Uncertainties in global land cover data and its implications for climate change mitigation policies assessment

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Abstract – Land cover maps provide critical input data for global models of land use. Urgent questions exist, such as how much land is available for the expansion of agriculture to combat food insecurity, how high will be competition for land between food and bioenergy in the future as well as how much land is there available for afforestation projects? These questions can only be answered if reliable maps of land cover exist.

We put this research in the framework of GEOSS, examine how modeling tools can be used for benefit assessment and design an assessment framework.

We illustrate the importance of good quality global land cover maps by using cropland extend from the currently best global maps of land cover namely GLC-2000, MODIS, GlobCover and CropLikelyhood as input for the EPIC model (to model crop yields) and global economic land use model GLOBIOM. We use all of the 4 maps and create a maximum crop extend and map. Based on a baseline map and the maximum crop extend map e model effects of climate policies (e.g. the potentials of substitution of fossil fuels with biofuels).

1.INTRODUCTION

There have been a plethora of research activities which have illustrated that currently global land cover datasets differ drastically in terms of the spatial extend of cropland distributions (Fritz and See 2008; Giri et al. 2005; McCallum et al. 2006). One of the data layers which differs the most is cropland area. Ramankutty et al. estimate that at the 90% confidence range the cropland area is between 1.22 and 1.71 billion hectares which translates to a 40% difference (Ramankutty et al. 2008). An accurate quantification of cropland area on a global level is difficult for mainly 2 reasons (i) because of the very similar behavior of seasonal vegetations indices (such as NDVI) of rainfed croplands and natural vegetation and (ii) due to very small scale heterogeneous cropland patterns which are below the sensor resolution of global datasets.

However, it is this cropland land cover class which is among the global land cover classes – besides forests- one of the most important global layers for land use and land use change modeling. For example, accurate estimates of cropland areas are essential to understand as to what extent under the current environmental and economic constraints expansion of cropland area into other potentially productive land is possible in order to combat food insecurity or to identify areas of additional land for biofuel crops.

Moreover, there have been questions as how reliable the FAO figures are, in particular with respect to crop area (EU representative Malawi, 2009, personal communication).

We evaluate here how models which are designed to help in policy design can be used to quantify the differences in implementation costs. By examining the differences in implementation costs we are able to quantify the benefit, hence avoiding the costs of the wrong decision.

This study, as part of the EC funded GEOBENE project, aims to assess the benefits of improvements in earth observation with respect to GEOSS. One way to undertake a benefit assessment is by using a suite of models. In this assessment we make use of the EPIC model and the GLOBIOM model (see section 3.) A similar methodology on the use of EPIC and a partial equilibrium agricultural sector model has been described on the value of improved long-range weather information (Richard M. Adams 1995). Details of the proposed assessment framework are outlined in the next section.

2. ASSESSMENT FRAMEWORK

A conceptual framework has been developed which outlines how a benefit assessment of GEOSS can be carried out and provides a checklist of the minimum requirements for such an assessment. A Non-GEOSS scenario is based on activities which would happen anyway and a GEOSS scenario is a scenario which clearly links regional, national and global EO products. A GEOSS scenario could be seen as having higher resolution as currently only available for certain countries or regions (e.g. EU-27) available on a global level.

Models, and thus the policy advice they can give, are only as good as their input data. We therefore examine the variability of model results with respect to different input data for a benefit assessment. In this context we illustrate how and to what degree biophysical process models and economic land-use models can be used to undertake benefit assessments and to better understand the importance of data collection. We focus mainly here on land cover datasets, but the general assessment framework can be applied to any Earth Observation (EO) or in-situ datasets.

We examine outputs of the EPIC and GLOBIOM model based on different quality input datasets. By injecting different types of input data (land cover in our case) into the models we are able to quantify the differences in model output. Figure 1 illustrates the differences with respect to data quality and the different levels when a sequence of GEOSS implementation levels is considered.

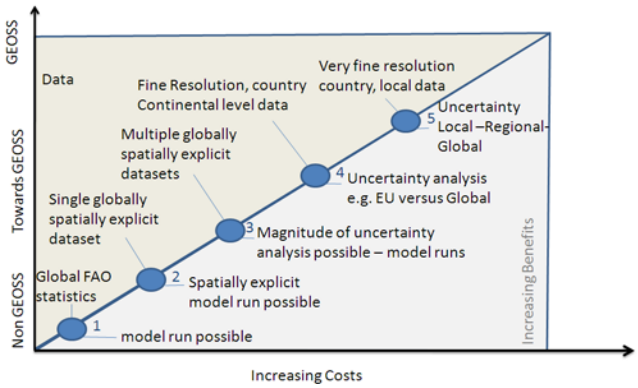

Figure 1: Levels of EO data and associated benefits differentiated towards GEOSS which can be modeled with a global land use model such as GLOBIOM

1) Model implementation 1 takes the official FAO statistics and spreads production statistics equally over the country

2) Model implementation 2 uses FAO statistics and downscales FAO outputs using the EPIC model based on the concept of Homogeneous Response Units (HRU) (see 3. Material and Methods)

3) Model implementation 3 uses multiple global input datasets and allows the quantification of uncertainty with respect to model outputs.

4) Model implementation 4 uses (additionally to model implementation 3) data which is collected on a regional level (e.g. EU-27). Such a model implementation allows a GEOSS versus a Non-GEOSS scenario to be examined. It allows to draw certain conclusions on the additional accuracy gain when outputs from EU-27 runs versus Global data runs are compared.

5) Model implementation 5 uses (additionally to model implementation 4) local very fine resolution datasets for e.g. one country. It allows more insight into the overall behavior of the costs-benefit ratio and understanding of the point at which the incremental benefit of further investment in data collection on a higher resolution and higher quality data is negligible.

By running the model for all the different data inputs we are able to understand the overall difference it makes in the model outputs of economic and land use parameters such as land requirements for biofuels, crop prices, intensification and irrigation of cropland. By undertaking such a data input sensitivity analysis it is possible to better understand those datasets which are most important, hence we could give recommendation on data collection needs as well as recommendations for prioritizing global data collection needs for land cover, land use, infrastructure and socio-economic variables and recommendations on the necessary resolution on which data should become available under GEOSS for land use modeling activities. In this context the questions arise as what are the likely costs of making the wrong decision. We envisage to also consider in the future the actual costs of gathering this data and therefore to get a full picture of the cost-benefit relationship of certain data collection activities.

We can assess the cost of mitigating GHG emissions through substitution of transport oil fuels by biofuels according to different energy pathways as we can examine what the difference would be in terms of a number of other parameters like crop prices with their direct impact on food security, irrigation water consumption as indicator of the necessary agricultural intensification, or the opportunity cost of avoiding deforestation as an alternative mitigation policy. This type of quantifiable measures can give an interesting insight into costs of the wrong climate policy design. In the following assessment we will focus on the third level of implementation where we can estimate the magnitude of uncertainty with respect to climate policy scenarios.

3 MATERIAL AND METHODS

As outlined in the paper we examine the response of the GLOBIOM model with respect to different global cropland input layers. However, other layers such as world protected areas, road networks together with an accessibility surface can be added in future analysis.

3.1 Datasets

1.1 GLC2000

The first land cover map used in this study is the GLC- 2000, a global product for the baseline year 2000. Based on the 1km (appr. at the equator) this data set was created via a bottom-up approach in collaboration with partners around the world using the VEGETATION sensor on board of SPOT 4 (Bartholome´ & Belward, 2005).

1.2 MODIS

The MODIS land cover product from Boston University (MOD12Q1 V004) was created using the Moderate Resolution Imaging Spectoradiometer instrument on the NASA Terra Platform using data from the period mid-October 2000 to mid-October 2001.

1.3 GlobCover

The objective of the GlobCover / ESA initiative is to develop a service to produce a global land-cover map for the year 2005-2006, using the fine resolution (300 m) mode data acquired over the full year 2005 by the MERIS sensor on-board the ENVISAT satellite

1.4 Cropl Likelihood Layer

The crop likelyhood layer is based on MODIS data and derived in a similar way as the Vegetation Continuous field products (Hansen, personal communication), .

3.2 Agreement scoring

In order to examine the variation in cropland extent of global land cover products we have undertaken an agreement scoring analysis. We define a number of thresholds taking into account minimum and maximum cropland extent in each cropland pixel of each global cropland layer. We then show in 28 different levels the degree of cropland agreement (see Figure 2).

Figure 2: Levels of disagreement between 4 different cropland layers from GLC-2000, MODIS, GlobCover and CropLikelyhood.

In order to show the impact of variation in cropland extent on outcomes of global economic models with respect to mitigation policy advice, we use the GLC-2000 dataset as a basis as for this dataset currently the model has been set up. This cropland area is termed Average Cropland Area (ACA). We also refer to this as the baseline scenario. We then create a new cropland map using a threshold where at least one of the dataset records cropland (either MODIS, GLC-2000, Globcover or if the CropLikelihood layer shows over 50% of cropland being present). The resulting global cropland extent map shows an overall cropland expansion of 26.9 percent with respect to GLC-2000 – still a conservative difference compared to Ramankutty (2008), (Ramankutty et al. 2008). This cropland layer is termed Maximum Cropland Area (MCA).

3.3 Scenario Analysis

3.3.1 The EPIC Model

The bio-phyiscal process model EPIC (Environmental Policy Integrated Climate;) has been used in this analysis. EPIC is able to simulate dynamic changes (50 – 100 years) of bio-physical indicators in agro-ecosystems, like biomass production, soil organic matter accumulation, soil erosion, greenhouse gasses emission and sequestration in order to bring an accurate view on global agro-ecosystems, and provides bio-physical data for alternative land use and management strategies. The major components in EPIC are weather simulation, hydrology, erosion-sedimentation, nutrient and carbon cycling, pesticide fate, plant growth and competition, soil temperature and moisture, tillage, cost accounting, and plant environment control. EPIC can be used to compare management systems and their effects on crop yields, on water, nitrogen, phosphorus, pesticides, organic carbon, and sediment transport, on organic carbon sequestration, and eventually on green house gas emissions. Like for any biophysical process model, the quality and completeness of input data is of substantial importance.

The simulation outputs are based on globally delineated Simulation Units (Skalsky et al. 2008), defined as intersection of Homogenous Response Units (HRU) - altitude, slope and soil texture, 30 arcmin grid and country boundaries. Simulation UnitsThe integration of the HRU layer with further data (weather, land use, crop management, political boundary layers, etc.) leads to individual simulation units (Skalsky et al. 2008). These define the spatial interface between EPIC and GLOBIOM model

3.3.2 The GLOBIOM model

The Global Biomass Optimization Model (GLOBIOM) is a global recursive dynamic partial equilibrium model integrating the agricultural, bioenergy and forestry sectors with the aim to provide policy analysis on global issues concerning land use competition between the major land-based production sectors. The general concept and structure of GLOBIOM is similar to the US Agricultural Sector and Mitigation of Greenhouse Gas (ASMGHG) model. The global agricultural and forest market equilibrium is computed by choosing land use and processing activities to maximize the sum of producer and consumer surplus subject to resource, technological, and policy constraints, as described by (McCarl and Spreen 1980). Prices and international trade flows are endogenously determined for respective aggregated world regions. The flexible model structure enables one to easily change the model resolution; in this analysis the model is run on 28 regions.

The market is represented by implicit product supply functions based on detailed, geographically explicit, Leontief production functions, using EPIC simulations, and explicit, constant elasticity, product demand functions. Explicit resource supply functions are used only for water supply.

In our model the initial cropland area impacts on two other major parameters – crop yields and initial areas of the other land cover types. Crop yields are obtained from distributing the crop production as reported in FAOSTAT over the spatially distributed crop areas from Liu and Wood (2000) differentiated by EPIC. If the cropland area, and thus the areas under different crops increase, the yields are decreased proportionally to maintain the same level of FAO reported production. Similarly, as cropland area expands, other land cover types have to shrink, and these areas are thus no longer available for additional cropland expansion due to future pressures. Two scenarios are presented here defined as “Average Cropland Area” (ACA) corresponding to (You and Wood 2006) and thus to FAOSTAT, and “Maximum Cropland Area” (MCA) scenario, defining as cropland also areas which are at least represented by one satellite product (see section 3.2)

4. RESULTS

Scenarios where run from 2005 to 2020 of biofuel consumption as projected by the World Economic Outloook (WEO) in 2008 (IEA, 2008). Very preliminary results for a few interesting parameters are presented and compared in Table 1. These results are presented in the form of indexes comparing the values corresponding to 100% of the WEO (2008) projected biofuel consumption with the 0% biofuel consumption corresponding to the 2005 “base year” biofuel consumption.

Index	Baseline Average Cropland Area (ACA)	Maximum Cropland Area (MCA)	Impact Percentage difference between ACA and MCA
Crop Price	1.04	1.06	50%
Ethanol Price	1.80	1.99	19%
Irrigation Water Use	1.02	1.04	100%
Opportunity Cost of Avoiding Deforestation	1.07	1.08	12.5%

Table 1: Percent difference in terms of Crop prices, Ethanol Price, Irrigation Water use and Opportunity Costs Avoiding Deforestation depending on the availability of land (ACA or MCA)

Generally, we can say that increased biofuel production (here only first generation biofuels are considered as available by 2020) leads to increases in crop and biofuel prices, irrigation water consumption and also in the opportunity cost of avoiding deforestation (these scenarios are run so that deforestation is not allowed – therefore we can calculate opportunity costs) and thus in the cost of potential programs aiming at Reducing Emissions from Deforestation and Degradation (REDD). The most pronounced impact of biofuel expansion is on the biofuel prices for which the absolute percentage differences are highest (index is 1.80 for ACA versus 1.99 for MCA. The impact on the other parameters is rather low but still can differ substantially between the scenarios, where for instance the increase in the irrigation water consumption is under the MCA scenario twice as high as under the ACA scenario. Also the difference in the indexes with respect to the opportunity cost of avoiding deforestation is low, however the absolute difference in the opportunity cost of avoiding deforestation expressed in USD per tCO2eq is about 50% (5.7 and 8.4 USD per t CO2eq for the ACA scenario and MCA scenario, respectively).

Conclusions

This example combining several greenhouse gas mitigation options and considering the data uncertainty illustrates the importance of gathering better quality land cover data for climate policy making. Not only that some mitigation programs may become more expensive in reality than what was calculated on the basis of inaccurate data, but this inaccuracy may also lead to wrong choices in support of different mitigation policies where just on the basis of inaccurate calculations e.g. more political support will go to biofuels rather than to REDD - although the real cost efficient solution may be REDD.

So far we have only considered the implementation stage 3 of the different GEOSS implementation levels. In follow up work we are going to examine the next level of the GEOSS implementation, comparing EU-27 input data with global input data.

Further work will also focus on calculating not only the marginal costs but also on the total cost of potential GHG mitigation programs including the uncertainty considerations in order to provide policy makers also with absolute values of the additional value of information which can be derived from more accurate data. Moreover, we have not yet considered the costs of the different linking the current observing systems and how much the additional costs are of acquiring more accurate and higher resolution data on a global level.

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