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Spatial and temporal uncertainty of crop yield aggregations

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ABSTRACT

The aggregation of simulated gridded crop yields to national or regional scale requires information on temporal and spatial patterns of crop-specific harvested areas. This analysis estimates the uncertainty of simulated gridded yield time series related to the aggregation with four different harvested area data sets. We compare aggregated yield time series from the Global Gridded Crop Model Intercomparison project for four crop types from 14 models at global, national, and regional scale to determine aggregation-driven differences in mean yields and temporal patterns as measures of uncertainty.

The quantity and spatial patterns of harvested areas differ for individual crops among the four data sets applied for the aggregation. Also simulated spatial yield patterns differ among the 14 models. These differences in harvested areas and simulated yield patterns lead to differences in aggregated productivity estimates, both in mean yield and in the temporal dynamics.

Among the four investigated crops, wheat yield (17% relative difference) is most affected by the uncertainty introduced by the aggregation at the global scale. The correlation of temporal patterns of global aggregated yield time series can be as low as for soybean ($r = 0.28$).

For the majority of countries, mean relative differences of nationally aggregated yields account for 10% or less. The spatial and temporal difference can be substantial higher for individual countries. Of the top-10 crop producers, aggregated national multi-annual mean relative difference of yields can be up to 67% (maize, South Africa), 43% (wheat, Pakistan), 51% (rice, Japan), and 427% (soybean, Bolivia). Correlations of differently aggregated yield time series can be as low as $r = 0.56$ (maize, India), $r = 0.05$

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(wheat, Russia), r = 0.13 (rice, Vietnam), and r = −0.01 (soybean, Uruguay). The aggregation to sub-national scale in comparison to country scale shows that spatial uncertainties can cancel out in countries with large harvested areas per crop type. We conclude that the aggregation uncertainty can be substantial for crop productivity and production estimations in the context of food security, impact assessment, and model evaluation exercises.

1. Introduction

Crop models are increasingly applied at the global scale to study how agricultural yields and total production over regions might be affected by global phenomena such as market dynamics and climate change. Simulations of crop productivity (yield) at different spatial and temporal scales have been used for example in the context of food security, land use, and climate change research (Asseng et al., 2015; Challinor et al., 2014; Mueller et al., 2012; Nelson et al., 2014a,b). Uncertainties associated with crop model projections have been widely recognized and discussed, including those attributed to input uncertainty (Roux et al., 2014), as to differences in climate forcing data (Rosenzweig et al., 2014), model structure and parameterization (Rötter et al., 2012), and assumptions on the effectiveness of CO_2-fertilization on crop yields (Deryng et al., 2016). The uncertainty in cropland extent and its implications for land use modeling have been addressed before by Eitelberg et al. (2015), Fritz et al. (2015), and See et al. (2015).

Gridded cropping system data sets on the spatial distribution of crops at the global scale have been reported by Leff et al. (2004), and more recently by Iizumi et al. (2014), and Ray et al. (2012) including distinct data on crop-specific harvested area. Anderson et al. (2015) directly compared four gridded cropping system data sets as MIRCA2000 (Portmann et al., 2010), SPAM2000 (You et al., 2014), GAEZ (Fischer et al., 2012), and M3 (Monfreda et al., 2008). They conclude that the data sets' differences in harvested area and yield could be attributed mainly to the input data used and the downscaling method applied, and report that the disagreement between data sets was largest in areas with minimal harvested area. Different schemes for the interpolation of site-specific yields for the aggregation to agro-climatic zones have been discussed by van Wart et al. (2013) within the context of yield gap and production analysis.

Global gridded crop model (GGCM) results e.g. yield (t/ha) are typically reported in a standardized half degree grid format. This output is aggregated at annual time steps to different spatial scales within the context of model skill assessment, impact studies, or as input variable to land use models. It is used for example when comparing different countries or evaluating modeled yields against agricultural statistics that are only available at the aggregated scale of administrative units. For this kind of aggregation, data sets on spatial patterns of crop-specific harvested area are applied, which are typically derived from data on cropland extent, national and sub-national census data, and allocation rules. To date, little attention has been paid to the uncertainty of aggregation of gridded crop model simulations induced by the choice of crop-specific harvested area data set. Thus the objective of this study is to assess this aggregation uncertainty at different spatial scales. We use the term "crop mask" in the following as a short version of "gridded crop-specific harvested area data set". The uncertainty in simulated yields related to aggregation masks is determined by two factors: a) the differences in quantity and spatial patterns of crop-specific harvested area data sets, and b) the spatial and quantitative heterogeneity of simulated crop yields, which is specific to individual GGCMs.

2. Material and methods

2.1. Model input data and crop yield simulations

In the Global Gridded Crop Model Intercomparison (GGCMI) project Phase 1 (http://www.agmip.org/ag-grid/ggcmi/) of the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013) 14 modeling groups performed historical global crop growth simulations according to the modeling protocol of Elliott et al. (2015). Crop growth has been simulated using the bias-corrected historical weather input data sets AgMERRA (Ruane et al., 2015) and the atmospheric CO_2-data based on the Mauna Loa Observatory time series (Thoning et al., 1989). AgMERRA provides daily data for the time period 1980–2010 and had been aggregated from the original resolution of 0.25° to 0.5° before being supplied to modelers. The Mauna Loa Observatory time series reports observed annual and monthly values of the atmospheric CO_2-mixing ratio, so that models simulated crop growth with a CO_2-mixing ratio of 339–390ppmv (here stating annual averages 1980–2010).

Four crop types were simulated by the modeling teams: maize (*Zea mays* L.), wheat (*Triticum aestivum* L.), rice (*Oryza sativa* L.), and soybean (*Glycine max* (L.) Merr.) These crops had been categorized in the GGCMI project as Priority 1 crops, because of their importance as agricultural commodity in terms of their global harvested area covered, production amount, level of trade, and direct or indirect contribution to human diet.

The participating models cover a broad range of model types and of implemented processes. Their basic characteristics and key literature references are listed in Table 1 (more details in *SI Appendix* Tables A.1–5).

For the crop growth simulations initial conditions of soil water, minerals, crop residues, and soil organic matter were derived by applying different soil input data and spin-up runs individual to each of the modeling groups (*SI Appendix* Table A.3). Modelers were asked to model all crops wherever a given crop can grow and at least on all current agricultural land. The GGCMI project distinguishes three levels of model harmonization with respect to agricultural management. We here used the simulations of the "default" model configuration if available, where every modeling team used their own assumptions on agricultural management (varieties, growing season, fertilizer etc.). The EPIC-TAMU model was run at the global scale for the first time and ORCHIDEE-crop never globally simulated soybean before and thus could not provide a "default" simulation. These teams used the global input data on sowing and maturity dates, and fertilizer data provided within the context of the GGCMI project for a rather harmonized simulation, so that for this study their "fullharm" model configuration was used. The modeling teams reported two separate yield time series per configuration type—one assuming rainfed and the other fully irrigated production conditions everywhere. The irrigated crop growth simulations were run assuming unlimited water supply without conveyance or application losses.

As a second step we used crop yield simulations of seven models for the same four crop types of the Intersectoral Impact Model Intercomparison (ISI-MIP) and The Agricultural Model Intercomparison