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Modelling drivers of Brazilian agricultural change in a telecoupled world

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ABSTRACT

Increasing global demand for agricultural commodities has driven local land use/cover change (LUCC) and agricultural production across Brazil during the 21st century. Modelling tools are needed to help understand the range of possible outcomes due to these 'telecoupled' global-to-local relationships, given future political, economic and environmental uncertainties. Here, we present CRAFTY-Brazil, a LUCC model representing production of multiple agricultural commodities that accounts for spatially explicit (e.g., land access) and temporally contingent (e.g., agricultural debt) processes of importance across our nearly four million km^2 Brazilian study area. We calibrate the model calibration for 2001–2018, and run tests and scenarios about commodity demand, agricultural yields, climate change, and policy decisions for 2019–2035. Results indicate greater confidence in modelled time-series than spatial allocation. We discuss how our approach might be best understood to be *agency*-based, rather than agent-based, and highlight questions more and less appropriate for this approach.

1. Introduction

It is now well understood that local land use/cover changes in many regions of the world are influenced by international demand for agricultural commodities and that socio-ecological systems are often 'telecoupled' over great distances (Liu et al. 2013, 2018). For example, increased Chinese demand for soybean over the last several decades has contributed to increased production in Brazil, making the country a key soybean production region in the global food system and driving change in local land use (Silva et al., 2017; Sun et al., 2017). Increased production has been achieved through a combination of expansion of agricultural land, increases in yields, and changes in farming practices, including the development of a double-crop system with maize (predominantly) as a second crop. Improvements in yields have come through improved seed varieties (including genetic modification), increases in agricultural inputs (fertilisers, pesticides, machinery) and economies of scale (Wesz 2016). These changes have come in tandem with significant economic changes in the Brazilian farming system, meaning that many farmers are faced by tough economic decisions to ensure the future viability of their businesses (Silva et al., 2020). Future uncertainty is further exacerbated by the spectre of climate change which may bring increased frequency of drought during the second crop and other conditions unfavourable to consistent production from year-to-year (Heinemann et al., 2017; Hampf et al., 2020).

To create a tool for examining the range of possible outcomes given such a range of drivers and uncertainties, we set out to develop a spatially-explicit land use/cover change model capable of representing both production and associated land use of multiple agricultural commodities that could be subsequently linked to a System Dynamics model of global trade (see Millington et al., 2017). The telecoupling framework within which we developed our model emphasises the importance of agents and flows as drivers of change in coupled human-natural systems that are linked across long distances. To represent agency in land use and agricultural production decision-making we use the previously developed Competition for Resources between Agent Functional Types (CRAFTY) modelling framework (Murray-Rust et al., 2014), adapting it to improve representation of spatially explicit (e.g., land access) and temporally contingent (e.g., agricultural debt) processes of importance in our Brazilian study area. The CRAFTY framework has been designed specifically with the intention of simulating broad-scale land use change over large spatial extents (national to continental). For example, Blanco et al. (2017) parameterised CRAFTY to examine ecosystem services and

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decision-making under scenarios of climate change for the entire land area of Sweden over many decades. Brown et al. (2019) used CRAFTY to simulate land use change across the entire European Union to investigate land manager behaviour at the continental scale. In work similar to that presented here, investigating the telecoupled effects of global food commodity trade between China and Brazil on land use, Dou et al. (2019, 2020) developed a bespoke agent-based model. Whereas the aims of that approach were to understand land use impacts at a fine scale for a single municipality, our work aims to understand land use across much broader extents and hence the use of CRAFTY is more appropriate (Millington et al., 2017).

In this paper, we present the description and first results from the application of the CRAFTY framework to simulate land use/cover change over several decades for ten Brazilian states, an implementation we call CRAFTY-Brazil. We provide an overview of the endogenous and exogenous processes represented, the data used to parameterize and calibrate the model, and results from using CRAFTY-Brazil to simulate scenarios of future change. Importantly, we developed and tested CRAFTY-Brazil using empirically-grounded data in a fashion that has not previously been achieved for other applications of the CRAFTY framework. This empirically-grounded approach aims to ensure internal model consistency, but also identify key areas of uncertainty. The model structure and results presented here are independent of the System Dynamics model (based on Warner et al., 2013) we ultimately intend to couple CRAFTY-Brazil with. However, by examining scenarios of commodity demand, agricultural yields, climate change, and policy decisions over land use rights, we are able to both identify important uncertainties in the model but also shed light on important processes influencing land use change in Brazil. Subsequently, we reflect on what we have learned from this initial use of the model and discuss future directions in which this work should proceed.

2. Methods

2.1. Study area and data

CRAFTY-Brazil was designed with the intention of subsequently connecting this spatial explicit model of land use/cover change with a System Dynamics model representing the international trade of three primary agricultural commodities: soybean, maize and beef. With this focus, our study area was designated as the 10 states in Brazil that have been the dominant producers of soybean and maize in recent years and for which pasture area is widespread (Fig. 1). Our aim to simulate this region of 3,850,000 km^2 for several decades required compromises on model spatial and temporal resolution to ensure feasible execution times while representing sufficient variation to explore system dynamics.

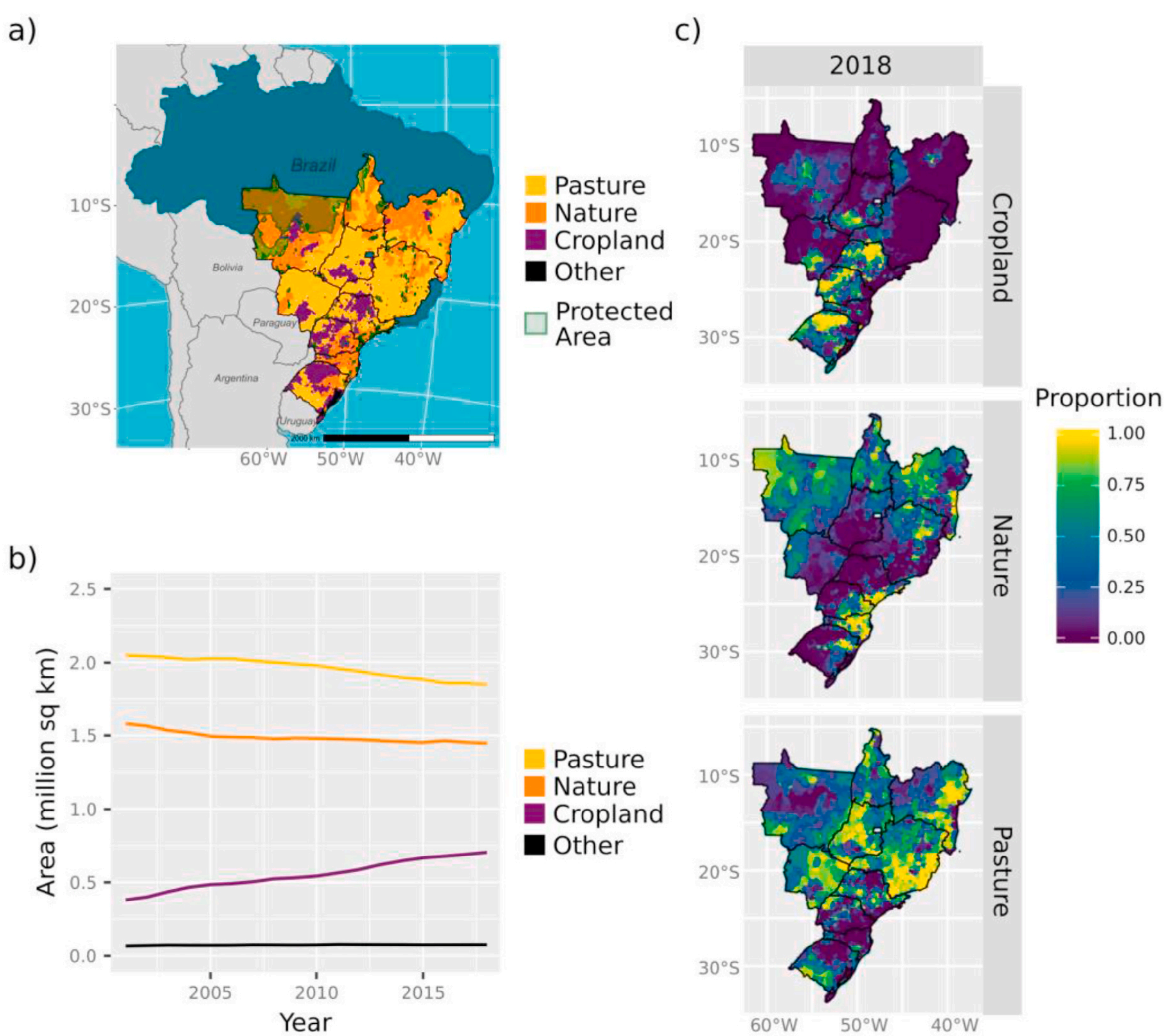

Fig. 1. Study area. a) Location of the ten Brazilian states composing the study area and their modal municipality land cover for 2018, b) Study area LUCC through time for the 2001–2018 calibration period, c) Municipality proportion of Cropland, Nature and Pasture for 2018 (scenario results are compared against these proportions).

Thus, the model operates on a raster grid at a 5 km spatial resolution (for a total of 162,026 simulated cells) and we aggregate results to municipality level (for our study area, mean and median municipality areas are 1,040 and 398 km^2 respectively). These resolutions are appropriate given the available data needed to calibrate the model, which comes from a variety of sources and with a range of original resolutions including many aggregated at municipality level (Table 1). Furthermore, the 5 km resolution is comparable to other applications of CRAFTY across large spatial extents (e.g., 1 km for Blanco et al., 2017 and 10 arcminute - approx. 18 km at the equator - for Brown et al., 2019). The model runs with an annual timestep and we calibrate using data for 2001–2018.

For model initialization and calibration, we use land use/cover (LUC) data from the MapBiomas project (version 4; MapBiomas 2018). Original 30 m data were resampled to 5 km (modal pixel class; see Millington 2019) and LUC classes were reclassified from 27 classes to four: 'Cropland', 'Pasture', 'Nature' and 'Other' (Appendix A). These LUC classes are associated with the production of 'services' by different agent functional types (as described below, Section 2.2.1). Cropland represents land used to produce soybean, maize and other crops (e.g., rice, sugarcane), while Pasture is assumed to represent all land area used for beef production. Nature represents vegetation cover not used for agriculture (i.e., crops or pasture); processes of natural vegetation dynamics are not explicitly represented (although see use of Nature capital in section 2.2.1 below) but simulated land that is no longer needed for human use reverts to the Nature class (and Nature cells can be converted to all other classes). Finally, Other represents land covers such as urban and inland water bodies and is assumed to not change in simulations that project into the future.

Given uncertainty in the MapBiomas data and the multiple alternative ways those data might be re-classified, we examined several reclassifications of the MapBiomas v4.0 data and used commodity planted area data (from IBGE) to disaggregate ambiguous classes. The overall accuracy for the MapBiomas v4.0 data for the period 2001–2018 (at the Level 2 classification) is estimated to be 88%, with the Grassland class consistently the most poorly classified of all classes (high rates of Natural Forest and Pasture commission error; see MapBiomas 2019b). On comparing the implied beef pasture yields for LUC classifications including/excluding Grassland in our Pasture class, we find a closer match with observed yields when Grassland is included (see Millington 2019). The MapBiomas class 'Mosaic of Agriculture and Pasture' is also problematic given that our focus is on distinguishing between pasture and cropland. To address this, we used planted-area data (IBGE 2019) to allocate pixels in the MapBiomas 'Mosaic of Agriculture and Pasture' class into either Cropland or Pasture classes (see Millington 2019).

2.2. Model description

2.2.1. Services, agents and capitals

The CRAFTY framework represents the production of land 'services' by Agent Functional Types (AFTs) through production functions for multiple 'capitals' available in each cell representing a land unit (Murray-Rust et al., 2014). Cobb Douglas production functions are used:

$$p_s = \prod_c c_i^{\lambda_{c,a}} \tag{1}$$

where $\lambda_{c,a}$ is a weighting factor specific to capital c and AFT a, and p_s is the productivity for service s (in abstract 'production units', later converted to kg for agricultural commodity services). Competition between AFTs is represented by calculating 'competitiveness' using a utility function that accounts for production and marginal demand for each service. In each timestep, the competitiveness of AFTs is calculated for cells based on current capital values (which CRAFTY assumes are scaled 0 to 1) and service demands (specified in abstract 'production units', which in our case represent demand for agricultural commodities in domestic and international markets); the AFT with the greatest competitiveness is allocated to that cell (subject to the 'giving-in' threshold of the currently occupying agent). Land may also be abandoned from agent use if competitiveness falls below an AFT's 'giving-up' threshold. For full details on the CRAFTY framework, see Murray-Rust et al. (2014).

Given our focus on soybean, maize and beef, CRAFTY-Brazil represents provision of the following 'services': Soybean, Maize, Beef, Other Crops (OCrops), Nature and Other. The Nature service represents the value of land not under human influence, while Other represents all other land not in other classes (e.g., urban, water). The AFTs represented are soybean producers, maize producers, soybean-maize double-crop producers (producing both services), beef producers, other crop producers, and other land managers (Table 2). We developed these AFTs

Table 2
Summary of agent functional types.

AFT	Representation	Capital Dependencies	Services Produced
Soybean	Soybean Farmer	Moisture-Main, Transport, Tech-Soy-Maize, Protection-Soy, Access-Nature, Access-Soy-Maize	Soybean
Maize	Maize Farmer	Moisture-Main, Transport, Tech-Soy-Maize, Protection-Maize, Access-Nature, Access-Soy-Maize	Maize
Double-Crop	Soybean-Maize Double-Cropping Farmer	Moisture-Main, Moisture-Second, Transport, Tech-Soy-Maize, Protection-Soy, Protection-Maize, Access-Nature, Access-Soy-Maize	Soybean, Maize
Nature	Vegetated land not under management	Land Value, Conservation	Nature
Other Crops	Farmer of crops other than soy or maize	Moisture-Main, Transport, Protection-OCrop, Access-OCrop	Other Crops
Other	Urban or non-vegetated land	Other, Protection-Soy, Protection-Maize, Protection-Beef,Protection-OCrop	Other
Pasture	Beef Rancher	Moisture-Main, Transport, Tech-Pasture, Protection-Beef, Access-Nature	Beef

Table 1
Data used for model calibration.

Variable	Type	Spatial Res.	Temporal Res.	Source	Use
Land Cover/Use	Raster	30 m	Annual	MapBiomas (2019)	Model initialization and calibration
Climate	Raster	0.5°	Annual	Harris (2020)	Moisture Capitals
Transport Network	Vector	NA	Quinquennial	Victoria et al. (2021)	Transport Capital
Protected Areas	Vector	NA	Annual	MMA (2019)	Protection Capitals
Land Price	Vector	Municipality	Annual	IEG/FNP (2017)	Land Value Capital
Commodity Production	Tabular	Municipality	Annual	IBGE (2019)	Study area selection, Tech-Soy-Maize and Tech-Pasture Capitals
Commodity Planted Area	Tabular	Municipality	Annual	IBGE (2019)	Land cover/use map disaggregation
Commodity Exports	Tabular	Municipality	Annual	IBGE (2019)	Commodity demand estimation

based on expert judgement and discussion with stakeholders in the study area based on the key services being simulated in the model and the key variations in strategies (e.g. single vs double-crop) that currently exist. A Nature AFT is also required for cells not under control of any other AFT and representing land not under direct human land use (regardless of whether that is primary or secondary vegetation). Representing double-crop farmers as an individual AFT is important as land managers have implemented the practice of sowing and planting a soybean crop early in the season followed by a late season crop (usually maize). The double-cropping system of soybean and maize was initiated in Brazil in the late 1990s, as raising maize following soybean harvest provides protective cover for soils and the system eventually improves soil quality (Silva et al., 2017). Initial yields using this method were low, but since the early 2000s many improvements have been made in management practices such as no-tillage agriculture, Nitrogen biological fixation serviced by soybeans, hybrid and GMO maize varieties, which boosted yields for the second crop. Consequently, this double-cropping practice has grown through the 21st century, pushed more by economic demand than by a desire for improved soil management (Silva et al., 2017). Although this system provides potential for both agronomic and economic gains over single-crop systems, the second crop growth is exposed to the risk of late-season drought and consequent production losses (Brunini et al., 2001; Gonçalves et al., 2002). For soybean, the double-cropping system has pushed production into a very short growing season forcing producers to adopt short-cycle GMO varieties (about 90 days from planting to harvest) that are impacting soybean yields (Oliveira Neto, 2017). We represent 'Other Crops' and 'Other' land managers as grouped AFTs that likely contain multiple management strategies because our focus here is on the production of soybean, maize, and beef.

2.2.2. Exogenous processes

We use multiple CRAFTY 'capitals' to represent the numerous influences on the production of services (Table 3). For example, important determinants of agricultural production in Brazil have been found to include human capital, technology generation and dissemination, climate conditions, and transport networks and land access (Pereira 2012; Rada 2013). All capitals vary spatially across the study area except for Tech capitals, which are spatially uniform because these represent improvements in technology that lead to broad-scale yield improvements through time (including due to improved seed varieties, machinery and fertilisers that are available widely). Values for capitals are provided exogenously (i.e., from ancillary data sources), except for the three Access (Nature, Soybean-Maize, Other Crops) capitals and the Conservation capital, which are calculated endogenously (i.e., during a simulation run) from the dynamic spatial configuration of AFTs. All endogenous and many exogenous capitals are updated in each timestep (i.e., annually), although some are updated less frequently (see Table 3) either because of data availability (e.g., transport network) or because the process they represent does not occur on an annual basis (e.g., the soybean moratorium occurred in a given year, see below). All scripts to create files for initializing and updating capital values are available online (Millington 2020a). We discuss exogenous capitals in the remainder of this section, and endogenous capitals and representation of other processes in the following section (section 2.2.3).

The Moisture capitals are derived from the monthly mean temperature and precipitation variables from the CRU TS v. 4.03 high-resolution gridded datasets (see Harris et al., 2020) and represent the role of climate on agricultural production. To understand climatic limitations associated with plant growth and agricultural production, we used the dryness index to describe the relation between water deficit and potential evapotranspiration (Pereira and Pruitt, 2004), both obtained from the Thornthwaite and Matter (1955) climatic water balance, as implemented by Victoria et al. (2007). This index represents the water deficit in percentage of potential evapotranspiration and is calculated by the equation:

Table 3
Capitals influencing modelled Services.

Capital	Description	Services Influenced	Update Years	Data Source[a]
Moisture-Main	Main growing season (Oct–Mar climate)	Soybean, Maize, Beef, Other Crops	All	Climate
Moisture-Second	Maize second-crop growing season (Jan–Jun climate)	Soybean, Maize	All	Climate
Transport	Import and export costs due to transportation	Soybean, Maize, Beef, Other Crops	2005,2010, 2017	Transport Network
Land Value	Land attractiveness for establishing new agriculture	Soybean, Maize, Beef, Other Crops	All	Land Price
Conservation	Conservation value of natural land	Nature	All	Endogenous
Tech-Soy-Maize	Technology and resources influencing yield	Soybean, Maize	All	Commodity Production
Tech-Pasture	Technology and resources influencing yield	Beef	All	Commodity Production
Other	Incentive for 'Other' uses	Other	All	Land Cover/ Use
Protection-Soybean	Prevents Soybean production in given cell	Soybean, Other	2006	Protected Areas
Protection-Maize	Prevents Maize production in given cell	Maize, Other	2009	Protected Areas
Protection-Beef	Prevents Beef production in given cell	Beef, Other	None	Protected Areas
Protection-OCrops	Prevents OCrops production in given cell	Other Crops, Other	None	Protected Areas
Access-Nature	Spatial: proximity to natural land	Soybean, Maize	All	Endogenous
Access-Soy-Maize	Spatial: proximity to soybean or maize cells	Soybean, Maize	All	Endogenous
Access-OCrops	Spatial: proximity to other crop cells	Other Crops	All	Endogenous

[a] Data Sources correspond to Variables in Table 1.

$$DI = 100 * DEF / PET \quad (2)$$

where DI (%) is the dryness index; DEF is the water deficit; and PET is potential evapotranspiration (see Table 2 in Victoria et al., 2007 and Millington 2020a for full definition). We calculate mean monthly DI for two different growing seasons (Oct–Mar and Jan–Jun) to calculate two sets of moisture capital values to represent climate influence on single-vs double-crop production. The use of these Moisture capitals also allows us to investigate the possible influence of climate change on agricultural productivity in simulations of alternative future scenarios (see section 2.3 below).

Transport infrastructure is a key variable influencing the spatial distribution and volume of agricultural production, related to land conversion (e.g., Soares-Filho et al., 2006; Weinhold and Reis 2008) and both imports of agricultural inputs and exports of commodities to markets (Rada 2013). The Transport capital uses data on the national road network (DNIT 2019) with locations (and operating years) of ports (ANTAQ 2019) to derive a spatial cost surface at a broad scale. This cost surface weights the quality of transport infrastructure such that paved roads present lower cost than unpaved roads for access to land (see Victoria et al., 2021). The use of the Transport capital allows us to investigate the possible influence of future alternative infrastructure development on land use change and agricultural productivity at a broad scale.

The Land Value capital is used to represent the incentive for agents to convert Nature land to Agriculture in places where agricultural potential and infrastructure (as represented by the previous capitals) are poor, but which have been converted (e.g., based on Mapbiomas LULCC between 1985 and 2018). In these 'frontier regions', land prices are lower compared to other developed regions of Southern Brazil, reflecting the challenges of making a profit from agricultural production in frontier lands. These lower land prices provide an incentive to those willing to take a risk on developing land for grain production, assuming that future improvements (e.g., logistics, infrastructure) in the region will improve yields to pay-off the risk. Previous studies have shown that as the agricultural sector develops in a given region, land prices tend to increase alongside infrastructure and social standards (Rezende, 2002; Ferro and Castro, 2013; Martinelli et al., 2017). To develop this capital we used data from IEG/FNP (2017) to represent the relative cost of land for new development. As noted above, improvement in agricultural productivity (yields) through time due to advances in technological resources – such as improved machinery and seed varieties (e.g., Pereira 2012) – are represented using the Tech capitals. Because these capitals represent the aggregation of multiple sources of improvements in yield, we calibrate their values by combining our observed land use/cover data with commodity production data to calculate yields that are internally consistent within the model (see Millington 2020b).

The four Protection capitals represent areas of land that cannot be used for soybean, maize, beef or other crops. This exclusion may be because an area is designated as National or State Parks, indigenous lands or because of a policy that excludes production of a given commodity (e.g., Soybean Moratorium). For example, the Protection-Soybean capital is used in calibration runs (section 2.3) to represent the Soybean Moratorium policy implemented in 2006 to discourage deforestation and limiting the market for soybean grown on deforested lands (Gibbs et al., 2015; Dou et al., 2018). These capitals therefore also allow examination of simulation runs that implement similar policies. Finally, the 'Other' capital is used to drive a high probability of cells being in the Other land cover category (e.g., urban and water), based on observed land cover change for calibration and potentially for representation of future expansion of this land type.

In the CRAFTY modelling framework, demand for services is provided exogenously, rather than incorporated as an endogenous process. Furthermore, this demand is specified in the same abstract units used to represent services production (section 2.2.1 above). As our focus here is on soybean, maize and beef we derive the abstract demand for these services from real production units (kg), while for Other Crops, Other and Nature we derive demand based on land area (ha; see Millington 2020b).

2.2.3. Endogenous processes

Processes driven by the spatial configuration or historical contingency of land resources and agent actions are represented in the model endogenously by updating cell- or agent-states dynamically during a simulation, dependent on their circumstances in each timestep. Specifically, we represent the spatial agglomeration effect of agricultural economies, the tendency of land conversion to be spatially contagious, vegetation regeneration processes, and producer debt. Representing these processes required additions to the CRAFTY source code (see Millington 2020c).

The importance of spatial proximity for driving land use change due to efficiencies afforded by agglomeration economies is well known (e.g., Fujita and Krugman 1995; Porter 2000) and has been shown to be important in Brazil (Vera-Diaz et al., 2008; Garrett et al., 2013; Picoli et al., 2020). To represent this in the model at a local level, the Access-Soy-Maize and Access-OCrops capitals are updated in each cell in each timestep during simulation runs based on whether one of these agent-types is present within the eight neighbouring cells (Moore neighbourhood; with value 0.05 if the target agent-type is not present, 0.95 if the agent-type is present, and 1.0 if the cell is occupied by the specified AFT). Similarly, conversion of natural land for agriculture is known to be well-modelled as a contagious process of spread from existing cultivated areas at the edge of natural lands (e.g., Rosa et al., 2013). To represent spatial access to natural land at a local level, the Access-Nature capital is updated in each cell in each timestep during simulation runs based on the adjacency of nature and non-nature land covers. For any given cell, if the Moore neighbourhood is composed entirely of nature cells, the capital takes a value of 1.0; if between 1 and 7 cells in the Moore neighbourhood are nature cells, the cell takes a value of 0.75; and finally a Nature Access capital value of 0.0 is taken if all neighbouring cells are non-nature.

Through time, we represent regeneration of natural vegetation following land abandonment by modifying Conservation capital cell values during a simulation based both on the time since last human disturbance but also the type of disturbance. Several recent studies support the hypothesis that forest regeneration rate is related to 'intensity' of previous land use (Mesquita et al., 2015; Jakovac et al., 2015; Martines-Ramos et al., 2016), and here we assume that the rate of regeneration is faster following extensive pasture land-use than intensive crop (soybean, maize) land uses. Hence, for cells in a simulation run that have never been disturbed (i.e., have always had a Nature land cover) the Conservation capital will have value 1.0. The Conservation capital value is reduced to 0.4 if converted from Nature to pasture and to 0.0 if converted to one of the other non-nature land covers. Following abandonment of a non-nature use, Conservation capital is increased by a value of 0.01 each timestep. The final endogenous process we represent is the accrual and repayment of debt by those producers changing land uses. New producers often need to take out loans to pay for land, new machinery, seed, and other start-up costs. Producers can be 'trapped' into activities needed to earn profits to make repayments (e.g., Silva et al., 2020) and changes in land use are unlikely during the repayment period. To represent this inertia following conversion, we prevent new agricultural agents from changing land use until the debt is repaid. Debt is measured in years (the number of years to pay off the debt) and is specified for transitions as shown in Appendix B.

2.3. Calibration, testing and scenarios

Previous implementations of the CRAFTY framework for modelling real-world regions have calibrated model parameters using methods that ensure internal consistency and produce expected system trajectories but without comparing model outputs to empirical observations (e.g., Blanco et al., 2017; Brown et al., 2019). In contrast, here we use empirical data for land cover/use and agricultural commodity production (Table 1) to parameterize AFT production functions and capital conversions (e.g., from climate dryness index to Moisture capitals), identifying values that reproduce trends and patterns observed over the period 2001–2018. This approach aims to both ensure internal consistency, but also identify key areas of uncertainty in the model and is one that has not been employed in previous CRAFTY modelling applications. Understanding this uncertainty is important and useful for assessing model outputs for scenarios that project future land cover/use and agricultural production. Here, we compare simulated land cover/use and agricultural production to observed data for the same variables, aggregated for the entire study area. We also compare observed and simulated municipality-level proportions of land cover/use for snap-shots in time (5-year intervals). Final calibrated production function values are shown in Appendix C and capital conversions are shown in Millington (2020a).

Once calibrated, we test the model to examine how exogenous processes influence simulated land use/cover and agricultural production.

Specifically, we test for changes in commodity demand and capitals associated with agricultural yields and climate change (Table 4). To understand the relative importance of these inputs on land use and production we vary each by the same proportion (+/- 20% of 2018 values over 2019–2035), holding all other values constant at 2018 values. For demand, we also examine tests in which demand for all services *except* for the Nature service are varied (to examine the impacts of changes in non-Nature demand). Comparing outputs from all of these tests, including to a simulation that holds all values constant, helps us to better understand the drivers and dynamics in the model and identify most important drivers of future change.

Finally, we examine future change in land use and production under alternative scenarios of demand, yield, climate change and protected land (Table 4). Scenario input values for commodity demand and yields are derived from projections by the Brazilian Ministério da Agricultura, Pecuária e Abastecimento (MAPA 2020). As these projections are only to 2030, we use proportional change as indicated in the projections for 2019–2030 then mean proportional change over that period for 2031–2035 (see Appendix D). For climate change scenarios we use regionally-downscaled projections of temperature and precipitation from the WCRP Coordinated Regional Downscaling Experiment (CORDEX). Our chosen driving model was HAD-GEM2 as this model has been shown to have better agreement with observed rainfall in Atlantic Forest, Caatinga and Cerrado biomes than other models, although biases do remain (Rosolem et al., 2018). We use monthly data for Daily Minimum Near-Surface Air Temperature (*tasmin*), Daily Maximum Near-Surface Air Temperature (*tasmax*) and Precipitation, (*pr*) from ensemble r1i1p1 and CORDEX region SAM44 (downscaling realisation v3). Projections were for representative concentration pathways RCP4.5 and RCP 8.5 and were accessed via the ESGF-CEDA project (CEDA 2019). Scripts that convert these data to Moisture capitals values are available in Millington (2020a). Finally, we also examine a scenario that includes removal of protected area designations (in addition to other changes), a possibility given the environmental policy direction the current Brazilian Federal government has taken recently (e.g., Abessa et al., 2019).

Table 4
Specification of tests and scenarios for 2019–2035. Percentage changes are over the entire period; 'invariant' uses values from 2018 for the remainder of the period.

Description [*label*]	Demand Conditions	Climate Conditions	Yield Conditions	Variations
Tests				
Constant [*Const*]	Invariant	Invariant	Invariant	None
All Demand Decreases [*Dem-All-Decr*]	Demand for all services decreases by 20%	Invariant	Invariant	None
All Demand Increases [*Dem-All-Incr*]	Demand for all services increases by 20%	Invariant	Invariant	None
Non-Nature Demand Decreases [*Dem-NNat-Decr*]	Demand for all services but Nature decreases by 20%	Invariant	Invariant	None
Non-Nature Demand Increases [*Dem-NNat-Incr*]	Demand for all services but Nature increases by 20%	Invariant	Invariant	None
Yield Decreases [*Yield-Decr*]	Invariant	Invariant	Yields for Soy, Maize, Beef decrease by 20%	None
Yield Increases [*Yield-Incr*]	Invariant	Invariant	Yields for Soy, Maize, Beef increase by 20%	None
Climate Decreases [*Climate-Decr*]	Invariant	Moisture capitals decrease 20%	Invariant	None
Climate Increases [*Climate-Incr*]	Invariant	Climate capitals increase 20%	Invariant	None
Scenarios				
Business As Usual [*BAU*]	Standard MAPA projections for Soy, Maize, Beef, OAgri; otherwise invariant	Moisture capitals from RCP45	Standard MAPA projections for Soy, Maize, Beef; otherwise invariant	None
Future Extremes [*EXT*]	Upper MAPA projections for Soy, Maize, Beef, OAgri; otherwise invariant	Moisture capitals from RCP85	Upper MAPA projections for Soy, Maize, Beef; otherwise invariant	None
Future Extremes with No Protection [*EXT-NP*]	As for EXT plus 10% lower Nature demand	Moisture capitals from RCP85	Upper MAPA projections for Soy, Maize, Beef; otherwise invariant	Protected Areas removed

3. Results

3.1. Calibration

Results from model calibration indicate that CRAFTY-Brazil is able to reproduce observed time-series of total area and production for the entire study area, but performs less well in terms of spatial allocation across the study area. Observed trends of decreasing Pasture and Nature area combined with increases in cropland area are reproduced well, with small year-to-year variation (Fig. 2a). The general trends of increases in production of Soybean and Maize are reproduced, although much of the large inter-annual variability in production is not captured (Fig. 2b). Interestingly, there is also a slight lag in the rate of increase in Maize production 2011–2014, and dramatic decreases in recent years are not captured. Correspondence between the two sets of time series can also be noted, for example with the under-estimation of cropland area 2003–2005 linked to under-estimation of Soybean production in these years.

Although time-series of observed trends are reasonably well reproduced, there are some disparities between observed and modelled locations of land use/cover (Fig. 3). For example, the model tends to locate more Cropland in the north east of the study area (Bahia state) than has been observed, with correspondingly less Pasture than observed in this area. Conversely, in the central part of the study area (São Paulo state), the model produces more Pasture than observed, at the expense of cropland. Nature is reasonably well modelled across the study area, although with some over estimation (at the expense of cropland) in the north west of the study area (Mato Grosso state). While we see generally consistent variation from observations in the simulated time-series, accuracy in spatial allocation of land use seems to deteriorate through time. For example, while the modal land use/cover was incorrectly modelled for 9.8% of municipalities in 2009, this had risen to 16.4% by 2018.

3.2. Testing

Assuming constant 2018 conditions into the future (*Const* scenario, Fig. 4), all land covers remain in a steady state, with the exception of Double-Cropping and Maize; DC replacing Maize as former is more competitive. Hence, Soybean production continues to rise while Maize production declines slightly.

Results for tests examining change in commodity demand (Fig. 4a and b), show that decreases in demand, whether for all services or only

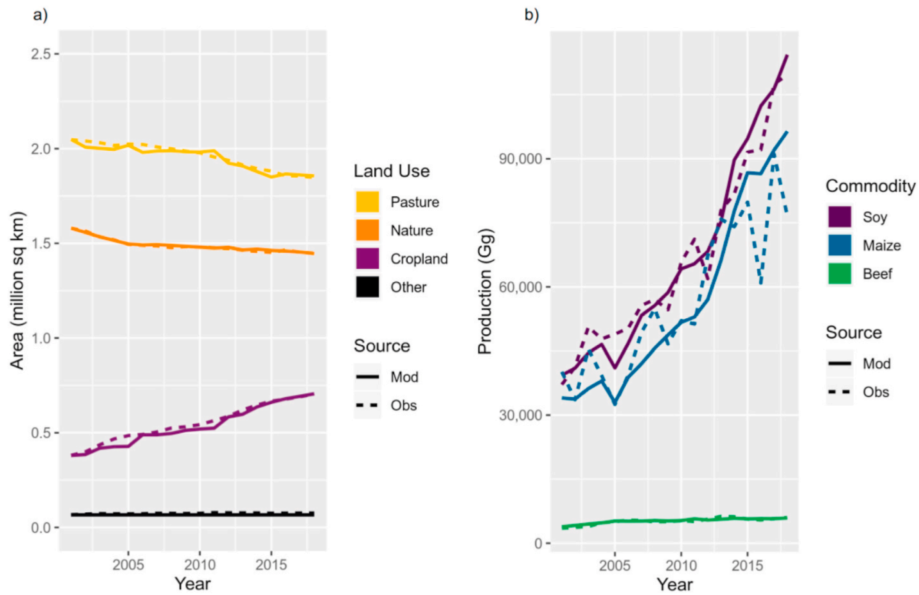

Fig. 2. Calibration time-series. a) land use/cover and b) commodity production.

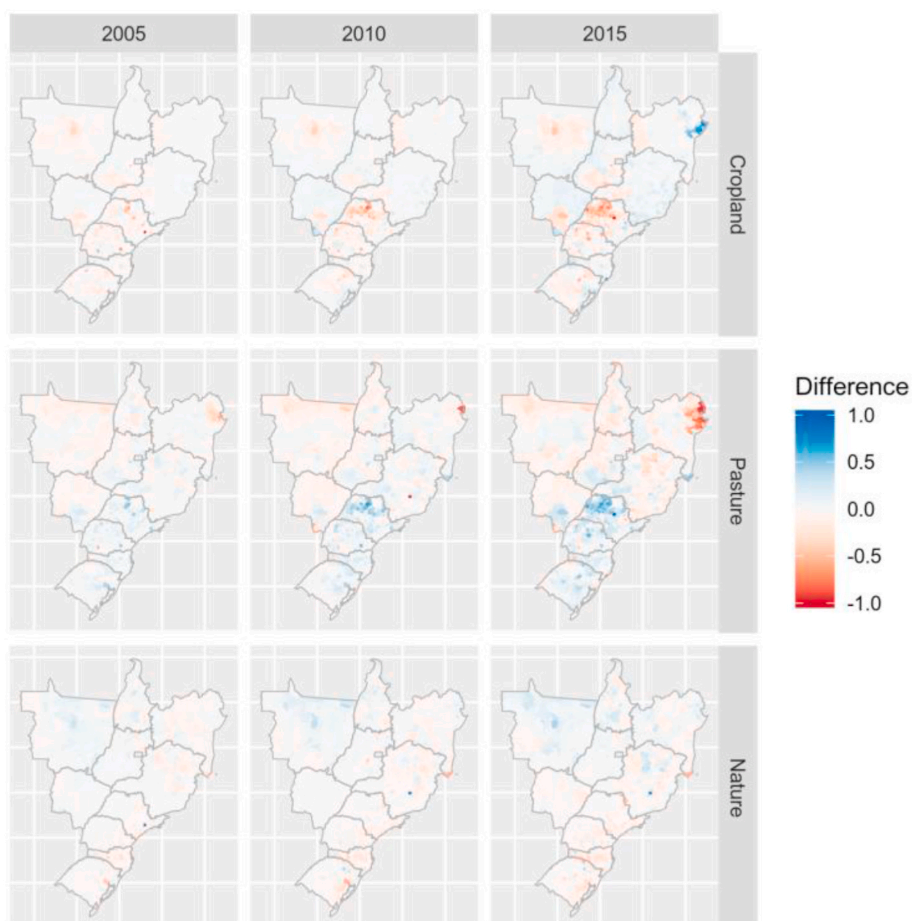

Fig. 3. Municipality proportional difference from observed, by land use/cover. Red shades indicate underprediction and blue shades overprediction relative to observed data (i.e., Fig. 1c).

for non-Nature services, result in decreases in production of services and decreases in agricultural area with commensurate increases in Nature area (all change is either ~ 20% or <20% relative to starting conditions). These changes are generally larger than changes observed in outputs from tests that examine increases in demand. This can be seen spatially in maps for tests with decreased demand (Fig. 5), which indicate much less change than increased demand tests (compared to the constant test) and with greatest differences in the north east and south

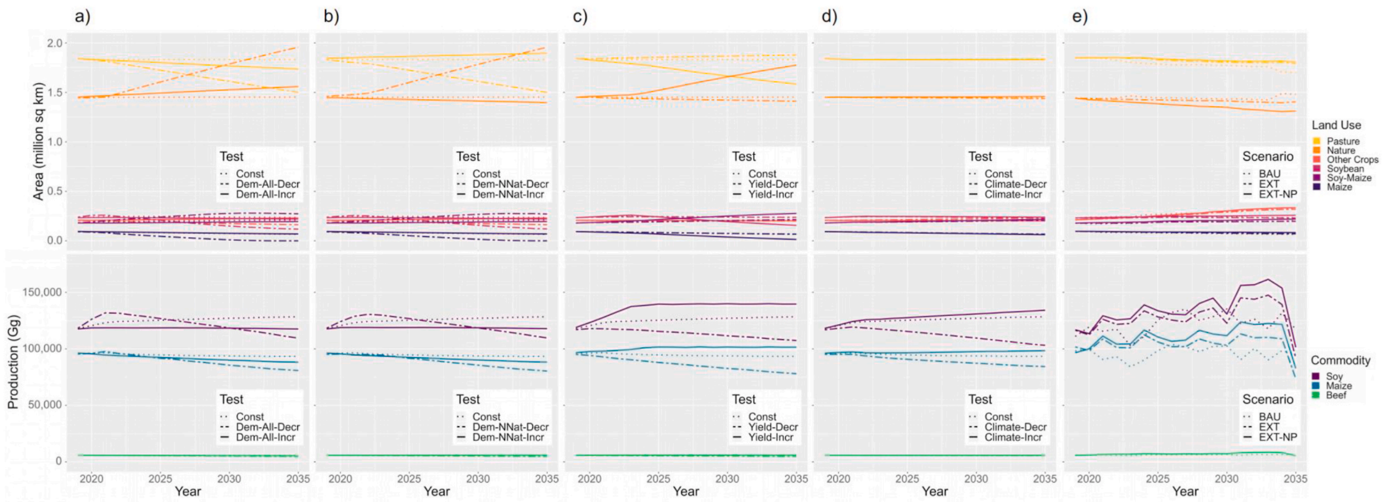

Fig. 4. Time series of land use and production for tests and scenarios. Specification and acronyms for names of tests and scenarios are presented in Table 4.

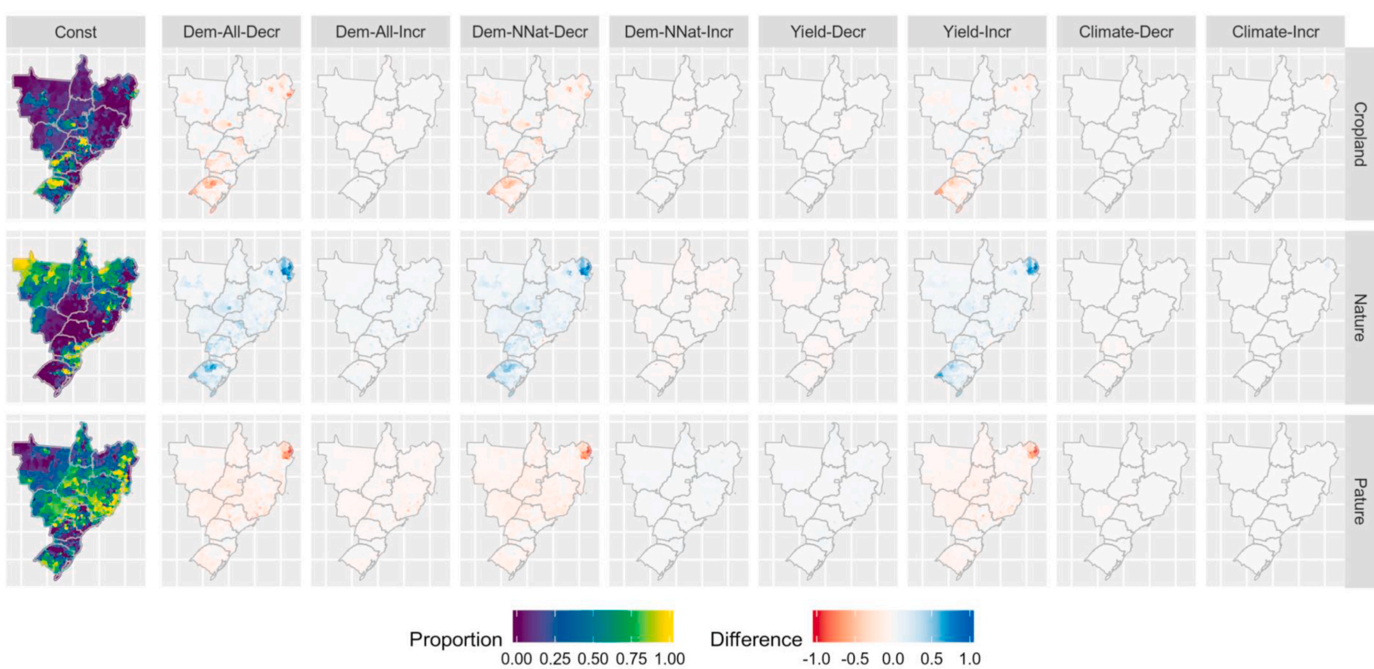

Fig. 5. Spatial variation in outputs for tests. Municipality Differences are calculated from Proportions for the *Const* scenario (shown at left) for simulated year 2033. Specification and acronyms for names of tests are presented in Table 4.

west of the study area.

Differing trends exist between increased demand scenarios that consider all services vs non-Nature services. When demand across all services increases, by 2035 Nature production (and land cover) is greater than the initial 2018 state and Beef/Pasture are lower. However, when demand increases only for non-Nature services, the reverse situation arises by 2035 - Nature production (and land cover) is less than the initial 2018 state and Beef/Pasture production/land cover are greater. Although there is a difference in trend, the final % change is less than the % change in input (i.e. <20%). Regarding the shape of production timelines in demand scenarios, initial production is below demandand so rises to meet that demand. In year 2022 demand decreases to a value similar to that actually being produced. Thereafter, demand continues to decrease and is at a value that can be met by existing land use. Consequently, agricultural land is abandoned and Nature land area increases more rapidly.

Yield scenarios (Fig. 4c) have similar sensitivity to Demand, except for Nature and Other Crops (which don't have changes in yield inputs). However, Maize and Soy have greater changes in yield tests than demand tests. For constant demans, production is greater with greater yields and lower with lower yields . There is minimal change in Nature area for decreases in yield (as relative pressure on land for all uses is high), but large increase in Nature area for increased yields (as less land is needed to meet demands). Production of Soy and Maize in the Yield increase test rise (until 2025) when greater yields mean demand can be met. High yields relative to demand from 2023 mean that this is the point at which the rate of abandonment and growth of Nature land increases.

Outputs are least sensitive to changes in climate inputs, particularly for land area. For climate scenarios, all change in land area is <20% except for Maize, which as for all other scenarios decreases due to replacement by soy-maize double-cropping. Limited change in land area means that there is very little difference between spatial distribution of LUC in climate tests compared to the constant state. Agricultural service production increases/decreases for increases/decreases in the Moisture capital, respectively, as would be expected by the relationships encoded in the model.

As would be expected, maps of spatial change (Fig. 5) indicate greatest change for tests in which timeseries (Fig. 4) indicate greatest aggregate change (i.e., Nature land area increases commensurate with decreases in agricultural land area). Maps show the location of these changes are focused in the north east and south west of the study area, with shifts from Pasture to Nature in the former and from Agriculture to Nature in the latter.

3.3. Scenarios

The results for scenarios (Figs. 4e and 6) exhibit combinations of the trends and patterns seen in the other scenarios (varying individual driving factors). All three scenarios result in increased overall production through time, in response to improving yields and increased demand. Greatest increases in production are found in the *EXT-NP* scenario, although corresponding increases in Cropland and Pasture land are not spatially confined to formerly protected areas (e.g., blue/red shades for Cropland/Nature respectively in Fig. 6 are found across the entire study area).

However, although inter-annual variation in land area outputs for scenarios is similar to that for tests (i.e. relatively low, with smooth transitions), it is much greater for production outputs. Greater inter-annual variation in production for scenario simulations is a result of variation in precipitation and temperature from GCM outputs which directly influence Moisture capitals, and therefore agricultural service provision. Of particular note is the large drop in production for *EXT* and *EXT-NP* scenarios (based on GCM output for RCP85*)* in the final year of the simulation, the result of a deep and widespread decrease in annual precipitation in GCM outputs. This drop in production does not produce a commensurate change in land cover (in the same year) as there is a lag in agent decision-making (e.g., to abandon land). The lag in decision-making can be seen in the noticeable decrease in Pasture and increase in Nature land covers (indicating Pasture abandonment) simulated in 2034 for the BAU scenario. This abandonment of Pasture is the result of consecutive years of low precipitation which also caused a period of relatively low Soybean and Maize production for 2030–2033 compared to 2025–2030, although with no effect on Cropland cover.

4. Discussion and conclusions

4.1. Calibrating CRAFTY

This paper represents one of the first attempts to calibrate the CRAFTY land use/cover modelling framework against observed data. Such an approach has not been used in the past, often because comprehensive data describing Capitals, Demand and spatial distribution of land use are unavailable at the broad (national to continental) scales CRAFTY is designed for (Brown et al., 2019). Other approaches to calibrate CRAFTY have used ‘stability checks’ with baseline inputs to

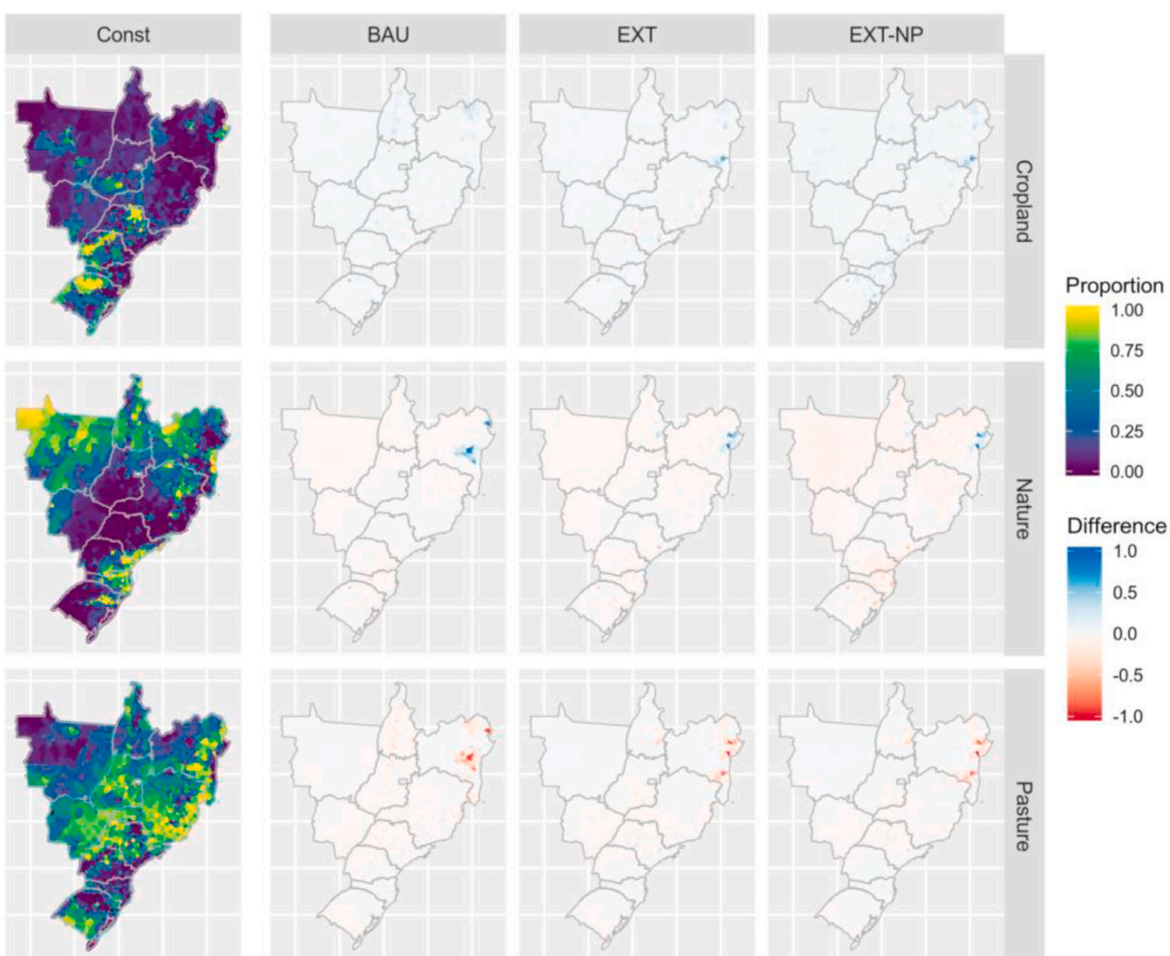

Fig. 6. Spatial variation in outputs for scenarios. Municipality Differences are calculated from Proportions for the *Const* scenario (shown at left) for simulated year 2033. Specification and acronyms for names of scenarios are presented in Table 4.

ensure outputs do not deviate or oscillate wildly from expected behaviour (e.g., Blanco et al., 2017; similar to our *Constant* conditions scenario) or to ensure 'sensible' outputs are produced when starting from a blank map of null land use (e.g., Brown et al., 2019). As described in Section 2.1, we have utilised multiple empirical data sets to enable our approach but have also needed to make assumptions about how data represent different processes. For example, commodity demands in any given year are difficult to assess and for our calibration here we have assumed continuous market clearing such that observed (2001–2018) production perfectly met demand in each year. The value of such a strong but simple assumption during calibration is that it enables clear understanding of the meaning of commodity demand in future scenarios, and matches data that can be readily produced by the System Dynamics model of global trade (based on Warner et al., 2013) that we plan to link with CRAFTY-Brazil. In the hybrid model produced, demand will be modelled endogenously by the System Dynamics model, adding further variation to CRAFTY-Brazil inputs that will need to be appropriately assessed (e.g. via sensitivity analyses).

Our calibration of CRAFTY-Brazil was more successful in reproducing observed aggregate land cover and production values than for the spatial distribution of variables (Figs. 2 and 3), a situation similar to previous applications of CRAFTY (Blanco et al., 2017; Brown et al., 2019). In particular, results from our calibration show Pasture outcompeting Cropland in the centre of the study area and *vice versa* in the north east, neither of which were observed historically. This is surprising as the north east of the study area is relatively marginal for Cropland uses, while the conditions further south and centrally are better. It seems that our calibration allows the marginal utility of the Beef service to increase at a rate faster than Cropland services, pushing the latter to less productive land. Such issues are likely further exacerbated by uncertainty in the land use/cover maps against which we calibrate our model (see section 2.1). Although the MapBiomas data are the best available, the uncertainty in classifying Grassland and 'Mosaics of Agriculture and Pasture' into the classes required for CRAFTY-Brazil may also contribute some level of error in our calibration (Fig. 3).

4.2. Tests and scenarios

Tests of the model using standard differences in model inputs (+/-20% of 2018 values) shows that production is insensitive to inputs (outputs vary by <20% or ~20%), but that land cover change is more sensitive (some change is >20%). All tests result in large (>20%) decreases in maize land area (with smaller, but also often large changes in Soy) due to large increases in double-cropping area. This shift away from maize-only land use is to be expected both due to intended model logic and observed (and expected) empirical shifts to double-cropping systems. More obvious in the time-series of land cover (Fig. 4) are the large simulated shifts in Nature in tests that represent decreased demand (*Dem-All-Decr* and *Dem-NNat-Decr* in Fig. 4a and b) or increasing yield (*Yield-Incr* in Fig. 4c). These shifts are due to abandonment of agricultural land (crops and pasture), which in our model logic then becomes Nature. Abandonment in these tests is driven by decreased demand in agricultural services (in the case of the demand tests), or a decreased pressure on land for agriculture due to increasing yields which in-turn means less land needed to meet the same demand (in the case of the *Yield-Incr* test). Land cover in other tests is relatively insensitive because of competition for land between services. In the *Dem-NNat-Incr* test for example, constant 2018 yields means that commodity production never reaches the required demand in these scenarios. Hence, production and land cover time series differ little from those seen in the *Constant* test as production is already at its limit at the start of simulations given the calibrated yield values. In contrast, when yields increase through time (*Yield-Incr* test), less land is needed for Pasture land to meet Beef demand and much is abandoned (reverting to Nature land cover). Yield increases in pasture and crops produce what previous studies defined as 'land sparing' where the increased volume of production per land unit (i.e., agricultural intensification) leads to a decrease in cropland, or at least alleviating the pressure for cropland expansion (Angelsen and Kaimowitz 2001; Hertel et al., 2014). In this test, production of all products is able to meet (the constant 2018) demand because of the high yields, resulting in production timeseries that flatline.

Scenarios were designed to enable examination of both the effects of variations in multiple input factors and potential alternative futures. For example, for all three scenarios we see inter-annual variability in Soybean and Maize production (due to climate) but with differing overall trend (due to variation between scenarios in yield and demand), a combined pattern we do not see in the tests. The *EXT-NP* scenario results in greatest agricultural production (and lowest Nature land area) as the ability to farm (formerly) protected areas plus decreased demand for Nature land allow greatest shifts in land from Nature to Cropland and Pasture. However, increases in Cropland and Pasture land in the *EXT-NP* scenario are not spatially confined to formerly protected areas as might have been expected. This is likely because these protected areas have relatively limited infrastructure, which is considered invariant through time in the *EXT-NP* scenario. With many of the indigenous and park lands some distance from the 'core' agricultural production areas and much pasture and other non-protected land available for conversion (processes also represented in the model), even under the scenarios we examine there is little pressure on the current protected areas. However, this is a general trend for the entire study area, which may be different in particular local realities (i.e., conservation areas that already suffer land use pressure). Furthermore, if restrictions on land use in protected areas really are relaxed (e.g. Abessa et al., 2019) we might expect improvements in infrastructure (e.g., road building), which may in-turn lead to a positive feedback and greater exploitation of these areas over the longer term (e.g., Weinhold and Reis 2008). Furthermore, in our scenarios demand for Nature is specified as an overall percentage change to reflect possible trajectories of policy or socio-economic change that value ecosystem. Demand for ecosystem services as implicitly provided by our Nature service is difficult to estimate (Carpenter et al., 2009; Hayha et al., 2015; Brown et al., 2017). This is reflected in the fact that while projections of future demand for agricultural commodities are regularly generated by formal government institutions (e.g., MAPA 2020), aligned projections of demand for ecosystem services are not common. Aligned projections of agricultural (e.g. soybeans) and non-agricultural (e.g. carbon sequestration) land benefits would improve our ability to model future scenarios, particularly with respect to demand for the Nature service.

Comparing results for scenarios with those for tests highlights qualitative differences in spatio-temporal variation. Tests used simple, temporally-uniform and spatially-invariant rates of change based on observed values, whereas scenarios used precipitation and temperature outputs from GCMs (to provide Moisture capitals values) which have much greater inter-annual variability (Fig. 4e). The qualitative differences in input time-series demonstrates a strong influence of climate inputs on production outputs, but not on land cover change. The inter-annual variability in production in our modelling is not sufficient for land cover change to occur through abandonment (as discussed by Silva et al., 2020), but many fine details of farm-level financing that may be vital for individual farm viability are not represented in this model and so we cannot conclusively argue that land cover change would not occur under the climate projections we have examined.

Spatially, land change is generally diffuse but with some focused regions of change. Tests that produce large increases in Nature area indicate greatest decreases in pasture and cropland in north east and south west regions, respectively, where these are initially (in 2018) widespread. These are prone to greatest decreases as Pasture land in the north east areas are the most marginal (with historically low stocking rates; e.g. Dias-Filho 2014) whereas the south-west is initially dominated by dense Cropland (and so has most to lose). Furthermore, this is also the region that was most poorly modelled during calibration and as above (section 4.1) we suspect land classification challenges (confusion between pasture, grassland, and pasture/agriculture mosaic) in the MapBiomas input data (MapBiomas 2019b) also play a role here. For similar reasons, spatial change is quite dispersed across the study area but with intense change in a focused region in the north east of the study area (in Bahia state), again with switches from Pasture to Nature.

4.3. Agency-based modelling

The tradeoffs necessary in spatial agent-based modelling of land-use systems have been well identified in the literature, in particular with respect to a perceived spectrum from empirically-grounded and complicated models to theoretically-focused and simple models (e.g., O'Sullivan et al., 2015; Sun et al., 2016). Here, our approach has been to build on the theoretical structure provided by the CRAFTY framework and remain relatively conceptually simple, but also incorporating empirical data where possible to ground our application for Brazil. In doing so, this version of CRAFTY-Brazil limited the number of agent-functional types and services represented (eight services aggregated to four land use/cover types) and yet this still required the representation of a greater number of capitals (15) and processes (multiple, including the accrual of debt) than we had initially expected. A limited number of AFTs may seem to produce what Sayer (1992, p.138) termed a 'chaotic conception', a group of agent-types that artificially "lump together the unrelated and the inessential" and inadequately represent differences between real world actors that are needed to reproduce empirical events. However, given that our model is implemented at a spatial resolution of 5 km, CRAFTY-Brazil does not represent individual actors as individuated agents but instead aggregates actors across space into grid cells within which human agency is represented by an AFT. This representation means CRAFTY-Brazil should be thought of as an *agency*-based model representing the behaviour of aggregate human actions rather than an agent-based model representing individual actors' activities (e.g. such as that developed by Dou et al., 2019). Furthermore, working with relatively coarse AFT representations aligns with the relatively coarse spatial representation that inherently lumps multiple real world actors together. The aggregation of 27 land types defined at 30 m spatial resolution to four types at 5 km (Appendix A) is robust given that the original classification was hierarchical, that we have aligned our reclassification on that hierarchy, and that we made further analyses of variability (see section 2.1 and Millington 2019).

Although appropriate for the scales we are working at, the combination of this agency approach with constraints of the CRAFTY framework presents challenges to representing some processes that influence land decision-making of individual actors in our study area. For example, the design of the CRAFTY framework to ensure computational efficiency means that the history of simulated agents is not retained and that agents cannot anticipate change beyond the next time step. We modified the CRAFTY source code to enable some coarse representation of temporally contingent processes (i.e. the debt that farmers incur when setting up a new farm; section 2.2) on the agency of multiple aggregated actors. However, the agency approach combined with the difficulty of tracking history and representing planning strategies presents a challenge for representing the processes that trap producers in cycles of debt and investment (Silva et al., 2020). This combination also limits our ability to understand possible vulnerabilities and responses of producers to temporal (e.g. inter-annual) variability in climate or other exogenous factors (as highlighted above). Such questions cannot be examined without incorporating representation of history and planning and/or working at finer aggregations and scales (such that individual actors are represented by individuated agents, for example). Readers considering their own agent-based modelling projects, whether focused on land use or other environmental issues, might learn from this example about aligning scale and detail of conceptualisation. In particular, we suggest readers compare our broad-scale agency-based approach for modelling soy and maize to the finer scale and explicitly agent-based approached taken by Dou et al. (2019) to consider for themselves the advantages and disadvantages of the different approaches at the different scales. Our modelling will continue to focus on broader-scale issues as we dynamically couple CRAFTY-Brazil to a System Dynamics model to create a hybrid simulation model for examining the land use impacts of telecoupled global trade (Millington et al., 2017; Liu et al., 2018).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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We are grateful to numerous colleagues for ideas and understanding gained from discussion on the subjects presented here. These include, but are not limited to, Steve Peterson, Jem Woods, Hang Xiong, Yue Dou and Jack Liu plus several local stakeholders in Brazil. We are grateful to Paul McCord for his early work with MapBiomas data. Thanks also to several anonymous reviewers for their comments which helped improve the manuscript.

Appendix A. MapBiomas v4.0 Reclassification

Code and Description are from MapBiomas, Reclassification is used here. Note that Cropland are further disaggregated into Soy, Maize and Other Crops using planted area data. Scripts used to resample, reclassify and disaggregated the MapBiomas data are available in Millington (2019).

Code	Description	Reclassification
1	Forest Formations	Nature
1.1	Natural Forest Formations	Nature
1.1.1	Dense Forest	Nature
1.1.2	Open Forest	Nature
1.1.3	Mangrove	Nature
1.2	Forest Plantations	Nature
2	Non-Forest Natural Formations	Nature
2.1	Non-Forest Formations in Wetlands	Nature
2.2	Grassland	Pasture (Nature in protected areas)
2.3	Salt Flat	Nature
2.4	Rocky Outcrop	Other
2.5	Other non-forest natural formations	Other
3	Farming	Cropland

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Code	Description	Reclassification
3.1	Pasture	Pasture
3.2	Agriculture	Cropland
3.2.1	Annual and Perennial Crop	Cropland
3.2.2	Semi-perennial Crop	Cropland
3.3	Mosaic of Agriculture and Pasture	Cropland
4	Non-Vegetated Areas	Other
4.1	Beaches and Dunes	Other
4.2	Urban Infrastructure	Other
4.3	Mining	Other
4.4	Other Non-Vegetated Area	Other
5	Water Bodies	Other
5.1	River, Lake and Ocean	Other
5.2	Aquaculture	Other
6	Not Observed	Other

Appendix B. Debt

Debt incurred by agents following land use change. Units are years.

Previous Land Use	Cropland Agent	Pasture Agent
Nature or Other	5	3
Soybean, Maize or Other Crops	3	3
Double-Cropping	0	3
Pasture	4	NA

Appendix C. Production Functions

Capitals, Agent-Functional Types and their production weighting factors for each Service.

a) Soybean AFT

	Soybean	Maize	Nature	OCrops	Other	Beef
Moisture-Main	0.8	0	0	0	0	0
Moisture-Second	0	0	0	0	0	0
Transport	0.5	0	0	0	0	0
Land Value	0	0	0	0	0	0
Conservation	0	0	0	0	0	0
Tech-Soy-Maize	0.8	0	0	0	0	0
Tech-Pasture	0	0	0	0	0	0
Other	0	0	0	0	0	0
Protection-Soy	1	0	0	0	0	0
Protection-Maize	0	0	0	0	0	0
Protection-Beef	0	0	0	0	0	0
Protection-OCrop	0	0	0	0	0	0
Access-Nature	1	0	0	0	0	0
Access-Soy-Maize	0.4	0	0	0	0	0
Access-OCrop	0	0	0	0	0	0
Production	*1*	*0*	*0*	*0*	*0*	*0*

b) Maize AFT

	Soybean	Maize	Nature	OCrops	Other	Beef
Moisture-Main	0	0.8	0	0	0	0
Moisture-Second	0	0	0	0	0	0
Transport	0	0.5	0	0	0	0
Land Value	0	0	0	0	0	0
Conservation	0	0	0	0	0	0
Tech-Soy-Maize	0	0.8	0	0	0	0
Tech-Pasture	0	0	0	0	0	0
Other	0	0	0	0	0	0
Protection-Soy	0	0	0	0	0	0
Protection-Maize	0	1	0	0	0	0
Protection-Beef	0	0	0	0	0	0
Protection-OCrop	0	0	0	0	0	0
Access-Nature	0	1	0	0	0	0
Access-Soy-Maize	0	0.4	0	0	0	0

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(*continued*)

b) Maize AFT

	Soybean	Maize	Nature	OCrops	Other	Beef
Access-OCrop	0	0	0	0	0	0
Production	*0*	*1*	*0*	*0*	*0*	*0*

c) Double-Crop AFT

	Soybean	Maize	Nature	OCrops	Other	Beef
Moisture-Main	0.8	0	0	0	0	0
Moisture-Second	0	0.5	0	0	0	0
Transport	0.5	0.5	0	0	0	0
Land Value	0	0	0	0	0	0
Conservation	0	0	0	0	0	0
Tech-Soy-Maize	0.8	0.8	0	0	0	0
Tech-Pasture	0	0	0	0	0	0
Other	0	0	0	0	0	0
Protection-Soy	1	0	0	0	0	0
Protection-Maize	0	1	0	0	0	0
Protection-Beef	0	0	0	0	0	0
Protection-OCrop	0	0	0	0	0	0
Access-Nature	1	1	0	0	0	0
Access-Soy-Maize	0.4	0.4	0	0	0	0
Access-OCrop	0	0	0	0	0	0
Production	*0.8*	*0.75*	*0*	*0*	*0*	*0*

d) Nature AFT

	Soybean	Maize	Nature	OCrops	Other	Beef
Moisture-Main	0	0	0	0	0	0
Moisture-Second	0	0	0	0	0	0
Transport	0	0	0	0	0	0
Land Value	0	0	1	0	0	0
Conservation	0	0	1	0	0	0
Tech-Soy-Maize	0	0	0	0	0	0
Tech-Pasture	0	0	0	0	0	0
Other	0	0	0	0	0	0
Protection-Soy	0	0	0	0	0	0
Protection-Maize	0	0	0	0	0	0
Protection-Beef	0	0	0	0	0	0
Protection-OCrop	0	0	0	0	0	0
Access-Nature	0	0	0	0	0	0
Access-Soy-Maize	0	0	0	0	0	0
Access-OCrop	0	0	0	0	0	0
Production	*0*	*0*	*1*	*0*	*0*	*0*

e) Other Crops AFT

	Soybean	Maize	Nature	OCrops	Other	Beef
Moisture-Main	0	0	0	0.8	0	0
Moisture-Second	0	0	0	0	0	0
Transport	0	0	0	0.5	0	0
Land Value	0	0	0	0	0	0
Conservation	0	0	0	0	0	0
Tech-Soy-Maize	0	0	0	0	0	0
Tech-Pasture	0	0	0	0	0	0
Other	0	0	0	0	0	0
Protection-Soy	0	0	0	0	0	0
Protection-Maize	0	0	0	0	0	0
Protection-Beef	0	0	0	0	0	0
Protection-OCrop	0	0	0	1	0	0
Access-Nature	0	0	0	0	0	0
Access-Soy-Maize	0	0	0	0	0	0
Access-OCrop	0	0	0	1	0	0
Production	*0*	*0*	*0*	*1*	*0*	*0*

f) Other AFT

	Soybean	Maize	Nature	OCrops	Other	Beef
Moisture-Main	0	0	0	0	0	0
Moisture-Second	0	0	0	0	0	0
Transport	0	0	0	0	0	0
Land Value	0	0	0	0	0	0
Conservation	0	0	0	0	0	0
Tech-Soy-Maize	0	0	0	0	0	0
Tech-Pasture	0	0	0	0	0	0
Other	0	0	0	0	1	0
Protection-Soy	0	0	0	0	1	0
Protection-Maize	0	0	0	0	1	0
Protection-Beef	0	0	0	0	1	0

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(*continued*)

f) Other AFT	Soybean	Maize	Nature	OCrops	Other	Beef
Protection-OCrop	0	0	0	0	1	0
Access-Nature	0	0	0	0	0	0
Access-Soy-Maize	0	0	0	0	0	0
Access-OCrop	0	0	0	0	0	0
Production	*0*	*0*	*0*	*0*	*1*	*0*

g) Pasture AFT	Soybean	Maize	Nature	OCrops	Other	Beef
Moisture-Main	0	0	0	0	0	0.2
Moisture-Second	0	0	0	0	0	0
Transport	0	0	0	0	0	0.5
Land Value	0	0	0	0	0	0
Conservation	0	0	0	0	0	0
Tech-Soy-Maize	0	0	0	0	0	0
Tech-Pasture	0	0	0	0	0	1
Other	0	0	0	0	0	0
Protection-Soy	0	0	0	0	0	0
Protection-Maize	0	0	0	0	0	0
Protection-Beef	0	0	0	0	0	1
Protection-OCrop	0	0	0	0	0	0
Access-Nature	0	0	0	0	0	0.2
Access-Soy-Maize	0	0	0	0	0	0
Access-OCrop	0	0	0	0	0	0
Production	*0*	*0*	*0*	*0*	*0*	*0.85*

Appendix D. Demand and Yield Projections

Values are % annual change, derived from MAPA (2020), used in scenarios specified in Table 4.

a) Demand

	Soy and Maize		*Beef*	
Year	*Standard*	*Upper*	*Standard*	*Upper*
2019	2.19	3.67	1.53	3.14
2020	2.19	3.67	1.53	3.14
2021	−1.34	3.67	2.89	7.81
2022	3.15	5.41	−0.30	2.46
2023	2.86	4.43	1.52	3.58
2024	2.68	4.09	5.26	6.50
2025	2.67	3.82	−2.14	−0.69
2026	2.51	3.41	−0.08	0.87
2027	2.44	3.22	3.85	4.26
2028	2.38	3.06	2.07	2.76
2029	2.32	2.89	−1.09	0.01
2030	2.25	2.75	3.37	3.84
2031	2.20	2.65	1.50	3.14
2032	2.15	2.55	1.50	3.14
2033	2.10	2.45	1.50	3.14
2034	2.05	2.35	1.50	3.14
2035	2.00	2.25	1.50	3.14

b) Yield

Year	*Soy and Maize*		*Beef*	
	Standard	*Upper*	*Standard*	*Upper*
2019	0.78	1.66	1.52	2.67
2020	0.78	1.66	1.52	2.67
2021	−1.51	1.66	1.66	5.50
2022	1.23	2.26	1.52	4.25
2023	1.10	2.14	1.08	3.26
2024	1.10	1.88	3.75	5.12
2025	1.05	1.72	−1.97	−1.22
2026	1.02	1.58	1.68	1.76
2027	0.99	1.47	1.71	1.77
2028	0.96	1.37	1.90	1.90
2029	0.93	1.28	0.53	0.79
2030	0.91	1.21	3.39	3.59
2031	0.89	1.16	1.50	2.67

(*continued on next page*)

(*continued*)

b) Yield				
Year	*Soy and Maize*		*Beef*	
	Standard	*Upper*	*Standard*	*Upper*
2032	0.87	1.11	1.50	2.67
2033	0.85	1.06	1.50	2.67
2034	0.83	1.01	1.50	2.67
2035	0.81	0.96	1.50	2.67

Software and data availability

Code for both the simulation model and our data analysis is freely available online; we refer to the relevant GitHub repositories in the text at the appropriate points. The model can be deployed via Docker using (Lane and Millington, 2021). Also see (Victoria et al., 2021).

Author contributions

Conceptualization, All authors; Software, JM and VK; Formal Analysis, JM, RBS and DCV; Data Curation, JM, RBS and DCV; Writing – Original Draft Preparation, JM; Writing – Review & Editing, JM, DCV, RBS and MB.

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