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Impact analysis of climate data aggregation at different spatial scales on simulated Net Primary Productivity for croplands

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Abstract

For spatial crop and agro-systems modelling, there is often a discrepancy between the scale of measured driving data and the target resolution. Spatial data aggregation is often necessary, which affects the uncertainty of the simulation results. Previous studies have shown that climate data aggregation has little effect on simulation of phenological stages, but effects on net primary production (NPP) might still be expected through changing the length of the growing season and the period of grain filling. This study investigates the impact of spatial climate data aggregation on NPP simulation results, applying eleven different models for the same study region (~34000 km^2), situated in Western Germany. To isolate effects of climate, soil data and management were assumed to be constant over the entire study area and over the entire study period of 29 years. Two crops, winter wheat and silage maize, were tested as monocultures. The results show only small impacts of climate data aggregation on averages over the entire simulation period and study region. Maximum differences between the five scales in the range of 1 to 100 km grid cells show changes of 0.4 – 7.8 % and 0.0 - 4.8 % for wheat and maize, respectively, whereas the simulated potential NPP averages of the models show a wide range (1.9 - 4.2 g C m^{-2} d^{-1} and 2.7 - 6.1 g C m^{-2} d^{-1} for wheat and maize, respectively). The impact of the spatial aggregation was also tested for shorter periods to test if impacts over shorter periods level out over longer periods, which shows larger impacts for single years (up to 9.4 % for wheat and up to 13.6 % for maize). An analysis of extreme weather conditions shows an aggregation effect to the vulnerability up to 12.8 % and 15.5 % between the different resolutions for wheat and maize, respectively. Simulations of NPP averages over larger areas (e.g. regional scale) and longer time periods (several years) are relatively insensitive to climate data aggregation, but the scale of climate data is more relevant for impacts on annual averages of NPP or if the period is strongly affected or dominated by drought stress. There should be an awareness of the higher uncertainty for the NPP values if data are not available in a high resolution. On the other side, the results suggest that there is no need to simulate in high resolution for long term regional NPP averages based on the simplified assumptions (soil and management constant in time and space) used in this study.

Keywords: net primary production, NPP, scaling, extreme events, crop modelling, climate, data aggregation

1 Introduction

Net primary production (NPP) is a crucial ecosystem variable characterising the condition of an ecosystem (Pan et al, 2014) and it is sensitivity to climate change. Spatial NPP is difficult to measure and often biased and uncertain (Pan et al., 2014), because measurements show several limitations (indirect determination, spatially and temporally limited). Spatial modelling is an important tool for interpolation and extrapolation of measurements or for providing spatial distributed projections for regional (Reich et al., 1999; Zaehle et al., 2006; Bandaru et al., 2013; Liu et al, 2015), continental (Ciais et al., 2010) or global scale (Hemming et al., 2013; Friend et al., 2014). The regional scale is relevant for policy makers to analyse adaptation and mitigation strategies, but NPP data for this scale are often derived by extrapolating measured information from the site scale to a region by applying models developed at site scale (Zhang et al., 2015). This model-based up-scaling requires a balance between accuracy and simulation time.

Spatial modelling of NPP relies on spatially distributed input and driving data like weather data and information on soil, land use and management characteristics. Depending on environmental parameters, ecosystem characteristics and the chosen resolution, the impacts of extrapolation or interpolation may be great or small since there is e.g. a higher uncertainty for high relief areas compared to relatively flat areas as shown by Pierce and Running (1995). For this reason, estimates of error and uncertainty arising from data aggregation across scales needs to be quantified.

Several studies have highlighted the impact of data aggregation on simulation results (Cale et al., 1983; Rastetter et al., 1992; Ewert et al., 2015; Zhao et al., 2015). De Wit et al. (2005) and Hoffmann et al. (2015) investigated the impact of climate data aggregation on crop yields. While de Wit et al. (2005) varied precipitation and solar radiation only on the resolutions 10 km and 50 km, Hoffmann et al. (2015) differentiated between five different resolutions between 1 and 100 km and also considered aggregation effects of temperature for 13 models. Both studies found only slight impacts of data aggregation on simulated yield over longer time periods at a regional scale. Van Bussel et al. (2011) investigated the impacts of climate aggregation on croplands and focused on phenological stages rather than primary production, but they also found minor effects on simulated average values. The impacts of climate data aggregation on NPP were tested by Nungesser et al. (1999) and Pierce and Running (1995), both for American forests. In both studies, the impact was minor for averages over the entire study area, but showed relevant impacts for smaller areas, especially areas dominated by strong relief changes (Pierce and Running, 1995). In both studies, the effects were tested by one model and for two resolutions of 10 and 50 km grid cells in Nungesser et al. (1999), and 1 km and 110 km in Pierce and Running (1995). The latter study investigated the effect for different input variables (relief, climate and soil) and found that climate data aggregation was the dominant variable affecting scale differences of NPP. They also observed larger scale effects for shorter time periods, which could be an indication of extreme weather events that average out over larger areas or longer time periods. Overall, regional simulation results over longer periods seem to be little affected by climate data aggregation. Over longer periods changes of NPP level out and the impact of extreme events may be not obvious in a long term average, but relevant for shorter periods. Reichstein et al. (2013) describe the temporal and spatial scale as very important to detect impacts of extreme weather conditions on the carbon balance and see a risk of miss out extreme weather conditions by integration of weather data across scales. Impacts of extreme weather are also depending on the temporal scale, which is not yet tested for impacts on NPP. However, there is a lack of studies determining the effect on NPP simulations of croplands, and no study to date has analysed the relevance of extreme events during climate data aggregation.

Therefore, the objective of this paper is to quantify error and uncertainty of NPP simulations of croplands caused by climate data aggregation across five resolutions (1, 10, 25, 50 and 100 km grid cell side length). This study addresses the three questions i) what are the impacts on long term NPP averages over the entire region? ii) how does the aggregation effect change over shorter time periods? iii) is the aggregation effect more pronounced in years with extreme weather conditions compared to “normal” years? These questions are answered by using a simulation approach involving eleven different models. Additionally, a vulnerability analysis helps to identify the impact of climate data aggregation for years with extreme weather conditions. Thus, we provide the first systematic analysis considering the impact of spatial weather data aggregation on NPP using five resolutions and 11 different models.

2 Methods

2.1 Aggregation effect

Spatial modelling approaches are containing uncertainty, because uncertainty of input data and limited data availability requires data aggregation, which also contribute to the uncertainty. In this study we focused on the impact of data aggregation on uncertainty. Spatial data base on point measurement, small scale measurements or approaches that averaging the data already during the measurement process. In the data aggregation these data sets get interpolated, extrapolated and averaged to provide data in its spatial distribution. This data aggregation increases the uncertainty of the data sets. Beside the impacts of data aggregation, the chosen format of the model approach adds uncertainty to the data, too. Spatial model approaches often using data organized in grid maps, while natural conditions do not follow any symmetric pattern. Therefore, gridded data already contain uncertainty, which also varies with changing scale. Our focus in this study is on the impact of changing scales of grid map data on simulation results. Because there is a strong interaction of different processes, we concentrate on the impact of changing weather data as an important driver for plant growth. As we only compare simulated NPP values, we are not using the term uncertainty, but aggregation effect ($E_{aggregation}$), which can be formulated as:

$$E_{aggregation} = \frac{max(VAL_{res\_1},...VAL_{res\_n}) - min(VAL_{res\_1},...VAL_{res\_n})}{VAL_{res\_1}} \qquad (1)$$

In this study the aggregation effect is defined as the maximum difference between the simulated NPP averages between the different resolutions and it is quantified by the difference between maximum NPP average and minimum NPP average of the five resolutions:

$$E_{aggregation,model} = \frac{max(NPP_{Res1,model},...NPP_{Res100,model}) - min(NPP_{Res1,model},...NPP_{Res100,model})}{NPP_{Res1,model}} \qquad (2)$$

This allows a model specific calculation of the effect and is independent of any trends towards the coarser resolution. The difference describes the maximum expected bias by picking one resolution in comparison to the results of another resolution. This calculation is applicable on different spatial or temporal averages.

The aggregation effect can also applied on ensemble runs, which is possible in two different ways. $E_{aggregation}$ can be calculate for the resolution specific averages over all models with the formulation:

$$E_{aggregation,average} = \frac{max(\overline{NPP_{Res1}},...\overline{NPP_{Res100}}) - min(\overline{NPP_{Res1}},...\overline{NPP_{Res100}})}{\overline{NPP_{Res1}}} \qquad (3)$$

This allows the quantification of the aggregation effect for ensemble runs.

2.2 Study area

The study area is the state North Rhine-Westphalia situated in the West of Germany. The state is 34084 km^2 in size with an elevation from 0 to 843 m above sea level, with lower plains in the North West and higher elevations in the South-East. The land-use is dominated by agriculture (more than 60 % of the area), but in this study the entire area (including the 40 % of forest, urban areas and infrastructure as well as water bodies) was considered to be cropland. To standardize the simulation runs monocultures of either winter wheat (*Triticum aestivum* L.) or silage maize (*Zea mays* L.) were assumed for the entire area.

The driving daily weather data are provided at five different resolutions (1, 10, 25, 50 and 100 km grid cells), while soil data (typical soil type) and management (good agricultural practice) were assumed to be constant during the study period and over the entire study area. The chosen soil type is a sandy loam, which is typical for this region and the management includes ploughing, sowing, harvest and three (130, 52, 26 kg ha^{-1}) and two (30, 208 kg ha^{-1}) fertilizer applications during spring for wheat and maize, respectively (for details see Hoffmann et al., 2015). The models were not calibrated for the study area, but were adjusted based on 30-year yield averages (1982-2011) of about 8 t ha^{-1} for winter wheat and 14 t ha^{-1} for silage maize. The weather data, presented and discussed by Zhao et al. (2015) and Hoffmann et al. (2015), show a 30 year average temperature of 9.7 °C, an average annual precipitation of 899 mm and mean annual global radiation of 3758 MJ m^{-2} a^{-1} (1982-2011) with the standard deviations of 1.2 °C, 214.0 mm a-1 and 169.4 MJ m^{-2} a^{-1}, respectively. The coldest year was 2004 with an average temperature of 8.9 °C and the warmest year was 1983 (11.2 °C). The driest year was 2001 with 516.2 mm precipitation. All coarser resolutions of the weather data were based on the grid cells of the 1 km resolution for daily time steps. The data show a decrease of temperature (from 9.7 °C to 9.4 °C) and precipitation (from 899 mm to 824 mm) starting from the 1 km resolutions towards the coarsest resolution of 100 km.

2.3 Modelling applications

There are three different approaches using different model settings to analyse the impact of different processes contributing to the simulation of NPP. In a first approach, no limitations to growth factors, other than temperature and radiation, are simulated explicitly (switched off or compensated in all models). We denote this potential, non-limited growth, potential NPP or PN. The second approach considers only water-limitation (WN), while the third approach considers nitrogen and water limitation (NN). The way limitations are switched off differs between the models. Some models switched off the stress factors, other models compensated the stress by providing additional water and nutrient applications.

The settings for management are presented by Hoffmann et al. (2015). The sowing date is fixed for all models, while for harvest only a latest date is suggested (if the phenological model does not determine maturity before this date, there will be an automatic harvest).

2.4 Models

Eleven models participated in this study; eight crop models and three biogeochemical models (Table1). All models provide data on a daily time step (except CENTURY which uses a monthly time step), consider the complete range of management practices (except AgroC that does not consider nitrogen limitation) and provide simulations for the two considered crops, wheat and maize (except COUP that only simulates wheat). The growing season for the crop models is determined by internal phenological models based on a fixed sowing date, while the three biogeochemical models CENTURY, DailyDayCent and LandscapeDNDC and the crop model STICS also used a fixed harvest date (i.e. fixed length of the growing season).

Five of the models determine NPP based on the radiation use efficiency concept (AgroC, APSIM, APSIMmod., COUP, LINTUL, STICS), while other models determine NPP based on the difference between gross primary production and respiration (HERMES, MONICA), calculated directly (DailyDayCent) or other approaches (LandscapeDNDC). More details about the models are provided in Hoffmann et al. (2015).

Table 1: List of the participating models.

No.	Model	References
1	HERMES	Kersebaum 2007, 2011
2	APSIM	Keating et al. 2003; Holzworth et al. 2014
3	COUP	Conrad & Fohrer 2009; Jansson & Karlberg 2004
4	DailyDayCent	Del Grosso et al. 2001, 2006; Parton et al. 2001; Yeluripati et al. 2009
5	LandscapeDNDC	Haas et al. 2012; Kraus et al., 2014
6	LINTUL	Van Ittersum et al. 2003; Shibu et al. 2010
7	MONICA	Nendel et al. 2011
8	STICS	Bergez et al. 2013; Brisson et al. 1998, 2008
9	APSIMmod	Chen et al. 2010; Keating et al. 2003; Wang et al. 2002
10	CENTURY	Parton et al., 1993, 1995
11	AgroC	Herbst et al., 2008

2.5 Evaluation of aggregation effects over different time periods

The simulation results (NPP averages over the entire study area) were averaged over different periods (1, 5, 10, 15, 20, 25, 29 years) to examine the maximum differences between the five resolutions as influenced by the different temporal scales. The number of averages considered varies for the different time periods (29, 6, 3, 2, 2, 2, 1, respectively). The analysis for the periods 20 and 25 years were applied twice, covering mainly the first and the last years with some data overlap. The results are presented as the mean aggregation effect as well as the maximum aggregation effect between the five resolutions.

2.6 Vulnerability Analysis

Vulnerability and risk are terms that are widely used in different communities and described in different contexts with different definitions. In this study we use an approach developed by van Oijen et al. (2014), designed to investigate impacts of extreme weather events on carbon dynamics. The approach, based on an abiotic definition of extreme periods, compares the impacts on a chosen biotic ecosystem variable on the defined “extreme” or “hazardous” and “not extreme” or “non-hazardous” conditions. Van Oijen et al. (2014) chose the standardized precipitation evapotranspiration index (SPEI), developed by Vicente-Serrano et al. (2010), as the abiotic factor separating hazardous from non-hazardous conditions. SPEI is a drought index based on the difference between potential evapotranspiration and precipitation. If the precipitation exceed the potential evapotranspiration for the given time period, SPEI shows positive values, while negative values represent a water deficit based on the calculated difference and indicate a drought impact. There is no fixed threshold, which defines an extreme drought impact or growth reducing conditions and SPEI can be calculated for any duration. The index is normalized and normal distributed. The average is about 0 for the considered period of 1982-2011 with 64 % of the values between -1 and +1 and 19 % below -1 for the 1 km resolution. These statistics stay the same for all resolutions, with the exception of the number of values in the -1 to +1 interval, which drops down to 63 % for the 100 km resolution. The potential evapotranspiration can be calculated with different approaches, while in this study the method developed by Thornthwaite (1948) is used.

SPEI is one of the indices that considers both, precipitation and temperature in the calculation, rather than only precipitation, but is still easy to apply, which makes it an attractive index to use in this study.. Van Oijen et al. (2014) suggest two thresholds to separate hazardous from non-hazardous conditions: SPEI < -1 and SPEI < -2. For the actual study region there is only a small number of SPEI values below -2, so SPEI < -1 was chosen as the threshold. Following van Oijen et al. (2014), the period to calculate the SPEI is restricted to half a year. In contrast to the approach of van Oijen et al. (2014), who suggested the period April-September, the period February – July was used in this study to better reflect the crop growth period. The system variable used in this study is NPP.

Vulnerability (*V*) describes a possible damage/impact on a system and the risk (*R*) is described by the product of the probability (*P*) that a hazardous event (*H*) occurs and its impact on the system.

$$R = P(H) \cdot V \qquad (2)$$

This equation represents the relation between probability, and vulnerability and can be expressed by using the reduction of the NPP by the hazardous periods, described as risk:

$$R = E(NPP|non - hazardous) - E(NPP) \qquad (3)$$

E(NPP|non-hazardous) is the average value of NPP for all grid cells and years with a SPEI ≥ -1 and *E(NPP)* is the overall average of NPP (including both, hazardous and non-hazardous conditions). The vulnerability describes the difference of the NPP averages for the non-hazardous and the hazardous years and grid cells.

$$V = E(NPP|non - hazardous) - E(NPP|hazardous) \qquad (4)$$

3 Results

3.1 NPP differences between the models

The different model simulations of NPP are compared for the 1 km grid resolution, which is considered to be the “best” result for each model separately and thus used as the baseline. The results for wheat vary for the different models with mean values for 29 years of simulation 1.9 - 4.2 g C m^{-2} d^{-1}, 1.9 - 4.1 g C m^{-2} d^{-1} and 1.8 – 4.1 g C m^{-2} d^{-1} NPP for PN, WN and NN, respectively (Figure 1). The simulation results of STICS and AgorC show the highest variation over the 29 years, while the results of COUP and LandscapeDNDC vary only within a narrow range. Some of the models are sensitive to water limitation (e.g. COUP), which is reflected by the differences between the PN and the WN approach (Figure 1), other models show minimal impacts of water limitation (e.g. STICS). The spatial distribution of the results shows a dependency on elevation (Figure 2). However, the spatial distribution of high and low NPP values is different between the models. While most models show higher NPP values for low elevation and lower values in the higher elevations, the other group of models (AgroC, COUP, LINTUL, APSIM and APSIMmod) show the opposite spatial separation of high and low NPP values.

The simulated NPP for maize (7.4 - 12.8 g C m^{-2} d^{-1}, 7.3 - 12.7 g C m^{-2} d^{-1} and 7.2 – 10.0 g C m^{-2} d^{-1} for PN, WN and NN, respectively) show higher maximum values than the NPP for wheat, and indicate an even lower sensitivity to water limitation, which is represented by a comparison of the simulation results of PN and WN (Figure 3). The extreme NPP values for APSIMmod and LandscapeDNDC for wheat and maize, respectively, are outside the range of the other models, but are included in all analyses.

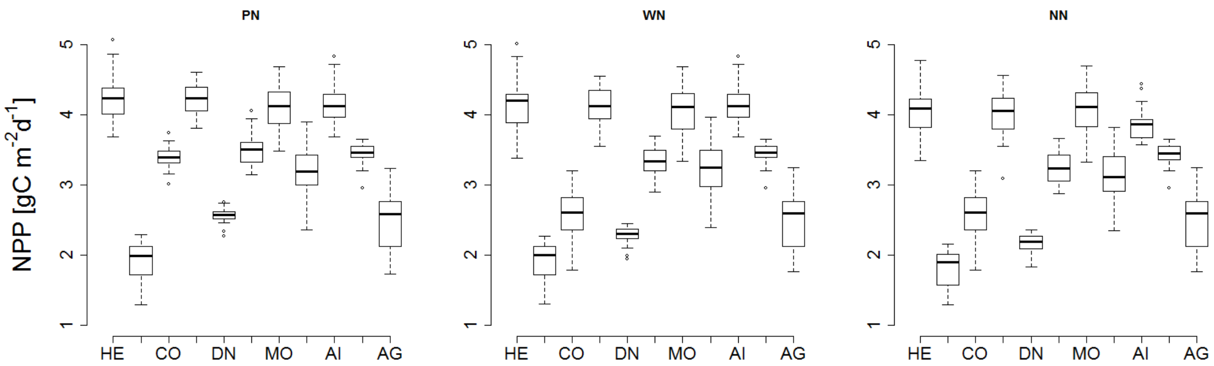

Figure 1: Simulated NPP for winter wheat at 1 km resolution for potential growth (PN), under water limitation (WN) and under nutrient and water limitation (NN). The models are in the order HERMES (HE), APSIMmod (A2), COUP (CO), DailyDayCent (DA), LandscapeDNDC (DN), LINTUL (LI), MONICA (MO), STICS (ST), APSIM (AI), CENTURY (CE) and AgroC (AG).

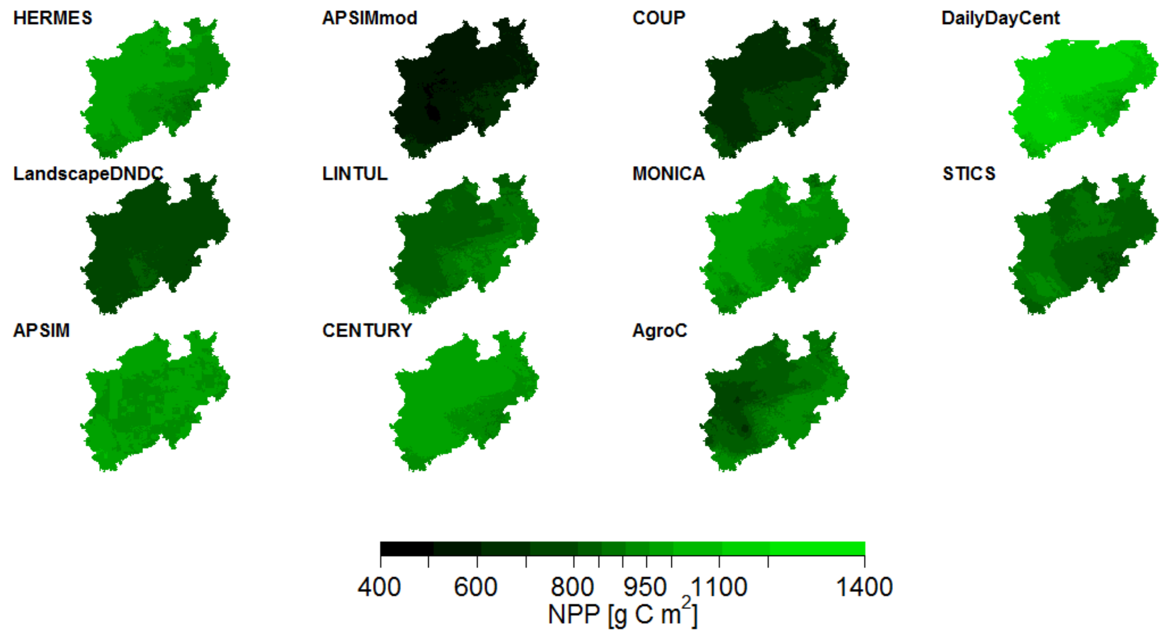

Figure 2: Spatial distribution of the 29 year averages of NPP for the 11 models assuming wheat mono-culture for the PN approach.

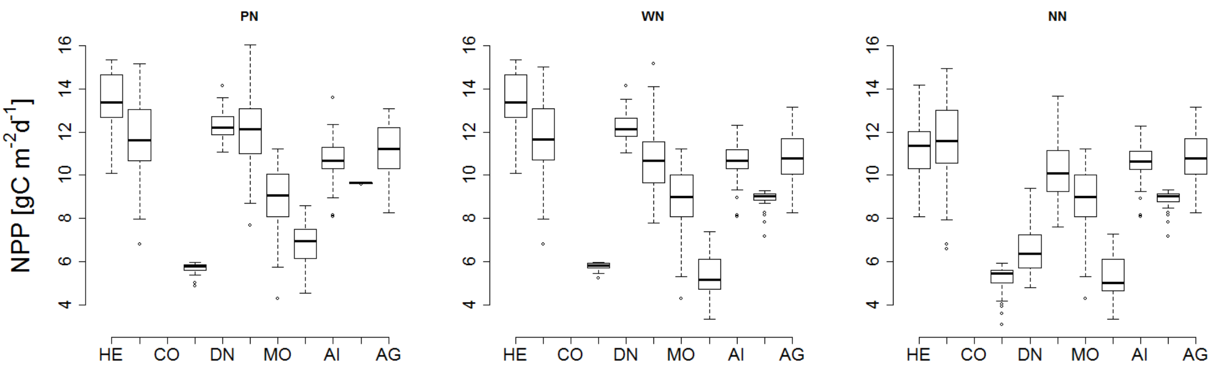

Figure 3: Simulated NPP values for silage maize at 1 km resolution for potential growth (PN), under water limitation (WN) and under nutrient and water limitation (NN). The models are in the orgerHERMES (HE), APSIMmod (A2), DailyDayCent (DA), LandscapeDNDC (DN), LINTUL (LI), MONICA (MO), STICS (ST), APSIM (AI), CENTURY (CE) and AgroC (AG).

3.2 Model specific aggregation effect

The aggregation effect as described in equation 1 shows a range for all models of 0.4 – 7.8 % and 0 - 4.8 % for wheat and maize, respectively (Table 2). The analysis of the medians shows slightly larger aggregation effects with 0.3 – 11.4 % and 0.0 – 10.0 % for wheat and maize, respectively (Table 2). There are no obvious trends in the changes of NPP from the 1 km resolution to 100 km resolution, neither for the crops nor for the different models (Figures 4 and 5). However, the models LandscapeDNDC, MONICA, CENTURY and DailyDayCent show relatively small changes (< 1.2 %) for both crops, and HERMES for the wheat simulations, while APSIM, APSIMmod and AgroC show relatively high aggregation effects (more than 4.8 %) between the different scales. The aggregation effect varies between the models as does the trend. While APSIMmod, LINTUL, AgroC and APSIM show increasing NPP values towards coarser resolutions for the wheat simulations, HERMES, MONICA, CENTURY and DailyDayCent show decreasing NPP. The simulation results of COUP and STICS show no trend, but a minimum NPP averages for the resolutions of 10 km and 50 km, respectively. The median is affected for some models, especially for the maize simulations, more than the average values and most models show stronger changes for WN and NN than for PN (Table 2). The results for maize support the findings of the wheat simulations, but the scale effect is smaller and effect and trends differ for some models between the two crops. HERMES and DailyDayCent show minimal differences between the resolutions, while APSIMmod, LINTUL, MONICA, STICS and APSIM show a decreasing trend with AgroC and LandscapeDNDC showing an increasing trend towards coarser resolutions.

The aggregation effect for the model ensemble is calculated for the resolution specific average over all models (equation 3). The effect is below 0.9 % for wheat and 2.0 % for maize, which is below all aggregation effects of the individual models.

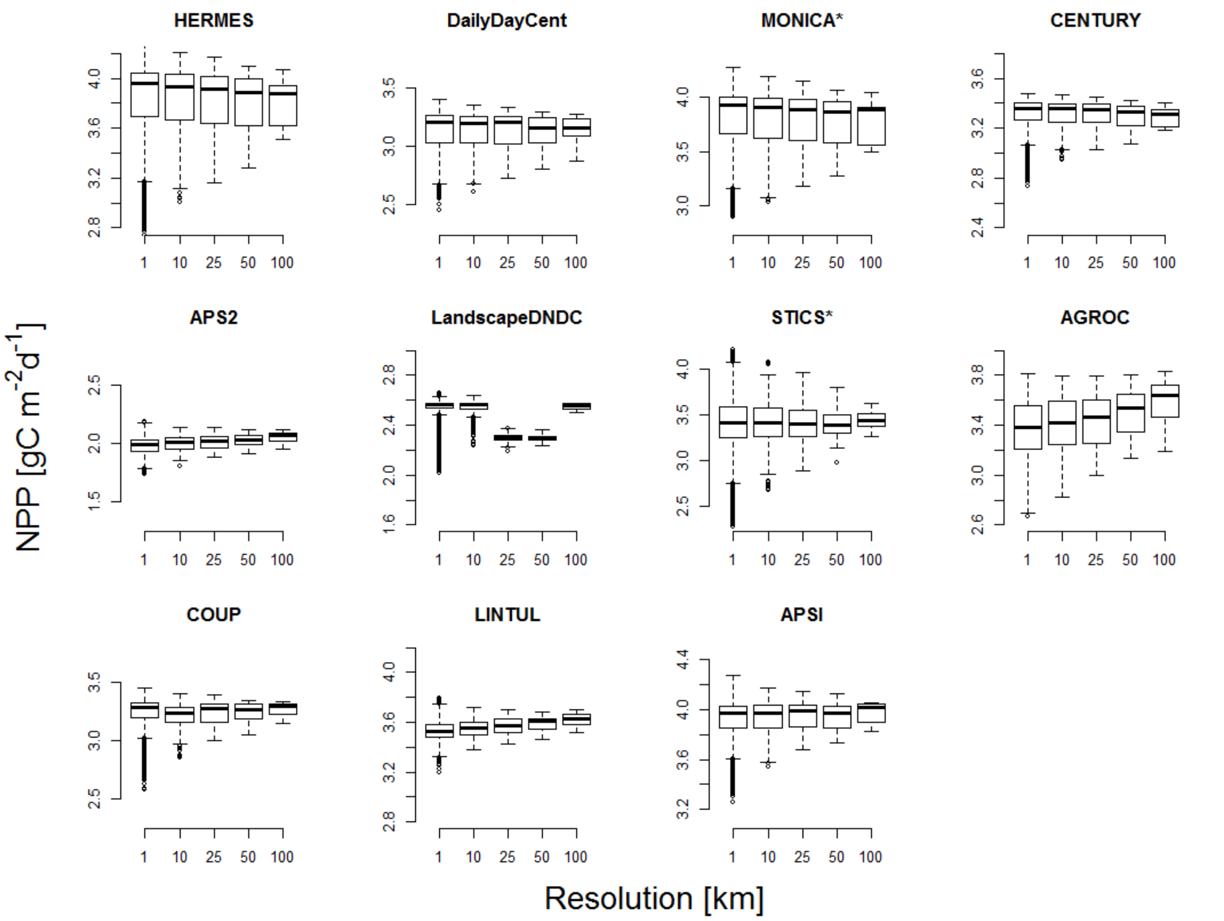

Figure 4: Simulated NPP of wheat for the potential growth (PN). These boxplots represent the variability over 29 NPP averages over the growing season for the five resolutions (1, 10, 25, 50 and 100 km).

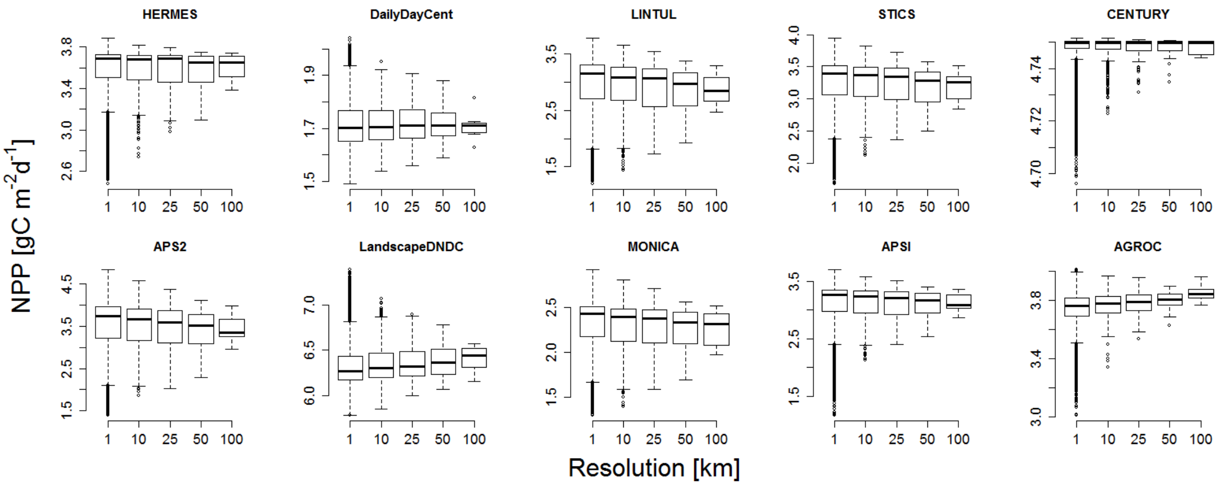

Figure 5: Simulated NPP of maize for the potential growth (PN). These boxplots represent the variability over 29 NPP averages over the growing season for the five resolutions (1, 10, 25, 50 and 100 km).

Table 2: Relative maximum differences of NPP averages (AVG) and median (MED) between the five resolutions [%]. The values represent the simulation results of wheat (W) and maize (M) for the three approaches (PN, WN, NN). All differences are related to the resolution with the lowest NPP average. The models are HERMES (HE), APSIMmod (A2), COUP (CO), DailyDayCent (DA), LandscapeDNDC (DN), LINTUL (LI), MONICA (MO), STICS (ST), APSIM (AI), CENTURY (CE) and AgroC (AG). Changes of greater 3 % are highlighted by grey boxes.

	HE	A2	CO	DA	DN	LI	MO	ST	AI	CE	AG
AVG W PN	0.9	5.0	2.2	1.1	n.s.	4.7	0.8	2.0	4.9	0.9	7.8
AVG W WN	0.8	4.8	2.2	0.7	0.2	2.4	1.1	1.8	4.8	0.8	7.8
AVG W NN	0.5	5.4	2.2	0.5	1.6	3.0	1.2	2.0	5.4	0.7	n.s.
AVG M PN	1.3	2.0	n.s.	0.1	1.3	2.0	2.0	1.5	2.0	0.0	3.2
AVG M WN	1.3	2.0	n.s.	0.3	1.2	2.5	1.5	2.0	2.0	0.5	3.5
AVG M NN	4.8	2.0	n.s.	1.2	2.8	1.7	1.5	2.0	2.0	0.6	n.s.
MED W PN	0.9	4.9	2.2	1.0	n.s.	4.7	0.8	2.0	4.9	0.9	7.8
MED W WN	1.5	7.8	2.3	1.8	0.3	3.2	2.9	2.1	7.8	1.4	11.4
MED W NN	0.9	8.8	2.3	1.6	1.0	3.8	3.0	2.3	8.8	1.3	n.s.
MED M PN	0.7	10.0	n.s.	0.1	2.8	8.7	3.8	3.3	10.0	0.0	3.1
MED M WN	0.7	10.0	n.s.	0.5	2.7	10.0	3.3	3.7	10.0	0.3	3.9
MED M NN	4.0	10.0	n.s.	0.7	5.5	8.8	3.3	3.8	10.0	0.3	n.s.

n.s. not simulated

3.3 Aggregation effect over different time periods

The impact of scales is also tested for periods shorter than 29 years (Figure 6 and 7). The simulation results are averaged for each time step (according to the considered period of 1, 5, 10, 15, 20, 25 years) over the entire area (for each resolution separately). While the maximum aggregation effect is strongest for a single year and does not change greatly for periods of 10 years or longer, the average aggregation effect stays almost the same, but decreases for the 29 year period. The effects are the same for all models for both crops (Figure 6 and 7), but the values differ.

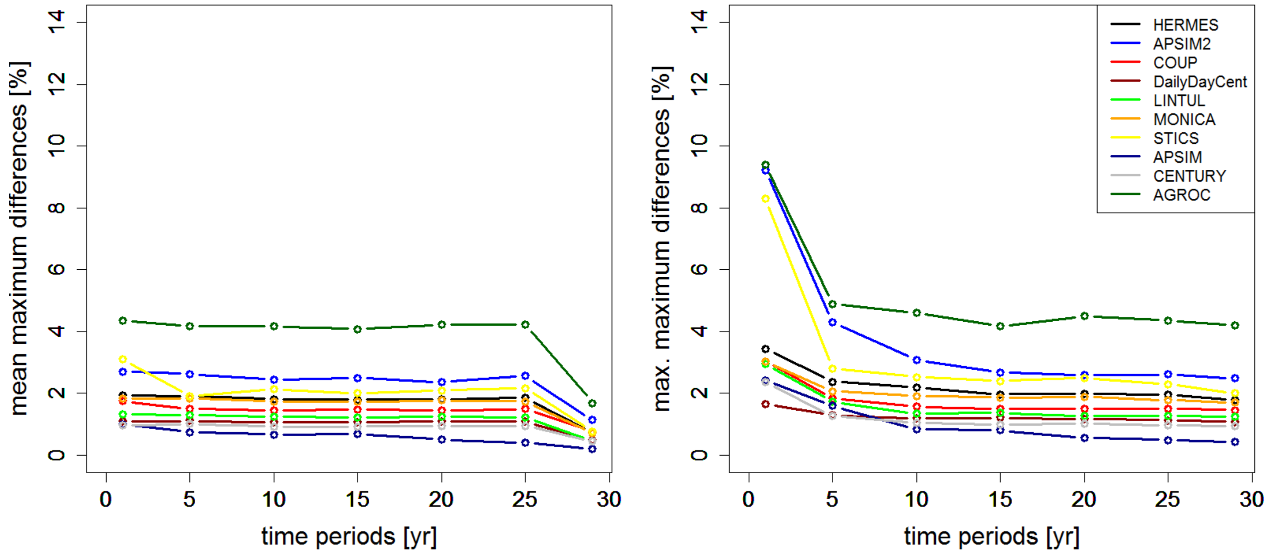

Figure 6: The relative differences between the maximum and minimum NPP (wheat PN) between the resolutions for data averaged over different time periods (annual to 29 year averages). On the left side the differences are averaged for each period, while the right side shows the maximum values for each period.

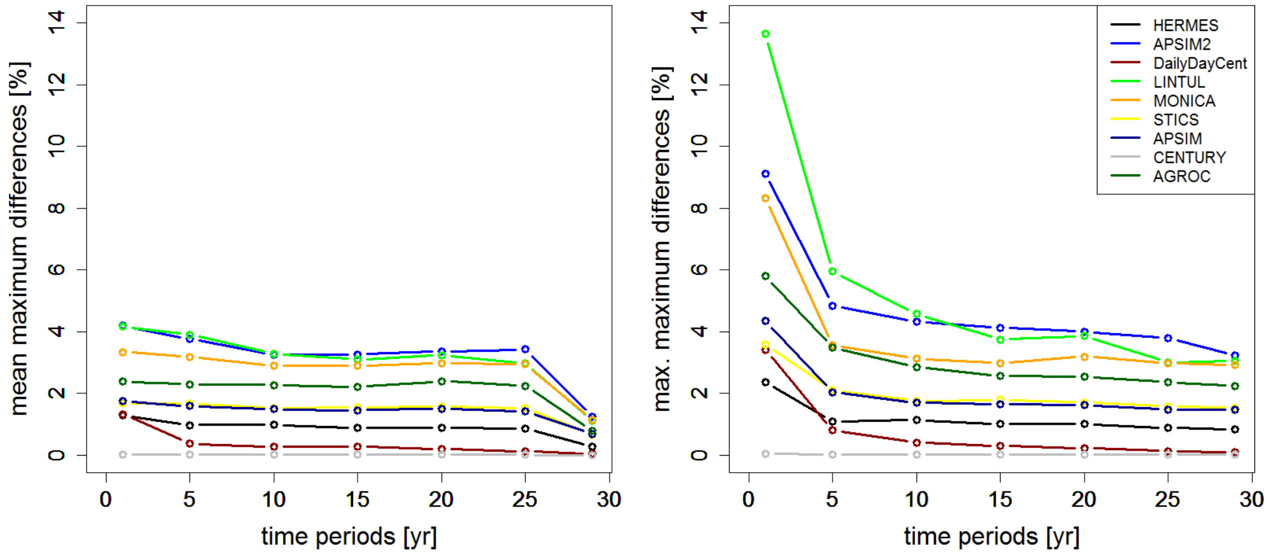

Figure 7: The relative differences between the maximum and minimum NPP (maize PN) between the resolutions for data averaged over different time periods (annual to 29 year averages). On the left side the differences are averaged for each period, while the right side shows the maximum values for each period.

Table 3: Minimum and maximum average length of the growing season of wheat for each resolution (overall averages) as determined in the different models. The shortest length represents, in all cases, the length of the growing season for resolution of 1km and longest growing season was for all models the resolution of 100 km.

model	min. length [d]	max. length [d]	change [d]
HERMES	256.1	257.6	1.5
APSIMmod	249.9	253.9	4.0
COUP	239.3	241.7	2.4
LINTUL	243.9	249.1	5.2
MONICA	259.5	261.1	1.6
STICS	236.4	239.0	2.6
APSIM	254.7	257.1	2.4
AgroC	238.2	243.3	5.1

The NPP values in this study represent NPP during growing season. Length of growing season varies between the different models and the different years (Table 3), because of different phenological sub-models and inter-annual variations of temperature. As already mentioned, the date for the latest possible harvest is fixed and this date is used as actual harvest by the models CENTURY, DailyDayCent and LandscapeDNDC. The highest differences between the lengths of the growing season are observed for LINTUL and AgroC, while there are relative little changes for HERMES and MONICA.

3.4 Vulnerability analysis

The results of the vulnerability analysis are represented in Figures 8 and 9, showing vulnerability (grey bars) and the risk (black bars) for each model and resolution. Negative values indicate a higher NPP average for hazardous conditions than for the non-hazardous conditions (vulnerability) or a higher NPP for the overall average than for the non-hazardous conditions (risk). The analysis shows positive values for vulnerability and risk for all simulation results of wheat, except for DailyDayCent and the two APSIM models (Figure 8). The values between the different resolutions vary for the different models. The vulnerability analysis for the maize simulations shows a negative risk and vulnerability for LandscapeDNDC, while LINTUL and DailyDayCent vary between the resolutions (Figure 9). Overall, vulnerability and risk differ for most models depending on the resolution, but there is no clear trend for increase or decrease of vulnerability or risk towards coarser resolution. The average risk for wheat simulations is about 0.02 g C m^{-2} d^{-1} ± 0.02 g C m^{-2} d^{-1}, with no trend between the different resolutions and the average vulnerability of 0.13 g C m^{-2} d^{-1} with a standard deviation of 0.10 g C m^{-2} d^{-1} shows also no clear trend. The differences of vulnerability between the five resolutions show the maximum difference between 1.6 % for CENTURY and 12.8 % for LINTUL (maximum difference relative to the average NPP of resolution of 1 km) for wheat and between 1.1 % (CENTURY) to 15.5 % (MONICA) for maize. In these calculations the models AgroC, APSIM, APSIMmod and DailyDayCent for wheat and APSIMmod, LandscapeDNDC and LINTUL for maize are not considered, because the results of these models indicate no vulnerability to drought under these conditions. In contrast to wheat, the vulnerability analysis of maize shows mainly negative values (Figure 9), except for STICS and AgroC (positive values), and DailyDayCent and LINTUL (varying values). The number of values (cells and years with a SPEI < -1) may affect the results, but the number of extreme cells (based on SPEI) is within a narrow range of 17.6 – 18.2 % for the different resolutions, so the relative numbers of hazardous cells stays about the same.

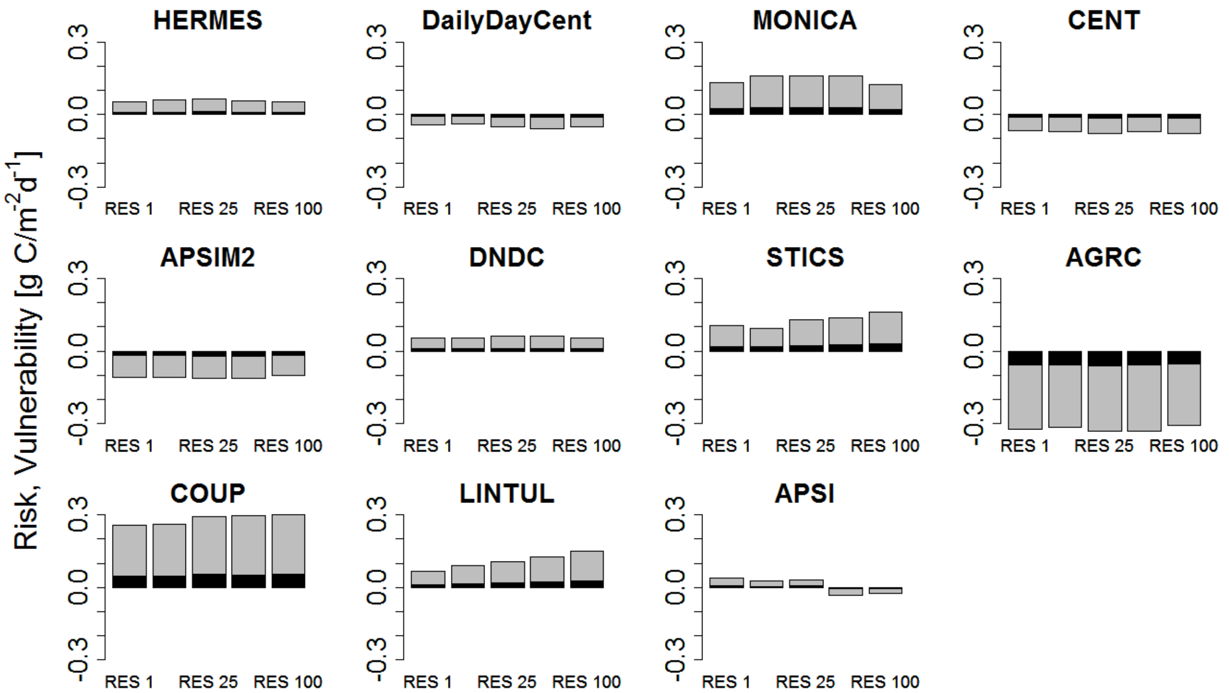

Figure 8: Vulnerability (grey bar) and risk (black bar) for 11 models for water limitation simulation results of NPP (WN). The results represent the simulation results for wheat for the period 1983-2011. The terms vulnerability and risk are used in the definition by van Oijen et al. (2014) and describe the impacts of hazardous in comparison to non-hazardous conditions (see also section 2.6).

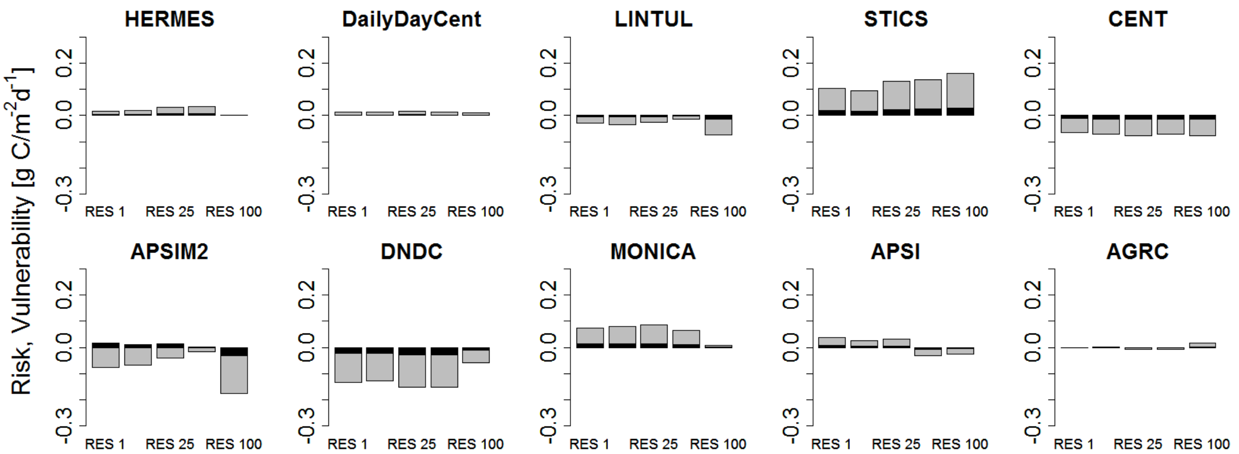

Figure 9: Vulnerability (grey bar) and risk (black bar) for 10 models simulated for water limitation considered (WN). The results represent the simulation results for maize for the period 1983-2011.

The terms vulnerability and risk are used in the definition by van Oijen et al. (2014) and describe the impacts of hazardous in comparison to non-hazardous conditions (see also section 2.6).

4 Discussion

4.1 NPP differences between the models

The simulated potential NPP averages of the growing season for the 1 km resolution range from 1.8 to 4.1 g C m^{-2} d^{-1} and 7.4-12.8 g C m^{-2} d^{-1} for wheat and maize, respectively, which is higher than annual NPP averages of European croplands (550 ± 50 g C m^{-2} yr^{-1}; Schulze et al., 2010)and this is expected for crops in the study region. Because the 1 km grid maps are the highest resolution, we assume these data as the most accurate of the available data and use these data as baseline, because detailed measurements with crop yields in its spatial distribution are missing. As mentioned, the results base on simulation runs of uncalibrated models, but adjusted to proxies for a 30 year average of crop yield. In spatial modelling data for calibration are rarely available or, if available, often restricted to one or some point measurements. This makes appropriate calibration for spatial modelling difficult and adjustment to a 30 year is an appropriate method to set up the model. The two models with low NPP for wheat (APSIMmod) and high NPP for maize (LandscapeDNDC) are most likely under- and over-estimates of NPP, because of the lack of calibration. As the results are not unrealistic for crop yields in central Europe, the results from both models are used in the analysis. The NPP differs between the models up to 2.3 and 5.4 g C m^{-2} yr^{-1} for wheat and maize, respectively, while the range for yield, the target variable of the model settings, is with 7.6 to 8.7 t ha^{-1} and 15.4 to 17.6 t ha^{-1} for wheat and maize, respectively, smaller (Hoffmann et al., 2015). As mentioned above, the approaches for calculating NPP are different and by grouping the models according to these approaches of radiation use efficiency, difference between GPP and respiration or direct calculation of NPP reduces the differences within the groups. The two exceptions for wheat (APSIMmod) and for maize (LandscapeDNDC) are already mentioned above. This means the model structure affects the NPP and the differences in the structure induce the wide range of NPP averages.

A comparison between the PN, WN and NN approaches enables water limitation and nitrogen limitation impacts on NPP to be detected. Nitrogen limitations play a minor role for the study region, because of sufficient fertilization. As Figure 1 shows, the results of the COUP model indicate a strong sensitivity to water limitation (26 - 30 % decrease of average NPP), and LINTUL is also sensitive to water limitation (4.7 - 6.1 % decrease of average NPP), while the other models only show little sensitivity to drought stress on the overall averages (all < 2 % difference). The differences of sensitivity between the models do not show a specific impact on the aggregation affect. Neither the strength of the effect nor the changes between PN and PW are similar to each other or different to the other models.

The contradicting spatial distribution of high and low NPP values reflect different crop parameters and phenological sub-models applied in the different models. In contrast to the NPP, the distribution of yield does not necessarily show a similar spatial pattern in the study area. These differences between NPP and yield are related to the different impacts of temperature changes on the simulation of phenological stages, which affects the lengths of the growing season differently to the length of the grain filling period. There is additional biomass production of wheat from the extension of the growing season, while the grain filling period does not necessarily benefit from warmer climatic conditions. The example shows the results for the year 2003, which was a severe drought period (Ciais et al., 2010) starting from mid-July and was considered by the calculation of the SPEI in the vulnerability analysis. The harvest at lower elevation started before the drought period, while the primary production at higher elevation was affected by the drought. The extension of the growing season allowed an over-compensation of NPP by a growing season that was 53 days longer, while the yield values were affected by drought, which could not be compensated for by a 7 day longer grain filling period. Both day of anthesis and day of maturity are determined based on temperature sums by the phenological model. For warmer areas, both will be earlier in the year compared to colder areas during the same period. In contrast, biomass production benefits from an extension of the growing season, due to additional days of production. However, the period between anthesis and maturity (both dates are represented by averages overall years and grid cells per resolution) is up to 5 days shorter when coarser resolution data are used for all models (Table 3). The models with the higher NPP in the higher elevated areas show the largest scale effect, which reflects a sensitive reaction of the phenological models to temperature changes. Van Bussel et al. (2011) reported minimal scale effects on the phenological stages, but these changes have still larger impacts on NPP.

4.2 Model specific aggregation effect

The differences between the resolutions of the wheat NPP simulations show three groups of models. APSIM, LINTUL, APSIMmod and AgroC show stronger effects (2.4-7.8 %) than the other models, and HERMES, CENTURY, DailyDayCent and MONICA show minimal impacts (<1.2 %), while COUP and STICS lie between (1.8-2.2 %). The groups of models with medium and strong aggregation effects are all models that determine NPP based on the radiation use efficiency, while the other models use temperature based approaches. Hoffmann et al. (2015) investigated the aggregation effect on yields for the same set of models and suggested that the aggregation effect on radiation may not be much higher than on temperature, but the models might be sensitive to changes in radiation. Despite trends of decreasing temperature and solar radiation at coarser resolution (Figure 2 and Table 2 in Hoffmann et al., 2015), some models show increasing potential NPP values (LINTUL, APSIMmod and AgroC for wheat and DailyDayCent, LandscapeDNDC and AgroC for maize). These contradictory trends are also related to an extended growing season caused by different approaches for the calculation of the phenological stages. Therefore, decreasing temperatures affect an extension of the growing season which compensates, or over-compensates, the effect of lower temperatures and radiation on crop growth as already discussed above. The growing season is extended by 1.5 to 5 days on average at coarser resolutions for wheat, and 1-2 days on average for maize simulations (Table 3), accompanied by a temperature decrease of 0.3°C (Hoffmann et al., 2015). As the model structure differs, the models show a different sensitivity to this effect and differ in their trends through the different resolutions. These results concur with the findings by van Bussel et al. (2011), who found only small impacts of climate aggregation on determined phenological stages. The models APSIMmod, LINTUL and AgroC showed the longest (4-5 days) extension to the average growing season towards the coarser resolutions, while all other models showed lower extensions (<2.5 days). The models with the larger aggregation effects are the same models that show large differences in the length of the growing season. The findings of the overall aggregation effect on NPP agrees to the findings of Nungesser et al. (1999), who found a mean uncertainty of < 2 % on NPP by modifying precipitation and solar radiation for resolutions of 10 and 50 km. The average differences for the wheat NN approach in this study (1.2 %) is also in this range, but includes a large increase for AgroC of up to 3.3 %. Pierce and Running (1995) determined an aggregation error of 15 – 30 %, depending on the time step, while the maximum time period is one year and the higher values are related to impacts on daily NPP. The relative small aggregation effect agrees also to the findings of de Wit et al. (2005), who found only small impacts of climate data aggregation on yield. Hoffmann et al. (2015) analysed the aggregation effect for yield and found an uncertainty of 0.2 t ha^{-1} (30 year average, over the entire study area and considering the simulation results of 13 models), which is about 2.5 % to the determined yield. A comparison with the maximum aggregation effects on yield for each model shows 4.2 - 8.4 % and 3.6 – 7.6 % for wheat PN and WN, respectively, higher impacts on yield than for NPP, but also only small changes of the aggregation effect between the PN and WN simulations. Despite the high differences of precipitation between the five resolutions, the aggregation effect do not change strongly for the approaches WN and NN. For most models the aggregation effect even decrease. This can be explained by the little relevance of drought and nitrogen limitation for long term averages in the considered region. In regions with higher drought or nutrient stress the aggregation effect might be higher. The region is picked to represent an agricultural managed area in central Europe and the results can be transferred to comparable regions. Regions of other climate conditions (higher drought stress) or with different management practices (higher nutrient stress) might show different aggregation effects and further work needs to be done in upcoming studies to get a conclusive answer on this.

The differences between the aggregation effect for the average and the median NPP reflects the impacts on the variance. Changes due to aggregation may be more relevant for more extreme years and show stronger impacts that are levelled out in the average values. It can be assumed that the extremes are more likely to impact negatively on the NPP values, since the maximum growth will be restricted. The strongest differences arising from the aggregation effect on averages and median are detected for models that show a decreasing aggregation effect towards the coarser resolution. The effect may be compensated by the general trend of the NPP values for coarser resolutions.

If the simulation runs are used as ensembles, the aggregation effect are relatively low. For the wheat simulation the aggregation effect is almost as low as the minimal effect on an individual model run and can be explained by the different trends of the individual simulation approaches of the different models. In contrast, the simulations on maize show similar trends from the high resolution to the low resolution for models that show a high aggregation affect, which is reflected in a higher aggregation effect than for the wheat simulation. However, with 2 % is this effect still small.

4.3 Aggregation effect over different time periods

The analysis considered 29 year averages, while the impact of scale increases for shorter time periods (Figures 6 and 7). The scale effect shows the highest differences for single years, and stabilises to constant differences or only minor changes for periods of 15 years and longer. This suggests that the resolution of choice depends on the temporal scale as well as on the research question. The mean uncertainty for longer periods will be below 4 %. The maximum aggregation effect for single years can be more than 9 % for wheat and more than 13 % for maize, but will decrease to below 4 % for time periods longer than 10 years. While the largest impact on the aggregation for the maximum differences is from 1 to 5 years, the mean aggregation effect shows the maximum change for the step from 25 to 29 years. The NPP is a non-linear process and is especially affected by extreme events (Reichstein et al., 2013). Extreme weather conditions have an impact for a short period and affect often only a year and can be reduced by spatial averaging of the climate data. This spatial averaging is represented by the higher aggregation effect for the annual data, but this effect is already compensated by averaging over longer time periods. The impact of the temporal averages is represented in the two graphs in figure 7, which shows lower impacts on the averaged short term aggregation effect than on the maximum impact for a year.

Pierce and Running (1995) also found changes of the aggregation effect depending on temporal scale. They observed decreasing aggregation errors for increasing periods, which supports our findings. However, their study considers daily to annual time periods and not period lasting 1 – 29 years. An error of 15 % is in agreement with the maximum values of the analysis of the annual aggregation effect, which shows a range of 1.6 – 9.4 % for wheat and 3.4 - 13.6 % for maize.

4.4 Vulnerability analysis

The impact of the the simulated phenological stages is already mentioned earlier in context of other effects, but is also important in the vulnerability analysis through varying the length of the growing season. Van Oijen et al., 2014 suggested the period from April to September as the best period to determine the drought index and found minimal impacts by starting this calculation of the drought index earlier, while we show a strong impact in this study. Van Oijen et al. (2014) used a biogeochemical model with fixed harvest dates for crop simulations or considered simulation results of forests and croplands with a fixed length of the growing season, but the models in this study are mainly crop models with dynamic growing season length. Therefore, in some years, the growing season ends before any drought impacts on crop growth occur, as for the year 2003. Van Bussel et al. (2011) described the scale impact on the modelling of phenological stages as minor, but these changes can affect other processes as, in this case, the impact of a drought period on primary production. In this study the relevant period to define hazardous conditions for the vulnerability analysis is from February to July, which is similar to the length of the growing season for most, but not all, models.

Not all models show sensitivity to the hazardous conditions defined by the SPEI. For the model DailyDayCent, the threshold of the SPEI = -1 is not significant in comparison to the internal drought effects. As the index SPEI is calculated by precipitation and temperature, there might be a discrepancy in the detection of extreme weather events by the APSIM models, which use the radiation use efficiency to determine NPP. In contrast to the vulnerability analysis of wheat, the analysis for maize shows no impact of drought or negative values for vulnerability, with the exceptions STICS and MONICA, because maize is a C_4 plant and is more drought tolerant (Lopes et al., 2011). The comparison of the WN and PN simulation runs support the findings of the vulnerability analysis, as most models show only small differences. Analysis for higher thresholds is not useful for the considered study area, because the number of grid cells for hazardous conditions becomes too small for solid statistics. Regarding the resolution, the results show either all positive or negative values (HERMES, STICS, CENTURY, APSIMmod, LandscapeDNDC, APSIM, AgroC), or marginal differences to zero vulnerability (DailyDayCent, LINTUL, MONICA). The number of extreme weather events is expected to decrease at coarser scales, but the overall averages show little change between the resolutions. The expected pattern of stronger impacts of extreme events for finer scales with lower impacts at coarser scales is not seen. Assuming a threshold from SPEI = -1 to define drought conditions affects the same ratio of hazardous grid cells for the different resolutions. In contrast to the initial assumption of less extreme events, the number of grid-cells defined as extreme show the same or even higher ratio for the coarser resolution. One reason is the temporal scale for the NPP calculation, which is annual. In the vulnerability analysis the extreme events are defined during the first half of the year, which includes the drought of 2003 which had negative impacts on cropland NPP (Ciais et al., 2010), but not all model results are affected by this drought, because of an earlier harvest. Extreme events, therefore, appear to play a minor role in this area for long term averages.

The aggregation effect is stronger for the vulnerability than for the NPP averages. Despite for AgroC and for the wheat simulation results of APSIMmod the aggregation effect for the vulnerability at least doubles in comparison to the long term averages. The effect might be influenced by fewer years considered in the vulnerability analysis, but the maximum values even exceed the effect for annual averages. This shows that especially periods with extreme weather conditions get stronger affected by the aggregation of climate input data than other years. Over long term averages these impacts may level out.

5 Conclusions

NPP differs, depending on spatial resolution of climate input data by up to almost 8 % and 5 % for wheat and maize, respectively. For most models, the overall averages are affected by only 2 % or less, but for shorter time periods (shorter than 15 years), the aggregation effect may rise for annual NPP to over 9 or over 13 % for wheat and maize, respectively. It is concluded that a large part of the aggregation effect is related to the changes in phenology. The aggregation effect affects the vulnerability stronger than long term averages, which shows the stronger impact of aggregation effects for periods with extreme weather conditions. A finer spatial resolution of climate input data will not greatly improve simulations for long term averages of NPP or vulnerability, but for periods shorter than 15 years, or areas with extreme conditions finer resolution matters and at most differed by 13 % for averages. The biggest changes are detected for the steps from 1 km to 10 km resolution and from 50 km to 100 km. The current study suggests that long term NPP averages over large areas (e.g. regional scale) are relatively insensitive to climate data aggregation, whereas data aggregation would influence average NPP under extreme weather conditions. Based on these results there is no need to simulate long term NPP averages for a high resolution, if soil type and management do not vary in time and space. As this is an unrealistic scenario, more work is required to investigate the impacts, for heterogenetic soil types and varying management conditions.

Acknowledgements

This study was supported by the BMBF/BMELV project on "Modeling European Agriculture with Climate Change for Food Security (MACSUR)" (grant no. 2812ERA115).

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