Spatial aggregation for crop modelling at regional scales: the effects of soil variability

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MACSUR CropM WP3 www.scale-it.net
More info on the soil-plant-atmosphere model www.coupmodel.com
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Intro.

Crop modelling at regional scale

- Soil-crop models developed at field scale are increasingly used in regional scale modelling for studying the impacts of climate change (CC) on agro-ecosystems [a]
- CC impacts strongly depend on site conditions (e.g. soils, climate, management practices) [b,c] that show large variation at regional scales

- How should we aggregate site conditions? (i.e. upscaling methods [d])
- What is the resulting Data Aggregation Error (DAE) [e]?
- **Can we link variability in site conditions (e.g. soils) to DAE?**

Meth. I

Simulations with the CoupModel

- A case study with the **CoupModel** [f]
- **North-Rhine Westphalia** Region (NRW) ~34000 km²
- **2648 soil mapping units** at resolution 1 km [e]
- **30 years** climate data time-series, regional average
- Monoculture of winter wheat, rain fed and fertilized (208 kg N ha^{-1}yr^{-1})
- Simulated variables: **yield**, **water drainage**, **C mineralization** and **N-leaching**

Meth. II

Sensitivity analysis & key soils

1. Ten clusters defined by *k-means* clustering analysis grouped soil mapping units with similar properties (texture, thickness and organic C content of three soil horizons)
2. Three clusters were identified that were associated with extreme values of model outputs, hereafter denoted as **key soils** (**Fig. 1**)
3. Spatial coverage of soil clusters (**Fig. 2 & 3**)

Figure 1

	1 Shallow	6 SOC rich	10 Clay rich
Topsoil (20-30 cm)		8% SOC	26% Clay
Root Zone (20-120 cm)	40 cm		33% Clay
Subsoil (10-80 cm)			35% Clay

Table 1: extreme values of model outputs data

	1	6	10
Yield (t DM / ha)	-20%	n.s.	n.s.
Water drainage (mm)	n.s.	n.s.	-20%
C mineralization (g C / ha)	-33%	+ 102%	n.s.
N leaching (kg N / ha)	+47%	+ 146%	n.s.

Deviation from all soil types average value

We studied the effect of aggregating soil mapping units by area majority (resolutions from 1km to 100 km) for regional crop model simulations

What is the influence of the distribution of key soils?

Results.

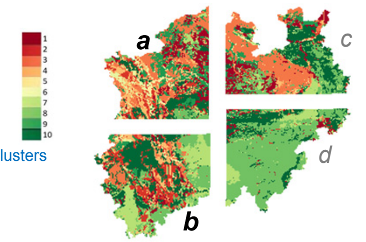
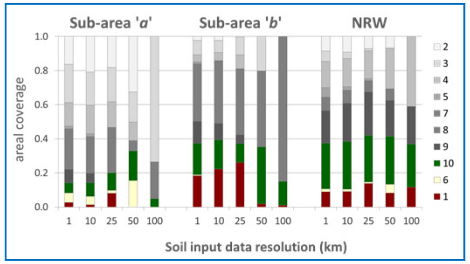


Figure 2
The NRW region divided into 4 sub-areas with different spatial distributions of 10 soil clusters

I. Key soils coverage

Figure 3
Spatial coverage of the key soils (clusters 1, 6 & 10) in the western part of NRW (sub-areas '*a*' and '*b*') and in the whole NRW at resolution 1,10, 25, 50 and 100 km .



II. DAE as explained by key soils distribution

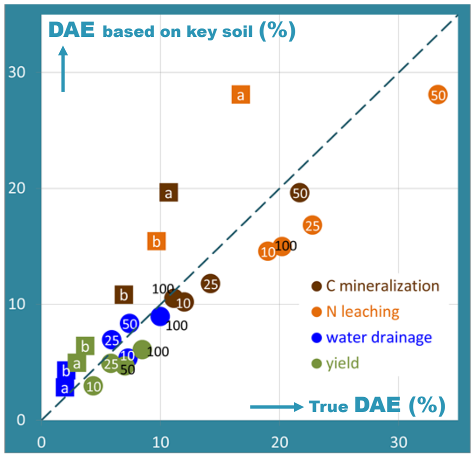
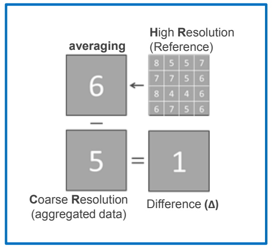


Figure 4
DAE using key soils plotted vs. the 'true' DAE obtained for the four variables:
(1) in NRW for the different soil data resolutions (10, 25, 50 and 100 km = CIRCLES)
(2) in the two western sub-areas of NRW at resolution 25 km ('*a*' and '*b*' = SQUARES).

Meth. III

Data Aggregation Error (DAE)



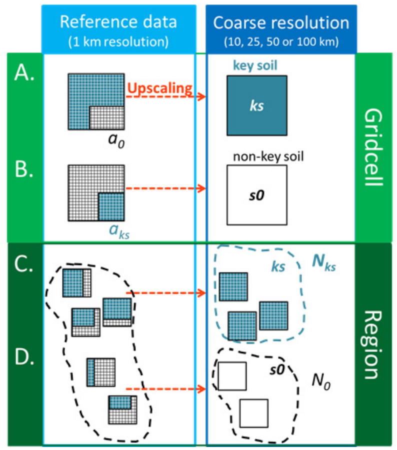
The simulated variables at the four coarser resolutions (10, 25, 50 and 100 km) were compared with those of the finest resolution (1 km, Δ).

DAE was quantified in terms of **rRMSE** (%).

Meth. IV

DAE based on key soils

Figure 5:
The DAE was approximated using the relative spatial coverage of key soils and the mean relative difference in simulated variables shown in Table1 (**Fig. 1**).
(A-B) Gridcell error depends on a_{ks} in **$s0$** or a_0 in **ks**
(C-D) Regional error (DAE) additionally depends on N_{ks} and N_0.



Conclusion & perspectives

- The spatial distribution of key soils explained a large part of the DAE observed for the different variables, resolutions and sub-areas of NRW (**Fig. 4**).
- A spatial analysis of the pattern of these key soils (i.e. presence / absence, coverage and aggregation) can help in defining the appropriate grid-resolution that would minimize the error caused by aggregated soil input data in regional model simulations
- The method will be applied and evaluated with respect to another European region (Tuscany) which is characterized by a warmer and drier climate

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