Global-to-local modelling with GLOBIOM: first ideas

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# Introduction

There is an growing awareness that climate change, land use degredation and loss in biodiversity are putting pressure on the boundaries of the earth. To assess policy trade offs, decision makers have great interest in the socio-economic impact of these global phenomena at different scales.

The GLOBIOM team is facing an increasing demand for subnational (as opposed to global) assessments of deforestation, climate change and food security. Examples of ongoing work include farm systems analysis for Ethiopia, deforestation scenarios for Brazil, Indonesia and Congo and modelling of consumption and diet change at the state-level for India. A new project along these lines is ISWEL, which aims to analyse the trade-offs between water, enery and food security (the nexus) in the Indus and Zambezi river basins. Subnational model studies and the often associated demand for socio-economic impact analysis (i.e. poverty, food security and health) can benefit from the use of plot, farm and households surveys that are increasingly available and provide micro-level information on consumption, production and income patterns.

Previously the use of this data was problematic because surveys only covered very small regions were organised in an ad hoc manner or were of low quality. Recently a number of efforts were undertaken to address these issues and collect nationally representative data using a systematic approach that allow for international comparisons and cover multiple years. A second interesting and related source of information to improve both the sub-regional and global modelling is spatially explicit data on number of socio-economic indicators that are often build using micro-level surveys. Although, spatially explicit information on socio-economic indicators is relatively thin (Otto et al. 2015), there is ongoing effort to improve data availability (Azzarri et al. 2016).

The aim of this document is to present some first ideas on how to expand and deepen the modelling with GLOBIOM by integrating and linking micro-level and spatial information (hereafter together referred to as micro-data) on socio-economic variables (for now I will refer to this process as 'global-to-local GLOBIOM' for lack of a better description). The main idea is that such data can provide more detail on several key building blocks of the model, including the modelling of production and consumption. In addition, these data might also be used to construct a number of development related indicators that benefit from micro-level data, such as poverty and food security indicators.

This document describes some of the possible directions we can be taken to use the available data in order to enrich the modelling with GLOBIOM. It partially builds on on previous work done by colleagues that already explored this type of information, including farm systems modelling in Ethiopia, consumption modelling in India and forest modelling in Brazil, Congo and Indonesia as well as an additional literature survey. The document serves as a basis for discussion and is expected to be updated, refined and expanded as the thinking on this topics progresses.

# Household level data sources

There are a number of data sources with plot, farm or household information that can be used to enhance the modelling of GLOBIOM, which are summarised below. All of the sources present information that is at least nationally representative and therefore can be used as input to country-level modelling. Regional coverage strongly differs across sources. Some datasets only cover a handfull of countries, while others have mode wider coverage. There also exists a number of other data collection initiatives (e.g. IMPACT-lite; ILRI/CCAFS-CGIAR; RIGA, FAO-World Bank) that provide interesting data but are probably less useful because the cover a limited number of countries, cannot be compared across countries or are not nationally representative.

## The Living Standards Measurement Study (LSMS)

The Living Standards Measurement Study (LSMS) is an ongoing household survey program supported by the World Bank. Since the 1980s the LSMS surveys have been organised in a large number of countries. Although the LSMS surveys provide a rich source of information, they are often not comparable over time and across countries. It is also not clear if they include location information and therefore can be linked to maps.

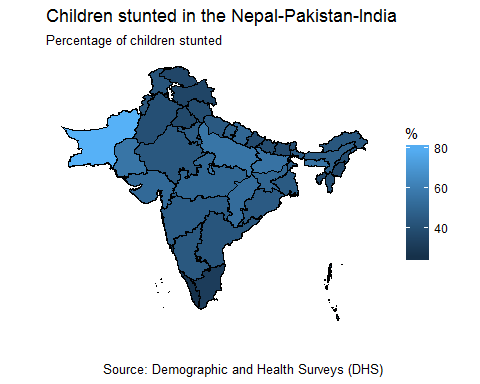
## The Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA)

The Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) is a project funded by the Bill and Melinda Gates foundation and implemented by the World Bank undertake nationally representative households surveys in a eight African countries: Burkina Faso, Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania and Uganda. In each country multiple survey rounds are supported that make it possible to analyse long-term developments and apply econometric panel approaches.

The surveys cover a wide range of topics and are particularly designed to improve the understanding between agricultural, socio-economic status and non-farm income activities. They cover around 3000 to 5000 households per country and includes questions on a large number of topics, including agricultural production (including fishery and livestock) at crop and plot level, diets and consumption patterns and household composition and income. The data also includes the coordinates of the sampling sites and can therefore can be linked with and compared to geo-spatial datasets. The database already includes information several spatial variables such as precipitation, temperature and infrastructure.

## The Demographic and Health Surveys (DHS)

The Demographic and Health Surveys (DHS) Program is a large survey program to collect nationally representative information on fertility, family planning, maternal and child health, nutrition, mortality, environmental health, HIV/AIDS, malaria, and provision of health services funded by USAID. To date, the program has has collected data for more 90 countries in more than 300 surveys. The advantage of the DHS surveys is that they can easily be compared internationally because of the use of (nearly) similar questionnaires. A disadvantage is that they are weak on agricultural activities, income and infrastructure. Recent DHS data has been geo-coded and can therefore be easily depicted on a map (see example below). Several recent studies have applied spatial interpolation techniques to increase the resolution of the DHS spatially explicit data.



## Ad hoc surveys

Several institutes and universities, often with support of national statistical agencies organise their own nationally representative households surveys that are similar to the LSMS and LSMS-ISA surveys. Examples are the Ghana EGC-ISSER Socioeconomic Panel Survey undertaken by the Economic Growth Center (EGC) at Yale University and the Institute of Statistical, Social, and Economic Research (ISSER) at the University of Ghana, Legon; the Zambia Rural Agricultural Livelihoods Survey, organised by the Indaba Agricultural Research Institute (IAPRI) and Michigan State University and Rural Household Survey, faciliated by the Tegemeo Institute and Michigan State University. It depends on the data sharing policy of the involved institutions if the data is publically available.

# Possible directions to develop a Global-to-local GLOBIOM framework

Broadly defined, micro-data can be used for two purposes to extend GLOBIOM:

1. Improve the input-side, including an improved representation of farming systems and consumption.
2. Improve the output-side, for example by providing new or more disaggregated indicators on issues like poverty, food security and health.

## Improvement of the input-side

Ongoing work to improve the input-side modelling of GLOBIOM has developed in two directions. Boere et al (**???**) used Ethiopian household survey data to refine the farming systems classification in GLOBIOM. Valin (**???**) estimated food demand functions for different food commodities using Indian panel household data to improve the food projections per state.

Using some of the data described above, it might be possible to extend these aproaches to other regions. However, this is only possible if the datasets are of sufficient quality. For the farmer systems classification, it is important that the data is geo-coded or regionally allocated so that classifications can be spatially allocated. For the consumption function estimation detailed information is needed on consumption patterns and, preferably, the panel data should cover a relative long period to investigate changes over time.

## Improvement of the output-side

### Poverty projections

A key indicator to evaluate policies and potential future scenarios is their impact on poverty/income, which in turn can be used to investigate changes in the access to food. Several global model teams have recently started to extend their models with poverty indicators on the basis of household survey data. Three different approaches can be distinguished that capture household heterogeneity within and across countries, all of which are related to global CGE models (see Bourguignon and Bussolo 2013 for a review).

GTAP-POV (Hertel et al. 2015) is a macro-to-micro modelling approach in which a micro-simulation household model is embedded in the GTAP model.It simulates household welfare at the poverty line for different strata of the population. Changes in poverty headcount by strata are estimated by combining model projections for the change in real income with information on the elasticity of poverty headcount with respect to real income. Hence the model only targets households in the neighbourhood of the poverty line, not the full distribution of households in a country. GTAP-POP identifies the following typical strata: agriculture, non-agriculture, urban labor, rural labor, transfer, urban diverse and rural diverse. In order to couple the micro-simulation and GTAP model, the demand and supply system of the latter was extended and refined to deal with multiple households. At the moment the GTAP-POV model contains information on 31 countries.

MYGTAP (Minor and Walmsley 2013) is an approach to bridge the gap between the GTAP model and single country CGE models, which have a much richer representation of households. It adopts a consistent approach to split the regional household and factors in the GTAP model into multiple households and factors using additional data. Model outcomes include factor income and consumption per type of household, which can subsequently be used to assess the impact of economic shocks on poverty and food security. Currently MYGTAP aproach to is used to extent the MAGNET mode as part of the FOODSECURE project.

A final macro-to-micro moddeling framwork is the Global Income Distribution Dynanmics (GIDD) model (Bussolo, De Hoyos, and Medvedev 2010). In comparison to GTAP-POV and MYGTAP it covers much larger share of countries - 132 in total, covering about 91% of the total world population for the base year of 2005. It has an explicit long-term focus and tries to capture the impacts of demographic changes, such as aging and the skill composition of a population, which are expected to influence growth and distribution dynamics. it is a dynamic modelling framework, which consists of the following steps: (1) Estimating structural relations between household income and determinants (age, education, etc) to create a global income distribution on the basis of household surveys; (2) Generate new sampling weights for the future using exogenos projections on education and population growth; (3) Run the CGE model that incorporates projections for labour supply on the basis of step and obtain information on sectoral composition of employment and relative wages; and (4) Simulate a new global distribution.

All the approaches above take a CGE approach and are able to model the full income of the households also including other activities than agriculture and combine this with (changes in) factor and output prices. Partial equilibrium (PE) models, like GLOBIOM, only cover the agricultural sector and do not explicitely model all (factor market) linkages with the rest of the economy. It will therefore be difficult to apply the GTAP-POV and MYGTAP approaches, which refine and extent the modelling of household behavious in a global model. The GIDD framework, which is 'soft-linked' with global (CGE) model probably provides a more feasible route but also here many questions remain on how to combine such a framework with a PE model.

### Combining GLOBIOM output with spatially explicit socio-economic indicators

As GLOBIOM presents spatially explicit results, it might be interesting to combine GLOBIOM output with spatially explicit socio-economic indicators. An example of such analysis could be the combination (overlay) of a map that depicts 'hotspots' of land use change and a poverty map to assess which people are most vulnerable. Unfortunately, spatially explicit socio-economic data is only available for a handfull of indicators and is often outdated (see below). The main reason is that the required raw micro-level data to construct such maps is not available at high-resolution because it is too costly to collect by means of surveys. An interesting development in this regard is the collection of poverty data by means of mobile phone metadata (Blumenstock, Cadamuro, and On 2015) and sattelite imagery (Jean et al. 2016), which will likely increase the availability of poverty maps at high resolution in the near future. Even if spatially explicit information is available, another question that needs to be dealt with is how the maps can be projected forward so that they can be compared with the scenario results that are presented by GLOBIOM.

# Thinking wider and broader: Global socio-economic modelling with GLOBIOM

The section above provides a brief review and some ideas on how to enhance the modelling with GLOBIOM using micro-survey data. Such an analysis will provide interesting insights on the socio-economic impact of major global changes and policies at the subnational level for which more detailed information is available. Another interesting and related avenue to improve GLOBIOM is the modelling and analysis of socio-economic indicators at the global level. Naturally the produced indicators and results are less comprehensive in comparison to global-to-local case-studies but the advantage is that conclusions can be drawn that are global in scope. Another advantage is that they can be used to evaluate expected progress on global developmental targets (e.g the SDGs) under different scenarios. The indicators also stimulate engagement and discussion with other communities that have an increasing interest in the global assessments. Examples of multi-disciplinary approaches are the CGIAR Agrigulture for Nutrition and Health (A4NH) program and a the recent Lancet Countdown in Response to Climate Change Health Crisis initiative.

Several model teams have already started to extend their models with global socio-economic indicators, specifically in the direction of food and nutrition security and health. The ongoing process to extend GLOBIOM with food and nutrition security indicators (e.g. people at risk of hunger) fits with this trend. As the data sources and construction of these global socio-economic indicators often resemble the micro-approaches discussed above, it useful to present a brief literature review on the indicators that are produced by other model teams in this section for discussion.

## People at risk of hunger

Several models present an indicator for people at risk of hunger/undernourishment (e.g. Baldos and Hertel 2015, Hilderink and Lucas (2008)). As GLOBIOM also recently introduced this indicator is it not discussed here.

## Vulnerability to hunger index

Biewald et al. (2015) analyse the impact of climate change on hunger for 2030. They use the MAgPIE model to provide spatially explicit projections on changes in the costs of food. These results are subsequently compared with a spatially explicit Vulnerability to Hunger Index under different scenarions. The index is constructed by combining global maps of child underweight, child mortality and prevalence of stunding under five and projected into the future on the basis of national level poverty scenarios.

## Child malnutrition

In their study on the impact of climate change on food security, Nelson et al. (2010) provide projections for child malnutrition up to 2050. The percentage of malnourished children is estimated using a cross-country regression analysis based on Smith and Haddad (2000) in which the IMPACT model projections on calorie availability per country are use as a dependent variable. Other dependent variables include projections for the ratio of female to male life expectancy at birth, total female enrollment in secondary education and access to safe water. A similar methodology is used in the GISMO-IMAGE modelling framework (Hilderink and Lucas 2008) of PBL to project child malnutrition.

## Health, morbidity and mortality

Springmann et al. (2016) assess the wider health impacts of climate change for 155 regions in the year 2050. More specifically the investigate the relationship between changes in fruits and vegetables consumption, red meat consumption and bodyweight on deaths coronory heart disease, stroke, cancer and other causes for six climate change scenarios.

The health module of GISMO (Hilderink and Lucas 2008) describes the causal chain between health-risk factors and health outcomes (morbidity and mortality) and takes into account the effect of health services. In comparison to Springmann et al. (2016), it takes a broader approach to health modelling by looking at a wide range of health-risk factors, not only including diets but also malaria, diarrhoea, pneumonia, chronic diseases, air pollution and other communicable diseases and injuries. Regression techniques are used to relate mortality rates with GDP, smoking behaviour and human capital.

## Poverty

The poverty module of GISMO (Hilderink and Lucas 2008) offers an alternative approach to estimate global poverty levels in comparison to the World Bank GIDD approach discussed above. it determines regional poverty on the basis of a log-normal income distribution that is parameterised by (projections) for per-capita income and income distribution (GINI-coefficient). A possible advantage of this approach is that it requires less assumptions than the macro-to-micro poverty modelling approaches discussed above and it is less demanding in terms of data pre-processing and availability. On the other hand, the gini-coefficent might not fully represent the distributional aspects of poverty and income, resulting in biased outcomes.

# Next steps

As a next step it would be useful to discuss the following questions:

* In the context of ongoing projects and needs, which of the possible avenues should be explored first? Input (e.g. farming systems and food demand) or output side improvements (e.g. poverty and food security)?
* What are key model variables (in the context of the ISWEL project) that would benefit from additional and more detailed information from micro-surveys (e.g. exogenous yield, nitrogen use, seed costs, etc)?
* What is the most suitable data to extent the model in the light of the above?
* At the moment do we prefer a more local or global approach to improve the (socio-economic) modelling with GLOBIOM?
* Can we develop a standardised modelling 'pipeline', involving GAMS, R, etc that make it easy to replicate micro-macro data linkages for multiple projects.

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