

Applying Occam's razor to global agricultural land use change



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ARTICLE INFO

Article history:

Received 29 May 2015

Received in revised form

16 October 2015

Accepted 17 October 2015

Available online 11 November 2015

Keywords:

Global agricultural land-use

Parsimonious models

Parameter uncertainty

Sensitivity analysis

Cereal yields

ABSTRACT

We present a parsimonious agricultural land-use model that is designed to replicate global land-use change while allowing the exploration of uncertainties in input parameters. At the global scale, the modelled uncertainty range of agricultural land-use change covers observed land-use change. Spatial patterns of cropland change at the country level are simulated less satisfactorily, but temporal trends of cropland change in large agricultural nations were replicated by the model. A variance-based global sensitivity analysis showed that uncertainties in the input parameters representing to consumption preferences are important for changes in global agricultural areas. However, uncertainties in technological change had the largest effect on cereal yields and changes in global agricultural area. Uncertainties related to technological change in developing countries were most important for modelling the extent of cropland. The performance of the model suggests that highly generalised representations of socio-economic processes can be used to replicate global land-use change.

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1. Introduction

Land-use is a crucial link between human activities and the natural environment (Foley et al., 2005). It is central to the sustainable development debate (Turner et al., 2007), especially concerning food security (Brown and Funk, 2008; Fresco, 2009; Lobell et al., 2008), but also climate change (Brovkin et al., 2006), soil quality (Guo and Gifford, 2002; Lal, 2008), water resources (Rockström et al., 2009; Scanlon et al., 2005), biogeochemical cycles (Barth et al., 2005; Ramankutty et al., 2007), biodiversity (de Chazal and Rounsevell, 2009; Scharlemann and Laurance, 2008), human

health (Xu et al., 2008) and fire activity (Cochrane and Barber, 2009). More than a third of the global land area is used for agriculture as cropland or pasture (FAOSTAT, 2012), with the remaining land consisting mainly of deserts, mountains, tundra, cities, and ecological reserves (Foley et al., 2011), that include forests and unmanaged grasslands. Between 1961 and 2009, the global population doubled, but agricultural area only increased by 10% (FAOSTAT, 2012). Increasing food demand was met by the intensification of agricultural production arising from the increased use of fertilizers and irrigation (Foley et al., 2011). Land-use intensification has caused detrimental environmental impacts such as salinization, biodiversity loss, and groundwater pollution and depletion (Foley et al., 2011). Expanding agricultural areas also encroach on natural ecosystems resulting in deforestation, conversion of natural grasslands and wetland drainage. These changes are predicted to have far-reaching consequences, impacting on many aspects of the Earth system (Foley et al., 2011). Knowledge about land-use change (LUC) is important, therefore, in understanding how to feed a growing global population whilst simultaneously avoiding environmental damage.

Land-use models are designed to systematically analyse these complex structures, interactions and feedbacks (Deffuant et al.,

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2012; Heistermann et al., 2006; Rounsevell et al., 2012) and have proven to be useful in both conceptualizing and testing our understanding of the role of different drivers and processes in LUC (Alcamo et al., 2011; Verburg et al., 2009). Because land systems are complex, a variety of land-use models have been developed that apply different methodological approaches (Schaldach and Priess, 2008) across global, continental, or regional scales (Heistermann et al., 2006; Letourneau et al., 2012). These include Markov Chains, empirical–statistical functions, optimization strategies, cellular automata, micro simulation and system dynamics models (Lambin et al., 2000; Parker et al., 2008), with a focus on biophysical or economic processes or both (Lotze-Campen et al., 2008; van Tongeren et al., 2001).

Integrated assessment models (IAMs) include interactions between society, the biosphere and the climate system (Heistermann et al., 2006; Hurtt et al., 2011). Land-use change and land management are one of the components of the broader IAM approach and has been the focus of considerable attention in recent years. For instance, in the IAM IMAGE (Integrated Model to Assess the Global Environment) the land-use module was refined by replacing a set of decision rules to allocate land cover change with an approach to represent land-use as land-use systems. Land-use systems are combinations of land cover, land-use (including livestock), population and accessibility, and represent the heterogeneity of landscape patterns and the interactions of humans with the environment (Letourneau et al., 2012). A similar approach is applied in other types of models, e.g. in the CLUMondo (Conversion of Land Use change Mondo) land-use allocation model. In CLUMondo changes in the land system are allocated to fulfil various demands at the same time and with multiple combinations of land systems (van Asselen and Verburg, 2013).

Other developments include the integration of the use of water for food production in global food security modelling, which is, for example, an integrated component of the Model of Agricultural Production and its Impact on the Environment (MAGPIE; Lotze-Campen et al., 2008). Another example of the integration of water for food production in global land use modelling is IMPACT (International Model for Policy Analysis of Agricultural Commodities and Trade), where cropland changes are modelled for food production units, accounting for interactions between land-use and the hydrology of the food producing watershed (Rosegrant et al., 2013). Furthermore, bioenergy is increasingly considered as a driver of global LUC, for instance in 7 out of 10 global agro-economic models that participated in a recent comparison of LUC trajectories up to 2050 (Schmitz et al., 2014). The GLOBIOM (Global Biosphere Management Model), for example, has been used to study the impact of first and second generation biofuel on direct and indirect land-use and its effects on greenhouse gas balances, but the model can also assess the impact of food production on land and water resources (Havlík et al., 2011; Kraxner et al., 2013; Schneider et al., 2011). While the above models are spatially explicit, the SIMPLE (Simplified International Model of agricultural Prices Land-use and the Environment) model is, by contrast, neither spatially explicit nor dynamic, but calculates cropland change at the global scale with a set of equations based on the supply and demand elasticity of agricultural products and land from one point in time (e.g., 1961) to another (e.g., 2006; Baldos and Hertel, 2013).

Hence, land-use models aspire to represent the effects and interactions of multiple global drivers, differing spatial extents and turnover times of key ecological and social processes, and connections between individual actions, institutional responses, and ecological changes across these multiple dimensions of scale. In practice, it is very challenging to develop global land-use models that simulate all of the key processes in the land system for both

human activity and the biophysical environment (Schaldach and Priess, 2008; Schaldach et al., 2011). All models are imperfect representations, or simplifications, of a real world observation. The nature and extent of these simplifications usually reflects the judgement of individual model developers and the research question addressed by the model. While more complex models arguably have a better representation of system processes, they are less transparent than simpler models and there is a greater potential for error propagation between coupled sub-models. Transparency is important in communicating results, especially where the purpose of a model is to inform policy making (Giupponi et al., 2013; Rounsevell et al., 2012). Additionally, the associated computational overhead of complex models is such that applications are limited by the number of possible model runs within a reasonable amount of time. Simpler models are easier to formulate, reducing the probability of human-induced errors, and are computationally inexpensive which makes them amenable to sensitivity experiments using probabilistic estimates of uncertain parameters (Tao et al., 2009; Tebaldi and Lobell, 2008).

Sensitivity analysis (SA) increases the credibility and utility of models and assists in identifying areas of model improvement (Norton, 2015). SA should be applied more commonly as part of modelling exercises, but is rarely undertaken especially for global scale land-use modelling studies (Letourneau et al., 2012). SA has emerged as part of “post-normal science” when dealing with highly uncertain systems, such that: “uncertainty is not banished, but is managed, and values are not presupposed, but are made explicit” (Funtowicz and Ravetz, 1993, 1990, p. 740). However, model simplification risks neglecting important system processes or scales that contribute to real-world phenomena. A model that is unable to replicate these phenomena, at least in part, with appropriate levels of realism is of limited value. Moreover, simplification of a modelled system increases the number and arguably the complexity of assumptions (Wainwright and Mulligan, 2004). Conversely, identifying simple models that perform well, i.e., in comparison with observations and for which parameter sensitivities are known, can support understanding of the key processes that control system behaviour. In this paper we address the question: can the temporal trends and large-scale spatial patterns in global agricultural land-use be understood from simplified socio-economic processes at the country level? We do this by:

1. Developing a simple conceptual model of the socio-economic processes that determine global agricultural land-use change (represented here by cropland and grassland areas);
2. Representing this simple conceptual model within the formulation of a parsimonious land-use model (PLUM);-
3. Testing the concept by evaluating the model against observational data for the period 1991–2010; and
4. Exploring the uncertainty and sensitivity of global cropland to the variability in global input parameters using a variance-based global sensitivity analysis.

2. Material and methods

2.1. The conceptual model

The conceptual model presented here aspires to follow the principle of Occam's razor, in which the parsimonious (as simple as possible, but not simpler) solution to a problem is preferred. The conceptual model is based on the understanding that changes in cropland occur based on changes in demand for agricultural products and changes in the productivity of cropland. It considers important socio-economic drivers such as population and income

level development, consumption, trade, food production and technological change. Changes in consumption and yield changes (due to technological change) are assumed to result in agricultural land-use change. Here agricultural land is assumed to comprise grassland and cereal land, or cropland. Cereal land is chosen as a proxy for cropland, which globally consisted of 60% cereal land in 2010 (FAOSTAT, 2012), while the other 40% was divided between oil-crops, pulses, roots and tubers, and vegetables. The main unit in the conceptual model is cereals (see Fig. 1). Changes in cereal consumption are expected to be proportional to changes in population (Fig. 1, purple area), as historically (1961–1990) per capita cereal consumption was constant for the majority of countries, albeit with some yearly variability (FAOSTAT, 2012). Changes in the consumption of animal products by contrast are assumed to be influenced by population, income levels and life-styles (Fig. 1, purple area). The historical per capita consumption of animal products showed an increasing trend for most countries (1961–1990), which correlated with rising per capita income levels. Additionally, the changes in animal-product consumption are still very different for countries with different cultures and, therefore, life-style is assumed to also influence animal-product consumption. The total use of cereals within a country is assumed to consist of cereals for food and cereals used to feed animals that are used to produce meat and milk.

The total use of cereals in a country depletes that country's cereal balance. It is assumed that the country cereal balance can be replenished by either importing cereals from the world cereal balance or by increasing domestic cereal production (Fig. 1, orange area). Countries that produce more cereals than are consumed domestically are assumed to export this production, and in so doing they contribute to the world cereal balance. Countries with a negative cereal balance import cereals from the world's cereal balance. A low world cereal balance and low country cereal balance is assumed to increase cereal production demand and vice versa.

An increased demand for cereal production is assumed to be satisfied by cereal yield increases in the first place (intensification). In the second place, a continued increase in cereal demand is assumed to lead to cereal land expansion (Fig. 1, green area). Cereal yield in turn is assumed to be affected by technological change and climate change. Technological change is considered to be indirectly related to income levels, as countries with higher income are more

likely to invest in yield improving technologies, such as fertilizers, machinery and irrigation. Climate change is acknowledged to be an important future driver for changes in yield, but is not considered further in the work presented here (hence the dashed line in Fig. 1). Similarly, bioenergy production will become an important component of land use change to meet high energy requirements and strict mitigation targets (Lotze-Campen et al., 2014). However, for the model evaluation presented here bioenergy is not modelled explicitly. In future applications of the model, bioenergy will be represented as an influence on the agricultural system (Fig. 1, dashed lines). Grassland and forests are treated as residual land covers (following cropland changes) with grassland comprising managed and unmanaged components.

2.2. Translating the concept into a parsimonious land use model

Implementation of the conceptual model within the visual modelling environment Simile (Muetzfeldt and Massheder, 2003) was based on statistical relationships and a set of rules describing the functional relationships represented in Fig. 1 to create the Parsimonious Land Use Model (PLUM), outlined in the following subsections. All equations are executed yearly on a per country basis if not stated otherwise (model unit, 162 countries, see Appendix). The countries are connected through global variables, such as the world cereal balance.

2.2.1. Consumption module

For the calculation of cereal consumption, the per capita consumption from 1990 was multiplied by each country's population. Population is an exogenous input to PLUM, supplied on an annual basis. Variability within cereal consumption was accounted for by introducing the global variable cereal consumption variability *indCerealVar* (Table 1). However, in scenario experiments *indCerealVar* could also be used to account for scenario specific assumptions regarding food waste (decreased cereal consumption) or the amount of processed food (increased cereal consumption).

Previous studies have reported a significant positive correlation between the consumption of animal products, milk (excluding butter) and meat (beef, pork, mutton, and poultry), and income levels (FAO and LEAD, 2006; Keyzer et al., 2005; Smil, 2002; Zuidema et al., 1994). In PLUM a functional relationship is

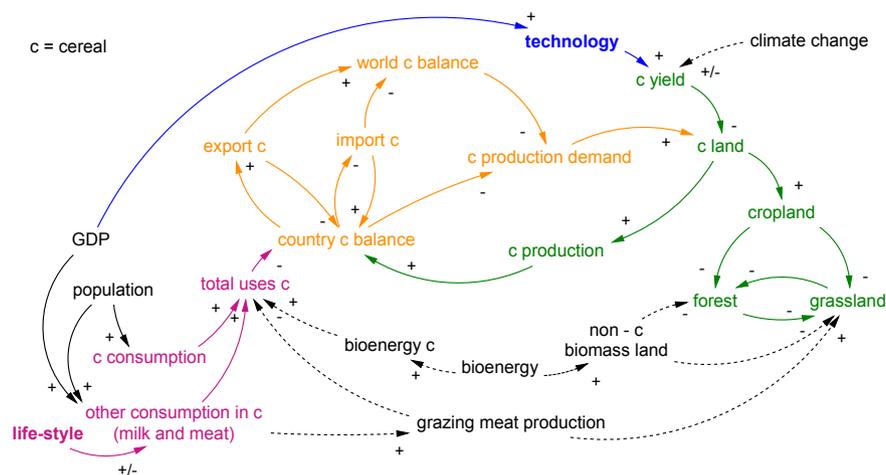


Fig. 1. The consumption of food (purple) is driven by economic development (GDP per capita), population and culturally-determined lifestyle choices. The demand for production drives the conversion of forest or grassland to cereal land and cropland (green). GDP drives technology (blue), which in turn increases yields. Relationships indicated with dashed lines (e.g. bioenergy and climate change) are part of the conceptual model, but are not yet implemented in the present version of PLUM. Factors printed in bold are implemented as global variables in PLUM; all other variables are country specific.

Table 1

Parameterizations used in the model evaluation runs (mean value) and sensitivity analysis (mean value and standard deviation). Classes 1–4 for meat and milk increase rates refer to 1: countries with traditionally high meat/milk consumption; 2: countries with traditionally low meat/milk consumption, despite high income levels; 3: emerging economy countries; 4: low income countries.

Nr.	Variable name (unit)		Mean value	Standard deviation
1	Overproduction rate (1/time)		0	0.035
2	Cereal consumption variability (1/time)		0	0.001
3	Meat increase rate (kg meat per capita/log(GDP per capita))	class 1	11.38	7.0
		class 2	6.56	4.3
		class 3	7.72	6.0
		class 4	1.14	4.4
4	Milk increase rate (kg milk per capita/log(GDP per capita))	class 1	15.95	23.1
		class 2	6.16	12.0
		class 3	4.37	16.4
		class 4	3.33	9.0
5	Feed conversion ratio improvement rate (1/time)		0.005	0.0025
6	Yield improvement rate (1/time)	low income countries	0.016	0.014
		middle income countries	0.022	0.011
		high income countries	0.020	0.006
7	Abandonment rate developed countries (1/time)		0.023	0.006–0.071
8	Abandonment rate developing countries (1/time)		0.015	0.004–0.054
9	New cereal land rate developed countries (1/time)		0.015	0.003–0.049
10	New cereal land rate developing countries(1/time)		0.029	0.002–0.046
11	Grassland forest ratio (unitless)		0.5	0.3
12	Forest degradation rate (1/time)		0.0001	0.00001
12	Cereal land degradation rate (1/time)		0.001	0.0001

adopted that increases consumption rapidly with income levels when very low income levels are surpassed until a maximum is reached (see Appendix). Gross Domestic Product per capita (GDP per capita) is used as an indicator of income levels, and except for population, is the only continuous input variable used in PLUM. Although this relationship is valid for most countries, cultural factors and resource conditions influence the rate of change in consumption levels and the maximum level attained (York and Gossard, 2004). Thus countries are divided into four classes to take account of these cultural differences. Class 1 includes high-income countries with a high per capita consumption of animal products, but where the increase in consumption has been observed to slow down (e.g. Germany). Class 2 includes countries that in spite of high income levels consume little animal products (e.g., for meat consumption in Norway or Japan), due to cultural factors or the availability of other protein sources (e.g., fish). Class 3 summarises countries that have presently surpassed very low income levels and are in a rapid transition from low or moderate consumption of animal products towards moderate or high levels of consumption. Class 4 includes countries that do not yet have the economic means to increase the consumption of animal products rapidly (e.g., Nigeria). Conceptually, countries should be able to transform from Class 4 to Class 3, but this was not implemented in the present version of PLUM. The rate of consumption change is different for the four classes and is regulated by the global parameters meat increase rate class 1–4 (*meat1*, *meat2*, *meat3* and *meat4*) and milk increase rate class 1–4 (*milk1*, *milk2*, *milk3* and *milk4*), see Table 1.

2.2.2. Conversion and trade module

The simulated consumption of milk and meat drives the demand for cereal feed. The demand for feed is based on the composition of consumed animal products (milk, beef, poultry, pork and mutton), the cereal feed available for each country in 1990 (see Appendix), and globally applied feed conversion ratios for poultry, pigs, beef and mutton (*fcrPoul*, *fcrPig*, *fcrBeef*, and *fcrMut*, see Appendix for baseline values). Technological change is assumed to affect the feed conversion ratios through the food conversion ratio improvement rate (*fcrImp*, Table 1). It is also assumed that as demand for meat and milk changes the ratio of grass to fodder

usage remains the same. Cereal consumption and cereal animal feed represent 70% of global cereal use, if compared with all uses listed in the FAOSTAT database (FAOSTAT, 2012). PLUM does not yet represent cereals used for bioenergy, seed production or waste, which globally account for about 15% of cereal use. Between 1990 and 2005 approximately 15% of global cereal production was produced without a specific purpose, other than as a buffer against harvest shortfalls (FAOSTAT, 2012). This known overproduction and other cereal uses, are accounted for in PLUM by introducing a global overproduction of 30%, which can vary over time with changes in *overProRate* (see Appendix).

The trade and production regulating mechanism in PLUM (Fig. 2) aims to decrease production in times of global overproduction and increase production in times of global underproduction. For each year and country, the balance of cereal production minus cereal use is calculated. Based on a free market assumption, countries with a negative balance import cereals, and countries with a surplus export this surplus. Each country's change in production demand is determined from the country's cereal balance and the world cereal balance (Fig. 2). The global variable world cereal balance connects all countries by summing up all country exports (positive) and imports (negative). In the case of global overproduction (i.e. positive world cereal balance, including the 30% overproduction) exporting countries are assumed to decrease their production (lower left box in Fig. 2). Exporting countries decrease production by their share of the global overproduction. Importing countries do not change production demand, except if they increase their cereal self-sufficiency by the amount of their domestic underproduction (lower middle left box in Fig. 2). In the model evaluation, only developing countries were given the possibility to increase cropland for self-sufficiency in times of global overproduction justified by the assumption that trade barriers and subsidies limit the full participation of developing countries in world trade. When the world is in a state of underproduction (world cereal balance is negative) both importing and exporting countries are assumed to increase their production (lower middle right and right box Fig. 2). Exporting countries are assumed to increase production by their share of the global underproduction, while importing countries increase production by either their share of global underproduction or their domestic underproduction,

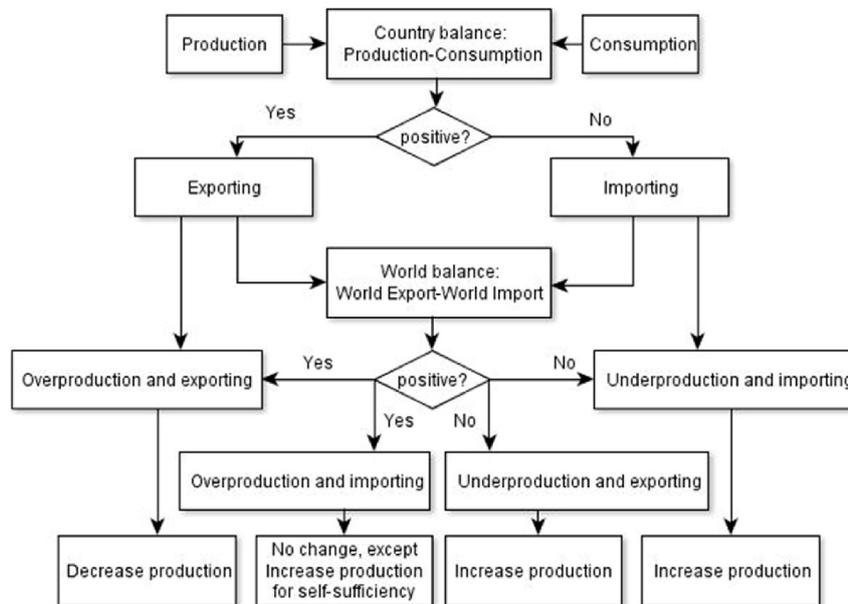


Fig. 2. Flowchart of PLUM's trade and production regulating mechanism.

whichever value is the largest (for details see Appendix). This trade structure maintains parsimony by not including prices, nor being explicit about trade patterns between countries. Additionally, these simplified trade flows are based on a free market assumption, as previously implemented in a European land-use model (Rounsevell et al., 2006).

2.2.3. Land conversion module

For each country, the expected change in cereal production from the trade module is divided by the cereal yield to calculate the potential change in cereal land area. To avoid demand-driven expectations of changes in cereal production causing implausible year to year fluctuations, an annual maximum rate of land conversion is imposed. This rate is assumed to differ between developing and developed countries, on the basis that land-use change in developing countries is less regulated by policy. Additionally, the approach differentiates between abandonment of cereal land (and cropland) and the conversion of grassland or forest to new cereal land (and cropland; *abandonmentRich*, *abandonmentPoor*, *newCLR*, *newCLPoor*, and *newCLSelfPoor*). However, in the evaluation runs these rates are maximum rates, which means that they are only applied to very large expected changes in production and do not have much influence on the model output during the evaluation period (more significant for scenarios).

Cereal yields increase at historic rates, assuming annual yield increase rates from 1.6% (low-income countries, *yieldR1*), through 2% (high-income countries, *yieldR3*) to 2.2% for medium-income countries (*yieldR2*). These rates were defined by analysing cereal yield data from FAOSTAT for the years 1961–1990 (FAOSTAT, 2012). Using the conceptual model the increase in yields is explained by rising income levels and technological change. In the relatively simple approach of PLUM, changes in the area of cereal land (either increases or decreases) are used to estimate cropland. It is assumed that the share of cereal land of cropland in 1990 remains constant over the simulation period. Cropland in turn is used to adjust forest and grassland areas. The proportional changes in forest and grassland areas are assumed to be 50:50 in the runs performed here. However, as this is a global parameter, it could be modified in scenario exercises e.g. to simulate stronger protection of forests. To

avoid complete deforestation or conversion of grassland, a minimum area is maintained equal to 10% of a country's forested or grassland area in 1990.

2.2.4. Data and parameterization

Processes (e.g. consumption) and stocks (e.g. cereal land) were initialised with country specific data from the Food and Agricultural Organization (FAOSTAT, 2012; Appendix). Time series (1991–2010) for economic and population development at the country level were used as continuous input data and were derived from the World Bank database (WB, 2012). Coefficients of the statistical relationships implemented in PLUM were set as either global parameters (for example the production rate) or at the country class levels (for example for rates of consumption, see Table 1). The global (or class) values were retrieved from the statistical analysis of FAOSTAT data for the period 1961–1990 (FAOSTAT, 2012; Appendix), which resulted in the values shown in Table 1. This time period was chosen to minimise the effect of inter-annual variability on the long-term trends.

2.3. Model evaluation and sensitivity analysis

To evaluate model performance at the global aggregated level, ensemble runs using Monte Carlo (MC) sampling and probability distribution functions (PDFs) created from the values in Table 1 were performed ($n = 5000$). We assumed normal distributions for all parameters, except for the land conversion rates. The land conversion rates are maximum conversion ratios, so we assumed that all values have the same probability of occurring, which led to the use of a uniform distribution. The World Bank population and GDP per capita data for 1991–2010 (WB, 2012; Appendix) were used as model input. The model uncertainty, which is the variance of outputs given the PDFs of the input parameters, was confined by the standard deviation. The standard deviation and mean were calculated from the ensemble runs for global consumption, production and land use model output. In the description of the aggregated global results by “range” we refer to the range spanned by the standard deviation. We compared these results with FAO time series (1991–2010, or in some cases 2009; FAOSTAT, 2012).

At the country level, over- or underestimation of modelled consumption and land use (running the model with mean values from Table 1) was mapped in comparison with FAOSTAT in 2009. Over- or underestimation was calculated as the modelled output minus the observed data in % of the observed data. At the country level modelled and observed time series were compared for cereal land change in selected countries or regions.

To summarise model uncertainty we calculated the relative standard deviation (standard deviation normalised with the mean) for global consumption, production and land use variables in 2010. To explore the sources of model uncertainty we used sensitivity analysis. Traditional sensitivity analysis uses partial differentials or response plots to vary a single parameter while others are kept constant; the so-called “one at a time” (OAT) method. OAT methods have several drawbacks: they are only appropriate for linear models; they sample only a subset of parameter space, whose relative size decreases as the dimensionality increases; and they give special emphasis to the central point in parameter space (Saltelli et al., 2006). Derivative based or OAT methods are commonly used because of the computational costs in running some models (van Griensven et al., 2006), but other approaches such as variance-based methods have also been used for environmental modelling (e.g. Collins and Avisar, 1994).

Variance-based methods seek to estimate the output variance due to variability in each input parameter. The total sensitivity can be described by the importance S_{Ti} which includes first and higher order effects (interactions) of factor X_i (X_{-i} being the matrix of all factors). The importance (S_{Ti}) of an input variable is defined as follows (Saltelli et al., 2008, 2010, p.21, p 260, (1)):

$$S_{Ti} = \frac{E_{X_{-i}} (V_{X_i}(Y|X_{-i}))}{V(Y)} \quad (1)$$

Here we applied a variance based Global Sensitivity Analysis (GSA), following the steps outlined in Lilburne and Tarantola (2009):

- i. The target functions of the study are global areas of the land-use classes in the model, which were treated as separate output variables for simplicity.
- ii. The inputs of interest are given in Table 1. It should be noted that in all cases these are parameter values and do not relate to model structure. Hence the global sensitivity analysis only assesses uncertainties related to input parameters and not to the model structure per se.
- iii. A PDF (Probability Density Function) was estimated for each input parameter using the values given in Table 1.
- iv. The Soboljansen method (Saltelli et al., 2010; Sobol' et al., 2007) from the R “sensitivity” package (Pujol, 2008), was used to create a sampling design ($n = 500$, $p = 26$) requiring 14000 runs.

The Soboljansen method was applied since it is based on the Monte Carlo sampling technique and provides an efficient method for calculating S_{Ti} , the total importance of parameters.

- v. The runs were automated, using the R interface to Simile.
- vi. For each output, the results were returned to the sensitivity package to compute the importance S_{Ti} of each input factor.

In addition to the GSA, the set of MC runs were used to generate response plots for each input to aid understanding of model behaviour. These MC response plots are different to an OAT response plot, as they include the variance of all parameters at

once, and hence do not suffer from the limitations discussed previously.

3. Results

3.1. Testing the concept by evaluating PLUM against observational data

3.1.1. Aggregated global outputs

At the global scale, the simulated model range covers the observed time series (1991–2010, FAOSTAT) for consumption and production variables as well as for agricultural land use (Fig. 3). The range of modelled cereal consumption contains observed cereal consumption, though during the first half of the evaluation period the observed consumption is slightly higher than the modelled range. In the second half of the evaluation period, by contrast, the modelled cereal consumption is overestimated compared to the observed values. The relative standard deviation of cereal consumption is 2.0% in 2010. For both milk and meat consumption, the modelled range is almost below the observed time series during 1990–2002, but picks up in the last years of the evaluation period. In 2010, the relative standard deviation of milk and meat consumption is 9.0% and 11.0% respectively. For milk consumption the observed value is at the upper end of the modelled range in 2010, while for meat consumption the observed value is in the middle of the modelled range. The relative standard deviation of cereal feed is 9.7% in 2010 and the modelled range of cereal feed corresponds well to cereal feed reported by the FAO. Only in the last years of the evaluation period does the simulated cereal feed show a stronger increase, while the observed cereal feed has a more fluctuating pattern. This fluctuating pattern might be due to high cereal prices, caused by weather-related harvest shortfalls (in several main cereal producing countries, such as the US, most European countries, Russia and Australia in 2006), policies to decrease cereal stocks, increased cereal demand for biofuel production, and investment in food commodities (Beddington, 2009; USDA, 2007).

The simulated range of cereal yield embraces the reported cereal yield during 1991 and 2010. In 2010 the relative standard deviation was 12.7% for cereal yield and 8.7% for cereal production. The observed cereal production is marginally lower than the modelled range in 1993–1995 and 2002, but in general the modelled range of cereal production contains the observed cereal production. Furthermore the modelled range in cereal land area is consistent with the observations of cereal land area, though it is mainly in the second half of the evaluation period that the modelled range contains the full extent of observed cereal land (Fig. 3). The relative standard deviation of cereal land is 5.2% in 2010. In PLUM, cropland is simply cereal land scaled by the ratio of cropland to cereal land in 1990. The modelled range of cropland includes the observed cropland. However, the observed cropland is closer to the upper end of the modelled range and it seems that the simple estimate of cropland in PLUM has a tendency to underestimate cropland. In 2010, the relative standard deviation for cropland was 5.6% and 1.4% for grassland. For grassland, the modelled range covers the observations, if they are adjusted for a data reporting inconsistency in Saudi Arabia between 1992 and 1993 (Fig. 3, dashed line). Between 1992 and 1993 Saudi Arabia's reported grassland increased from 56% to 79% of its land area (FAOSTAT, 2012).

3.1.2. Model outputs at the country level

The temporal trends at the global scale do not show how the simulated outputs for single countries compare with the observational data. In Fig. 4 we compare simulated and observed cereal, milk and meat consumption, cereal yield, cereal land and cropland for the year 2009. For 131 out of 162 countries, the simulated cereal

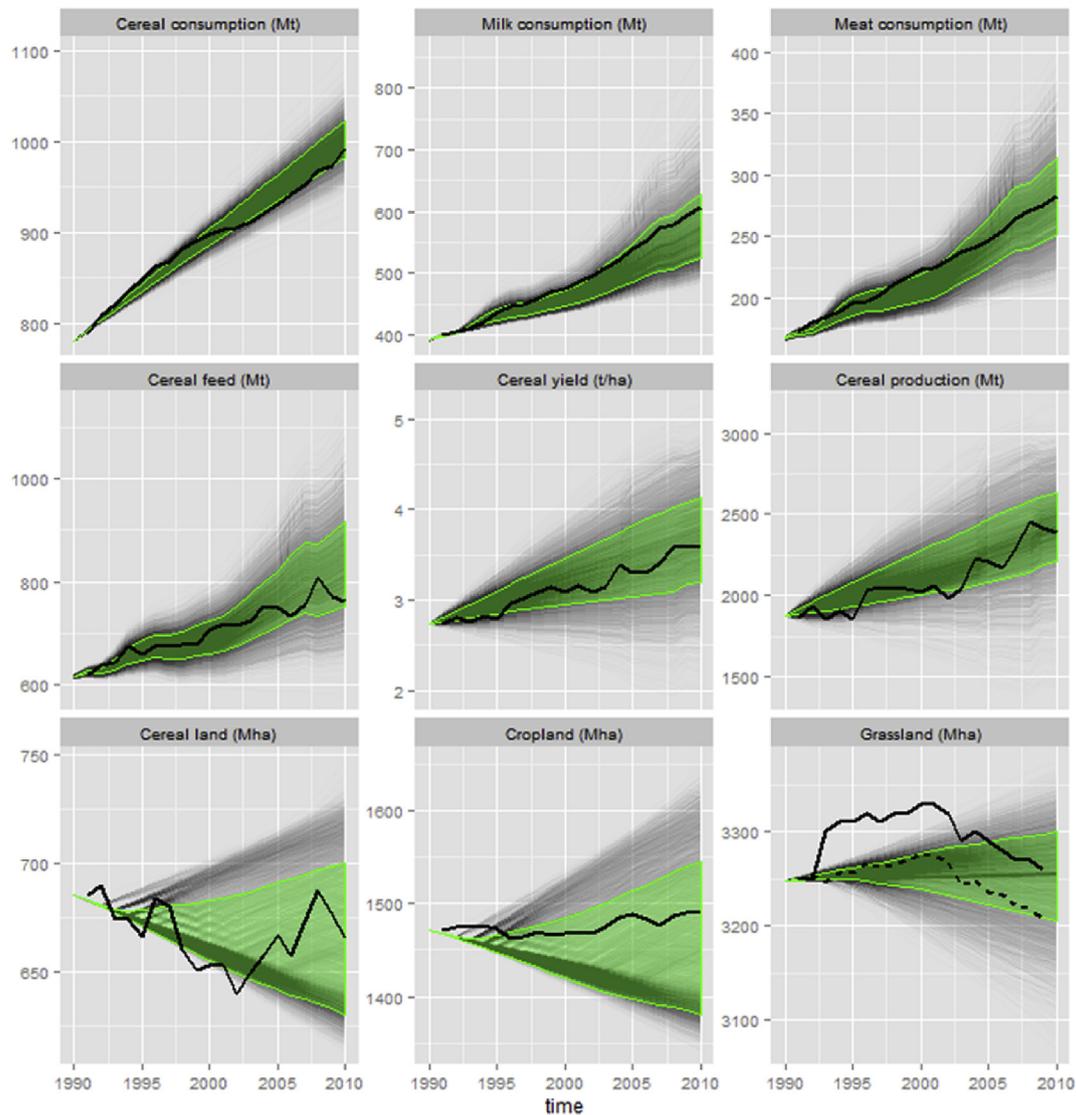


Fig. 3. Model runs (faint grey lines) and thereof calculated standard deviation (green shaded area) for global consumption (cereals, milk and meat; Mt), global cereal feed (Mt), yield (t/ha) and production (Mt) and Cereal Land, Cropland and Grassland (Mha). Global observed time series (FAOSTAT) are indicated with black lines. For Grassland an adjusted time series (subtracted data reporting inconsistency for Saudi Arabia between 1992 and 1993) is displayed using a black dashed line.

consumption is $\pm 20\%$ of the observations in 2009 (Fig. 4 panel a, countries displayed in light yellow and in the centre of the distributions in the histograms). For almost half of all the countries (77) the modelled milk consumption deviates by less than $\pm 20\%$ of the observed consumption (Fig. 4, panel b). Milk consumption was underestimated by 51.3% in China compared with observed milk consumption in 2009, as well as by 69.8% in the DRC. However, a clear geographical pattern of over- and underestimation does not emerge, as for other countries in Middle and Eastern Africa (i.e. Congo, Angola, Zambia and Mozambique) simulated milk consumption is overestimated compared to observed consumption. Similarly the comparison of modelled and observed meat consumption does not show a clear geographical pattern of countries that are over or underestimated (Fig. 4, panel c). Interestingly for some African countries where milk consumption was underestimated (DRC) or overestimated (Angola, Mozambique), the reversed pattern was observed for meat consumption. In general, consumption was simulated within the $\pm 20\%$ range for the five countries accommodating half of the world's population (US,

Indonesia, China, India and Brazil). Exemptions are the underestimated milk consumption for China and Brazil (51.3% and 27.8% respectively), the overestimation for meat consumption in India by 27.6% and the underestimated meat consumption in Brazil by 29.9% compared with observed values in 2009.

For most countries in America, Asia, and North, South and Western Europe the simulated cereal yield when compared to observed cereal yield was within the $\pm 20\%$ range (Fig. 4, panel d). Yield was overestimated for all Eastern European countries, except Belarus, but also Saudi Arabia and Australia. For African countries the pattern is more diverse, neighbouring countries are over- and underestimated, e.g. Zimbabwe and Mozambique (Fig. 4, panel d).

For cereal land the deviation between modelled and observed data in 2010 shows a large variation across all countries (Fig. 4, panel e). For two thirds of countries, cereal land deviates by more than 20% of observed cereal land. However, larger deviations occur mainly for island states and/or countries with very little cereal land (e.g. Botswana, Libya and Saudi Arabia). Large cereal producers such as India, China, the US, Brazil and Nigeria, are all within the $\pm 20\%$

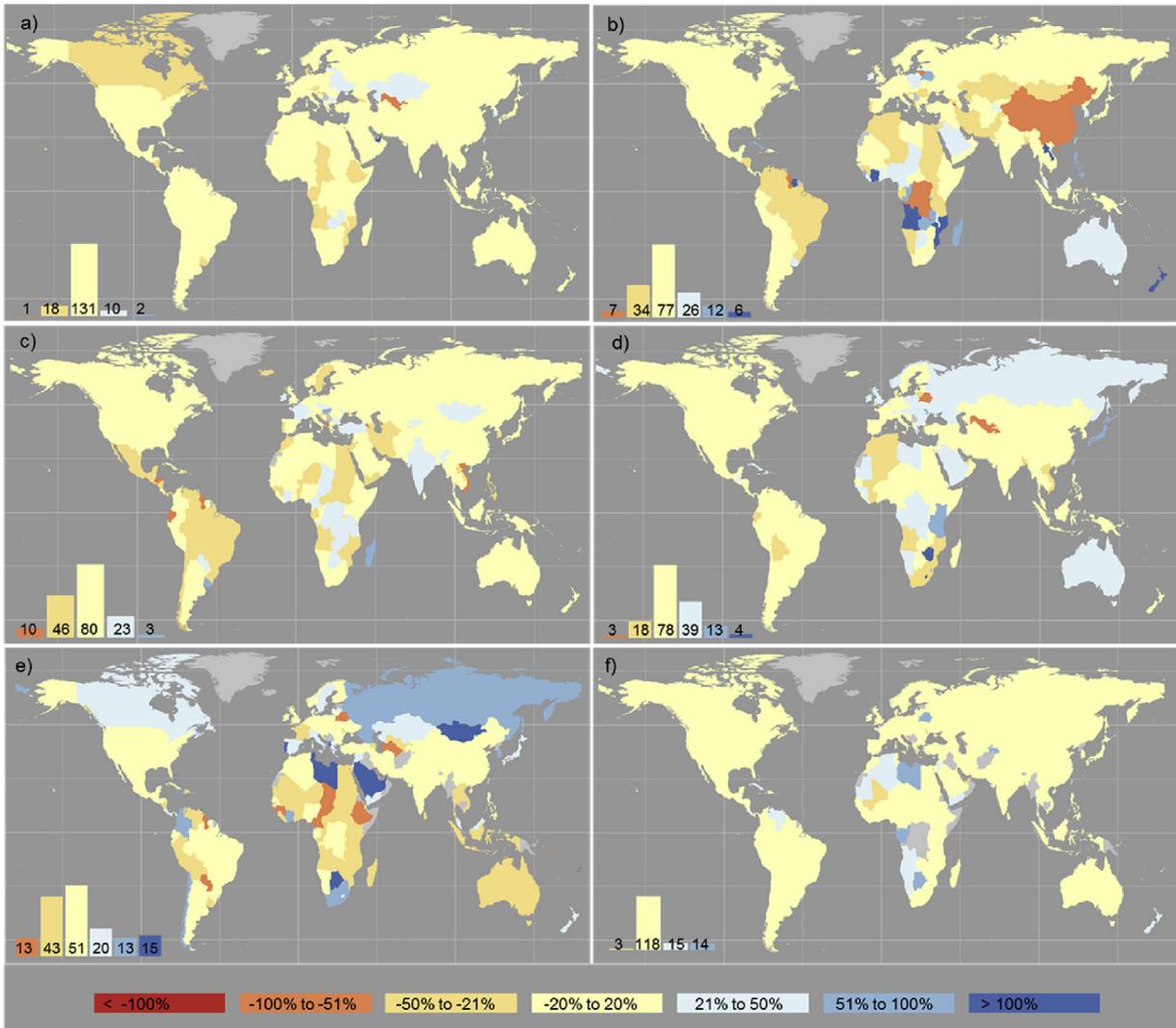


Fig. 4. Underestimation (red) and overestimation (blue) in % for a) cereal consumption, b) milk consumption, c) meat consumption, d) cereal yield in 2009 and e) cereal land and f) cropland in 2010. The numbers in the histograms are the country-count of each bin. Countries that are not included in the model or the comparison (see Appendix) are displayed in light grey.

range of deviation. For two other large producers, the modelled cereal land area was overestimated by 65.3% in Russia and underestimated by 42.3% in Australia in 2010.

When the changes in cereal land are scaled to cropland (using the same ratio of cereal land to cropland as in 1990), for the majority of countries, including Russia and Australia, the simulated changes are within the $\pm 20\%$ range of over and underestimation (Fig. 4, panel f). In general, cropland changes are more frequently overestimated than underestimated, as the skewed distribution in Fig. 4 panel f shows.

Looking at the entire evaluation period, the model-data discrepancy for Russia and Australia starts prior to 1995 and continues to grow until 2010 (Fig. 5). While it is not clear why PLUM does not capture the increase in cereal land in Australia, the decrease of cereal land in Russia can be attributed to structural changes following the end of the Soviet Union, which are not included in PLUM.

3.2. Responses to input variables and sensitivity analysis

The variability of the input parameters resulted in relative standard deviations calculated from the multiple model runs

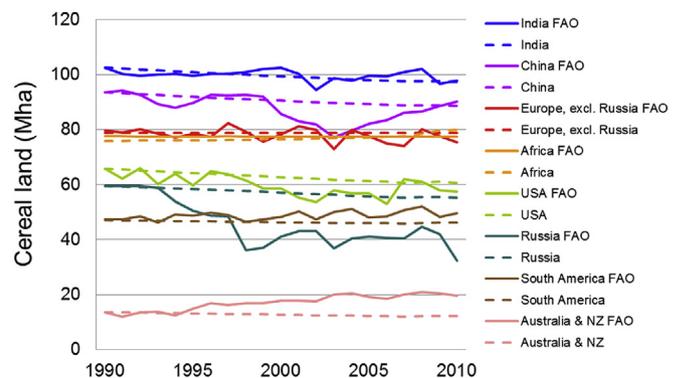


Fig. 5. Simulated (solid lines) and reported (dashed lines; FAOSTAT, 2012) cereal land (Mha) during the evaluation period.

between 1.4% for grassland and 12.7% for cereal yield in 2010. The global sensitivity analysis reveals the parameters and their uncertainties that have large effects on model outputs as shown by the ‘importance’ values (S_{Tj}) for each input, see Fig. 6.

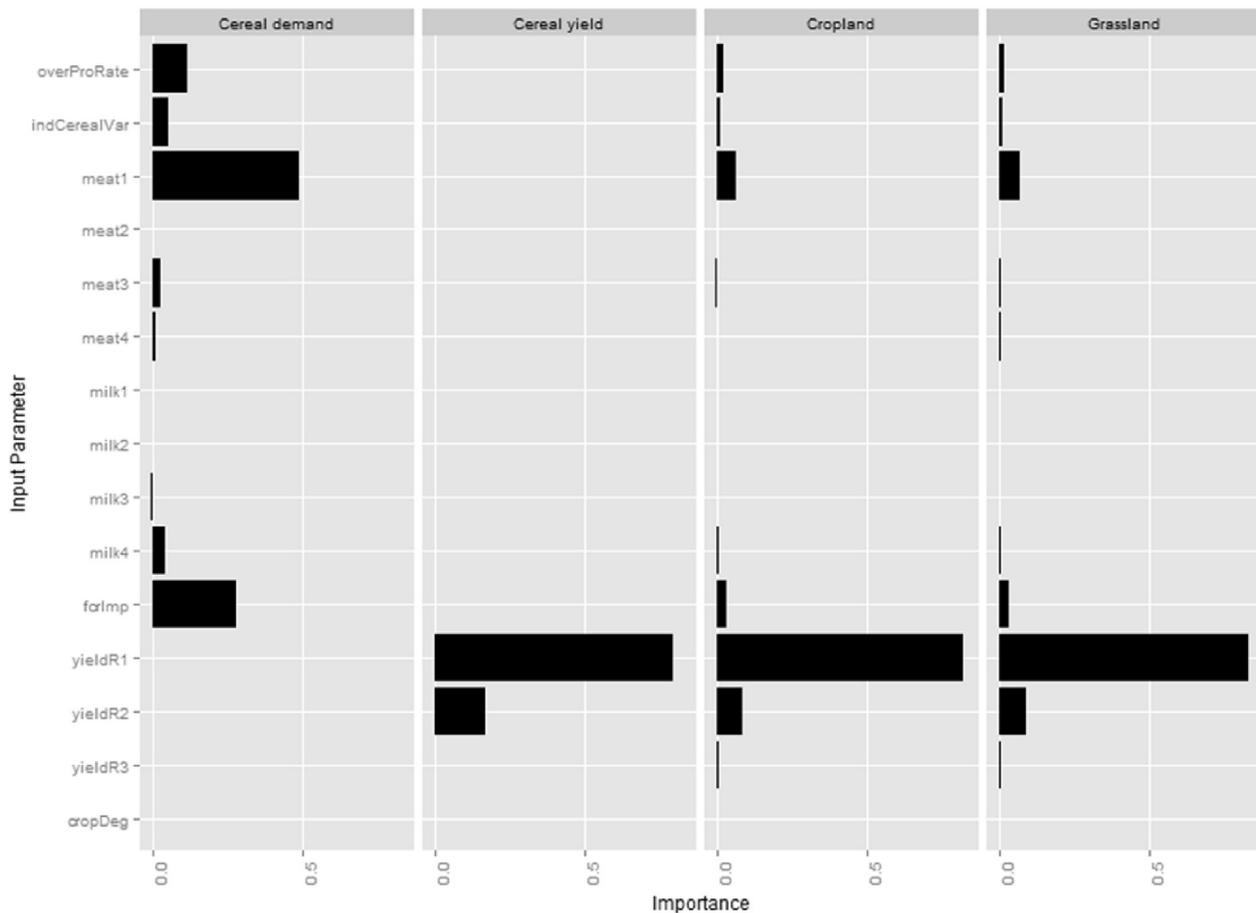


Fig. 6. Importance S_{π} of input parameters (left) for selected outputs (top). For an importance plot and response plot including all input parameters and outputs see supporting material.

Of the consumption input parameters (*indCerealVar*, *meat*, *milk*), *meat1* has the highest importance for cereal demand. Countries that belong to meat class 1 have a meat-rich diet and variability in this diet (e.g. a decrease or further increase in meat consumption) proves to be very important for global cereal demand. The improvement of the feed conversion ratios (*fcrImp*) is also important for global cereal demand, as is the level of global cereal stocks (influenced by *overProRate*, Fig. 6).

The global sensitivity analysis shows that the variability in the technological development and thus yield improvement rates of low income countries (*yieldR1*) is essential for the outcome of global cereal yield. The current yields in developing countries are often very low in comparison with yields achieved in high input agriculture practised in mostly developed countries (Licker et al., 2010). The potential to increase yields, but also the variability in yield increase is highest in low income countries. During the evaluation period most countries with large areas of cereal land belong to low income countries, such as India, China, Kazakhstan and Nigeria. Low income countries together account for two thirds of global cereal land in 2010, while the high income countries only account for 2.1% of global cereal land. The variability in yield for low income countries has a very strong effect on global yield, while variability of yields of high income countries has no effect (Fig. 6). The model output cropland responded to consumption (*indCerealVar*, *meat1*, *meat3* and *milk4*) and production input parameters (*overProRate*, *fcrImp*, *yieldR1* and *yieldR2*), with clearly the largest effect being the uncertainty of the input parameter *yieldR1*, as the importance of *yieldR1* is as large as the sum of importance of all of

the other input parameters combined (Fig. 6).

4. Discussion

4.1. General model performance

Successfully representing global agricultural land-use change depends firstly on whether the model includes the dynamics that drive global agricultural land-use change at the level of detail adequate for the research question, and secondly on the parameterisation applied in the model. In this study we found that the socio-economic processes of food consumption and production, trade and yield development are sufficient to derive global outputs of cereal land that are consistent with the main trends in the observational data. The comparison of simulated cereal land with observed cereal land showed that the land-use allocation mechanism in PLUM works for several large cereal producers, such as India, China and the US. For other countries over and underestimation of cereal land occurred, but for aggregated regions, e.g. Africa and Europe, simulated cereal land is consistent with observed data. The observed cereal, milk and meat consumption and cereal feed are all within the range of one modelled standard deviation at the global scale.

Overall, PLUM performs best at the global and regional scale and less well for single countries. Better model performance at a higher level of aggregation is a common phenomenon, as exemplified by the validation of the global partial equilibrium model SIMPLE (Baldos and Hertel, 2013). Despite model evaluation being crucial in

identifying potential misrepresentations of concepts, missing processes or improper parameterisation, it is not commonly carried out. Exceptions are the evaluation of MAGPIE (Lotze-Campen et al., 2008) and the global land use allocation model by Meiyappan et al. (2014). MAGPIE simulations during the period 1970–1995 of cropland patterns (with the exception of the regions of Sub-Saharan Africa and Middel East/North Africa) and changes in cropland area and yield were shown to agree well with observed (from FAOSTAT (2005) in Lotze-Campen et al., 2008) and observed and fitted data (from Ramankutty and Foley (1999) in Lotze-Campen et al., 2008). Meiyappan et al. (2014) evaluated their global land use allocation model against historical reconstruction data (based on Ramankutty (2012) in Meiyappan et al., 2014). They found that their integrative framework of economic theory, observed land use history and socio-economic and bio-physical land use change related data, is able to replicate general land use patterns, but also the timing and magnitude of spatial shifts observed in historical land use for the time period 1901–2005 (Meiyappan et al., 2014). However, this land use allocation model requires more input data (i.e. regionally aggregated land use information) than PLUM, which explains why e.g. the land use allocation model was able to replicate spatial patterns of land use changes during the end of the Soviet Union, while PLUM was not. Model evaluation, including sensitivity assessments, increases confidence where models do well and helps to identify shortcomings and potential reasons for these shortcomings (Norton, 2015). Confronting model output with observations needs to become standard in the LUC modelling community as a necessary (but not always sufficient) step to strengthen the credibility of models used to simulate the future.

4.2. Appropriated level of model structure complexity

PLUM performs well in reproducing temporal trends at the global level, even though it has a simplified representation of trade processes compared with general equilibrium models (e.g. AIM and FARM (Schmitz et al., 2014)). It was shown previously that simple supply and demand functions can be applied successfully to modelling agricultural land-use change at the continental scale for Europe (Rounsevell et al., 2005, 2006). The study presented here demonstrates that this is also possible at the global scale. Additionally, depending on the purpose of the modelling exercise, simulating global agricultural land-use change does not necessarily require an explicit treatment of prices. However, the period of time over which a model can reasonably be projected into the future, is dependent on the validity and stability of the underlying assumptions through time. This is a challenge that applies to all modelling approaches. For empirical and rule-based models, such as PLUM, results must be interpreted with care when the model is used far into the future when conditions might not resemble those under which the model was developed. However, more process-oriented modelling approaches, such as those used in the climate science community (Collins et al., 2013; Friedlingstein et al., 2006) or agro-economic partial and general equilibrium models (Schmitz et al., 2014) also show large divergence in projections beyond the coming few decades. One advantage of the parsimonious approach in PLUM is the transparency of the model's underlying assumptions and algorithms, which are reported in the Appendix of this paper. Their validity under future conditions can therefore be assessed if data to do so become available.

The model evaluation showed that while for several large producing countries cereal land was reproduced by less than 20% deviation of the observed values, the spatial performance of PLUM could be improved. Information about the bio-physical components of land suitability and yield development are commonly part

of more complex land use models. GLOBIOM, for instance, requires geographical information (slope, soil, and elevation) and land profitability of crop allocation (based on information about potential cropland management options based on policies and biophysical processes) for its land allocation (Havlík et al., 2011; Schmitz et al., 2014). CLUMondo includes 30 combinations of land cover and land intensity that can represent the heterogeneity of landscape patterns and takes into account the dynamic interactions between humans and the environment (van Asselen and Verburg, 2013). The addition of information about the suitability of land for agriculture and bio-physical potential of yield development could improve three parts of PLUM. First, the trade and regulating mechanism could be informed by land suitability and the land allocation procedure refined. Second, the yield development process could be complemented with information on country specific maximal potential yield in order to ensure realistic yield projections (this could be extended to include different climate scenarios). Third, information about land suitability could support the process that describes the intensive (cereal fed) and extensive (grazing) livestock production.

Overall, complementing socio-economic processes with bio-physical information on land suitability and yield development is an approach commonly adopted by global land use models (Schmitz et al., 2014) and would also be a valuable addition to PLUM. In PLUM, bio-physical information about land suitability would also allow potential arable land to be derived independently from the FAOSTAT data for permanent pastures and meadows. The FAOSTAT data for permanent pasture and meadows is limited, since this land use class includes everything from very productive and intensively managed pastures to nomadic grazing areas (Ramankutty et al., 2008). Additionally, there are reporting inconsistencies in these data (see Appendix for details), which could explain the discrepancy between the modelled and observed grassland during the evaluation period. In general, comparing model output to observation can be problematic where errors occur in the observational data.

Other conditions that explain discrepancy between modelled and observed properties include extreme climatic events and unforeseen events such as geo-political and structural change, e.g. the collapse of the Soviet Union. However, it would be problematic to represent the complex processes that influence extreme weather events or geo-political and structural changes in a model such as PLUM. Moreover these are often surprise events that are difficult to anticipate in practice. Overall, the presented parsimonious concept of socio-economic processes driving land-use change highlights the trade-offs that exist between selection and simplification of processes and model performance when confronted with observations. For instance, the aggregation of several cereal types is a simplification and masks potential higher variation and dynamics in the supply and demand of specific cereal types. There is a fine line in deciding what to include within a model and what not, and this is highly dependent on the aim of the modelling exercise. Using a model such as CLUMondo allows the study of research questions related to land-use intensity at detailed/disaggregated levels, while the PLUM model is better suited to the development of global rather than local land-use scenarios. PLUM can also be useful in providing global scale boundary conditions for regional and local scale studies (e.g. see Rounsevell et al., 2012) to study environmental issues, such as the impact of land-use change on isoprene emissions (Hardacre et al., 2012).

4.3. Parameterisation and sensitivity analysis

The global parameterization of PLUM is a methodological trade-off. On the one hand, the global parameterization compromises the

variability across countries. On the other hand, the reduction to global (or class related) parameters for all countries makes the model parsimonious and allows global sensitivity experiments to be undertaken more easily. With the global sensitivity analysis uncertainties in model input parameters are made explicit and the uncertainty ranges for each model output are efficiently quantified. This is important, as for instance, small differences in income elasticities, which are used in global models such as GCAM, GLO-BIOM and IMPACT (von Lampe et al., 2014) have been shown to have large effects on projected food demand (Schmitz et al., 2014; von Lampe et al., 2014). Changes in income elasticity are conceptually similar to changes in the parameters of the logarithmic functions that determine food consumption in PLUM, with the advantage that these changes in global parameters (lifestyle, technological change) can be systematically tested with the sensitivity analysis. In this way, the variability across countries was covered by the multiple runs.

The quantification of the uncertainty in output related to the uncertainty in input is also very important for global parameters that describe processes that we do not understand very well or lack data to quantify in the first place, but which nonetheless are conceptually important. In PLUM this is especially the case for the impact of technological change on the feed conversion ratios, which were assumed to increase by 0.5% per year. One could argue that this improvement rate is over-parameterized, but we believe that this it is not the case since the parameter is linked to a conceptually important process. However, as the estimation of the feed conversion improvement rate is uncertain, we estimated the standard deviation to be rather high at 50% of the value.

From the global time-series of the main model outputs, which also displayed all single runs, it becomes apparent that the quantification of uncertainties related to input parameters is relevant because they can change model outputs by the same magnitude as the observed changes in the evaluation period. The quantification of uncertainties in land-use change is important in understanding the future demand for land-use and to develop strategies that allow the efficient and sufficient supply of food and other land-use based products to the global population. For example, if future land-use for food production, including the attached uncertainties, can be projected, the remaining land can be used for other purposes without compromising food security. The global sensitivity analysis performed here showed the importance of yield developments for agricultural land-use change. Parameters that have the largest influence on model output should be explored in more detail (Norton, 2015), which supports the need to complement the yield development process with bio-physical information, as discussed above.

4.4. Implications and contextualization of findings

The importance of using land productively, and thus the importance of changes in cereal yields were highlighted by the global sensitivity analysis. More than half of the total variation in cereal land is explained by the sensitivity of the yield improvement rate for developing countries. The role of increases in yields for developing countries in meeting (future) food demand has been demonstrated by others (Balmford et al., 2005; Fischer et al., 2009; Foley et al., 2011). Also, PLUM showed a greater sensitivity in the variability of meat consumption for countries with meat-rich diets, compared to developing countries. The opposite pattern was observed for milk consumption, which reflects a greater potential to increase consumption in developing countries. The greater potential in developing countries is due to low initial consumption levels, as well as the large part of the global population belonging to the developing country group.

In general, the potential for increases in consumption and yields

in developing countries is positive as malnutrition and yield gaps are reduced. However, it should be noted that the simulated food production increase does not automatically imply an increase in food security, which requires more than making more food available through production. The distribution and trade of food, as well as access to food and its utilization are equally important in achieving food security (Ericksen, 2008). Also, the modelled increase in yield is based on the assumption that technological change improves yields, but specific management options that are stimulated by technological change and result in yield improvements are not distinguished. In principle, the increases in yield can be achieved through various approaches, some being more desirable than others. Historically, yield increases were often accompanied by negative consequences for the environment, such as ground water and air pollution through excessive fertilization, decreased biodiversity in large monocultures and loss of soil organic carbon (Foley et al., 2011). A more desirable path towards increasing yields in developing countries and sustaining high yields in developed countries is that of sustainable intensification (Campbell et al., 2014; Tilman et al., 2011). The path chosen will depend on a country's capacity and institutional support to implement sustainable intensification (Kuyper and Struik, 2014; Titonell, 2014). Thus, for future simulations, model results and their feasibility need to be discussed consistently within the context of the scenario narratives. It is also important to note that the improved sustainability of agricultural production needs to co-evolve with improvements in the whole food system, including shifts in diets for countries with meat-rich diets and a reduction in food loss and waste (Smith, 2013).

5. Conclusion and outlook

We conclude that the generalised process representations of the PLUM model captures the essential dynamics of global agricultural land-use in response to our initial research question: "Can the temporal trends and spatial patterns in global agricultural land-use be understood from simplified socio-economic processes at the country level?" In spite of the limitations in modelling unforeseen, rapid and extreme events, simple supply and demand processes, driven by population, economic development, life style choices and technological change offer insights into understanding the temporal trends of global agricultural land-use change. However, we acknowledge that in pursuit of model parsimony some important processes may potentially not be represented. The inclusion of bio-physical information about land suitability and yield development would be a valuable addition to the model in order to improve performance at the country level. PLUM is currently less well able to capture the variability of agricultural land-use change across all countries, while it still captures the trend for many large cereal producers. However, it is important to note that the purpose of this study was not to represent each country precisely. Moreover, the parsimonious nature of the model allows the efficient exploration of the uncertainty range of model input parameters, which demonstrated that global cereal land is strongly affected by changes in cereal yields in low income countries. Because of its capacity to efficiently explore parameter uncertainty and transparency of underlying assumptions (see Section 4.2), the model could be used to develop probabilistic land-use futures. Probabilistic futures have already been used for population and emissions projections conditional on a broader set of scenarios (O'Neill, 2005; van Vuuren et al., 2008), and could be used to assess the importance of scenario parameters such as rates of consumption increase and technological change for land-use change. Due to its low computational overhead the model is also suitable for rapid scenario assessments including normative (target orientated) visions.

Acknowledgements

This study was initiated by a study supported by NERC (Natural Environment Research Council, CH was supported by grant number NE/F003919/1) and was carried out under the Formas Strong Research Environment grant to AA, Land use today and tomorrow (LUsTT; dnr: 211-2009-1682). AA and MR acknowledge support from the EU FP7 LUC4C (grant no. 603542). The author would like to thank Sara Broogard and Jonathan Seaquist for valuable discussions during the model building process.

Appendix A. Supplementary data

Supplementary data related to this article can be found at <http://dx.doi.org/10.1016/j.envsoft.2015.10.015>.

Appendix: Technical model description

All equations are applied on an annual basis, for the results described in this paper from 1990 to 2010. If not stated otherwise, equations are calculated for each of the 162 countries. The model is initialized with FAOSTAT data for the year 1990, but for variables with high inter-annual variation a 10 year average (1986–1995) was used. Additionally, for countries formed after the end of the Soviet Union, data were retrieved from the earliest year available in FAOSTAT. (FAOSTAT, 2012). Data were available for 162 countries. Afghanistan, Kiribati, Iraq, Oman, Singapore, Somalia, Qatar, Equatorial Guinea, Bahrain and the Democratic Republic of Congo were excluded because of a lack of data for consumption variables. The small island states were also excluded because GDP per capita and population data were not available.

For population and income World Bank data was used for the evaluation runs (indicator: Population, total; indicator code: SP.

(indicator: GDP (current US\$); indicator code: NY.GDP.MKTP.CD; 1990–2010; WB, 2012) and country-level downscaled GDP projections in 5 year time-steps for the SRES (1990–2100; CIESIN, 2002).

Cereal consumption (*cerealCon*) was assumed to be proportional to population development, but a consumption variability (*indCerealVar*) was included (A.2), [ton].

$$cerealCon = \left(\frac{cerealConPc1990}{1000} + \frac{cerealConPc1990 * indCerealVar}{1000} \right) * population \quad (A.2)$$

cerealConPc1990 = cereal consumption per capita in 1990 [kg person-1 year-1] *population* = population [person] *indCerealVar* = variability in cereal consumption [1/time]

Data was retrieved from FAOSTAT Food supply, Crops Primary equivalent, Cereals – Excluding Beer + (Total) for cereal consumption; and for population from World Bank for evaluation runs (1990–2010; WB, 2012) and country-level downscaled population projections in 5 year time-steps for SRES (1990–2100; CIESIN, 2002). For *indCerealVar* the mean value is set 0 (following the assumption that cereal consumption is proportional to population), but for the sensitivity analysis the standard deviation was estimated to be 0.01. This was based analysing the inter-annual variation of cereal consumption during the time period 1961–1990.

The consumption of milk (A.3) and meat (A.4) [ton] was modelled using a logarithmic function:

$$milkCon = \left(\frac{milk_j * (\log(gdpPc) - \log(gdpPc1990)) + milkConPc1990}{1000} \right) * population \quad (A.3)$$

$$meatCon = \left(\frac{meat_k * (\log(gdpPc) - \log(gdpPc1990)) + meatConPc1990}{1000} \right) * population \quad (A.4)$$

POP.TOTL; WB, 2012) but can be replaced with data based on the SRES (Special Report on Emission Scenarios; CIESIN, 2002) for scenario runs (results are not reported here).

Consumption module

The relative income level of a country compared to other countries (*gdpPcRatio*) was calculated to establish differences between countries in, for example, land conversion rates and yield increases (A.1) [unitless].

$$gdpPcRatio = \frac{gdpPc}{\sum_{i=0}^n \max(gdpPc)} \quad (A.1)$$

gdpP = Annual GDP per capita [US\$].

Data was retrieved from World Bank for evaluation runs

j = 1–4; number of milk classes

k = 1–4; number of meat classes

milk_j = global parameter, rate of increase in milk consumption [kg milk per capita/log(GDPpc)]

meat_k = global parameter, rate of increase in meat consumption [kg meat per capita/log(GDPpc)]

milkConPc1990 = milk consumption per capita 1990 [kg person-1 year-1]

meatConPc1990 = meat consumption per capita 1990 [kg person-1 year-1]

The four classes are differentiated based on cultural factors, separating countries that historically ate much meat (class 1) from countries that historically ate less meat (class 2), countries which cannot afford high meat consumption due to low income levels (class 4) and the rest (class 3), see Table A1. Conceptually countries

in class 4 were assumed to progress to class 3 countries when their income levels surpass 2200 US\$ per capita, but this was not implemented in the current version of PLUM. The rate of increase in milk and meat consumption is different for the four classes, see Table A1. To find the parameters linear regression ($y = a \cdot \ln x + b$) was performed for all countries with a complete dataset available over the time period 1961–1990) for each class (see Table A1). However, the slope of the regression overestimates the value drastically if the division into classes is rough. Therefore the slope was calculated for each country and the median of all slopes for one class used as value. Similarly, the standard deviation was calculated from the regression values retrieved for each country within each class (1–4).

Table A1
Methods and values of mean and standard deviation of $meat_j$ and $milk_j$.

Variable	Class division	Median	Regression	SD
$meat1$	$meatConPc1990 \geq 80$ kg/person, incl. China	11.38	13.54	7.08
$meat2$	$meatSpending \geq 300$ US\$/kg meat	6.56	9.02	4.31
$meat3$	$meatConPc1990 < 80$ kg/person, $meatSpending < 300$ US\$/kg meat, $gdpPc1990 \geq 2200$ US\$	7.72	11.10	6.01
$meat4$	$gdpPc1990 < 2200$ US\$	1.14	6.02	4.45
$milk1$	$milkConPc1990 \geq 255$ kg/person	15.95	9.26	23.13
$milk2$	$meatSpending \geq 200$ US\$/kg milk	6.16	27.01	11.99
$milk3$	$meatConPc1990 < 255$ kg/person, $meatSpending < 200$ US\$/kg milk, $gdpPc1990 \geq 2200$ US\$	4.37	35.89	14.09
$milk4$	$gdpPc1990 < 2200$ US\$	3.33	15.71	9.04

For countries with very low or decreasing GDP per capita the function could result in negative values. This was avoided by including a GDP per capita minimum. If GDP per capita was smaller than GDP per capita minimum, the per capita consumption was kept constant. To account for individual consumption levels per country, the consumption per capita in 1990 year 1990 was used as a starting value. Data was retrieved from FAOSTAT Food supply, Livestock and Fish Primary Equivalent, Milk – Excluding Butter + (Total) and Meat + (Total) respectively (FAOSTAT, 2012).

Conversion and trade module

The potential demand for cereal feed due to milk and meat production was calculated using (A.5) and (A.6) [ton].

$$milkConverted = milkCon * \left(\frac{meatYield1990}{milkYield1990} \right) \quad (A.5)$$

$meatYield1990$ = livestock productivity in 1990 [hg animal-1 (carcass weight)]
 $milkYield1990$ = livestock productivity in 1990 [hg animal-1 yr-1]

Data was retrieved from FAOSTAT, Production, Livestock Primary, Cattle meat, Yield and Cow milk, whole fresh, Yield respectively (FAOSTAT, 2012).

$$potentialCrealFeed = \left(\left(\sum_{i=Poultry}^{Beef} r_i * \frac{meatConPc1990 * population1990}{1000} \right) + milkConverted * fcr1990_{Beef} \right) * fcr1990_i \quad (A.6)$$

$i = Poul, Pig, Mut, Beef$

$fcr1990_i$ = baseline values for feed conversion ratios for poultry, pigs, mutton and beef of 4.5, 9, 10 and 25 [kg cereals kg carcass weight-1] respectively.

The baseline values for poultry, pigs and beef were adopted from Smil (Smil, 2002) and the value for mutton was estimated.

The ratio of meat and milk that was produced using cereal feed 1990 with (A.7) [unitless].

$$feedRatio1990 = \frac{cerealFeed1990}{potentialCerealFeed} \quad (A.7)$$

$cerealFeed1990$ = Cereal feed in 1990 [ton].

Data downloaded from FAOSTAT, Food Balance Sheets, Food Balance Sheets, Cereals – Excluding Beer + (Total), Feed (FAOSTAT, 2012).

The feed conversion ratio improvement rate ($fcrImp$) was used to calculate cereal feed (A.8) [ton].

$$cerealFeed(t) = \left(\left(\sum_{i=Poultry}^{Beef} r_i * meatCon * fcr1990_i - (fcr1990_i * fcrImp * t) \right) + milkConverted * fcr1990_{Beef} - (fcr1990_{Beef} * fcrImp * t) \right) * feedRatio1990 \quad (A.8)$$

$i = Poul, Pig, Mut, Beef$

$t = 0, 1, 2, \dots, 20$ (time, corresponds to year 1990–2010) and

$fcrImp$ = feed conversion rate Improvement rate [1/time]

r_i = share of bovine, pig, poultry and mutton meat on total meat consumption in 1990 [unitless]

The mean value for $fcrImp$ was estimated to be 0.5% per year, based on the improvement in feed conversion observed during the evaluation period. However, as this estimation is a rather uncertain, we estimated the standard deviation to be rather high with 50% of

the mean value, which equals 0.25% per year. r_i was calculated using data from FAOSTAT, Food supply, Livestock and Fish Primary Equivalent, Bovine Meat, Pigmeat, Poultry Meat and Mutton & Goat Meat and Meat + (Total) (FAOSTAT, 2012).

The country's cereal balance was calculated with (A.9) [ton].

$$\text{cerealBalance} = \text{cerealProduction} - \text{cerealCon} - \text{cerealFeed} \quad (\text{A.9})$$

cerealProduction = see (A.30).

Depending on the cereal balance, countries were assumed to import cereals (negative cereal balance) or export cereals (positive cereal balance) and contribute to world import (A.10) and world export (A.11), both being global variables [ton].

$$\text{worldImport} = \sum_{i=1}^{260} \min(\text{cerealBalance}_i, 0) \quad (\text{A.10})$$

$$\text{worldExport} = \sum_{i=1}^{260} \max(\text{cerealBalance}_i, 0) \quad (\text{A.11})$$

i = FAO country code

overProRate1990 = overproduction rate in 1990 (see text below)
 overProRate = rate that changes overProRate1990 with time [1/time], 0 in evaluation runs.

The overproduction rate in 1990 was estimated, comparing global cereal production with cereal consumption and cereal used as feed for the period of 1961–1990. The average rate of surplus production is the value for overProRate 0.3, that is 30% per year. Standard deviation was calculated from the time series (1961–1990) of overProRate and resulted in 0.035 [1/time].

The variable $\text{expectedProduction}$ was included to describe how much production should be potentially decreased (negative value) or increased (positive value). This depends on the cereal balance in the country and the cereal balance on the world market (see also Fig. 2).

Negative value for importing countries when world cereal balance is larger than overproduction demand (A.14) [ton]:

$$\text{expectedProduction}_{\text{impHigh}} = \text{cerealBalance} \quad (\text{A.14})$$

Negative value for exporting countries when world cereal balance is larger than overproduction demand (A.15) [ton]:

$$\begin{aligned} \text{expectedProduction}_{\text{expHigh}} = \max(& -(\text{cerealBalance} + \text{cerealBalance} * (\text{overProRate1990} + \text{overProRate1990} * \text{overProRate} * t) \\ & \times), -(\text{newDemand} * \text{worldCerealBalance} + \text{newDemand} * \text{worldCerealBalance} * (\text{overProRate1990} \\ & + \text{overProRate1990} * \text{overProRate} * t))) \end{aligned} \quad (\text{A.15})$$

i = FAO country code.

The global variable world cereal balance (A.12) in the model was described by the state of the cereal world market [ton].

$$\text{worldCerealBalance} = \text{worldExport} + \text{worldImport} \quad (\text{A.12})$$

The cereal consumption for seeds, biofuels, and waste and

newDemand = country's share on worldExport or worldImport [unitless].

Positive value for importing countries when world cereal balance is smaller than overproduction demand (A.16) [ton]:2

$$\begin{aligned} \text{expectedProduction}_{\text{impLow}} = \max(& -(\text{cerealBalance} + \text{cerealBalance} * (\text{overProRate1990} + \text{overProRate1990} * \text{overProRate} * t) \\ & \times), -(\text{newDemand} * \text{worldCerealBalance} + \text{newDemand} * \text{worldCerealBalance} * (\text{overProRate1990} \\ & + \text{overProRate1990} * \text{overProRate} * t))) \end{aligned} \quad (\text{A.16})$$

overproduction on purpose was not directly included in the model. But this was accounted for by the overproduction demand (A.13) [ton].

Positive value for exporting countries when world cereal balance is smaller than overproduction demand (A.17) [ton]:

$$\text{overproDem} = \left(\sum_{i=1}^{260} \text{cerealCon} + \text{cerealFeed} \right) * (\text{overProRate1990} + \text{overProRate1990} * \text{overProRate} * t) \quad (\text{A.13})$$

$$\text{expectedProduction}_{\text{expLow}} = \text{newDemand} * \text{worldCerealBalance} + \text{newDemand} * \text{worldCerealBalance} * (\text{overProRate1990} + \text{overProRate1990} * \text{overProRate} * t) \quad (\text{A.17})$$

Land conversion module

The cereal yield was calculated using the baseline average cereal yield for each country and accounting for yield improvements over time depending on income levels. A maximum of cereal yield was defined by the *cerealYieldCeiling* (A.18) [hg ha⁻¹].

gdpRatio ≤ 0.1; class 2: gdpRatio >0.1 and ≤ 0.5; class 3: gdpRatio >0.5). Standard deviation was calculated from the yearly increase values for each country within each class (1–3). As upper limit for the average cereal yield we assumed 75000 hg ha⁻¹, which is little above the yields reported for the country with highest yields (the Netherlands, with yields around 70 000 hg ha⁻¹ in 1990)

$$\text{cerealYield}(t) = \min((\text{cerealYield1990} * \text{yieldR}_{1,2,3} * t), (\text{cerealYieldCeiling} + \text{cerealYieldCeiling} * \text{yieldR}_3)) \quad (\text{A.18})$$

cerealYield1990 = cereal yield in 1990 [hg ha⁻¹]
yieldR_{1,2,3} = yield increase rate [1/time]
cerealYieldCeiling = upper limit for average cereal yield [hg ha⁻¹]

(FAOSTAT, 2012).

For *cerealYield1990* data was retrieved from FAOSTAT, Production, Crops, Cereal, Total (+Total), Yield (FAOSTAT, 2012) and the average (1986–1995) calculated and used as 1990 value. The yield increase rates were derived from the average yearly increase of cereal yield over the time period 1961–1990 for 3 classes (class 1:

The variable *landConversion* was included to introduce the areal changes of each countries (A.19)–(A.24) [1000 ha]. To avoid implausible large land conversions, we assumed that the land conversion rates multiplied with the cereal land area would provide the maximum yearly land conversion. The land conversion rates were assumed to be different for developed and developing countries (Table A2).

$$\text{landConversion}_{\text{abandExportingRich}} = \max\left(\frac{\text{expectedProduction}}{\text{cerealYield} * 10}, -\text{abandonmentRich} * \text{cropland}\right) \quad (\text{A.19})$$

$$\text{landConversion}_{\text{abandExportingPoor}} = \max\left(\frac{\text{expectedProduction}}{\text{cerealYield} * 10}, -\text{abandonmentPoor} * \text{cropland}\right) \quad (\text{A.20})$$

$$\text{landConversion}_{\text{newCLSelfImportingRich}} = \min\left(\frac{-\text{expectedProduction}}{\text{cerealYield} * 10}, \text{newCLSelfRich} * \text{cropland}\right) \quad (\text{A.21})$$

$$\text{landConversion}_{\text{newCLSelfImportingPoor}} = \min\left(\frac{-\text{expectedProduction}}{\text{cerealYield} * 10}, \text{newCLSelfPoor} * \text{cropland}\right) \quad (\text{A.22})$$

$$\text{landConversion}_{\text{newCLRICH}} = \min\left(\frac{\text{expectedProduction}}{\text{cerealYield} * 10}, \text{newCLRICH} * \text{cropland}\right) \quad (\text{A.23})$$

$$landConversion_{newCLPoor} = \min\left(\frac{expectedProduction}{cerealYield*10}, newCLPoor*cropland\right) \quad (A.24)$$

abandonmentRich, abandonmentPoor, newCLSelfRich, newCLSelfPoor, newCLRich, newCLPoor = see Table A2, [1/time].

Cropland degradation (soil erosion, salinization, desertification), was assumed to be on average 0.1% of cereal land. Degraded cropland is assumed to become grassland. For standard deviation 10% of the mean value was assumed. For cereal land in 1990 data was

Table A2
Methods and values of mean and standard deviation of land conversion rates.

Land conversion rate	Abbreviation	Method and data sources	Mean	Min & max value
Abandonment rate developed countries	<i>abandonmentRich</i>	Average observed yearly decrease in cereal land in developed/developing countries (1961–1990). The maximum is the observed significant maximal negative rate of change for cereal land in all developed/developing countries. With data from FAOSTAT (cereal production; area in ha)	0.023	0.006 –0.071
Abandonment rate developing countries	<i>abandonmentPoor</i>	Average observed yearly decrease in cereal land in developed/developing countries (1961–1990). The maximum is the observed significant maximal negative rate of change for cereal land in all developed/developing countries. With data from FAOSTAT (cereal production; area in ha)	0.015	0.004 –0.054
New cereal land rate developed countries	<i>newCLRich</i>	Average observed yearly increase in cereal land in developed/developing countries (1961–1990). The maximum is the observed significant maximal positive rate of change for cereal land in all developed/developing countries. With data from FAOSTAT (cereal production; area in ha)	0.015	0.003 –0.049
New cereal land rate developed countries for self sufficiency	<i>newCLRich Self</i>	Average observed yearly increase in cereal land in developed/developing countries (1961–1990). The maximum is the observed significant maximal positive rate of change for cereal land in all developed/developing countries. With data from FAOSTAT (cereal production; area in ha)	0.015	0.003 –0.049
New cereal land rate developing countries	<i>newCLPoor</i>	Average observed yearly increase in cereal land in developed/developing countries (1961–1990). The maximum is the observed significant maximal positive rate of change for cereal land in all developed/developing countries. With data from FAOSTAT (cereal production; area in ha)	0.029	0.002 –0.046
New cereal land rate developing countries for self sufficiency	<i>newCLPoor Self</i>	Average observed yearly increase in cereal land in developed/developing countries (1961–1990). The maximum is the observed significant maximal positive rate of change for cereal land in all developed/developing countries. With data from FAOSTAT (cereal production; area in ha)	0.029	0.002 –0.046 ^a

As the land conversion rate are upper boundary values, instead of a normal distribution around the standard deviation a uniform distribution was assumed when performing the sensitivity analysis. Additionally, values from the statistical analysis that were below 0.005 (0.5%) were replaced with 0.005 in the model runs. The division between developed and developing countries was made on the basis of the *gdpPcRatio*. If *gdpPcRatio* < 0.2 countries are

retrieved from FAOSTAT, Production, Crops, Cereal, Total (+Total), Area (FAOSTAT, 2012).

A minimum of 10% of the initial land cover type was assumed to be sustained at any time.

Cropland was estimated using the share of cereal land of cropland in 1990 and applying this share on cereal land (

$$shareCropland = \frac{((arableLand1990 + permanentCrops1990)/100)*((agriculturalLand1990/100)*landArea)}{cerealland1990} \quad (A.26)$$

assumed to be developing countries, otherwise if *gdpPcRatio* ≥ 0.2 then countries are considered as developed countries in the model.

The land area which is converted to cereal land was assumed to be taken from grassland and forest. Vice versa, if cereal land is abandoned, the land area is allocated to grassland and forest. The proportion between forest and grassland was introduced by the grassland to forest ration *grassForestR*, which was 0.5 [unitless] for the evaluation runs (A.25) [1000 ha].

$$\frac{cerealland}{dt} = \frac{cerealland1990}{1000} + (grassForestR*landconversion_i) + ((1 - grassForestR)*landconversion_i) - (cropDeg*cerealland) \quad (A.25)$$

i = *abandExportingRich*, ..., *newCLPoor*; (A19–A24);
cropDeg = cropland degradation [1/time]
cerealland1990 = cereal land in 1990 [ha]

arableLand1990 = FAOSTAT [% of agriculturalLand1990]
permanentCrops1990 = FAOSTAT [% of agriculturalLand1990]
agriculturalLand1990 = FAOSTAT Agricultural area [% of LandArea]
landArea = FAOSTAT [1000 ha]

$$cropland = shareCropland*cerealland \quad (A.27)$$

Grassland and forest were treated as residuals of cropland (A.28) and (A.29) [1000 ha]. Natural forest degradation was assumed to contribute to the formation of new grassland. Cereal land degradation was assumed to fall into the forested area.

$$\frac{grassland}{dt} = grassland1990 - ((1 - grassForestR)*landconversion) + (forestDeg*forest) \quad (A.28)$$

$$\frac{forest}{dt} = forest1990 - (grassForestR * landconversion) + (cropDeg * cerealLand) \quad (A.29)$$

forestDeg = forest degradation rate [1/time]
 grassland1990 = grassland in 1990 [1000 ha]
 forest1990 = forest in 1990 [1000 ha]

The forest degradation rate was assumed to be due to natural loss of forest land to grassland with a rate 0.01% of forest per year. For standard deviation 10% of the mean value were assumed. For grassland1990 data was downloaded, from FAOSTAT, Resources, Land, Permanent meadows and pastures, Area (FAOSTAT, 2012). The “permanent pastures and meadows” category in FAOSTAT is problematic as it includes intensive and extensive managed grasslands, and suffers from reporting inconsistencies. For the evaluation period in this paper the mismatch of global modelled and reported grassland starting in 1993 is partly due to reporting inconsistencies in the observed data, in particular for Saudi Arabia. In 1990, 56% of Saudi Arabia’s land area was classified as grassland (FAOSTAT category “permanent pastures and meadows”), but from 1993 onwards 79% was reported as grassland (FAOSTAT, 2012), which accounts for most of the discrepancy (FAO adj. in Fig. 3, = FAO global – change in grassland in Saudi Arabia from 1992 to 1993). Data for forest was downloaded from FAOSTAT, Resources, Resources, Forest area, Area (FAOSTAT, 2012). Finally, cereal production was calculated as the product of cereal land and cereal yield (A.30) [ton].

$$cerealProduction = \frac{cerealLand * cerealYield}{10} \quad (A.30)$$

Aggregated Global variables

The global variables Cereal consumption, Milk consumption, Meat consumption, Cereal feed, Cereal production, Cereal land, Cropland and Grassland are the sums of the country level variables cerealCon, milkCon, meatCon, cerealFeed, cerealProduction, cereal landcereal land, cropland and grassland respectively and were converted from ton to Mt (megaton) and 1000 ha to Mha (megahectare). Cereal yield was estimated by dividing global Cereal production with Cereal land (ton/ha).

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