

# **COSMETIC STORE MANAGEMENT**

**SALESFORCE NAAN MUDHALVAN**

**PROJECT REPORT**

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***in partial fulfilment for the award of the***

***degree of***

**BACHELOR OF ENGINEERING**

**COMPUTER SCIENCE AND ENGINEERING**

**MAHENDRA ENGINEERING  
COLLEGE FOR WOMEN**

**TIRUCHENGODE,NAMAKKAL-**

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Received: 20 November 2018 – Discussion started: 7 December 2018

Revised: 21 February 2019 – Accepted: 5 March 2019 – Published: 3 April 2019

**Abstract.** The open-source modeling framework MAgPIE (Model of Agricultural Production and its Impact on the Environment) combines economic and biophysical approaches to simulate spatially explicit global scenarios of land use within the 21st century and the respective interactions with the environment. Besides various other projects, it was used to simulate marker scenarios of the Shared Socioeconomic Pathways (SSPs) and contributed substantially to multiple IPCC assessments. However, with growing scope and detail, the non-linear model has become increasingly complex, computationally intensive and non-transparent, requiring structured approaches to improve the development and evaluation of the model.

Here, we provide an overview on version 4 of MAgPIE and how it addresses these issues of increasing complexity using new technical features: modular structure with exchangeable module implementations, flexible spatial resolution, in-code documentation, automatized code checking, model/output evaluation and open accessibility. Application examples provide insights into model evaluation, modular flexibility and region-specific analysis approaches. While this paper is focused on the general framework as such, the

publication is accompanied by a detailed model documentation describing contents and equations, and by model evaluation documents giving insights into model performance for a broad range of variables.

With the open-source release of the MAgPIE 4 framework, we hope to contribute to more transparent, reproducible and collaborative research in the field. Due to its modularity and spatial flexibility, it should provide a basis for a broad range of land-related research with economic or biophysical, global or regional focus.

## 1 Introduction

Global land use is expected to undergo major changes over the coming decades caused by population growth, climate change, climate change mitigation and various other socio-economic changes. Climate change has already had significant impacts on crop yields (Lobell et al., 2011; Rosenzweig et al., 2014), water availability (Strzepek and Boehlert, 2010) and biodiversity distribution (Foden et al., 2013). Mitigation of climate change could entail large repercussions on



the land-use system (Popp et al., 2017) by implementing strategies such as bioenergy mandates (Humpenöder et al., 2018), afforestation policies (Humpenöder et al., 2014) or induced changes in dietary habits (Stevanović et al., 2017). The land-use sector is also affected by the prospects of demographic and economic changes, including the increase in demand for agricultural products (Alexandros and Bruinsma, 2012; Bodirsky et al., 2015). Finally, the global political discourse framed by the Sustainable Development Goals (SDGs) (United Nations, 2015) will most likely cause further transformations of the land-use sector (Humpenöder et al., 2018; Pradhan et al., 2017).

In light of these challenges, methodological tools that quantify and analyze such effects and inform decision makers are required. To this end, models such as GCAM (Wise et al., 2014), AIM (Fujimori et al., 2017), GLOBIOM (Havlík et al., 2014; Kindermann et al., 2006), IMAGE (Stehfest et al., 2014), MAgPIE (Lotze-Campen et al., 2008) and others are being developed. They combine biophysical (e.g., plant growth, land availability, water cycles) and economic (e.g., trade, production costs, policies) aspects and can be applied to a broad set of questions. Driven by the motivation to comprehensively represent many interactions and consequences of land-use and land-related processes, these models have become more detailed and complex over time. Moreover, the range of questions and applications has become wider. These advancements come with the burden of increased computational requirements and increased challenges in manageability and transparency. New approaches are required to make models more manageable, efficient and open.

This paper presents the MAgPIE 4 (Model of Agricultural Production and its Impact on the Environment 4) modeling framework which has been built to cope with the aforementioned challenges of complexity, manageability and transparency. The framework addresses these challenges via two conceptual foundations; it rests on modularity and flexibility in the level of detail.

Modularity denotes the concept of building a model as a network of separate modules reflecting its different components, instead of handling the model as a whole. A module can have different realizations, each of which gives a different representation of the subsystem it models. Building the model as a network of modules eases the understanding of the model as well as the modification of components of it.

Flexibility in the level of detail means adjusting the temporal and spatial resolution. It also means that module realizations can be chosen based on the research question and thereby adjusting the model complexity appropriately.

The flexibility and the modular concept enable a tailor-made setup of simulations consistent with the spatial, temporal and contextual scope of the analysis. It allows for reducing complexity where it is not needed and increasing simulation detail where it makes a difference. The resulting indefiniteness in model specification is reflected by a shift in termi-

nology from model (MAgPIE before version 4) to framework (MAgPIE 4 and beyond), reflecting that very different models of the land-use sector can be built with the same framework.

In the subsequent sections, we present the concept of the modeling framework of MAgPIE 4, starting with a brief description of the model history, the new features in version 4 and a short overview of the modules in version 4. This is followed by a methodological section about the modeling framework explaining its technical properties such as modularity and spatial flexibility. The main text is completed by an output section – showing some specific use case of the modular structure and spatial flexibility provided by the framework – as well as a discussion and conclusion section. Supplementary material provides model code, model documentation and extended evaluation information to better embed the presented work.

## 2 Model features

### 2.1 A brief history of MAgPIE

MAgPIE was first introduced in Lotze-Campen et al. (2008) as a recursive dynamic cost-minimization model, simulating crop production, land-use patterns and water use for irrigation in a spatial resolution of  $3^\circ \times 3^\circ$  and interregional trade between 10 world regions. Spatially explicit biophysical information was derived by a link to the global gridded crop and hydrology Lund–Potsdam–Jena managed Land (LPJmL) model (Bondeau et al., 2007). Prices are implicitly modeled as marginals of the model constraints. Intensification as well as other decisions in the model arise from an interplay of physical constraints and costs associated with activities in the model. While not being versioned at the time of publication, this variant is ex-post referred to as “version 1”. Follow-up publications based on version 1 introduced different categories of unmanaged land such as undisturbed natural forests (Krause et al., 2009, 2013). Intra-regional transport costs accounting for the travel distance to the nearest market were also introduced in this version (Krause et al., 2013). Further additions included bioenergy production (Lotze-Campen et al., 2010), CO<sub>2</sub> emissions from land-use change (Popp et al., 2012) and agricultural non-CO<sub>2</sub> greenhouse gases (Popp et al., 2010, 2011b). Moreover, this early version of MAgPIE was already coupled to an energy-system model by exchanging price and demand information on bioenergy, thereby establishing the integrated assessment modeling framework REMIND-MAgPIE (Popp et al., 2011a).

Version 2 of the model was the first step towards spatial flexibility. The spatial  $3^\circ \times 3^\circ$  cells were replaced by clusters, which are aggregates of spatial  $0.5^\circ \times 0.5^\circ$  grid cells with similar properties. Moving from cells to clusters improved



both accuracy and model performance at the same time (Dietrich et al., 2013).

In terms of content, version 2 introduced endogenous yield increases through investments into research and development (Dietrich et al., 2014), a more detailed estimation of food demand (Bodirsky et al., 2012, 2015) and marginal abatement cost curves (MACCs) to model technical greenhouse gas (GHG) emission abatement (Popp et al., 2010; Lucas et al., 2007). The livestock sector was modeled in more detail based on livestock and region-specific feed baskets (Bodirsky et al., 2012; Schmitz et al., 2012; Weindl et al., 2010, 2015). Moreover, the scope of the model was further broadened by accounting for climate impacts on cropland and pasture productivity, their implications for land-use dynamics and agricultural production costs and possible adaptation options (Weindl et al., 2015). In addition, MAgPIE was extended by a comprehensive representation of biomass and nitrogen flows in agriculture and upstream in the food supply chain, covering, for example, nitrogen budgets of cropland soils, the production and different uses of crop residues and conversion byproducts, animal waste management systems and soil organic carbon accounting (Bodirsky et al., 2014, 2012). Moreover, while MAgPIE 1 only simulated a single baseline scenario, MAgPIE 2 translated the Special Report on Emissions Scenarios (SRES) storylines (Nakicenovic et al., 2000) into multiple scenarios with diverging drivers and scenario assumptions (Bodirsky et al., 2015, 2012). The representation of agricultural water use and water scarcity was strengthened by accounting for changes in irrigation efficiency over time (Schmitz et al., 2013) and by differentiating between green and blue water consumption (Biewald et al., 2014).

Structurally, the next evolution came with version 3 introducing the concept of modules, allowing to split the code into thematic components and to have different realizations of the same component. Content-related extensions in version 3 were the introduction of afforestation as a climate mitigation measure that is endogenously calculated and incentivized by a tax on GHG emissions (Humpenöder et al., 2015, 2014), the endogenous simulation of future pasture area driven by feed demand and opportunity costs of grazing land (Popp et al., 2014), and dynamic feed baskets where feed efficiency and feed composition depend on livestock productivity trajectories (Weindl et al., 2017a, b). Model capacities with regard to agricultural water use were further improved by the inclusion of annual costs for irrigation (e.g., for water, fuel, labor and the maintenance of irrigation infrastructure), the exogenous representation of non-agricultural water demand for domestic use, industry and electricity production, the implementation of environmental flow requirements and the calculation of the annual volume of available irrigation water considering seasonal variations, growing periods of crops and water storage facilities provided by dams (Bonsch et al., 2014, 2015). The evaluation of climate impacts and mitigation measures was deepened across a broad range

of studies using MAgPIE version 3, where an increasing emphasis was placed on socioeconomic indicators such as food prices (Kreidenweis et al., 2016) and agricultural welfare (Stevanović et al., 2016). In addition, governance scenarios were incorporated into the model by using lending interest rates as discount rates to represent risk-accounting factors (Wang et al., 2016). The increasing complexity and scope of the model also allowed for multi-criteria sustainability assessments, e.g., regarding large-scale bioenergy production (Humpenöder et al., 2018). This is an important model feature that allows to address research questions in the context of the SDGs. The model was also used in the assessment of climate policy entry points to mitigation pathways consistent with the Paris Climate Agreement goals (UNFCCC, 2015). To that end, MAgPIE was broadened to represent near-term policies given by nationally determined contributions (NDCs) and covering land-based national targets for avoiding deforestation and targeted afforestation (Kriegler et al., 2018).

Linked to the global gridded crop model LPJmL (Bondeau et al., 2007) and coupled with the energy and macroeconomic model REMIND (Popp et al., 2011a), MAgPIE began to form the Potsdam Integrated Assessment Modeling (PIAM) framework (Kriegler and Lucht, 2015). MAgPIE 3 coupled with REMIND was among the Integrated Assessment Models (IAMs) that were applied to translate the storylines of the SSPs into quantitative scenarios of possible societal developments, e.g., land-use and energy futures (Bauer et al., 2017; Kriegler et al., 2017; Popp et al., 2017).


## 2.2 New features in MAgPIE4


While the modularization concept was introduced with version 3, the code was only partly modularized and a full modularization was only achieved with version 4 of the model. In addition to the modularization, version 4 increases spatial flexibility by introducing the concept of flexible regions. In addition to the flexible number of clusters within a world region, it allows the user to freely choose the number and shape of world regions to be simulated in the model. While all previous model versions were limited to the regional aggregation introduced in version 1, it is now possible to choose a regional aggregation, with the country level (ISO 3166-1:2013) as the highest possible level of detail. The combination of full modularization and additional spatial flexibility in version 4 also marks the transition from model to modeling framework.


Content-wise, MAgPIE 4 includes a new food-demand module, which couples MAgPIE 4 iteratively with a stand-alone food-demand model. The module estimates the distribution of body mass index, height and food intake by age group, sex and country. Moreover, it estimates food waste and a more detailed dietary composition. For a given level of income, changes in food prices affect food demand through their effects on purchasing power. Furthermore, version 4 includes a more detailed representation of food processing.





 *Climate* provides information on climate zones for other modules.


 *Nr soil budget* estimates cropland and pasture soil nitrogen budgets, including withdrawal of nutrients by harvested biomass, biological fixation, crop residue management, manure application, inorganic fertilizer, atmospheric deposition and soil organic matter loss (Bodirsky et al., 2012).


 *Nitrogen* estimates nitrogen-related emissions in the forms of  $N_2O$ ,  $NH_3$ ,  $NO_x$ ,  $NO_3$  and  $N_2$  from managed soils and animal waste management (Bodirsky et al., 2012).


 *Carbon* estimates terrestrial carbon stock changes and emissions, aggregating over different land cover types (Popp et al., 2014).


 *Methane* estimates methane emissions from enteric fermentation, rice cultivation and animal waste management.

 *AWMS* calculates the nutrient flows within animal waste management systems (AWMSs) (Bodirsky et al., 2012).


 *GHG policy* simulates the impacts of taxing GHG emissions, air pollutants and water pollutants. It estimates anticipated future benefits of mitigation (Humpenöder et al., 2014).


 *MACCs* estimates the impact of GHG abatement technologies on emissions based on prescribed marginal abatement cost curves (MACCs) and computes mitigation costs.


 *SOM* estimates the change in soil organic matter under changing land cover and soil management (Bodirsky et al., 2012).

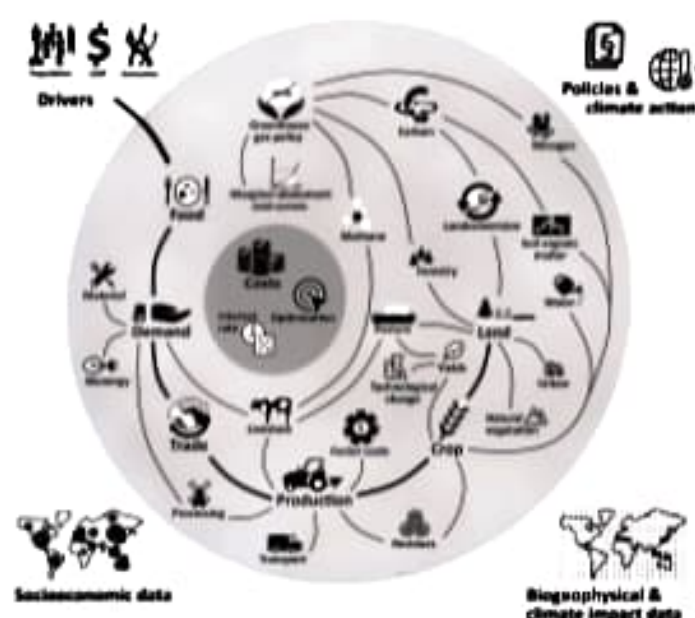
 *Bioenergy* derives the demand for first- and second-generation bioenergy (Lotze-Campen et al., 2010; Klein et al., 2014).

 *Material* derives the demand for non-energy material usage of bio-based products.

 *Livestock* estimates the feed demand under consideration of the produced livestock products accounting for changing feed mix and feed conversion efficiencies under exogenous increases in livestock productivity. It estimates costs of livestock production but excluding costs for feed which are already accounted in other modules (Weindl et al., 2017a, b).

 *Disagg lvt* distributes regional livestock production spatially among all cells belonging to this region by linking it to fodder or pasture production as well as urban areas.

 *Optimization* minimizes total costs of the optimization problem for each time step using different optimization strategies to reduce runtime.

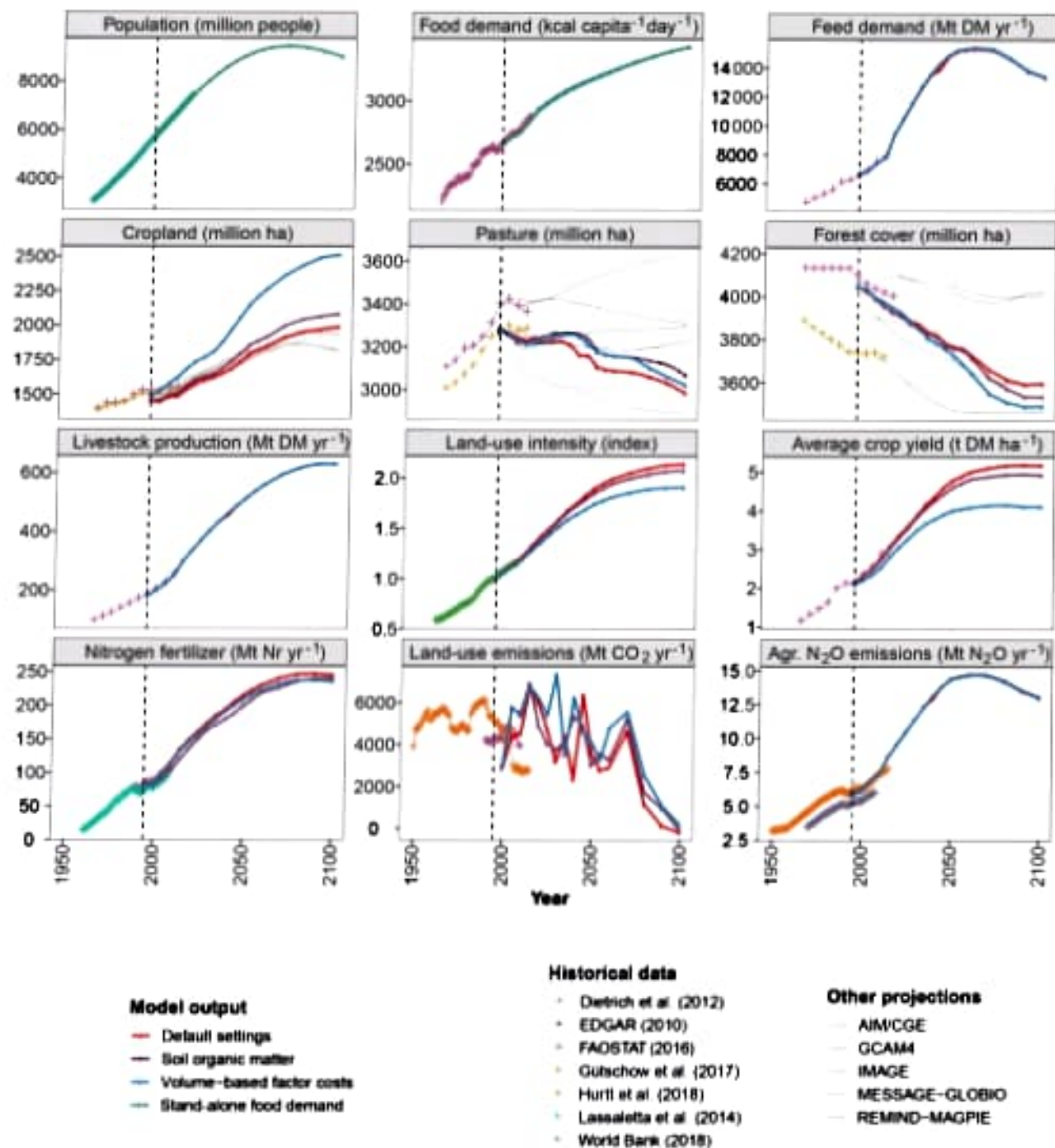


**Figure 1.** MAgPIE 4 framework with simplified modular structure and module interactions. See the model documentation (Dietrich et al., 2018d) for a more detailed presentation of module interactions and their implementations.

Figure 1 provides a simplified visualization of the module interactions in the MAgPIE 4 framework. Simplification was required due to the vast number of existing interfaces and modules. Therefore, the figure only shows the most important linkages and modules or module groups in terms of relevance to the framework or representation of the underlying concept. An exact representation of all interfaces and modules can be found in the technical model documentation (Dietrich et al., 2018d). If modules are not directly linked, it does not mean that they do not interact with each other. In some cases, the feedback loops go through a combination of modules rather than being direct links. An example is the livestock module, which is triggering feed demand in the demand module, which is, via the trade and production module, triggering production in the crop module.

### 3 Framework architecture

The framework consists of two layers. An outer layer written in R (R Core Team, 2017) handles the pre- and post-processing of data, manages and applies model configurations and initial calibrations. It also adjusts spatial resolutions of model runs and organizes the parallel execution of run ensembles. It includes software libraries for code manipulation and analysis used for preparation and inspection of code in the inner layer (lucode: Dietrich et al., 2018g), packages for general data handling (magclass, lucode, madrat: Dietrich et al., 2018b, c, a), data analysis (gdx, magpie4, magpiesets: Dietrich et al., 2018f; Bodirsky et al., 2018a,



**Figure 2.** Evaluation plots for MAgPIE 4 inputs and outputs for the default settings, a run with soil organic matter explicitly modeled, a run with an alternative factor requirement setup with costs proportional to the production volume and a stand-alone run of the food demand module. Sources of historical data: Dietrich et al. (2012), EDGAR (2010), FAOSTAT (2016), Gütschow et al. (2017), Hurtt et al. (2019), Lassaletta et al. (2014) and World Bank (2018). Sources of other projections for SSP2 reference scenario: IAMC (2016).

ulation provides the total food demand in the model which triggers total feed demand through consumption of livestock products. Also here the identical scenario assumption leads to the same results in all three runs. Differences can be observed in the global land cover and the productivity measures (land-use intensity and average crop yields). Cropland shows higher expansion in the alternative scenarios compared to

the default scenario, while both scenarios show less intensification and lower yields. While the differences are rather small in the case of soil organic matter, the differences are quite pronounced in the alternative factor requirement case. In the case of soil organic matter, this effect is triggered via the natural availability of nitrogen in the soil. Having SOM switched off, the model assumes that all required nitrogen is



provided as fertilizer, while simulating SOM explicitly uncovers the already available nitrogen in the soil. This reduces the overall fertilizer requirements and slightly incentivizes land expansion as it gives the model access to more nitrogen. As the food demand is rather independent of this decision, more land expansion leads to lower intensification requirements, lowering land-use intensity as well as average yields. Having factor requirements primarily linked to the production rather than to the area on which it is produced strongly reduces the incentive in the model to intensify. Area-dependent factor requirements strongly favor high yielding locations for production, giving the model a strong incentive to concentrate production on high productive areas and to further boost productivity via intensification. Production-dependent factor requirements on the other hand do not favor locations based on productivity, making also rather unproductive areas interesting for production and thereby reducing the incentive for intensification. In combination, this leads to significantly higher cropland expansion, higher forest reduction, less intensification and significantly lower crop yields. One can also observe that the difference in average yields is higher than in land-use intensity, owing average yields to drop for two reasons: the lower land-use intensification and the expansion into low productive areas.

CO<sub>2</sub> emissions show strong fluctuations in all scenarios due to missing constraints linking carbon stocks with the goal function of the model (e.g., carbon pricing). This makes it in many cases an arbitrary decision for the optimizer to expand cropland into carbon-rich or carbon-poor areas. Besides its fluctuations, the plot also shows higher overall emissions in the case of volume-based factor costs due to the overall higher expansion of cropland and reduction in forest areas.

## 4.2 Impact of spatial resolution

Figures 3 and 4 feature the spatial flexibility in MAGPIE 4. Compared are two scenarios with identical settings except for the spatial distribution of world regions and choice of clusters.

Figure 3 shows the default regional setup with 12 world regions<sup>1</sup> and 200 clusters. All regions are treated equally in the sense that the distribution of clusters among them follows the same rules and all regions are faced with the same type of constraints in the model.

Figure 4 shows a setup with a specific focus on Brazil. To gain higher spatial detail in Brazil, it comes with a higher number of clusters in total. Brazil (BRA) is simulated as a world region together with its most important trade partners (rest of Latin America (LAM), United States (USA), China (CHA) and Europe (EUR)). The remaining countries,

less relevant for a Brazil-centric study, are merged to a single region (ROW). Furthermore, the cluster allocation of 500 clusters in total has been shifted in favor of Brazil. Roughly 4 times more clusters are allocated to Brazil (306) compared to a default distribution of clusters. At the same time, the ROW region receives only roughly 0.7 times the number of clusters it would usually get (37), leaving room for a balanced number of clusters for all other regions. Detail gained for Brazil is attained with reduced detail for the rest of the world to keep the model complexity manageable for the applied solver.

Figure 5 shows the development of forest cover globally as well as for Latin America as a whole for both model setups. The plots show that the mapping has an effect on the overall forest cover development, both globally and regionally.

Comparison with historical data sets as well as projections on forest cover show that the differences between mappings are rather small compared to the overall uncertainty in these numbers. Nevertheless, a deeper look into the simulations uncovers that the global numbers of the Brazil-centric setup are unreliable, as the reduced deforestation rate compared to the default setup is a consequence of the applied mapping. As the ROW region basically acts as a huge free-trade region, it can fulfill strong demand pressure coming from Sub-Saharan Africa with production from elsewhere, while trade limitations in the default setup limit this exchange and trigger deforestation within Sub-Saharan Africa (Dietrich, 2019b, compare [m4p\\_default\\_validation.pdf](#) p1558 and [m4p\\_brazil\\_validation.pdf](#) p1465).

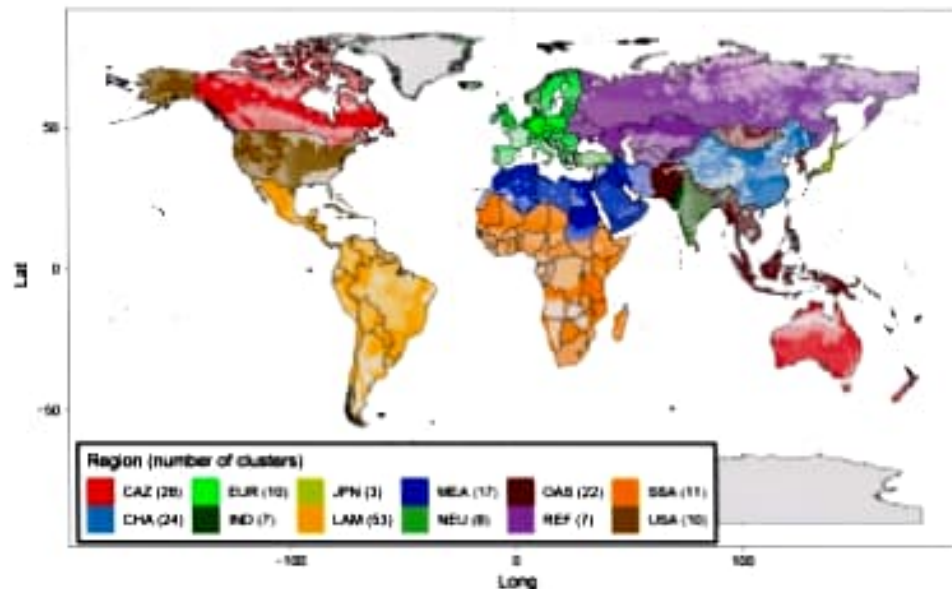
In the case of LAM, both runs show a rather similar picture in the aggregated forest cover projections for the region and it is not possible to clearly reject one of them. This is particularly important as the regional aggregates in LAM are in the scope of both mappings and therefore should be sound. When choosing between them, one has to decide whether spatial details in Brazil or global trade patterns are the more decisive factor for accurate estimates of regional forest cover in LAM.

Looking at forest change patterns in Brazil and neighboring countries between 2000 and 2050, it becomes easier to introduce a ranking between the setups (Fig. 6). While both settings show a tendency towards spatial specialization, this effect is much more pronounced in the default setup. Here, deforestation is nearly exclusively concentrated in Bolivia, Paraguay and south Brazil, along with strong reforestation in the MATOPIBA region (which in reality is Brazil's deforestation frontier) and without deforestation in eastern Brazil. With Brazil-specific settings, the model shows a more balanced behavior. The big deforestation cluster in Bolivia disappears and while deforestation in Brazil primarily takes place in the south, it is less condensed and extends more to the north, which is more consistent with observations.

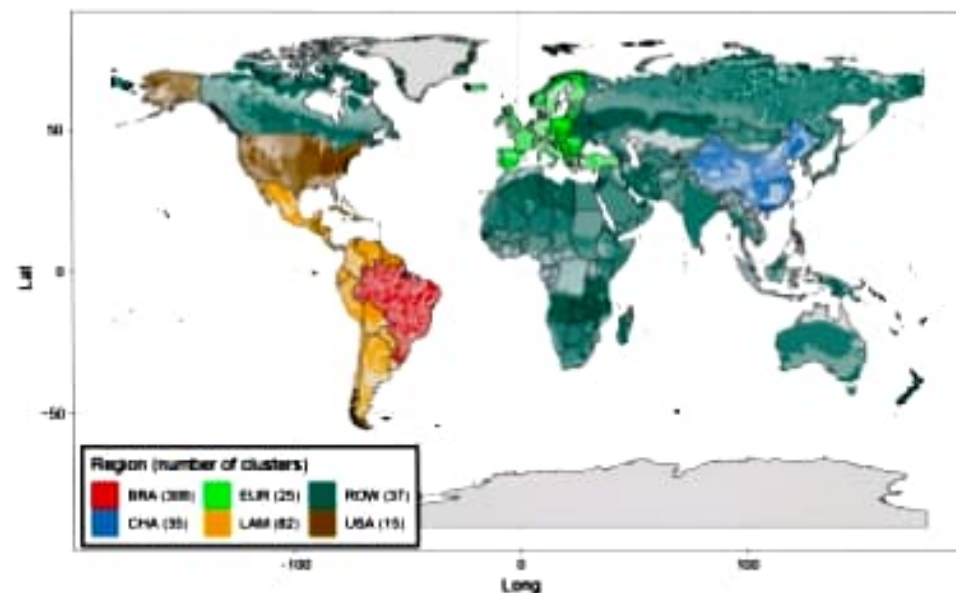
The observed specialization is a consequence of the homogeneous biophysical characteristics within each cluster which lead to either/or decisions in the model. It will either fully take a cluster into production or ignore it completely.

<sup>1</sup>Canada, Australia and New Zealand: CAZ; China: CHA; European Union: EUR; India: IND; Japan: JPN; Latin America: LAM; Middle East and north Africa: MEA; non-EU member states: NEU; other Asia: OAS; reforming countries: REF; Sub-Saharan Africa: SSA; United States: USA.





**Figure 3.** Standard MAGPIE-4 world regions and cluster setup: 12 equally treated world regions with 200 clusters in total.



**Figure 4.** Study setup tailored to assessments with a focus on Brazil, with six world regions and 500 clusters: Brazil (BRA) in increased spatial resolution, its major trade partners Latin America (LAM), United States (USA), China (CHA) and Europe (EUR) in default resolution and the rest of the world (ROW) combined to one region with reduced resolution.

In the default setup, this effect is very pronounced due to the low number of clusters within Latin America. With more clusters, as in the Brazil setup, clusters better grasp the real spatial distributions of biophysical characteristics in the region and therefore lead to a more diverse picture. Whereas this effect is especially relevant for regional studies with a focus on spatial patterns, it is less critical for global dynamics as long as the spatial aggregation is not introducing any systematic biases to the model.

While the Brazil setup improves the spatial representation of Brazil, it is only a first step as deforestation patterns show. As a second step towards a regional study, which is missing in this paper, it is always required to adopt regional distinctiveness into the model, such as region-specific policies relevant at this level of detail for this specific region.



Only the name of the model (`cfg$model`) has to be changed in the configuration file from `main.gms` to the name of the new dummy model.

## Appendix B: Key evaluation examples

For the model evaluation, we set up an extensive database with historical and projected data for the various outputs the model can produce. In Fig. B1, we show evaluation plots for 12 model inputs and outputs and five Shared Socio-economic Pathway (SSP) scenarios at global level (O'Neill et al., 2017). A complete evaluation output for all scenarios shown in this paper can be found in the Supplement (Dietrich, 2019b). The purpose of Fig. B1 is threefold: first, the figure illustrates how the evaluation plot is structured. Second, the evaluation plot for each key land-use variable demonstrates the model performance compared to historical data and other projections at global level. Third, the figure shows how contrasting scenario assumptions based on SSPs 1–5 shape model outputs.

Note that the first three evaluation plots in Fig. B1, population, food demand and feed demand, show model drivers, while the other nine evaluation plots show endogenous model outputs. Checking consistency of the model drivers is done via comparison to alternative data sources. For instance, population projections are taken from the SSP database. Comparing these projections to historical population data from the World Bank (World Bank, 2018) shows that both data sets match with respect to levels and trends for the period 1995–2015. While population is a completely exogenous driver, food and feed demand are calculated endogenously in the model but calibrated to FAOSTAT (FAOSTAT, 2016) until the year 2010. Here, the evaluation plots for food and feed demand show that the calibration routine works as expected and that projections for the coming decades continue recent trends.

Spatially explicit land cover in MAGPIE 4 is initialized with a modified version of the LUH2v2 data set for the year 2000 (Hurt et al., 2019). The main modification is calibration of forest cover to data provided by FAOSTAT at country level. Overall, the land cover dynamics for cropland, pasture and forest produced by the model framework for the period 1995–2015 are comparable with respect to level and trend to LUH2v2 and FAOSTAT (Fig. B1). The land cover projections until 2100 for the five SSP reference scenarios (SSPs 1–5) mainly depend on the underlying socioeconomic assumptions because these reference scenarios include only currently implemented climate policies but not ambitious climate policies such as the global carbon prices needed for the 1.5 or 2° target. For instance, the SSP3 “regional rivalry” scenario with the strongest population growth and limited trade reflects highest cropland expansion and deforestation. In contrast, the SSP1 “sustainability” scenario with declining world

population after 2050 and globalized trade shows a decline in cropland after 2050 along with regrowth of forests.

The evaluation plots for cropland, pasture and forest also show projections from other models for SSP 1–5 reference scenarios (IAMC, 2016). With some exceptions (e.g., cropland expansion in SSP3), the MAGPIE 4 projections for cropland, pasture and forest are mostly within the range of these other projections. Land-use intensity and average crop yields projected by MAGPIE 4 compare well to historical data with respect to level and trend. Annual CO<sub>2</sub> emissions from land-use change is a highly uncertain variable, which is illustrated by the spread of the four different historical sources (Canadell et al., 2007; FAOSTAT, 2016; Harris et al., 2012; Gütschow et al., 2017) included in the respective evaluation plot (Fig. B1). The MAGPIE 4 projections for annual land-use change emissions start at the upper end of these historical data and develop in the future in line with the projected land cover dynamics. For instance, land-use change emissions in the SSP3 scenario remain rather constant until 2100 due to ongoing deforestation for cropland expansion. In contrast, CO<sub>2</sub> emissions in the SSP2 “middle of the road” scenario decline towards zero by 2100 and even become negative in SSP1 after 2050 due to regrowth of forests. Finally, the agricultural N<sub>2</sub>O emissions show again good agreement in level and current trend with comparison data. While projections in SSP1 and SSP4 show a continuation in trend till 2050, all other SSP projections show a steeper increase in emissions in this time frame compared to historical observations. All projections have in common that they project a significant change in trend around 2050 with declining emissions in all scenarios, except SSP3, in which emissions continue to increase but at a lower speed.

More information about the runs can be found in the corresponding evaluation documents (Dietrich, 2019b) and model runs (Dietrich, 2019a). The latter contains, for instance, NetCDF files with spatial land cover information of the corresponding runs (`cell.land_0.5.nc`).



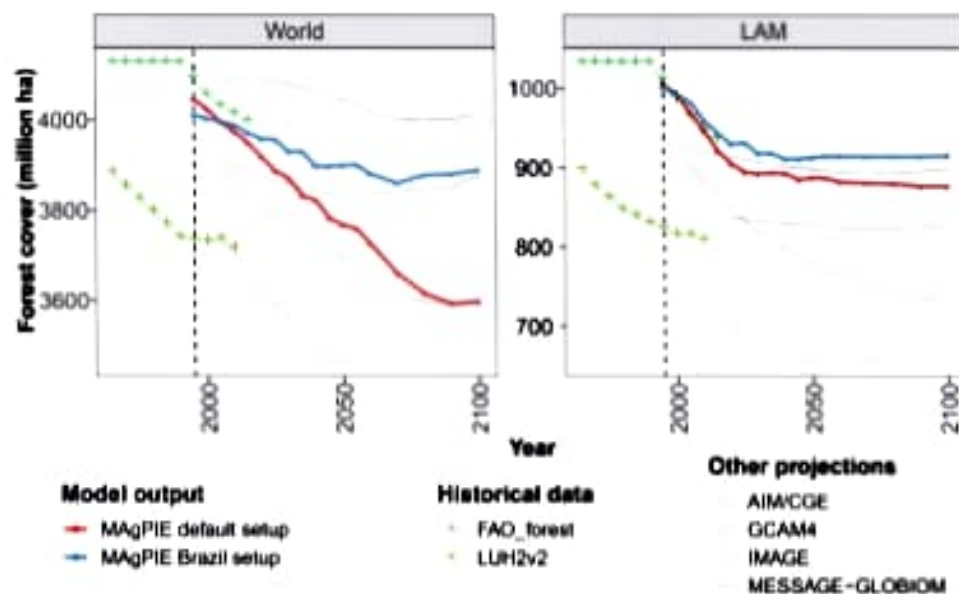


Figure 5. Comparison of global and Latin American forest cover with historical data sets and projections of other models.

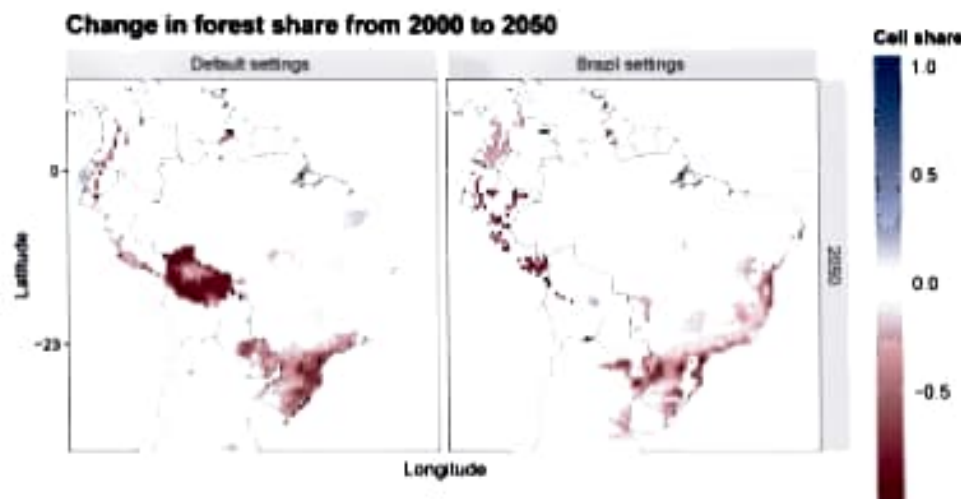


Figure 6. Comparison of changes in forest share from 2000 to 2050 in Brazil between the default setup and Brazil setup.

## 5 Discussion and conclusions

Since the first version of MAGPIE, the model has evolved from a crop-focused land-use allocation model to a modular open-source framework with a broad range of covered processes.

One main improvement introduced in MAGPIE 4 is the full code modularization. It is used as a tool to make the model more manageable as it structures the code in self-containing components which are interacting via interfaces with each other. It makes existing and missing interactions in the model more visible and allows to easily replace components by alternative implementations. While the modular structure is rather intuitive for a system with loosely linked components, one could argue that it might prevent a proper implementation of strongly integrated systems. Our experi-

ence is that, while the modular concept is working best for clearly separable systems, it also works in all other cases. The difference with strongly integrated systems is that the amount of interfaces and the required effort for developing new realizations are higher. Nevertheless, it still improves transparency in terms of model interactions and does not exclude any systems or dynamics from being represented in the model. Modules are also not static and the modular structure itself can and will also be changed if required. Modules might get created, deleted, merged or split over time. Module interfaces might get extended, reduced or modified. As both happen less frequently than changes within modules, the modular structure can be best described as semi-static.

Besides modularization, MAGPIE 4 introduces a series of other features such as automatic documentation of the GAMS code, the possibility to run parts of the model in a