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**Paper prepared for presentation at the EAAE 2011 Congress
Change and Uncertainty
Challenges for Agriculture,
Food and Natural Resources**

August 30 to September 2, 2011
ETH Zurich, Zurich, Switzerland

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Abstract

Concerns about future food security in the face of volatile and potentially lower yields due to climate change have been at the heart of recent discussions on adaptation strategies in the agricultural sector. While there are a variety of studies trying to quantify the impact of climate change on yields, some of that literature also acknowledges the fact that these estimates are subject to substantial uncertainty. The question arises how such uncertainty will affect decision-making if ensuring food security is an explicit objective. Also, it will be important to establish, which options for adaptation are most promising in the face of volatile yields. The analysis is carried out using a stochastic version of the Global Biosphere Management Model (GLOBIOM) model, which is a global recursive dynamic partial equilibrium bottom-up model integrating the agricultural, bio-energy and forestry sectors with the aim to give policy advice on global issues concerning land use competition between the major land-based production sectors. The source of stochasticity is the interannual crop yield variability, making it more risky to rely on average yields and thus requiring stochastic optimization techniques. The results indicate that food security requires overproduction to meet minimum food supply constraints also in scenarios of negative yield shocks, where the additional land needed is sourced from forests and other natural land. Trade liberalization and enhanced irrigation both appear to be promising food supply stabilization, and hence land saving, mechanisms in the face of missing storage.

Keywords: food security, food price volatility, optimization under uncertainty, adaptation, land use change

1. Introduction

With relatively inelastic demand and variable supply, which depends on many uncertain factors such as the weather, government policy and technology, volatility has always been at the heart of food markets. However, volatility supposedly will increase in the medium to long run, as temperatures rise and precipitation patterns change due to climate change. A study by Lobell et al. (2008), for example, prioritizes specific crops in particular regions for adaptation. Those crops are assessed by their importance for a region's food-insecure population and their vulnerability to shocks without adaptation. Amongst other results such as significantly negative impacts on many crops, they also find that there are many cases with high uncertainty, i.e. impacts ranging from highly negative to positive. They explain the finding by those crops'

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strong dependence on historical rainfalls and the large uncertainty in future changes in precipitation patterns. As the uncertainty differs among crops, this also indicates that different actors might have different priorities depending on their risk preferences.

Adaptation mechanisms that have long been deemed promising by e.g. Rosenzweig and Parry (1994) include the development of new crop varieties that are more robust to drought, for example, and irrigation expansion. Of course, these measures are rather costly for the producer (Lobell et al, 2008) and, in the absence of higher storage capacity, the focus in the adaptation debate has recently shifted to trade liberalization, where production shocks in one region would be cushioned by output and trade adjustments in other parts of the world (see e.g. Foresight Report, 2011).

While uncertainty analysis in itself is not a new topic in agricultural economics (see for review e.g. OECD, 2009), there are relatively few attempts to implement such analysis in large-scale models. In addition, there is currently a lack of analysis of impacts of climate change on socio-economic factors (see e.g. the IFPRI study by Nelson et al, 2009, for an exception), to which this analysis also contributes. Typically, uncertainty is examined through scenarios or sensitivity analysis: Nelson et al. (2010) use the IMPACT partial-equilibrium dynamic model to investigate drought in South Asia between 2030 and 2035 by letting rain fed crop areas in Bangladesh, India and Pakistan fall by 2% annually and then return to the baseline. They find a sharp increase in world prices during the drought, e.g. 32% for wheat, leading to an increase in malnutrition. The authors also find that during the drought, the region becomes a net importer for crops it had previously exported pointing again to the importance of trade. Similarly, Robinson and Willenbockel (2010) examine a drought in the NAFTA area, China and India using the GLOBE static computable general equilibrium model by simulating a 20% yield drop in the USA, Canada, Mexico, China and India. Again, crop prices rise by up to 40%. Trade can cushion some of this impact, but if an export tax is introduced, crop prices are significantly higher in all regions, also those not directly affected by the drought.

While this and other research gives a very good impression of the magnitudes involved in impacts, the associated uncertainty and the potential importance of adaptation mechanisms such as trade liberalization, the aim of this study is to assess the effect that this has on production decisions. In other words, rather than optimizing for given scenarios or introducing shocks into a deterministic model to observe the response over time, we want to optimize production decisions under uncertainty. Therefore, our study is better placed with the work in e.g. Beach et al. (2010), Chen and McCarl (2009) and Butt et al. (2004), who extend the objective function of the US forestry and agricultural sector model (FASOM) to include a function of the yield variance. Applying their extended model to the case of Mali, they find that the model incorporating risk outperforms the model without risk consideration when comparing predicted to observed crop area. In this study, we have to restrict ourselves to a relatively stylized approach due to the difficulty that model results become more difficult to interpret, if not less meaningful, if we add the variance to the objective. In the first step, we optimize under uncertainty, i.e. maximize the expected value of welfare under different scenarios of yield developments, and then in the second step observe the implications of this decision depending on the yield scenario realized, i.e. the outcomes in terms of prices and allocations and the realization of trade etc for each possible scenario.

The analysis is carried out using the Global Biosphere Management Model (GLOBIOM)¹ (Havlík et al., 2010). GLOBIOM is a global recursive dynamic partial equilibrium bottom-up model integrating the agricultural, bioenergy and forestry sectors with the aim to give policy advice on global issues concerning land use competition between the major land-based

¹ www.globiom.org

production sectors. Concept and structure of GLOBIOM are similar to the US Agricultural Sector and Mitigation of Greenhouse Gas (ASMGHG) model (Schneider, McCarl and Schmid, 2007).

In GLOBIOM, the world is divided into 28 economic regions representing either individual large countries or aggregates of countries. Demand and international trade are represented at the level of these regions. The supply side of the model is based on a detailed disaggregation of land into Simulation Units – clusters of 5 arcmin pixels belonging to the same country, altitude, slope and soil class, and to the same 30 arcmin pixel (Skalský et al., 2008). Crop, forest and short rotation coppice productivity is estimated together with related environmental parameters like greenhouse gas budgets or nitrogen leaching, at the level of Simulation Units, either by means of process based biophysical models, e.g. Environmental Policy Integrated Climate Model EPIC (Williams, 1995), or by means of downscaling (Kindermann et al., 2008). Changes in the demand on the one side, and profitability of the different land based activities on the other side, are the major determinants of land use change in GLOBIOM.

In this paper, we extend the model to investigate the impact of stochasticity on decisions when ensuring food security is an explicit constraint. The source of stochasticity stems from weather variability and climate change, making extreme weather events more frequent and hence more risky to rely on average yields and thus requiring stochastic optimization techniques. In particular, if we impose a safety level of nutrition, which the social planner does not want to fall short of, stochastic yields pose a threat to this objective: the larger the fluctuations are, the more prone will we be to underpass the safety level.

We use the yield projections from the EPIC model, which is a crop process model. For this study it uses climate information from the Tyndall Centre for Climate Change Research. In particular, it uses the A1 scenario and produces projections for 2050 and 2100, which are analyzed in the next section and then used to generate yield distributions as input to GLOBIOM. GLOBIOM will be presented in Section 3. Section 4 describes and discusses the results. Section 5 concludes.

2. Data & Yield Distributions

The data used as input for the GLOBIOM model in this study is in the form of yield distributions. Multiple yield scenarios have been simulated with the global EPIC model for 2050 and 2100. The information for this comes from the Tyndall Climate Change Data, where the A1fi Scenario has been used. These data are characterized by progressively increasing temperatures globally and decreases in precipitation in Southern Europe, Sub-Saharan and Southern Africa, parts of Asia and Australia, Middle America and parts of North-East America.

Fig. 1 tries to visualize the impacts of the climatic changes that EPIC finds to have on yields for the example of wheat. Note that the management systems in EPIC are irrigated, high-input/rain-fed, low-input/rain-fed and subsistence management (You and Wood, 2006). However, in order to capture the full impact of changes in temperature and precipitation patterns on yields, we focus on the results for the subsistence management, thus abstracting from adaptation through increases in irrigation and fertilization. In the upper map of Fig. 1, the relative difference in yields between 2050 and 2100 is shown. While Northern regions generally show increases of 15% and partially more, Sub-Saharan Africa, South-East Asia and large parts of Latin America show painful reductions of 30% and more. Not surprisingly, the regions where yield falls substantially and to a very low level, volatility will also be lower in 2100 compared to 2050 (see lower map for the relative difference in the relative variance for these periods), while higher yields offer also more scope for volatility to be higher. Interestingly, however, even keeping this in mind, there are several areas e.g. in Europe and Russia, where yields seem to stabilize, even though they are higher, or changes in averages are modest. Similarly, some areas in Sub-Saharan Africa suffer substantial losses in terms of

average yields across the board, but also experience increases in volatility in relatively large areas, which indicates that climate change might affect different regions asymmetrical and could lead to higher yield volatility in the future.

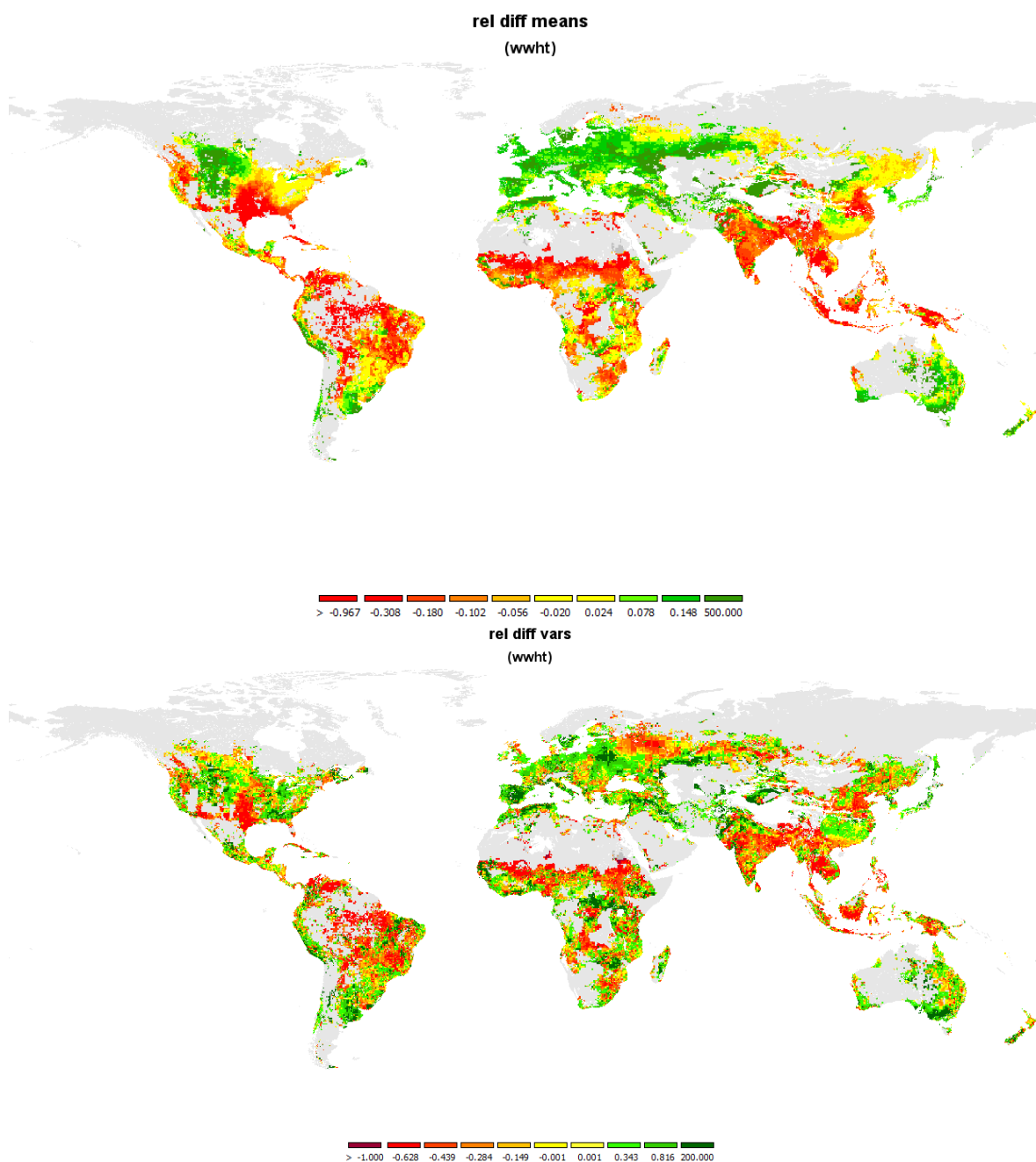


Figure 1: Relative difference 2050 vs. 2100 averages (upper map) and variances (lower map) for wheat

In Table 1, we have computed the variances for the historical wheat yields from FAO and compare them to the projections for 2050 (FAO-2050) and 2100 (FAO-2100). It reflects a similar pattern as observed in Fig. 1, where “winners” from climate change (e.g. Europe) in terms of increased average yields also suffer higher volatility. Since these regions are already nowadays major suppliers of agricultural commodities, volatility will impact substantially also the global markets.

Compare	<-50%	<-30%	<0%	>0%	>+30%	>+50%	>+100%
FAO-2050	ANZ, CongoBasi n, Mexico, Pacific Islands, RSEA_OPA, South Korea	China, EU_North, SouthAfr, SubSaharAfr	Brazil, ROW E	India	EU_Baltic, RSA_PAC, Turkey	EU_Mid W, EU_South, RCEU, RSAS	Canada, EU_Centr, Former_USSR, Japan, MidEastN, USA
FAO-2100	ANZ, China, CongoBas, Mexico, Pacific Islands, RSA_OPA, South_Afr, South Korea, SubSaharAfr	Brazil, EU_North	India	RCEU, RSEA_PAC		EU_Baltic, EU_Centr, EU_Mid W, RCAM, RCEU, RSAM, RSAS, USA	Canada, EU_South, Former USSR, Japan, MidEastN, Turkey

Table 1: Comparison of variances computed from historical wheat yields from FAO to variances of the projected yields in 2050 and 2100.

3. Description of the Stochastic Model

The model used in this paper builds on the stochastic version of the Global Biosphere Management Model (GLOBIOM). GLOBIOM is a global recursive dynamic partial equilibrium bottom-up model integrating the agricultural, bio-energy and forestry sectors with the aim to give policy advice on global issues concerning land use competition between the major land-based production sectors. In this paper, the model is extended to capture the yield volatility and its effect on the decisions in the presence of different energy- and nutrition-related objectives. The yield volatility emanates from different sources of uncertainty such as weather, occurrence of pests, management changes due to changes in input prices, etc. In this study, we focus on weather-related crop yield uncertainty and we restrict ourselves to a relatively stylized approach in order to keep the model traceable.

In order to explain how the yield stochasticity can be introduced into the model, we will first start with a short description of the deterministic version. For a detailed formulation, see Havlík et al. (2010).

The objective function of GLOBIOM is the maximization of welfare, which is defined as the sum of producer and consumer surplus, subject to resource, technological and policy constraints. Prices and international trade are determined in an endogenous way for the respective 28 aggregated world regions. Product supply functions are included implicitly and are based on detailed, geographically explicit Leontieff production functions. Demand is included explicitly and elasticities are mostly constant. More detailed information on this and on the data concept and processing can be found in Havlík et al (2010).

Concerning the model structure, production comes from three major land cover types, which are cropland, managed forests and areas suitable for short rotation tree plantations. The biophysical simulation model EPIC (Williams, 1995) simulates management-related yield coefficients for 20 crops, which represent more than 80% of the 2007 harvested area as reported by FAO.

Supply of crops enters either consumption, or livestock production or bio-fuel production. Primary forest production from traditional managed forests includes saw logs, pulp logs, other industrial logs, traditional fuel wood and biomass for energy, where the latter can be converted through combined heat and power production, fermentation for ethanol, heat, power and gas production, and gasification for methanol and heat production. Furthermore, woody biomass for energy can also be produced from short rotation tree plantations.

The model allows for endogenous change in land use within the available land resources, where the total land area is fixed over the simulation horizon. Land use change possibilities are limited in basically two ways: (1) through explicit constraints on conversion from one land use to another and (2) by linking land suitability criteria to production potentials. For details on suitability analysis, the reader is referred to Havlík et al (2010), where also all basic assumptions (i.e. exogenous parameters on population developments etc) are presented in detail.

For this paper, we do not want to reproduce the formal detailed description of the deterministic model, but prefer to explain how stochasticity is introduced. Generally, the deterministic model can be formulated as an optimization problem to maximize the social welfare under given constraints. The maximization is done over several decision variables². The deterministic model assumes that the yield for a given year is known in advance (as a matrix containing the yield for each crop, under a given crop management, in a given region / Simulation Unit). This, however, is not true in reality.

Therefore the decision variables are in fact of two types. Some of them have to be chosen prior to the time the actual yield is observed (we denote them collectively by x and will refer to them as first stage variables), whereas the remaining³ are made afterwards (denoted by y and further referred to as second stage variables). The deterministic GLOBIOM can thus be formulated as

$$\begin{aligned} \max_{x,y} & f_1(x) + f_2(x, y) \\ \text{s.t.} & g_1(x) \leq 0 \\ & g_2(x, y) \leq 0 \end{aligned} \quad (1)$$

for some functions f_1, f_2, g_1, g_2 , with functions f_2, g_2 depending also on the yield Y . At this stage the separation of decision variables into two categories is purely superficial. However, it is not the case in the stochastic extension of GLOBIOM.

For the stochastic formulation let us assume that the yield Y is a random variable with known distribution. The realization of Y happens only after the first stage decisions are chosen. Thus the first stage variables do not depend on the particular yield realization and have to be based only on the information about the distribution. On the other hand, the second stage decisions are taken after the observation of the actual yield and thus the choice of the second stage decision depends on the realized yield. Under the assumption of stochastic yield the problem becomes a standard problem of stochastic programming:

² Specifically the decision variables are: land use/cover change Q , the land in different activities A , livestock production B , processed quantity of the primary input P , and inter-regionally traded quantity T , final consumption of agricultural products C (see Havlík et al., 2010, Appendix)

³ The first stage variables are in this case Q, A, B and P , the second stage variables C, T .

$$\begin{aligned}
& \max_{x,y} f_1(x) + E[f_2(x, y(Y))] \\
& \text{s.t. } g_1(x) \leq 0 \\
& \quad g_2(x, y(Y)) \leq 0
\end{aligned} \tag{2}$$

It is important to realize that the second constraint has to be fulfilled for any realization of yield Y . In our case we will assume the yield being discretely distributed with n possible different outcomes (which we call scenarios), the distribution being uniform over values Y_1, \dots, Y_n (implying the second stage decisions are scenario dependent, i.e. $y_s, s = 1, \dots, n$). Since the distribution is discrete, the model can be written in the extended form (Birge and Louveaux, 1997) as

$$\begin{aligned}
& \max_{x,y} f_1(x) + \frac{1}{n} \sum_{s=1}^n f_2(x, y_s) \\
& \text{s.t. } g_1(x) \leq 0 \\
& \quad g_2(x, y_s) \leq 0, \quad s = 1, \dots, n
\end{aligned} \tag{3}$$

This results in the model with the same complexity as the original one with the dimension of the second stage variables multiplied by the number of scenarios used. We see that here the objective function is the expected value of the social welfare. The decision-maker thus optimizes under uncertainty and subsequently observes the implications in terms of outcomes in the different yield scenarios or realizations of yield levels.

Note that we do not incorporate the variance or another measure of risk directly into the objective function, which solely consists of the described expected value. However, this does not mean that risk aversion is not included. As explained in the introduction, risk aversion is introduced via the social planner's preference, where the risk-averse planner requires a minimum amount of food to be available for consumption in every state of nature, while a "risk-neutral" (or less risk-averse) one will be interested in the average value only.

4. Experiments & Results

As explained in the previous section we introduce a safety-first constraint to ensure that a given consumption of vegetable calories is always met. In mathematical terms, the applied safety-first constraint is captured in function g_2 in equation (3) and, more specifically in this application, we have:

$$C(y_s) \geq T * SF, \quad s = 1, \dots, n, SF = 0..1$$

where T refers to the minimum amount of kcal required, while $SF=1$ indicates that this amount has to be covered in all states of the nature. Sensitivity analysis for lower values would then allow to test for the sensitivity of the results if not meeting the constraint in some states of the world would be acceptable to the decision-maker.

In the current setting we test a 0 versus a 100% constraint. The scenarios are defined as follows:

- BAU is the business as usual scenario. Note that this assumes no exogenous growth of yield.
- IRR is the BAU scenario with facilitated irrigation expansion. (This is mimicked by setting the elasticity of water supply to 3 instead of 0.3.)

- TRD is a scenario with increased trade barriers (globally at the level of initial trade cost) which are modeled as approximately a doubling of the trade cost.

We have tested the impact of the yield distributions projected for 2050 and 2100 on the set up representing 2020. The results using the projected 2050 yield distributions show that prices are systematically higher under food security. They are relatively highest with trade barriers and relatively smallest with better irrigation, as can be seen in Fig. 2, where the columns denoted by SF0 (safety first coefficient at zero) represent the calculations without food security constraint and SF1 denotes the situation with a binding minimum food requirement (safety first coefficient set to 1).

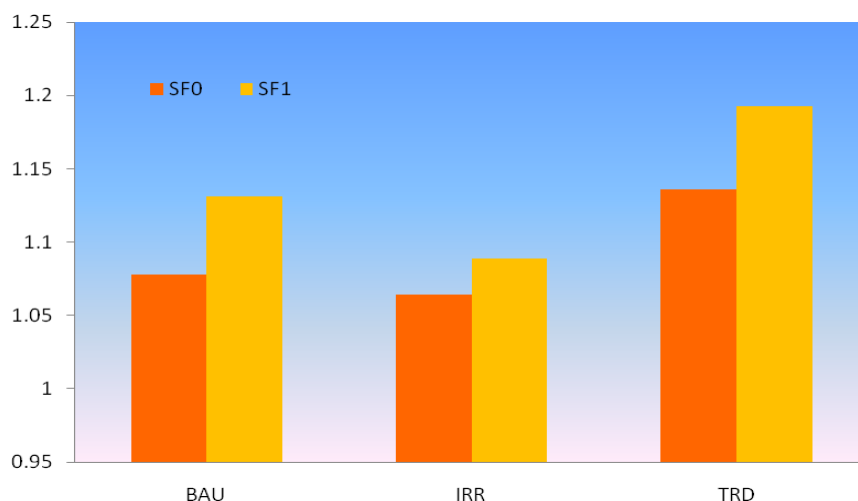


Figure 2: Average price index in 2020 compared to 2000

Even more important, however, is the impact that the minimal food requirement has on price volatility, which is presented in Fig. 3 by the standard deviation (normalized by the average). It is clear that ensuring food security comes at the cost of higher volatility in all scenarios.



Figure 3: Price volatility (standard deviation relative to average prices)

Fig. 4 shows that land requirements are lowest with cheaper irrigation. In the BAU and TRD scenarios, there is systematically higher land demand under the food security constraint; the difference amounting up to 11Mha. Note also the shift in optimal managements chosen: In the

BAU scenario less of the cropland area is managed by high-input/rainfed systems and more is automatically irrigated.

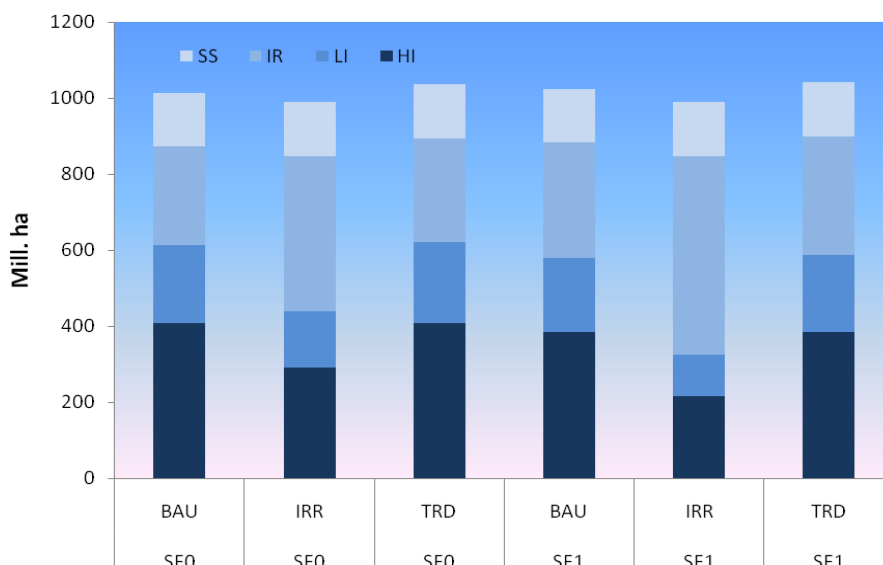


Figure 4: Total cropland under different management systems in 2020: high-input/rain-fed (HI), low-input/rain-fed (LI), automatic irrigation (IR) and subsistence management (SS)

Overproduction is needed to guarantee food security – also in states of the world, in which there is a shortfall in crop production. Fig. 5 corroborates this finding by indicating higher calorie consumption per capita under SF1. Again this effect is enhanced by trade barriers and dampened by cheaper expansion of irrigation.

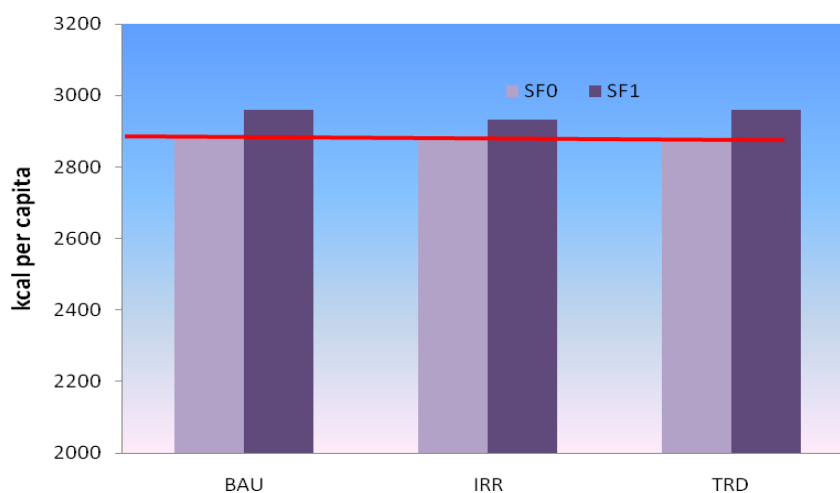


Figure 5: Average kcal per capita consumption in 2020

In general, we can say that the IRR scenario is close to S0, as we assume that irrigated land provides stable yields. Also, global average imports under SF1 are higher, which points to trade as an adaptation option.

Finally, we also looked into environmental implications considering the example of land cover change: the highest additional cropland demand occurs in BAU, followed by TRD, see Fig. 4. This is mainly sourced from forests and other natural land, as can be seen in Fig. 6, implying that food security requires several Mha land in addition (especially without yield stabilization).

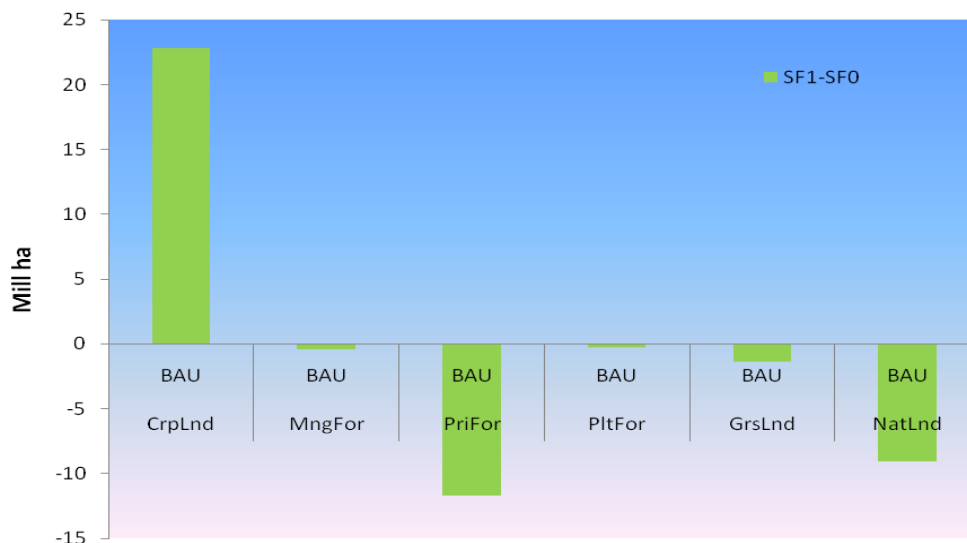


Figure 6: Global land cover change from 2000 to 2020 – relative difference between runs without and with food security constraint

Note that the results presented in this section are based on the yield distributions projected until 2050. As mentioned above, we examined also the impacts of the project 2100 climate induced yield distributions. While some of the indicators examined fare even worse than in the 2050 case, the patterns and directions of effects are the same. Therefore we do not present them in detail here and keep them for the final paper..

5. Conclusion

In this study we have explored the effects of climate change on yield volatility and thus on food security. The results have shown that considering stochasticity and a food security constraint in a large-scale economic land use model indeed has a significant effect on price levels, price volatility, trading, cropland expansion and shifts between management systems and thus also on deforestation, as the additional land required to produce sufficient amounts of food also for the cases where yields fall, is mainly sourced from forests and other natural land.

We conclude that not only the yield level, but also yield variability impacts environmental indicators linked to preservation of natural habitats like forests and other natural land.⁴ If food security is to be ensured in environmentally sustainable way, management systems stabilizing yields should be developed in the future.

Concerning strategies for adaptation, trade liberalization and – to a higher extent – also cheaper expansion of irrigation haven proven to have great potential in dampening the adverse effects from increased yield volatility. Future research should also explore the stabilizing effect of technological change aimed at making crops more robust to e.g. drought, which in our framework would have a similar effect as irrigation expansion. Another channel of adaptation would be the introduction of storage, which is planned as a next step for implementation in GLOBIOM.

Current modelling efforts are directed in several directions. First, more work needs to be done in the analysis of the climate data and their impact on yields, also to explain the relatively small changes between 2050 and 2100, which could be related to yield increases in Northern regions, for example. Second, it is important to note that biophysical constraints such as increased water shortages have not been implemented into the GLOBIOM as of yet. Implementing this feature

⁴ This would affect GHG emissions, biodiversity and other environmental indicators.

will probably make the impacts of climate change on yield volatility more severe and thus also affect food price volatility adversely. Finally, policymakers might have different risk preferences and e.g. require the food constraint to hold less than 100% of the time. This can, in principle, easily be implemented in the model as it is now. However, the yield distributions also need to be examined in more detail to identify potentially fat tails emanating from extreme weather events entailing large losses at low probability, which policy-makers might want to avoid at higher cost.

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Acknowledgements

The research leading to these results has received funding from the European Community's Seventh Framework Programme (FP7) under grant agreement n° 244766 – PASHMINA, n° 212535 and Climate Change – Terrestrial Adaptation and Mitigation in Europe (CC-TAME) and the EU LIFE program-funded EC4MACS project (www.ec4macs.eu).