover map (Grasser et al. 2014). Calculated from previous year's land cover map, defined as areas where pastureland was added.	no
Mean Annual Precipitation	Static	Calculated from mean monthly precipitation from worldclim.org (Fick & Hijmans, 2017)	no
Mean Annual Temperature	Static	Calculated from mean monthly precipitation from worldclim.org (Fick & Hijmans, 2017)	no
Elevation	Static	(Jarvis, Reuter, Nelson, & Guevara, 2008)	no
Slope	Static	Calculated from Elevation (Jarvis et al., 2008)	No
Soils	Static	Sourced from (Hengl et al., 2017)	yes
Distance to Slaughterhouses	Static	Calculated from Slaughterhouse locations from Moore Foundation	no
Distance to Processing facilities	Static	Calculated from Processing facilities locations from Moore Foundation	no
Protected Areas	Static	("Protected Planet," 2018)	yes
Ecoregions	Static	(The Nature Conservancy, 2018)	yes
Brazilian Biomes	Static	("Global Forest Watch," 2018)	yes
Distance to Towns	Static	("Populated Places | Natural Earth," 2018)	no
Agricultural Rents	Dynamic	Calculated from multiple sources: (Graesser et al., 2015; Jarvis et al., 2008; le Polain de Waroux, Garrett, Heilmayr, & Lambin, 2016; "OpenStreetMap," 2018; Pekel et al., 2016)	no
Ports	Static	Compiled from multiple government and company documents and websites, as well as news.	yes
Soy Suitability	Static	(B. Soares-Filho et al., 2016)	yes

Table 2: Spatial Variables Used in Simulation Model. These were picked as they are expected to influence land cover change in the region.

Country	Transition From	Transition To	Variable Removed
Argentina	Cropland	Pastureland	Lost Crop
Argentina	Cropland	Shrubs	Temperature
Argentina	Forest	Cropland	Precipitation
Argentina	Forest	Other	Precipitation
Argentina	Non-Cropland	Cropland	Precipitation
Argentina	Other	Forest	Precipitation
Argentina	Other	Pastureland	Ecoregions
Argentina	Pastureland	Forest	Ecoregions

Table 3: Weights of Evidence variables removed from Argentina. These were removed since they had a crammer coefficient higher than 0.45. See section: Spatial Variables

Country	Transition From	Transition To	Variable Removed
Bolivia	Cropland	Forest	Elevation
Bolivia	Cropland	Other	Elevation
Bolivia	Cropland	Pastureland	Processing Facilities
Bolivia	Cropland	Shrubs	Ecoregions
Bolivia	Cropland	Shrubs	Lost Crop
Bolivia	Forest	Cropland	Elevation
Bolivia	Forest	Other	Temperature
Bolivia	Forest	Other	Elevation
Bolivia	Forest	Pastureland	Deforestation
Bolivia	Forest	Pastureland	Processing Facilities
Bolivia	Forest	Pastureland	Elevation
Bolivia	Forest	Shrubs	Elevation
Bolivia	Non-Cropland	Cropland	Elevation
Bolivia	Other	Cropland	Temperature
Bolivia	Other	Forest	Temperature
Bolivia	Other	Pastureland	Temperature
Bolivia	Pastureland	Cropland	Elevation
Bolivia	Pastureland	Forest	Elevation
Bolivia	Pastureland	Forest	Lost Pasture
Bolivia	Pastureland	Other	Elevation
Bolivia	Pastureland	Shrubs	Elevation
Bolivia	Shrubs	Cropland	Ecoregions
Bolivia	Shrubs	Forest	Ecoregions
Bolivia	Shrubs	Other	Temperature
Bolivia	Shrubs	Pastureland	Elevation

Table 4: Weights of Evidence variables removed from Bolivia. These were removed since they had a crammer coefficient higher than 0.45. See section: Spatial Variables

Country	Transition From	Transition To	Variable Removed
Brazil	Cropland	Forest	Protected Areas
Brazil	Cropland	Other	Protected Areas
Brazil	Cropland	Pastureland	Protected Areas
Brazil	Cropland	Shrubs	Protected Areas
Brazil	Forest	Cropland	Protected Areas
Brazil	Forest	Other	Protected Areas
Brazil	Forest	Pastureland	Protected Areas
Brazil	Forest	Pastureland	New Pasture
Brazil	Forest	Shrubs	Protected Areas
Brazil	Non-Cropland	Cropland	Protected Areas
Brazil	Other	Cropland	Protected Areas
Brazil	Other	Forest	Precipitation
Brazil	Other	Pastureland	Protected Areas
Brazil	Pastureland	Cropland	Protected Areas
Brazil	Pastureland	Cropland	Protected Areas
Brazil	Pastureland	Forest	Protected Areas
Brazil	Pastureland	Other	Elevation
Brazil	Pastureland	Shrubs	Protected Areas
Brazil	Shrubs	Cropland	Protected Areas
Brazil	Shrubs	Forest	Protected Areas
Brazil	Shrubs	Other	Protected Areas
Brazil	Shrubs	Pastureland	Protected Areas

Table 5: Weights of Evidence variables removed from Brazil. These were removed since they had a crammer coefficient higher than 0.45. See section: Spatial Variables

Country	Transition From	Transition To	Variable Removed
Paraguay	Cropland	Forest	Temperature
Paraguay	Cropland	Pastureland	Ecoregions
Paraguay	Cropland	Shrubs	Temperature
Paraguay	Forest	Other	Ecoregions
Paraguay	Forest	Pastureland	Cattle Heads
Paraguay	Forest	Pastureland	Ecoregions
Paraguay	Forest	Shrubs	Precipitation
Paraguay	Forest	Shrubs	Temperature
Paraguay	Non-Cropland	Cropland	Precipitation
Paraguay	Other	Forest	Precipitation
Paraguay	Other	Pastureland	Precipitation
Paraguay	Pastureland	Cropland	Precipitation
Paraguay	Pastureland	Cropland	Cattle Heads
Paraguay	Pastureland	Forest	Cattle Heads
Paraguay	Pastureland	Forest	New Forest
Paraguay	Pastureland	Forest	Temperature
Paraguay	Pastureland	Forest	Temperature
Paraguay	Pastureland	Other	Cattle Heads
Paraguay	Pastureland	Other	Temperature
Paraguay	Pastureland	Shrubs	Precipitation
Paraguay	Pastureland	Shrubs	Processing Facilities
Paraguay	Shrubs	Forest	Ecoregions
Paraguay	Shrubs	Other	Ecoregions
Paraguay	Shrubs	Other	Processing Facilities

Table 6: Weights of Evidence variables removed from Paraguay. These were removed since they had a crammer coefficient higher than 0.45. See section: Spatial Variables

Classification	Cost per kilometer (US$/ton)
Paved road	0.05
Unpaved road	0.15
Agricultural field	0.20
Grasslands and Savannas	0.30
Forest	3.00
Flooded Forest	3.00
Water Bodies	3.00

Table 7: Transport Cost for Soy Derived by (Vera-Diaz et al., 2008). While these are for 2008 dollars, these were adjusted for inflation to 2015 values.

Company	Pledge year	Cut off/ Target Date	Deforestation Measurement	Forest definition	Source
ADM	2015	n/a	Zero-Gross	No definition given	(Ermgassen et al., 2019; NYDF Global Platform, 2018)
Cargill	2014	2030	Ambiguous	Cargill adopt the FAO definition of forest - "Land with tree crown cover of more than 10 % and area of more than 0.5 ha^3" . Their policy also commits to "protect native vegetation beyond forests. This includes the Cerrado, Gran Chaco and Llanos."	(Ermgassen et al., 2019; NYDF Global Platform, 2018)
Bunge	2015	2025	Zero-Gross	No definition given	(Bunge, 2019; Ermgassen et al., 2019; NYDF Global Platform, 2018)
Amaggi	2017	as soon as possible (stated in plan as 2025)	Zero-Gross	"Our commitment applies to all locations where I operate, in and outside Brazil, including the Cerrado and Amazon biomes."	(Amaggi, 2019; Ermgassen et al., 2019; NYDF Global Platform, 2018)
Denofa	2015	2030	Zero-Gross	Denofa is committed to 100% sustainability certification of all imports of soy from South America	(Ermgassen et al., 2019; NYDF Global Platform, 2018)
Louis Dreyfus	2018	n/a	Zero-Gross	Commitment includes eliminating "conversion of native vegetation in the Cerrado biome"	(Ermgassen et al., 2019; NYDF Global Platform, 2018)
Glencore	2019	n/a	n/a	n/a	(Glencore, 2019)

Table 8: Global ZDC Commitments. All of these are yet to be implemented by companies in their respective supply chain.

From	To	Similarity With 2.25 km window	Similarity with 3.25 Km window
Other	Shrubs	67.01	73.72
Other	Pastureland	53.84	63.50
Other	Forest	49.74	56.91
Shrubs	Other	58.26	64.29
Shrubs	Pastureland	62.01	71.38
Shrubs	Forest	55.55	65.69
Cropland	Other	52.57	58.01
Cropland	Shrubs	51.70	59.44
Cropland	Pastureland	67.92	76.68
Cropland	Forest	47.17	55.12
Pastureland	Other	55.39	64.62
Pastureland	Shrubs	60.73	69.51
Pastureland	Forest	59.63	67.92
Forest	Other	40.61	49.42
Forest	Shrubs	70.79	76.20
Forest	Pastureland	58.68	68.20

Table 9: Non-Cropland Expansion Similarities. Cropland similarities can be found in Figure 11 and they fall in line with previous studies (see section Validation).

Category	2014 Areas (ha)	2030 - No ZDC Scenario Areas (ha)	2030 - 2025 ZDC Scenario Areas (ha)	2030 - Gran Chaco and Cerrado Moratorium Scenario Areas (ha)
Forests	579,006,213	537,909,563	538,152,169	538,063,388
Pastureland	357,480,875	334,612,800	334,317,025	334,405,000
Cropland	91,662,438	119,402,988	119,404,431	119,405,138
Shrubs	180,116,356	213,713,663	213,846,950	213,827,444
Other	63,153,656	65,721,544	65,639,981	65,659,588

Table 10: 2014 and 2030 Land Cover Area in Brazil, Bolivia, Argentina, and Paraguay (BBAP). Scenarios with ZDC implementation result in more remaining forests and shrubs and less remaining pastureland and other.

Country	Category	2014 Areas (ha)	2030 - No ZDC Scenario Areas (ha)	2030 - 2025 ZDC Scenario Areas (ha)	2030 - Gran Chaco and Cerrado Moratorium Scenario Areas (ha)
Argentina	Forests	27,768,663	25,544,344	25,571,731	25,568,375
Argentina	Pasture	119,297,275	116,873,594	116,838,000	116,835,175
Argentina	Cropland	35,428,331	38,537,000	38,536,969	38,536,950
Argentina	Shrubs	63,266,988	67,963,700	67,970,131	67,976,450
Argentina	Other	31,595,075	28,437,694	28,439,500	28,439,381
Bolivia	Forests	59,922,200	63,095,844	63,095,925	63,096,794
Bolivia	Pasture	33,093,563	30,646,100	30,645,900	30,644,994
Bolivia	Cropland	706,431	1,015,775	1,015,744	1,015,725
Bolivia	Shrubs	1,138,831	1,689,306	1,689,306	1,689,306
Bolivia	Other	12,581,419	10,936,438	10,936,588	10,936,644
Brazil	Forests	473,451,488	432,440,844	432,639,088	432,558,488
Brazil	Pasture	186,701,938	168,836,575	168,593,600	168,679,875
Brazil	Cropland	52,117,244	75,339,306	75,340,850	75,341,575
Brazil	Shrubs	115,708,281	144,059,988	144,186,844	144,161,056
Brazil	Other	18,624,681	25,926,919	25,843,250	25,862,638
Paraguay	Forests	17,863,863	16,828,531	16,827,606	16,839,731
Paraguay	Pasture	18,388,100	18,256,531	18,229,563	18,244,956
Paraguay	Cropland	3,410,431	4,510,906	4,538,863	4,510,888
Paraguay	Shrubs	2,256	669	619	631
Paraguay	Other	352,481	420,494	420,481	420,925

Table 11: 2014 and 2030 Land Cover Area By Country across different scenarios. Scenarios with ZDC implementation result in more remaining forests and shrubs and less remaining pastureland and other.

Region	Category	2014 Areas (ha)	2030 - No ZDC Scenario Areas (ha)	2030 - 2025 ZDC Scenario Areas (ha)	2030 - Gran Chaco and Cerrado Moratorium Scenario Areas (ha)
Amazon	Forests	342,743,588	338,384,988	338,511,125	338,472,156
Amazon	Pastureland	61,550,881	58,651,719	58,536,325	58,511,419
Amazon	Cropland	2,661,825	8,341,338	8,405,700	8,451,800
Amazon	Shrubs	654,194	350,619	351,219	354,988
Amazon	Other	7,314,619	9,186,175	9,110,469	9,124,475
Cerrado	Forests	54,151,769	47,016,119	47,077,156	47,051,938
Cerrado	Pastureland	51,347,550	41,367,063	41,314,125	41,356,550
Cerrado	Cropland	23,580,969	36,110,931	35,984,538	35,997,894
Cerrado	Shrubs	72,754,750	77,102,356	77,228,581	77,193,450
Cerrado	Other	1,911,394	2,149,963	2,142,031	2,146,600
Gran Chaco	Forests	37,735,550	30,158,088	30,178,044	30,186,463
Gran Chaco	Pastureland	28,283,788	35,955,738	35,948,669	35,947,706
Gran Chaco	Cropland	5,327,806	6,076,231	6,063,794	6,052,563
Gran Chaco	Shrubs	5,275,781	4,808,488	4,806,106	4,812,613
Gran Chaco	Other	2,042,281	1,665,400	1,667,331	1,664,600

Table 12: 2014 and 2030 Land Cover Areas by Ecoregion across different scenarios. Scenarios with ZDC implementation result in more remaining forests and shrubs and less remaining pastureland and other.

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