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YSSP Report
Young Scientists Summer Program

Sub-national Land Use Change of Future International Demand for Agri-commodities in Argentina - In-depth Assessment of Linkages of GLOBIOM with TRASE

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Approved by

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It was finished by Carina Mueller and has not been altered or revised since.

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Abstract

Tropical forests provide important ecosystem services through the storage of carbon in their biomass. Increasingly countries recognize this service as one of the solutions to meet the Paris climate goal. A driver of tropical deforestation is consumption of agri-commodities. Therefore to inform trade strategies, robust models to project future global land use change at high spatial resolution are needed that link drivers to impacts. Most of these models combine global-scale dynamic land use models with downscale approaches by finding relationships between drivers and observed sub-national land use change patterns to project future land use change spatially-explicit. However explaining relationships between drivers and spatial land use change patterns was found to be more complex and challenging than initially thought, such as found for Argentina. Therefore this report aims to contribute to this body of research via developing understanding of how supply chain data and the trade-modelling approach of the Trase.earth programme, which is improving the transparency of existing supply chains at high-resolution, as well as local data, which are more accurate than global data, would change the spatial pattern of projected land use change from the GLOBIOM model. When compared to the default DownScale calibration, including TRASE- and local data lead to more concentration of the cropland expansion at the detriment of forest in few grid cells which were located in the northeast of the Chaco. We conclude that including spatially-explicit, local data can improve the understanding of where within a country land use change is likely to happen in future. This would allow to focus efforts to reduce detrimental environmental impacts to few geographies. However we describe how more research would be helpful to improve the robustness of these early findings.

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About the author

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Introduction

In the last two decades, agricultural expansion driven by global demand for commodities has become a major driver of the destruction of natural ecosystems in tropical and subtropical regions releasing large amounts of greenhouse gas emissions into the atmosphere contributing to the acceleration of climate change and the loss of biodiversity (Harris et al., 2012). Especially the hunger of European countries and growing populations scarce in land resources like China for oils (palm oil), meat and other animal-based products for which animal feed such as soybeans need to be imported is driving detrimental land use change in producing countries such as Brazil, Indonesia and Argentina (Baumann et al., 2017). Therefore commitments have been established such as the Amsterdam Declaration in Europe or the UN New York Declaration on Forests that aim to halt deforestation linked to imported products. It is argued that to understand implications of future consumption and trade strategies on food security, biodiversity and climate mitigation, a systems-based approach is needed that links both the supply (i.e. production) and the demand side (i.e. consumption) (West et al 2014). As by now the places of production are often very distant from the places of consumption, a global scale approach is needed (Sun et al. 2017). However at the same time, land-based solutions to global sustainability challenges are highly localized and context-specific (depending on factors such as investment, infrastructure availability, agricultural productivity) while supply chains are very complex, improving the spatial resolution of consumption-to-production models would allow to prioritize which strategies would be most effective.

Therefore to guide strategies about land-based solutions towards global sustainable development, models are needed which on the one hand have the global scale but also the fine resolution to take into account differences in local land characteristics. One example of a model which tries to achieve this is the dynamic partial equilibrium model 'Global Biosphere Management Model' (GLOBIOM) (Havlík et al., 2011) which depicts future land use patterns and trade pathways. To improve the robustness of these kind of models, the observed land use change needs to be calibrated with highly spatially refined data (Krisztin and Woegerer, 2021; Leclère et al., 2016). To test the benefit of including more spatially-refined data for the calibration, we chose Argentina as a case study where sofar land use change was challenging to predict.

Argentina has become an important global producer and exporter of products like soybeans, corn, sugarcane and cattle (FAOSTAT, 2021). Soybeans are the most valuable export product for Argentina and around 90% of Argentinean soybeans are exported worldwide (OECD, 2021), making it very dependent on world market prices. The production increases were possible through improvements in both yield and expansion of planted area (FAO, 2017). In recent years, a further increase of export taxes in 2008 seems to have negatively affected export volumes by hindering investment into agriculture (FAO, 2017). Giancola et al. (2009) reported that compared to its competitors Brazil and USA, Argentina has higher commercialization costs such as for transportation, storage and export taxes despite having a competitive advantage in terms of production. As global demand for agricultural commodities is increasing, driven by increases in population and wealth (Alexandratos and Bruinsma, 2012), world market prices will increase. However it is not clear how changes in commercialization costs or increases in soybean demand will affect production and cropland expansion in future in Argentina.

Deforestation accelerated in Argentina since the 2000s with a peak in 2008 (Vallejos et al., 2015) which was driven largely (46%) by pastures for cattle raising and to a lesser extent (33%) by soybean production (Pendrill et al., 2019). In 2014, deforestation contributed 14.5% to Argentina's greenhouse gas emissions (FAO, 2019). Within Argentina, most deforestation takes place in the Chaco ecoregion which has become one of the frontier regions of cropland expansion in Latin America (Hansen et al., 2013). Within the Chaco, the provinces Salta and Santiago del Estero are two of the top 14 jurisdictions of high deforestation in Latin America directly driven by the conversion to soybean (Song et al., 2021). However since 2013 deforestation rates have decreased by 60% in Argentina (Hansen et al., 2013). This decline can be partly explained by a reduction of world market soybean prices by half between 2012 and 2016 (Sly, 2017; see Figure 1), increases in export taxes of the Argentinean government and the introduction of a federal forest law introduced in 2007 (Nolte et al., 2017). However due to limited enforcement, the success of the Argentinean forest law to reduce deforestation is debated (Sly, 2017) and restricted to few jurisdictions (Nolte et al., 2017). As greenhouse gas emissions of land use change depend on the carbon-density of the converted natural land, especially for countries mostly covered by non-forest habitat like Argentina, a sub-national approach is needed accounting for heterogeneity of carbon-density of converted land within the producing country.

Figure 1: Change in soybean world market prices (Source: indexmundi.com)

While at national level in Argentina, land use change is driven by global demand for commodities (Fehlenberg et al., 2017), other factors influence land use change within the country. Variables explaining cropland expansion of companies in the Gran Chaco were proximity to current investment and availability of cheap forest land; less strong was low deforestation regulations and low enforcement (Le Polain de Waroux et al., 2016). Here, positively correlated but not significant were high yields and land prices (De Waroux et al. 2016). The variable which was not significant in Le Polain de Waroux et al. (2016)'s study was transport costs. In the Amazon in Brazil, factors reducing deforestation rates were the enforcement of the Brazilian Forest Code, interventions in soybean and cattle supply chains, restrictions to access to credit, protected area expansion (Nepstad et al. 2014; Arima et al. 2014). Le Polain de Waroux et al. (2018) argued that frontier expansion depends on change in accessibility (e.g. road building), environmental conditions, technology, producer prices and/or demand, subsidies or other policies.

Therefore, we were interested in the following research questions:
1.) Will some new variables derived from the spatially explicit supply chain data from Trase.earth be significant in explaining observed land use change in Argentina?
2.) How will these updated and new variables change the spatial patterns of the land use change projections?

We re-calibrate the DownScale model used to downscale the global land use change projections from the global biosphere management (GLOBIOM) model, to test the effect of accounting for TRASE and local data. GLOBIOM is a global dynamic bottom-up partial equilibrium model projecting future land use change (Havlík et al., 2011) at the scale of 37 regions, one of them being Argentina as a country. Sofar the default DownScale model was based on variables explaining biophysical characteristics (e.g. mean temperature, altitude, soil characteristics) and socio-economic factors (e.g. distance to market, wood harvest cost, total population). However other possible factors explaining land use change such as distance to export market, crop-specific harvested area and local biophysical data were missing. In this approach, the allocation of future land use change within Argentina depends on the interplay between future agricultural demand and biophysical characteristics and distance to the first logistic hub in the supply chain and distance to ports. This allowed us through the re-calibration to explicitly account for the relationship between land use change and the spatial distribution of different end-market specific soybean supply chains in Argentina based on our model projections and the TRASE (Transparent Supply Chains For Sustainable Economies) dataset (Trase.earth) for market share by department and distance to logistic hub.

Methods

DownScale model

The potential to improve the allocation of land use change by including spatially-explicit supply chain information was explored using the DownScale model (Krisztin and Woegerer, 2021; Leclère et al., 2016) which links to IIASA's GLOBIOM model (Havlík et al., 2011; Valin et al., 2013). The DownScale model aims to allocate to a higher spatial resolution the land use change projected by GLOBIOM, using as much as possible observed high-resolution data (Krisztin and Woegerer, 2021).

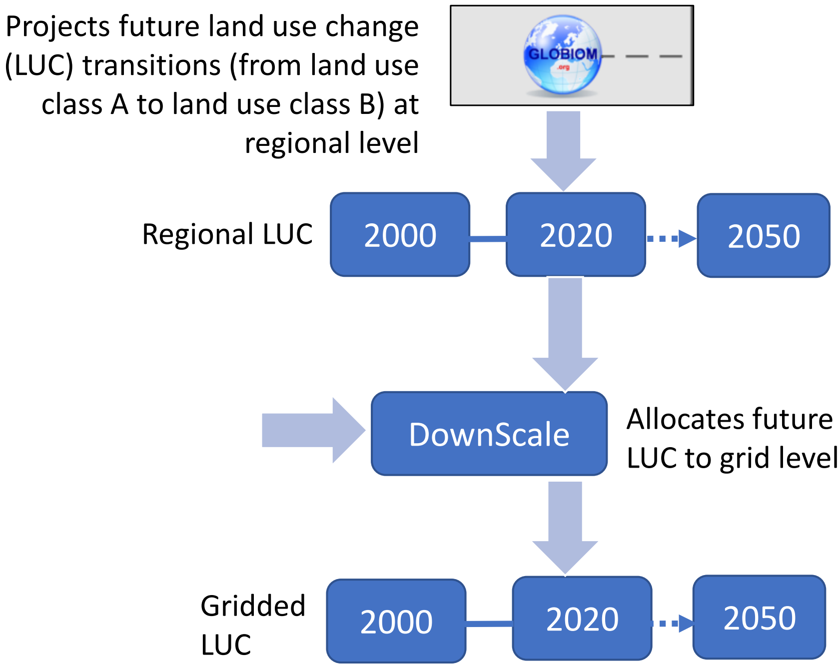

Figure 2: Description of how the land use change transitions projected from GLOBIOM are connected to the Downscale Model to generate high-resolution land use change (LUC) projections.

The DownScale model consists of an econometric model assessing the competition between different land uses. The land use change projections were taken from GLOBIOM which resolves recursively global land use competition between different land use sectors (agriculture, forestry and bioenergy) in 10-year time steps starting in 2000 until 2050 depending on constraints in resources and technology. Changes between different land use types in each pixel are determined by maximizing the consumer and producer surpluses (Valin et al., 2013).

The DownScale model is spatially-refined with grids of 5 x 5 arcminutes which results in 6488 pixels for Argentina which is equivalent to around 10 x 10 km at the equator (Leclère et al., 2016). Data were aggregated to the different major soybean producing biomes in Argentina: Chaco, Humid Pampas and Espinal (Figure 3).

Prior Module variables setup

The prior module was run with four different variable set-ups: default version (D), default together with the TRASE-variables (T), default together with SPIPA variables (S) as well as default variables combined together with both TRASE and SPIPA variables (C).

Land use classes in GLOBIOM are cropland, grassland, managed forest, plantation forest, primary forest and natural land. However priors are only estimated for the following land use changes:

- From unmanaged or managed forest to Grassland and Cropland
- From Grassland to Cropland
- From other natural land to Grassland and Cropland and the way back.

The GLOBIOM output in terms of changes in different land cover classes is shown in Figure 4.

As dependent variable the global land cover map from the ESA CCI (European Space Agency Climate Change Initiative) was used (Defourny, 2017). This dataset is available yearly between 1992 and 2015 at a resolution of 300 x 300 m at the equator.

For the modelling, we took the following assumptions:

- Supply chain patterns will be constant over time.
- Using only soybeans is representative for the observed spatial pattern of general cropland expansion as soybeans are one of the major drivers of cropland expansion in Argentina (Pendrill et al., 2019).

Table 1: Updated and new prior module variables which were all aggregated to Simulation Unit. Rows with variables from the default set-up in red, TRASE variables in yellow and SPIPA variables in green.

Type	Variable	Description	Source
Transportation	Mean time to Market	Gridded travel time for goods to closest market	Uchida and Nelson (2008)
Transportation	Travel distance to first logistic hub OR port (km) Travel distance to first port in supply chain (km)	Gridded travel distance of soy producing municipalities to hub in supply chain [km]	Trase.earth internal data; originally from: Open Street Map
Transportation	d_rutas_2014 d_local2000_2010_pais	Distance to routes in 2014 Distance to village?	SPIPA
Lant rent	Forest yield Wood harvest cost Pasture yield	Harvested wood yield (tons) Wood harvest cost (USD) Harvested grass yield (tons)	G4M (Spatialy explicit forest management model) at IIASA
Land rent	Soybean yield Market Share	Gridded soybean yield in 2017 (tons) Gridded Marketshare for each GLOBIOM region (US Dollar)	Trase.earth Trase.earth (originally customs data)
Land-use	Harvested Soybean area in 2001, 2010 and 2020	Soybean harvested area share in grid cell	Trase.earth (original from Song et al. 2021)
Biophysical	Mean temperature, Mean Precipitation, Altitude, Slope, Soil parameters	Mean within pixel of temperature, precipitation, altitude (m) and slope (in degrees) as well as dominant soil type	Skalsky et al. (2008)
Biophysical	APP, Bal_hid, d_riosyarroyos dem250m_f4	 Distance to rivers and ponds Dem(digital elevation model)	SPIPA

	Evapotranspiration, OTBN, annual precipitation, ProfEfec, Prov_pais		
Socio-economic	Total population, Rural population		

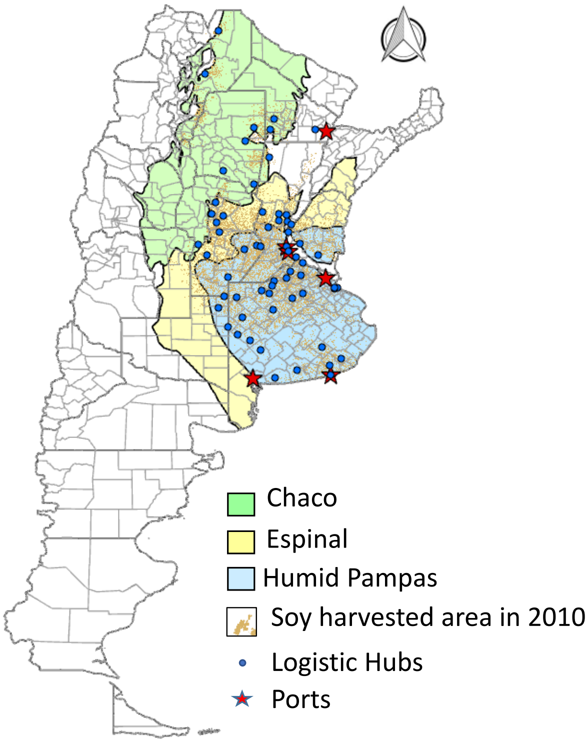

Figure 3 Map of harvested soybean area in brown; names of provinces with high deforestation rates, red stars are locations of the majority of ports (98% of soybean export); in blue locations of crushing facilities

Data sources and processing

To update existing explanatory variables or test improvement of variables, we used multiple different data sources (Table 2, Figure 3).

Table 2: Overview of data sources

Data sources	Resolution	Time period	Source
Soybean yield	Department	2016-2018	Trase.earth (from national statistics)
Soybean harvested area	30 x 30 m	2001, 2010, 2020	Song et al. (2021)
Price	Shipment	2016-2018	Trase.earth (freight on board from customs data)
Flow of soybeans to importing country	Department	2016-2018	Spatially explicit model on Production to Consumption (Godar et al. 2015); data on Trase.earth
Distance to port	Department	2016-2018	Internal Trase calculations

Soybean harvested area

We derived Argentinean data on harvested soybean area in 2001, 2020 and 2020 using the dataset of the Global Land Analysis and Discovery (GLAD) laboratory (Song et al., 2021). While the GLAD dataset is available yearly at 30 x 30 m resolution, we aggregated these to the simulation grid unit as percentage of harvested soybean area as this is the finest shared resolution at which the variables for the model of land use change are available here.

Soybean yield

Yearly average soybean yield data for each department were used from Trase.earth. To generate these data, Trase.eaerth mainly used the data available from the Ministry of Agroindustry Argentina (MoA, 2020). As for some departments the data were missing, yields were approximated using department-specific soybean production data from MoA (2020) together with Song et al. (2021)'s harvested area maps (TRASE, 2020). This dataset was aggregated as yield [ton/ha] to the simulation grid unit.

Soybean price

Prices of exported soybean were derived from the Freight on Board (FOB) financial values on Trase.earth which are based on customs data and specific for each export market (TRASE, 2020). As this dataset did not include prices for the domestic market, we took the price of 274.75 US Dollar per ton soybean for 2017 from (TESEO, 2021).

Distance to Logistic Hub

We estimated distances between soybean producing department and first logistic hub in the supply chain (i.e. silo or crushing facility in the case of crushed soybeans and port in the case of uncrushed soybeans) using intermediate outputs calculated for Trase.earth [not freely available]. Trase.earth estimated these distances by minimizing the distance between supply node (i.e. producing department) and demand node (i.e. logistic hub or domestic consumption hub) using the road network available by OpenStreetMap.org. It has to be noted that this dataset included only distances from the middle of the producing department to the middle of the logistic hub department, not accounting for distances within these departments. As each department supplies more than one logistic hub, in this study we have calculated a weighted average distance depending on percentage soybean tonnage flowing through each logistic hub for each exporting market. For departments which are not yet producing soybeans, we have calculated the distance as distance to the closest trade hub of which each market is already sourcing from. For departments which are already producing soybeans but not yet for a certain export market, we have included as distance a high value (i.e. 1000 kilometer) to artificially decrease the likelihood of sourcing from this department as we assumed a static supply chain in this study. This dataset was aggregated as distance [km] to the simulation grid unit for each export market.

Distance to Port

To test sensitivity to a different choice of distance in the supply chain, we have additionally calculated the distance to port. Distances between soybean producing department and exporting port were calculated using intermediate outputs calculated for Trase.earth [internal data]. Trase.earth linked ports specific for each export market with producing departments based on a variety of sources such as national trading, customs data, optimizing by travel distance if better information was unavailable following the methodology of the Spatially Explicit Information on Production to Consumption Systems (SEI PCS) model published in (Godar et al., 2015) available on Trase.earth (see TRASE, 2020 for more details). We took the distance between each producing department to department of port from internal data which were based on the shortest distance of the trade network from OpenStreetMap.org. Again, it has to be noted that this dataset included only distances from the middle of the producing department to the middle of the port department, not accounting for the specific location of the port within these departments. As some departments supply more than one port, in this study we have calculated a weighted average distance depending on percentage soybean tonnage flowing through each port for each exporting market. For departments which are not yet producing soybeans, we have calculated the distance as distance to the closest port of which each export market is already sourcing from. This dataset was aggregated as distance [km] to the simulation grid unit for each export market.

Soybean tonnage flow

We used the flows of soybean tonnage produced in each department and exported to each consuming market from (TRASE, 2020); methodology is published in Godar et al. (2015). While the Argentinean Trase dataset is available yearly between 2016 and 2018 for more than 90 different countries, we have aggregated these to the 30 different countries included in the GLOBIOM model as this is the smallest geographic unit the model works in. As the publicly available data from Trase.earth did not include domestic consumption within Argentina, we have used a TRASE-internal dataset which was developed as part of the SEI PCS model.

Soybean harvested area

We derived Argentinean data on harvested soybean area in 2001, 2010 and 2020 using the dataset of the Global Land Analysis and Discovery (GLAD) laboratory (Song et al., 2021). While the GLAD dataset is available yearly at 30 x 30 m resolution, we aggregated these to the simulation grid unit as percentage of harvested soybean area as this is the finest shared resolution at which the variables for the model of land use change are available here.

Scenarios for future projections

To explore the potential consequences of future changes in demand for food and feed as well as trade on land use change in Argentina, we used a scenario based on the Shared Socioeconomic Pathway (SSP): SSP3 'Regional Rivalry' (Popp et al., 2017). SSP3 would be described by hardly regulated land use change, reduced trade flows and a reduction in crop yield increases (Popp et al., 2017). In the GLOBIOM model, the SSP3 scenario translates into a 51% increase in Argentinean population between 2000 and 2050, and a 68% increase in the yield of oil crops over the same period. This scenario corresponded to historical climate mitigation efforts ("Reference" Representative Concentration Pathways and SPA0 (Shared Climate Policy Assumptions, see Kriegler et al., 2014).

Net total land cover change for each land cover category at the scale of Argentina projected from 2010 to 2050 is the following: cropland increases by 2.6 million hectares (Mha), grassland by 0.7 Mha, plantation forest by 1.5 Mha, managed forest by 0.01 Mha and primary forest decreases by 4.6 Mha and Natural land decreases by 0.1 Mha (Figure 4) [Calculations based on GLOBIOM output shared by David Leclere].

Whereas for some land cover categories net land cover change is small, there can be large changes in their gross land cover change. For example for natural land, over the same time period from 2010 to 2050 there is a loss of 4.6 Mha (of this 4.2 Mha are converted to grassland and 0.4 Mha to plantation forest) but at the same time an increase of 4.5 Mha (of this 4.4. Mha stem from abandoned grassland and 0.1 Mha from abandoned cropland) leading to a 'net' decrease of 0.1 Mha. Another example of large gross changes is in the land cover category grassland: 7.1 Mha are lost during the period 2010 to 2050 (2.2 Mha to cropland, 0.5 Mha to plantation forest and 4.4 Mha to natural land) while there is also an increase of grassland by 7.9 Mha (3.7 Mha from primary forest and 4.2 Mha from natural land) [Calculations based on GLOBIOM output shared by David Leclere].

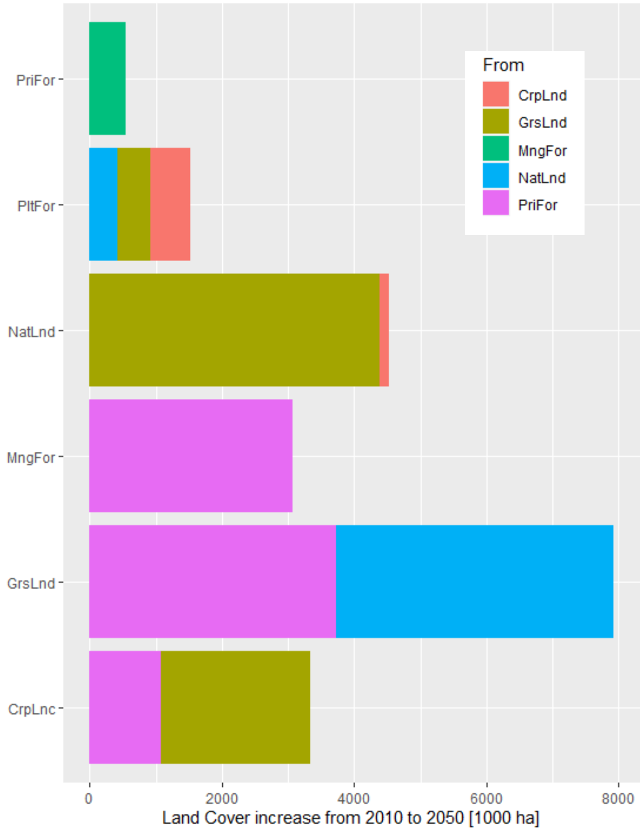

Figure 4: Overview of absolute land use change transitions projected by GLOBIOM at national Argentinian level between 2010 and 2050 from land cover class to another. For example, the last row indicates the gains in cropland (over primary forest and grassland), which differs from net change in cropland cover as some cropland is abandoned (leading to an increase in natural land) and some other converted to forest plantations. Listed land cover classes refer to Primary Forest (PriFor), Plantation Forest (PltFor), Natural Land (NatLnd), Managed Forest (MngFor), GrsLnd (Grassland) and Cropland (CrpLnd)

Results

Prior model results to explain land cover change

Across all prior model setups, significant correlation was obtained for each variable for at least one land cover change transition with cropping input systems (except for irrigated area, HI_MEAN, LI_MEAN and SS_MEAN), distance to water (d_cuerposaguas), soy harvested area in 2010 as well as some export-market specific market shares, distances to port and distance to trade hub (In the default variable set-up the model picked up as significant the coverage of cropland, grassland and natural land at the beginning of the period, mean time to market, total population, altitude and slope.

- Adding to the default variables additionally the 'TRASE'-variables (T in Table 3) lead from the TRASE variables only soy yield being picked-up as significant. However from the default variable data-set only one variable got dropped: cropland coverage at the beginning of the period; whereas the model picked up as new compared to only the default variable dataset (D) grass yield.
- Adding to the default variables additionally the SPIPA variables (S), lead the model to pick-up as significant only two variables from the SPIPA dataset, namely distance to cities (d_local2000_2010_pais) and annual precipitation. Dropped compared to the default variable combination were coverage with cropland and natural land at the beginning of the period, altitude, slope; whereas still significant were grassland coverage at the beginning of the period, mean time to market and total population.
- Adding to the default variables additionally both TRASE and SPIPA variables combined lead the model to drop from the default variables compared to running the model only with default variables (D) cropland and grassland coverage at the beginning of the period, altitude and slope. Though still significant compared to the default variable version (D) were natural land coverage at the beginning of the period, mean time to market and total population. The model picked up as newly significant compared to the default only (D) version forest coverage at the beginning of the period. From the TRASE variables the only variable which got picked up as significant was soybean yield which was already significant in the default plus Trase (T) variable combination. From the SPIPA-variables the same variables appeared significant compared to running the model only with the default plus SPIPA variables: distance to cities (d_local_2000_2010_pais) and annual precipitation.

Table *3*). Instead, the model showed significant effects for biophysical variables (e.g. temperature, precipitation, slope, altitude, soil parameters), economic variables (e.g. wood harvest cost, mean time to market, grass yield, soybean yield), share of existing land cover at the beginning of the period (e.g. forest, natural land, grassland) and country-specific supply chain variables (e.g. distance to trade hub, distance to port, market shares).

Across all prior model setups, the significance of variables depended on the type of land conversion and the variable setup considered. The land conversion from grassland to cropland had only six significant variables across all model setups. In contrast across all model setups conversion from primary forest to cropland had 16 significant variables; from primary forest to grassland had 22 significant variables; grassland to natural land had 21 significant variables; cropland to grassland had 12 significant variables and cropland to natural land had eight significant variables.

Explanatory variables varied across land cover transitions:

1) In the case of the <u>conversion of primary forest to cropland:</u>

- In the default (D in Table 3) variable set-up the model picked up as significant the share of existing cropland, forest as well as natural land at the beginning of the period, wood harvest tonnage, total population, rural population and slope.
- Adding to the default variables additionally the 'TRASE'-variables (T in Table 3) lead to additionally pick-up as significant soy yield, soy harvested area in 2001 and 2020; Marketshare of EU Central East and Distance to Tradehub of EU Central East. However running the prior model with both default and Trase variables also led to default-variables being dropped, namely share of forest cover at the beginning of the period, wood harvest and rural population.
- Adding to the default variable set-up additionally local data variables (SPIPA S in Table 3), lead to the model picking-up as significant from the SPIPA-variables distance to rivers (d_riosarroyos), evapotranspiration and annual precipitation. However now the model dropped all default variables except cropland coverage at the beginning of the period.
- Adding to the default variables additionally both TRASE and SPIPA variables combined (C in Table 3) lead the model now only to pick-up from the default variables cropland coverage at the beginning of the period, wood harvest cost and total population; from the TRASE-variables only soybean harvested area in 2001 but from the SPIPA variables still distance to rivers, evapotranspiration and annual precipitation got picked up. However the model dropped compared to the default variable set-up slope; compared to default plus TRASE, soy yield, soybean harvested area in 2020 as well as both Marketshare EU Central and Trade Hub Distance EU central got dropped. Though compared to default plus SPIPA, the model did not drop any of the 'SPIPA' variables.

2) For the <u>conversion of primary forest to grassland:</u>

- In the default variable set-up the model picked up as significant the share of existing cropland, forest and natural land at the beginning of the period, wood harvest tonnage, wood harvest cost, grass yield, total population, altitude, slope and soil parameters.
- Adding to the default variables additionally the 'TRASE'-variables (T in Table 3) lead to no variables from the 'TRASE' dataset being picked-up as significant. The only two variables which got dropped from the default set-up was forest coverage at the beginning of the period and total population.
- Adding to the default variable set-up additionally local data variables (SPIPA), lead to the model picking-up as significant from the SPIPA-variables, distance to cities (d_local2000_2010_pais), distance to rivers, altitude (dem_250m_f4), OTBN, annual precipitation (Precip_anual) and effective depth (ProfEfec). However now the model dropped from the default variables both

forest and natural land coverage at the beginning of the period, wood harvest cost, grass yield, altitude and soil parameters.

- Adding to the default variables additionally both TRASE and SPIPA variables combined lead the model to pick-up from the default variables, cropland and natural coverage at the beginning of the period, mean temperature, soil parameters and irrigation area (dropped compared to the default only were forest coverage at the beginning of the time period, wood harvest tonnage, wood harvest cost, grass yield, total population, altitude, and slope). In this combined (C) variable-set, from the TRASE-variables as significant were being picked up only the marketshare of China which was actually not picked up as significant in any of the other variable combinations. From the SPIPA-variables, picked up as significant which were already significant in the default plus SPIPA (S) version were d_local2000_2010_pais, elevation (dem250m_f4), native forest and managed by law (OTBN), annual precipitation and effective depth (ProfEfec). New variables being picked up which were not already being picked-up with the default plus SPIPA set-up were National parks (APP) and distance to roads (d_rutaas2014). Dropped was only the variable distance to rivers (d_riosyarroyos) compared to default plus SPIPA.

3) In the case of the conversion of grassland to cropland:

- In the default variable set-up the model picked up as significant only the variables coverage of natural land at the beginning of the period and total population.
- Adding to the default variables additionally the 'TRASE'-variables (T in Table 3) lead to only the variable Marketshare China being picked up as significant from the Trase variables whereas from the default variables, only the variable total population got dropped.
- Adding to the default variable set-up additionally local data variables (SPIPA), lead the model picking-up not a single variable as significant from the SPIPA variables, but lead to drop from the default variables the coverage of natural land at the beginning of the period.
- Adding to the default variables additionally both TRASE and SPIPA variables combined lead the model to pick-up from the default variables only rural population (was not significant in any of the other variable combinations for this land transition) as well as the coverage of natural land at the beginning of the period which already got picked up as significant from the default and the default plus TRASE (T) but not the default plus SPIPA (S) variable set. From the TRASE variables, only the Marketshare of USA got picked-up as significant which was not significant in any of the other variable combinations for this land use transition. From the SPIPA variables only the variable distance to rivers got picked up as significant which was not significant in any of the other variable combinations for this land use transition.

4) For conversion of cropland to grassland:

- In the default variable set-up the model picked up as significant the coverage of cropland, grassland and natural land at the beginning of the period, mean time to market, total population, altitude and slope.
- Adding to the default variables additionally the 'TRASE'-variables (T in Table 3) lead from the TRASE variables only soy yield being picked-up as significant. However from the default variable data-set only one variable got dropped: cropland coverage at the beginning of the period; whereas the model picked up as new compared to only the default variable dataset (D) grass yield.
- Adding to the default variables additionally the SPIPA variables (S), lead the model to pick-up as significant only two variables from the SPIPA dataset, namely distance to cities (d_local2000_2010_pais) and annual precipitation. Dropped compared to the default variable combination were coverage with cropland and natural land at the beginning of the period, altitude, slope; whereas still significant were grassland coverage at the beginning of the period, mean time to market and total population.

- Adding to the default variables additionally both TRASE and SPIPA variables combined lead the model to drop from the default variables compared to running the model only with default variables (D) cropland and grassland coverage at the beginning of the period, altitude and slope. Though still significant compared to the default variable version (D) were natural land coverage at the beginning of the period, mean time to market and total population. The model picked up as newly significant compared to the default only (D) version forest coverage at the beginning of the period. From the TRASE variables the only variable which got picked up as significant was soybean yield which was already significant in the default plus Trase (T) variable combination. From the SPIPA-variables the same variables appeared significant compared to running the model only with the default plus SPIPA variables: distance to cities (d_local_2000_2010_pais) and annual precipitation.

Table 3: Overview of significant variables showing positive (+) and negative (-) correlation to ESA CCI land cover changes from 2000 to 2010; estimated with quantile analyses. Tested variable sets were in each column default-DownScale variables (D); Default together with TRASE-derived variables (T); Default together with SPIPA-derived variables (S) and Default combined with both TRASE and SPIPA-derived variables (C). Rows with variables from the default set-up (red), TRASE (yellow) and SPIPA (green).

Variable	**PriFor to CrpLnd**				**PriFor to GrsLnd**				**GrsLnd to CrpLnd**				**GrsLnd to NatLnd**				**CrpLnd to GrsLnd**				**CrpLnd to NatLnd**			
Variable-sets	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C
Cropland	+	+	+	+	+	+	+	+									-				-		-	
Grassland							+										+	+	+		-			
Forest	+				-									+	+	+				-				
Natural Land	-	-			-	-		-	-	-		-					-	-		-				
Mean Temperature								+								+								
Mean Precipitation													-	-	-	-								
Wood harvest, tons	+				-	-	-						-	-	-	-								
Wood harvest cost, USD		+		+	+	+							+	+	+	+					+			
Grass yield, tons					-	-							-		-			-			+	+		+
Mean Time to Market																	-	-	-	-				
Total Population	-	-		-	-		-		-		-						-	-	-	-	-			
Rural Population	+											+												
Altitude					-	-								+			-	-						
Slope	-	-			-	-	+										+	-						
Soil parameters					+	2		+4					-	all	4	-4					-	3		-3
Irrigated area in ha						-	-	-																
Yield_Ton per Ha		+																-		-				
Soy Harvested Area (2001)		-		-																				
Soy Harvested Area (2020)		+																						
Mshare China								-		-														
Mshare USA												-		-										
MShare EU Central East		-																						
MShare.WestAfrSSA																-						-		
Distance to Port EU North														+		+								
Distance to TH EUCentralEast		-												-		-								
Distance to TH MiddleEastNAfr														+										

Variable	**PriFor to CrpLnd**				**PriFor to GrsLnd**				**GrsLnd to CrpLnd**				**GrsLnd to NatLnd**				**CrpLnd to GrsLnd**				**CrpLnd to NatLnd**			
Variable-sets	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C	D	T	S	C
APP (National Parks)								-							-	-								
Bal_hid (Hydric Balance)															+									-
d_local2000_2010_pais (Distance to cities)							+	+							+				+	+				
d_riosyarroyos (distance to rivers)			+	+			+					-				-								
d_rutas2014 (distance to roads)								+							-	-								
dem250m_f4 (altitude)							-	-																
Evapot (evapotranspiration)			+	+																				
OTBN (native forest and managed law)							-	-							-	+								
Precip_anual (annual precipitation)			-	-			-	-											-	-				
ProfEfec (effective depth)							-	-							-	-								
Prov_pais (provinces)															-	-								-

Impact on land use change projections to 2050

We estimate the effect of including further explanatory variable-sets on the spatial distribution of projected land cover change by comparing the outcome of the DownScale model if including Trase-variables and SPIPA-variables compared to the default-version (Figure 5). As explained in the methodological section, the prior model setups do not affect the absolute amount of land cover change (determined by GLOBIOM), but only it's allocation.

Only considering the three land cover classes for which most land cover change is projected, namely cropland, grassland and primary forest, we find that adding either TRASE-variables or SPIPA variables increase the amount of cropland expansion in middle-northern Argentina compared to the output using only default-variables (Figure 5). However besides this observation there are only few other differences visually observable from the national raster maps.

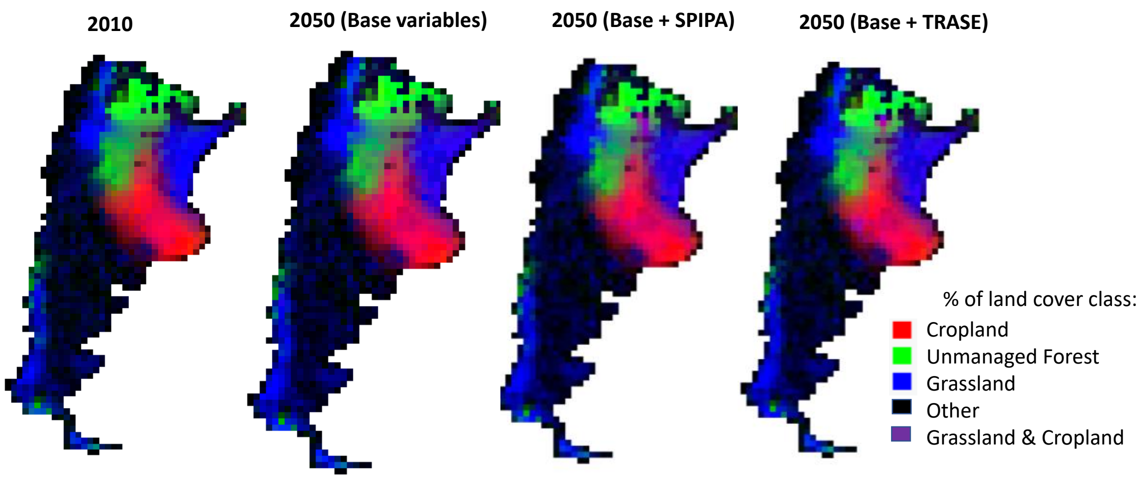

Figure 5: Raster map of Argentina showing the continuous color code depending on the percentage of the dominant land cover class in each grid cell: the more red it is, the higher the percentage of cropland in this grid cell; the more green it is the higher the percentage of unmanaged forest in this grid cell; the more blue it is, the higher the percentage of grassland in this grid cell. Thefore violet is a mix of the colour blue (grassland) and red (cropland). Black means here that it is not dominated by any of the three key land covers here (i.e. cropland, unmanaged forest or grassland.

Figure 6 shows the pattern of projected net land conversion at pixel level for four different land cover types: cropland, grassland, primary forest and natural land. Compared to the default-version, including TRASE- and SPIPA variables leads to more 'hotspots' of land cover change rather than distributing it more equally across Argentinian existing agricultural land. For example cropland increases in the TRASE and SPIPA variable combinations by around 20% per grid cell whereas this stark increase cannot be observed for the default version. Similarly, for grassland including TRASE- and SPIPA variables leads to more increases in grassland in western Humid Pampas and Chaco biomes (see Figure 3). In the case of primary forest, including TRASE and SPIPA variables leads to primary forest loss of up to 40% in some grid cells.

The areas of highest cropland expansion are in the province Chaco and to a smaller extent in the province Santiago del Estero; mainly in the departments General Belgrano, Chacabuco, Doce de Octubre and Fray Justo Santa Mario de Oro.

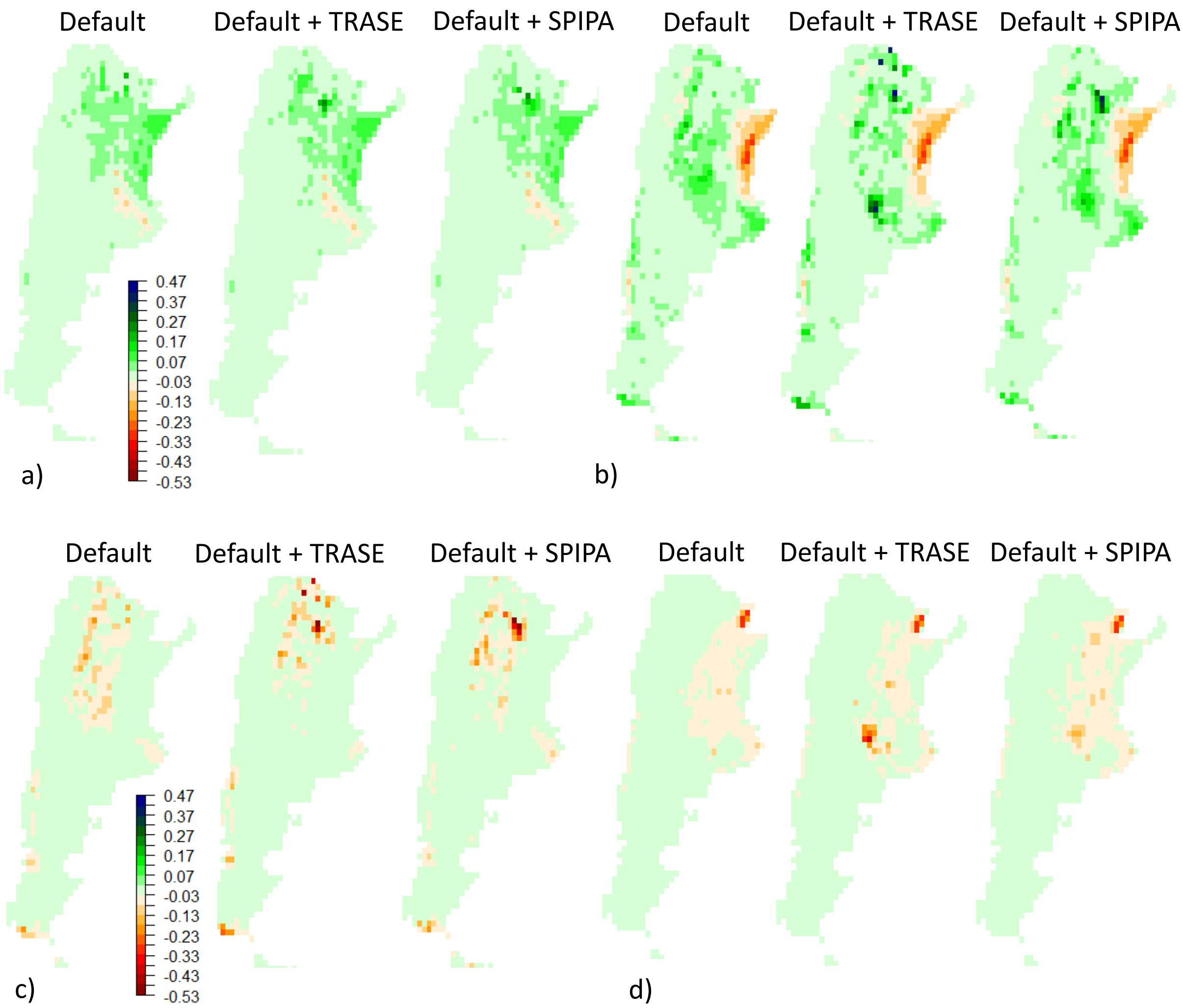

Figure 6: Percentage of change of total land from 2010 to 2050 for cropland (a), grassland (b), primary forest (c) and natural land (d) in each simulation unit. Comparison of output using either the default downscale version only or together with either SPIPA or TRASE variables.

Land cover change projections within Argentina are not equally distributed among the biomes. Using the default variable combination, cropland is projected to expand by 2.5 Mha between 2010 and 2050 according to the RCPRef SPA0 SSP3 scenario with the biggest increase within the Chaco biome: 1.5 Mha of new cropland will likely appear within the Chaco compared to only 0.6 Mha in the Espinal and even a likely decrease of 0.04 Mha in the Humid Pampas (Figure 7). Similarly, with the default variable combinations of projected 4.6 Mha of primary forest loss across Argentina, the majority will be in the Chaco with 2.2 Mha for the default variable combination compared to a loss of only 0.7 Mha in the Humid Pampas and 0.4 Mha in the Espinal. In contrast, the majority of the loss of natural land will be in the Humid Pampas with 0.6 Mha and in the Espinal with 0.02 Mha (using the default variable combination).

Differences between the three variable combinations (default, default and TRASE, default and SPIPA) are biggest for primary forest, grassland and abandoned grassland (Figure 7). Including TRASE-variables compared to the default setup leads within the Chaco to a conversion of 0.5 Mha more primary forest but an increase of grassland by almost 0.5 Mha from 2010 to 2050 compared to the default variable-set. In contrast, including TRASE variables compared to only the default variables leads to less conversion of primary forest in the Humid Pampas (0.4 Mha) and the Espinal (0.3 Mha). Including SPIPA variables compared to the default variable-set leads to around 0.2 Mha more expansion of grassland in the Humid Pampas, but 0.2 Mha less grassland conversion in the Espinal.

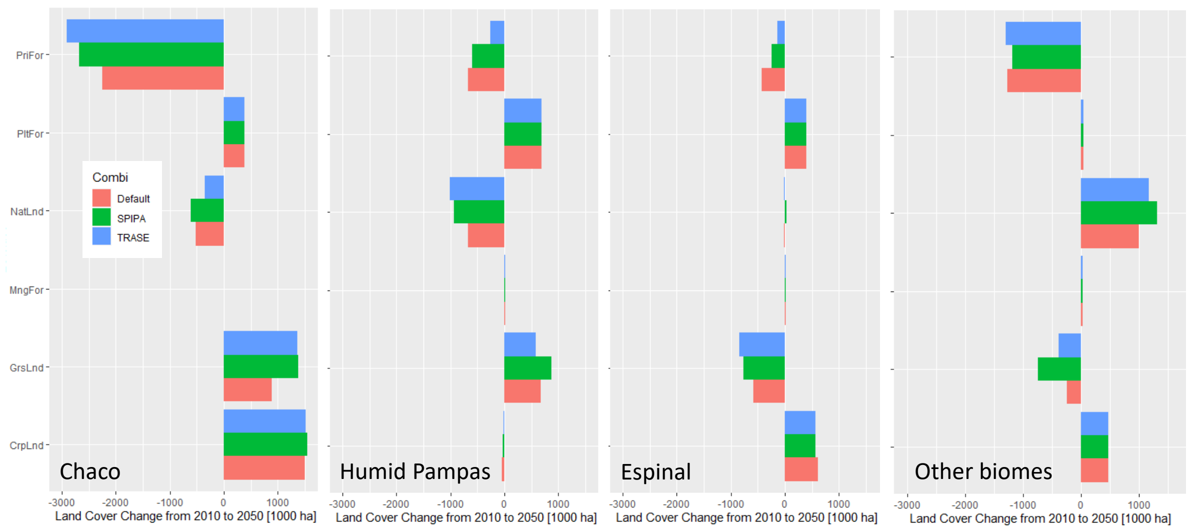

Figure 7: Net land use change of different land cover classes between 2010 and 2050 across different biomes in Argentina. Please note the different values on x-axis.

Discussion

This study aimed to identify additional relevant variables explaining historical land cover change at sub-national level within Argentina using the DownScale model with the ultimate aim to improve the accuracy of spatial explicit land cover change projections. For this purpose we have incorporated into the prior model of DownScale spatially explicit supply chain data from the Trase.earth platform as well as spatially explicit biophysical data from 'SPIPA'. This report showed that at least some of these additional variables are significant in explaining historical land cover change.. We found that including either SPIPA or Trase variables lead to primary forest loss being much more restricted to few departments (namely General Belgrano, Chacabuco, Doce de Octubre and Fray Justo Santa Mario de Oro) within the Chaco rather than more equally distributed using default-variables (Figure 5).

The limited differences in the spatial distribution of projected land cover change by 2050 between the three different variable combinations could be possibly explained by the fact that we did not include variables which might have strongly influenced land cover change in the analyzed time period between 2000 and 2010. Agricultural production in Argentina is known to be affected by export taxes on soybeans as 90% of Argentinian soybeans are produced for export (Nolte et al., 2017), but also drought evens are affecting farmer's income and therefore financial capacity to expand production (Thomasz et al. 2018).

Another challenge in explaining historical land cover change in Argentina could be the differences in available land cover maps and their land cover classifications. For this study we chose the global-scale ESA CCI land cover maps. It is possible that a national land cover map might be better in distinguishing native natural vegetation such as savannah-type land covers or pasture from grassland. In a recent global study of historical cropland expansion between 1992 and 2015 by Eigenbrod et al. (2020), these authors also used the ESA CCI land cover map though to avoid error, they excluded the land cover classes 30 and 40 (mosaic of cropland) whereas in this study the ESA land cover classes 30 and 40 were included in 'cropland' (see Krisztin and Woegerer, 2021). Eigenbrod et al. (2020) considered land cover classes 30 and 40 to be smallholder agriculture. As deforestation in Argentina is not driven by smallholder agriculture, including classes 30 and 40 as 'cropland' might overestimate deforestation. Perey-Hoyos et al. (2017) found that the ESA CCI land cover maps overestimate cropland globally. To which extent this is the case in Argentina is unknown.

Several simple assumptions had to be made which may limit the validity of the findings. Firstly, we assumed that supply chain patterns are static over time. It is likely that some supply chain variables such as distances to ports are more static over time than distance to logistic hub (e.g. silos or crushing facility) as over time it is likely that additional silos get built or traders using those silos change. Furthermore as we estimated many supply chain variables specific to consumer markets, it is likely that some consumer market's supply chain configuration is more static (e.g. Europe) than others whose population and meat consumption is increasing such as China or other Asian countries. It is also possible that political factors such as the China-USA tradewar could re-shape sourcing decisions and therefore proportionally increase demand from some biomes within Argentina much more than from others. A consequence from the US-tradewar could be that China would buy more soybeans from Argentina likely increasing the demand in their existing sourcing region in the Humid Pampas rather than Chaco in the north of Argentina.

Areas for Future Research

As this was only an explorative study with limited time available to analyze the benefits of including spatially-explicit supply chain data from Trase.earth, there are many areas future research could focus on. One limitation of the study was that supply chains were assumed to be static. This limitation could be overcome by for example including information about the establishment of crushing facilities which would be available yearly from CIARA (http://ciaracec.com.ar/ciara). Possibly with this dataset a relationship could be established between the year of crushing facility establishment, soy processing volume of the crushing facility and localized land use change. Another limitation of this study is that we used explanatory variables from the time period of 2016-2018 to explain land cover change observed between 2000 and 2010. Therefore for consuming markets which changed their supply chain between that period, it would be unlikely that these variables would be significant.

Additionally, this study focused on adding variables explaining cropland expansion. However Trase.earth also has data available to improve pasture expansion such as livestock density or egg production per department (Trase, 2020). Furthermore as the land cover maps and their classifications vary for Argentina, it would be interesting if the projected land cover changes would be different with a national land cover dataset likely better to differentiate local natural habitat and natural grassland from human-used pastures.

Furthermore future research could try to include the variables in a different way. In this study we included up to 150 different variables all at the same time together to explain land use change. However some variables especially of the SPIPA dataset are very similar to the variables from the default dataset (e.g. yearly temperature). Therefore some of the default dataset variables could be replaced with some from the Trase or SPIPA dataset to test whether this might improve the explanatory power?

Finally, for simplicity we did not change the national level amounts of land use change which came out of the GLOBIOM model but only the spatial pattern of land use change within Argentina. However it would be interesting to test whether Trase could help to improve the dynamic aspects of GLOBIOM as well. Trase data include the yearly changes of export flows per export market which could help here. Possibly for this purpose it might be better to use Brazilian Trase data which are available yearly from 2004 to 2018.

Conclusions

This study showed many of the supply chain variables as well as local national variables were found to be significant in explaining observed land use change, so worth including. However it was very much depending on the land cover transition which variables were significantly explaining the land transition. Additionally this study showed that including additional spatially-explicit variables from the Trase and Spipa-datasets increases conversion of forests to grassland and cropland to fewer smaller regions. This would make it easier for governments and private sector actors to focus their efforts onto few forest frontiers. However more research is needed to verify these initial findings.

Appendix

In the following the equations used to calculate each variable are described.

Market share for each producing Department *j* and Export market *i* is calculated as follows:

$$Marketshare_j = \%\ tonnage\ exported\ to\ country_i \times Soy\ price\ \left[\frac{USD}{Ton}\right] \times Total\ soy\ production\ in\ Department\ [Ton]$$

Distance from producing Department *j* to first Logistic Hub *l* in the supply chain for each Export market *i* (weighted average depending on soy tonnage)

$$Average\ Distance_j = \sum \%\ tonnage\ exported\ via\ Logistic\ Hub\ _{l,j}\ x\ \ Distance\ to\ logistic\ hub_{l,j}$$

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