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Gridded agroecosystem and SOC modeling with EPIC model

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Highlights of the quantification approach:

- Up-scaling of the SOC-related dynamics and processes from on-site measurements/observations to wider defined spatial and temporal domains (countries, regions, global)
- Linking observed common practices with theoretical land and soil management scenarios applied for formulating and testing of regional policies
- Adding spatial quantities to SOC balance at regional scales as opposed to site-specific SOC quantification focusing more on quality of the processes and their results
- Introducing spatial variability of the SOC balance and its drivers for exploring the options/impacts of sustainable SOC management in large scale studies (regional to global)
- Adding complexity to SOC balance modelling directly quantifying impact of wide range of measurable management options within the particular spatial context
- Neglects many important details/processes of organic carbon cycling present at local scale on exchange for wider spatial extent and attribute complexity of the simulation outputs

Regional or gridded modelling is commonly used approach to quantification variety of SOC/GHG processes, their drivers and outcomes at regional or global scales (e.g. Wang et al 2016, Gottshalk et al. 2012, Easter et al. 2007, Smith et al. 2005).

Gridded version of EPIC model being developed and used at IIASA (Balkovic et al. 2013, Balkovic et al 2014, Folberth et al. 2012) couples bio-physical agroecosystem model EPIC (Williams 1995) including the SOC routine implemented by Izaurrealde et al. (2012) with the spatial data on climate, soil, topography, land cover, and land use harmonized and organized within the regular grid (Skalsky et al. 2008, Balkovic et al 2007). Gridded EPIC enables for up-scaling important bio-physical processes and management impacts from local to larger scales (national, regional, or global) providing at output spatially explicit and quantitative estimates on variety of landscape qualities such as biomass production, water and nutrient cycling, or environmental impacts of agricultural systems (soil erosion, nutrient leaching); precision of the results depending on the input data and regional model calibrations (Balkovic et al. 2013, Balkovic et al 2014, Xiong et al. 2014, 2016, Ma et al. 2016, van der Velde et al. 2014, van Oijen et al. 2014).

Spatial estimates from gridded EPIC can feed to many practical applications such as SOC/GHG mitigation policy impact studies (e.g. Frank et al 2014, Elshout et al. 2015, Havlik et al. 2011, Schneider et al. 2011). It provides precise enough data for regional or global studies, yet the use of the gridded outputs could be not precise enough (both in spatial and attribute meaning) for other applications having their focus on site-level processes and relationships.

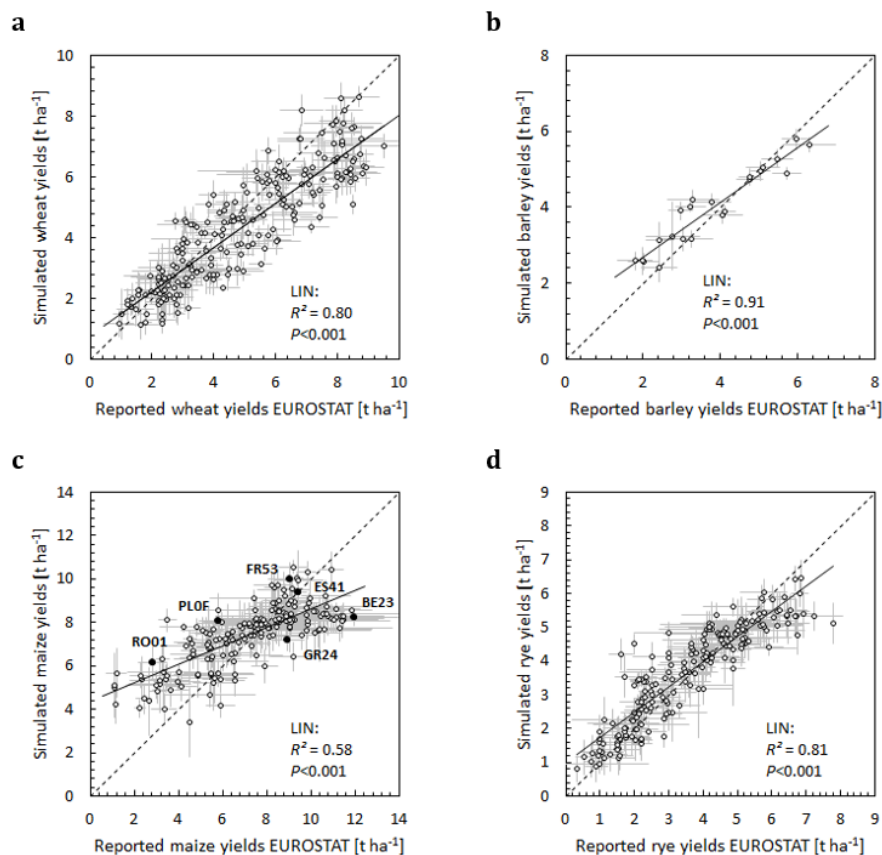


Fig. 1 Scatter plots with means and \pm one SD of simulated versus observed regional yields for EU regions (average of 1997-2007) for (a) winter wheat, (b) spring barley, (c) maize, and (d) winter rye (Source: Balkovic et al. 2013)

When compared to observations or measurements gridded EPIC can provide robust and accurate estimates for larger regions (Fig. 1); also reflecting well inter-annual variability patterns of simulated agroecosystem qualities changing with main drivers such as climate or crop management (e.g. Balkovic et al. 2013, Balkovic et al 2014).

Specific problem of the model accuracy check is the lack of appropriate observations and measurements for many landscape qualities other than biomass production (water and SOC dynamics, nutrient content, etc.) not allowing for proper accuracy assessment of the gridded outputs (e.g. van der Velde et al. 2014, Ma et al 2016).

The gridded EPIC performance closely relates to manifold biases coupled with spatial data used to run the model which can generate high uncertainty in the simulation results. Knowing not exactly the crops and crop types (cultivars), nutrients and water inputs, or planting/harvesting dates can result in many possible estimates of crop production with observed value somewhere within the simulated theoretical range (Fig. 2, Balkovic et al. 2013).

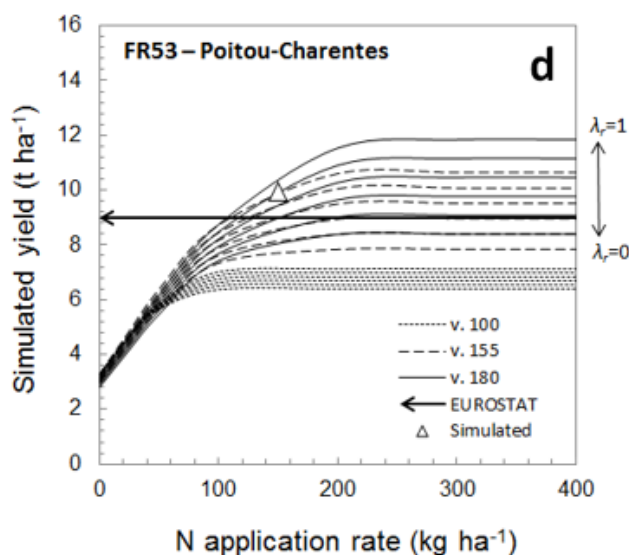


Fig. 2 Relationships between simulated maize yields and N-fertilizer application rates for different maize varieties (v. 100 – early maize, v. 155 – medium-early maize, and v. 180 – late maize) and different irrigation intensities (λ_r from 0 to 1, with 0.2 increments, double-arrow denotes the λ range for v. 180); triangle represent maize yield realization used in the EU EPIC implementation; horizontal arrow denotes EUROSTAT reported yields (Source: Balkovic et al. 2013)

Representation of key landscape and land management elements (qualities and their spatial representation) in the gridded data infrastructure (e.g. Skalsky et al. 2008, Balkovic et al. 2007), as well as their mutual relationships at given scale can significantly add to produced uncertainty of spatial estimates. Study of Folberth et al. (2016) shows that with global gridded EPIC runs for maize system under the projected climate change an unambiguous cropland allocation can result in significantly different crop yield estimates for alternative soil types. This applies specifically for SOC dynamics studies

where initial SOC stock should be properly allocated within the respective land cover classes to limit the uncertainties of the model outputs (e.g. Ma et al. 2016, Frank et al. 2014).

Spatial coverage of the gridded EPIC can theoretically range from farm to global scales reflecting the purpose of the modelling; with the EPIC model being currently available at IIASA for EU (Balkovic et al. 2013), Sub-Saharan Africa (Folberth et al 2012, 2014), and global (Balkovic et al. 2014) set-ups.

Gridded modeling approach implicitly reflects that quantification happens over a pre-defined spatial domain and implicitly, the coverage depends on the spatial domain selection (region, global). This is clearly opposed to any site- or point-based quantification approaches with the ‘coverage’ likely being one of the main added values of the gridded modelling to the SOC quantification.

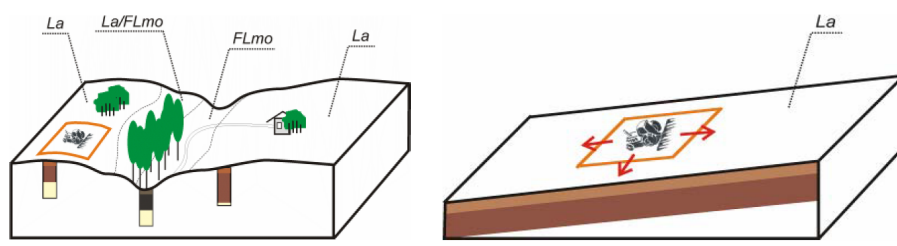


Fig. 3 Limited spatial resolution of gridded EPIC model – an image of ‘real’ cropland with variable soil characteristics (La – Albic Luvisols, FLmo – Mollic Fluvisols), different land-cover patches and different land uses juxtaposed to a ‘representative’ field, which reflects available data at given scale with likely site conditions and management, and field impacts uniformly extrapolated to the entire simulation unit (Source: Balkovic et al 2007)

Setting up gridded data infrastructure requires complex approach to harmonize and organize all necessary spatial inputs (e.g. Skalsky et al. 2008, Balkovic et al. 2007). But at some point it is not possible anymore to process the data in such a spatial, temporal, or attribute detail which could fully satisfy all the SOC quantification needs. Spatial data infrastructure becomes then rather an approximation than a full landscape variability representation (Fig. 3) with e.g. replacing full variability of slopes or soil types presented with only dominant one (e.g. Skalsky et al 2008, Balkovic et al 2007). Other possible way how to secure some reasonable landscape variability in the spatial data infrastructure is to use alternative classes to mimic real landscape variability in the outputs (e.g. Folberth et al. 2016).

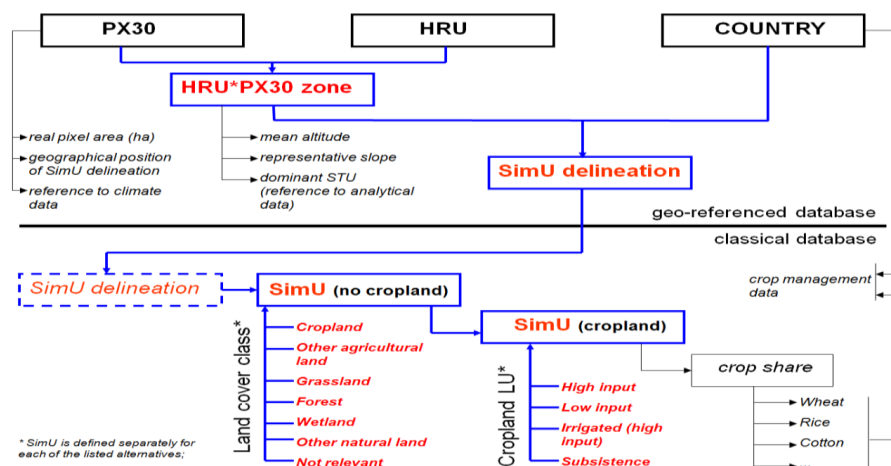


Fig. 4 Spatial and geo-coded information used in global gridded EPIC spatial data infrastructure to handle the landscape variability beyond the spatial resolution of the simulation units; PX30 – 30 arcmin resolution grid, HRU – Homogenous Response units – a grouping of 5 arcmin resolution gridcells based on altitude, slope and soil texture classification, COUNTRY – country borders, STU – soil typological units delineated on soil map, and SimU – simulation units – a grouping of the gridcells providing direct spatial reference for running the gridded simulations (Source: Skalsky et al. 2008).

Spatial resolution of the gridded model can be user defined and depends on the purpose. With gridded EPIC developed at IIASA the spatial resolution ranges from 1k to 5/30 arc min spatial resolution with regional or global setup, respectively (Balkovic et al. 2013, Balkovic et al. 2014, Skalsky et al. 2008, Balkovic et al 2007). Some landscape qualities with high spatial detail such as land cover or land use could be treated as geocoded data attributed to spatial domains in the data infrastructure (Fig. 4). This allows then for keeping higher attribute detail within the limited spatial resolution of simulation units.

The EPIC model (Williams 1995) operates at daily time steps and outputs can be aggregated directly by the model executive to monthly or yearly balances. Simulations can run from couple of years to over several tens or hundreds of years with climate change impact studies (e.g. Balkovic et al. 2014, Folberth et al. 2016, Xiong et al. 2016). It can reflect gain or loss in the SOC pool with the variability of key controls driving the SOC balance and provide spatial estimates of inter-annual rates of SOC pool dynamics with direct link to management measures such as grazing, crop residua management, tillage operation types and frequencies, adding of organic fertilizers or irrigation (e.g. Ma et al. 2016, Folberth et al. 2014, Balkovic et al. 2013). A trade-off is always necessary with simulating SOC balance over large regions by balancing simplified representation of the real landscape system complexity in gridded data infrastructure (Fig. 3, Skalsky et al. 2008, Balkovic et al. 2007) with necessary detail of all key elements of the SOC balance. This could optionally become serious limitation of the gridded EPIC model application for many practical applications strongly focusing on site-level elements/processes.

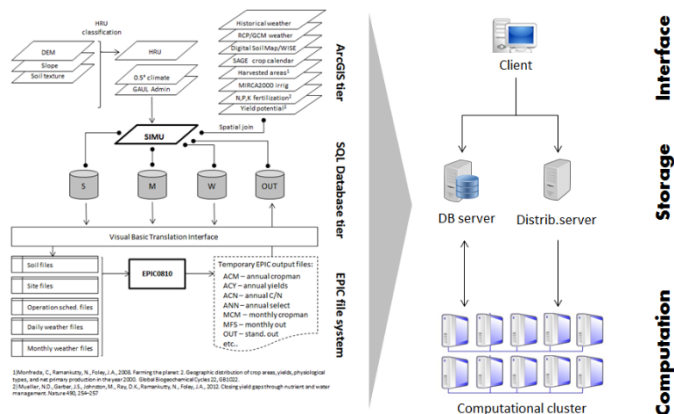


Fig. 5 Data flow and computational infrastructure of EPIC IIASA global gridded crop model

EPIC model executive can be used for free for all non-commercial applications (<http://blackland.tamu.edu/models/epic/>). To set-up and run gridded EPIC model trained experts are required which puts the most potential costs of this quantification approach to development and operational team. If computational infrastructure is absent, additional costs are required for hardware, software, and the maintenance. Setting up the data infrastructure for the model, to perform calibration and validation, and simulations can take time and efforts depending on the coverage, spatial resolution,

and complexity of the model set-up. The most time consuming part being commonly gathering and preprocessing input spatial data and securing spatial and thematic consistency of all modelling inputs and regional calibration of the key processes.

Gridded version of EPIC model as implemented at IIASA uses distributed computational environment with parallel computation (Fig. 5). This solution is supported with shared data storage environment and GIS and database software for input/output processing. Partly parallelised computation is possible also with using single computer but this having limitations in number of simulations per time unit and/or number of simulation dimensions defined by climate or crop management scenarios. Development of input/output communication interface translating between the database and the input/output data format required by the model must be set prior to run the gridded simulations (e.g. VBA codes implemented with SQL database, Fig. 5).

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