Effects of input data aggregation on simulated crop yields in temperate and mediterranean climates

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Abstract

Soil-crop models are used to simulate ecological processes of the soil-plant-atmosphere system from the field to the regional scale. Main inputs are soil and climate data in order to simulate model response variables such as crop yield. The objective of this paper is to investigate the effect of changing the resolution of input data on simulated crop yields at a regional scale using up to ten dynamic crop models simulating two crops. We compared the effects of spatial input data aggregation on simulating crop yields of wheat and maize crops for two regions with contrasting climate conditions (1) Tuscany (Italy, Mediterranean climate) and (2) North Rhine Westphalia (NRW, Germany, temperate climate). Soil and climate data of 1 km resolution were aggregated to resolutions of 10, 25, 50 and 100 km (grid side length) by selecting the dominant soil class and corresponding soil properties and by arithmetic averaging, respectively. Differences in yield simulated at coarser resolutions from the yields simulated at 1 km resolution were calculated to quantify the effect of the aggregation of the input data (soil and climate data) on simulation results.

The mean yield difference (bias) at regional level was positive due to productive dominant soil at coarser resolution which could potentially be negative bias that would have been non-productive soil aggregated in respective region. In both regions, aggregation effects i.e. errors in simulation of crop yields at coarser spatial resolution due to the combined aggregation of soil and climate input data increased with decreasing resolution for both crops but the aggregation error in Tuscany was larger than in North Rhine Westphalia (NRW). Over Tuscany, the average percentage absolute differences between grid cell yields at the coarsest resolution (100 km) compared to the finest resolution (1 km) were up to 20 % and 30 % for winter wheat and silage maize, respectively. In contrast, in NRW, the average percentage absolute yield differences in the coarsest grid cells were <15 for wheat and <20 % for maize. This implies that for regional yield simulations in temperate humid regions of central Europe coarser resolutions may be sufficient to achieve reliable yield estimations , whereas, in Mediterranean areas higher spatial resolutions are required avoiding prediction errors of the spatially averaged yield of up to 60 % as observed for individual crop models. For generalization of these outcomes, further investigations in other sub-humid or semi-arid regions will be necessary.Additionally, aggregating soil data caused larger aggregation errors in both regions than aggregating climate data.

Keywords: Data resolution, Temperate, Mediterranean, Crop yield, Crop modelling

1 Introduction

The agro climatic condition and associated field processes (soil water movement, nutrient cycle and nutrient uptake) are incorporated in crop models. The crop models are applied to simulate crop yield under different agro-climatic and management conditions and to assess climate change impacts on crop yield among other agroecosystems. The agro-climatic conditions in the field along with crop-management practices are represented by measured soil and climate data. . In general, crop models are based on different mathematical algorithms which describe various agro-ecological processes of the soil-plant–atmosphere system that e.g. control water flows, nutrient turnover, root water and nutrient uptake and that support crop growth and development. Soil and climate data are the main input data for crop models that drive the processes implemented in the model. Most crop growth models were developed at the plot or field scale (F. Ewert et al., 2015), where the input data can be measured to initialize and drive the models.

In general, field scale crop models have been validated and applied for multiple locations. The field based crop models are applied for multiple grid cells at different resolution to cover entire area of interest. The spatial distinction among the applied grid cells are characterized by data variability of agro-climatic (such as soil and climate) condition of the studied area. Therefore, these models are also run beyond the scale of development to predict yields at regional to global scale, whereby spatially aggregated input data are used (Rosenzweig et al., 2014; Rosenzweig and Iglesias, 1998; Rosenzweig and Parry, 1994). In climate change studies crop models are applied using climate change data produced by global circulation models (GCMs) at larger scale to assess climate change impacts on crops and environment (Donatelli et al., 2015) and to design comprehensive adaptation strategies such as optimization of sowing date from regional to global level.

Classically, at the larger scale input data such as soil or climate data are interfered from smaller scale measurements and aggregated to the resolution of the simulation, whereby the aggregation of input data from finer resolution to coarser resolution will lead to losses spatial variability which depends largely on the aggregation methods (Ewert et al., 2011).

Climate input data from two relatively small regions in Northern and Central Europe aggregated to different resolutions was used in a range of crop models in Angulo et al., 2013 to study the characteristics of the response variable (i.e. crop yield distribution) as a result of the input data aggregation (climate data). Further, soil data at different resolutions were used to simulate crop yield and analyze yield distribution from two contrasting sites in Angulo et al. (2014). In these two studies (Angulo et al., 2014, 2013), the impact of input data (soil and climate respectively) aggregation on simulated yield distribution were not different within each model. While, simulated yield distributions (‘figureprint’) were different for various models. Thus, the authors insist to use a multi-model ensemble (average of all model output) approach to analyze input data aggregation impact on regional crop yield simulation. A multi-model ensemble approach was also used by Zhao et al, (2015a) who quantified the climate data aggregation error for regional simulations of several model output variables such as yield, evapotranspiration, and water use efficiency in North Rhine-Westphalia (NRW) in Central Europe. The authors used aggregated climatic data at different resolutions (10, 25, 50, and 100 km). They concluded that weather data aggregation error was highest for simulated crop yield compared to crop evapotranspiration or water use efficiency, but was below 10% in all cases. In the same region, the characteristics (variability and spatial variance) of climatic data aggregated to coarser resolution was compared to simulated crop yield (winter wheat and silage maize) from an ensemble mean calculated at different aggregation levels in Hoffmann et al, (2015). The aggregation error for simulated crop yield was significantly increasing for decreasing resolution of the climate data The application of simultaneous aggregation of soil and climate data to simulate regional crop yield by different crop models were further investigated by Hoffmann et al, (2016). The results showed, that the aggregation errors were amplified with decreasing resolution of soil and climate data input compared to the aggregation error made by aggregating only one input variable.

Nevertheless, the aggregation effects of soil and climate data on regional crop yield simulations were focused only on temperate, humid region, namely North-Rhine Westphalia (NRW) in Germany (Hoffmann et al., 2017, 2016; Zhao et al., 2015a) or a boreal one (Angulo et al., 2014, 2013) and no such study has been performed in a Mediterranean region. Additionally, no study has been reported so far to compare the aggregation effect between regions with different soil and climatic conditions. In general, the climate in the Mediterranean region is characterized by higher average air temperature during the crop growing season compared to temperate regions and less precipitation either at the end of the growing season in the case of winter crops or during the growing season in the case of spring crops. In addition, the soils in the Mediterranean region show higher spatial variability with more soils having lower available water capacity due to either finer soil texture or lower soil depth with higher gravel or stone content. Therefore, periods of water shortage for rainfed crops are more frequent. Under water-limited production conditions, the spatial aggregation of soil type in combination with aggregation of climate variables, is expected to have a stronger impact on simulated crop yield compared to temperate, humid regions.

Therefore, this study compares aggregation effects of soil and climate data on regional yield simulation for two contrasting climatic region for water-limited production conditions based on the hypotheses that (1) input data aggregation affects regional yield simulations more in Mediterranean than in temperate region and (2) input data aggregation error is higher for spring crops (silage maize) compared to winter crops (winter wheat).

2 Material and Methods

2.1 Study regions

The aggregation effects of input data (soil and climate) on crop yield simulations were compared between a region under temperate, humid climate conditions North Rhine Westphalia (NRW, 51° 46' 4.1" N and 7° 26' 38.4" E, Germany) and a region under Mediterranean climate conditions, Tuscany (TUS, 43° 41' 14.1 " N and 10° 29' 10.3" E , Italy). Figure 1 presents the geographical location of the study regions. A summary of the main climatic conditions for these two study sites are presented in Table 1.

[Table 1 Here]

The long-term annual means of selected climatic variables were calculated based on the respective climate data from 1995 to 2011. The annual mean temperature for NRW and TUS are 9.6 ^{o}C and 16.1 ^{o}C, respectively. The annual mean precipitation sums are 821 mm y^{-1} for NRW and 949.4 mm y^{-1} Tuscany.

[Figure 1 Here]

2.2 Preparation of model input data

2.2.1 Soil data

- NRW

The soil data at 1 km resolution for NRW, Germany was originally already aggregated by dominant soil type from approximately 300 m resolution to grid cells of 1 km resolution (Hoffmann et al., 2016). The soil data source for NRW and the methods to derive several soil properties including topsoil organic carbon, soil texture, soil bulk density, and soil albedo are explained in Hoffmann et al, (2016). In a second step the soil data at 1 km resolution was aggregated to coarser resolution by dominant soil type from the 1 km resolution to 10, 25, 50, 100 km as well as to a NRW mean (S_{NRW}). The results of the soil data aggregated from 1 km resolution to 100 km resolution for NRW is shown in Fig. 2. The dominant soil type for NRW (S_{NRW}) was a Cambisol.

[Figure 2 Here]

- Tuscany

The soil distribution including soil physical and chemical properties were obtained from the data base of Gardin and Vinci (2006). The data base contains soil layer-wise information about soil layer thickness, soil texture, gravel and soil organic carbon content. Additional soil properties for each layer (such as soil hydraulic properties) required as input to different crop models were prepared based on soil texture and gravel content information using pedotransfer functions (PTF) (https://de.mathworks.com/matlabcentral/fileexchange/45468-soil-classification-sand--clay--t-varargin-). In Tuscany, information on soil classification at the soil order level was not available. Therefore, the dominant soil texture in the topsoil at the resolution of 1 km was used to aggregate the soil properties to the resolution of coarser grids

(10 – 100 km). The soil data at a coarser resolution of 10, 25, 50 and 100 km were prepared by selecting the dominant soil texture among the 1 km soil grids (Fig. 3).

[Figure 3 Here]

The dominant soil type aggregated at the regional level for Tuscany is loam. The associated soil properties for dominant soils at the regional level such as soil depth, bulk density, wilting point and field capacity are presented in the annex table AT1.

The variability of soil properties of top soil layer for NRW and TUS at 1 km resolution is shown in Table 2 and the properties for other soil layers are presented in the supplementary material (Table S2). The soil database with similar soil properties among others at the different level of aggregation were used as soil input data to different models.

The soil depth of the most dominant soil in NRW is about 2.3 (range 0.1 – 2.3 m for soil various layers in 1 km grid cells) m while for Tuscany it is 1.36 (range in 0.18-1.5 for different soil layers in 1 km grid cells) m. The field capacity of the first soil layer for the dominant soils are 0.36 and 0.23 m^3 m^{-3} for NRW and Tuscany, respectively. Other soil parameters required to simulate the crop yields are provided in Hoffmann et al. (2016) mainly for NRW region and in the supplementary material (Table S2).

[Table 2 Here]

2.2.2 Climate data

- NRW

The climate data set for NRW at 1 km include daily time series of minimum, mean and maximum air temperature, precipitation, global radiation, wind speed and relative humidity for the period 1982 to 2011 and was established by interpolation of measured climate variables at 280 weather stations provided by the German Meteorological Services (DWD). All climate variables were aggregated to coarser resolutions from 1 km resolution data by arithmetic averaging. The climate data source and the aggregation process to coarser resolution for NRW are explained in detail in Hoffmann et al, (2016).

- Tuscany

The daily meteorological data for Tuscany at 1 km resolution from 1995 to 2013 were provided by the Lamma Consortium of Tuscany Region (http://www.lamma.rete.toscana.it/) This dataset includes gridded daily records of minimum, mean and maximum temperature, precipitation, solar radiation, wind speed and relative humidity (about 22,000 grids cells over Tuscany region), which were calculated from the local meteorological network. In particular, daily maximum and minimum temperatures and total daily-cumulated precipitation, collected from 94 and 159 stations, were interpolated according to the DAYMET procedure (Thornton et al., 1997) to produce the relevant daily digital maps as described in Chiesi et al. (2007). These maps were in turn used as input of the MT-CLIM procedure to produce additional daily maps of solar radiation based on algorithm presented in Thornton et al., 2000 was specifically calibrated for Tuscany region (not published). Relative humidity was calculated by using daily minimum temperature and mean temperature as explain in Allen et al. 1998.. Daily data of wind speed at a height of 2 meters were obtained by interpolating the data from 45 weather stations using a nearest neighbour approach.

The meteorological data at 1 km resolution were aggregated similar to the approach applied on NRW to coarser resolution of 10 , 25 , 50 and 100 km by averaging all grid cells at 1 km included within the respective coarser resolution. The spatial variability of average minimum, mean and maximum temperature for the period from 1995 to 2013 aggregated across resolutions is shown in Fig 4.

The daily climate variables for each year during the growing period of the respective crop where averaged from 1995 to 2011 (Table 6). The mean temperature during the growing season for silage maize in NRW and Tuscany are respectively 16 and 22 ^{o}C while, the average of mean temperature during the growing period of wheat are 8 ºC for NRW and 12 ºC for Tuscany. The sum of precipitation during growing season of maize in NRW and Tuscany are similar with the approximate value of 350 mm, while, the precipitation sum during growing season of winter wheat in NRW is about 632 and 591 mm for Tuscany Italy. The climate water balance (cwb: ET0−Precipitation, mm) for respective crop growing season and regions is higher for Tuscany than for NRW. The summary statistic of the climatic variables for each region for the respective crop during growing period is presented in Table 3 and the soil properties of the dominant soil type in each region is presented in Table S2.

[Figure 4 Here]

[Table 3 Here]

2.3 Model setup

The model ensemble consisted of a total of nine field scale crop models (AgroC, Century, CoupModel, DailyDayCent, EPIC, HERMES, MONICA, SIMPLACE<LINTUL5;SLIM>, STICS) which have been frequently used in climate change impact studies at field to regional scale (Table 4) and the respective abbreviations of the models in figures where it stated are in AGRC, CENT, COUP, DayC, EPIC, HERM, MONI, LINT and STIC. All models were run for both crops (wheat and maize) except the CoupModel model, which was only run for wheat. The model runs were constrained by the climate and soil properties as explained in 2.1 and 2.2 and management rules (see below). In NRW all models were run constraining the maximum root depth to the maximum soil depth (unrestricted root growth).

[Table 4 Here]

Aggregated soil and climate as well as crop management data were used for the crop model ensemble to simulate the yield of silage maize and winter wheat. The crop management data with respect to tillage, sowing, and fertilizer application (timing and amount) were fixed for both regions while the date of harvest for each crop was either simulated or observed harvest dates were used depending on the requirements of individual models. The detailed crop management data for winter wheat and silage maize in the two regions are shown in Table 5 and 6.

[Table 5 Here]

[Table 6 Here]

Initially the crop models were calibrated at 1 km resolution for crop phenological stages by minimizing the root mean square error (RMSE) between observed and simulated harvest date in order to match the area weighted average of observed yield for NRW and Tuscany. The calibration procedure for NRW is further explained in Hoffmann et al., 2016. The yield for winter wheat refers to grain yield while for the silage maize it refers to the aboveground biomass. Finally, all crop models were run for respective crops and different combinations of soil and climate data resolutions as listed in Table 7.

[Table 7 Here]

The combination of input data at different aggregation levels is abbreviated as $S_y x C_z$ (where S_y is the soil data at resolution *y* and C_z is the climate data at resolution *z*). Altogether, 15 combinations of spatial resolutions of soil and climate input data were used to simulate silage maize and winter wheat for the each region. The modelled output i.e. yield from each individual crop model was summarized for each soil and climate combination to calculate the model ensemble mean and the impacts of soil and climate data aggregation were further analyzed for the simulation results based on this model ensemble mean. The general modelling framework used in this study is presented in Fig. 5.

[Figure 5 Here]

2.4 Calculation of the aggregation errors

In general, the aggregation errors were calculated as the differences in model output at a given resolution (e.g., 10, 25, 50, 100, Tus or NRW) with respect to the model outputs generated at the highest resolution at 1 km. The error indicators were calculated from the following equations. The effects of aggregation of soil and climate input data on the yield simulations of the model ensemble mean are quantified for each spatial resolution. Equation 1, quantifies the aggregation error relative to the pixel level of the finest 1 km resolution, while the other equations quantify the aggregation error at the regional level (average of all pixels at 1 km resolution).

$$AbsPD_j = \left(\frac{|YC_j - YF_j|}{YF_j}\right) * 100 \qquad (1)$$

where, $AbsPD_j$ is the absolute percentage difference with YC_j as the yield simulated at coarser resolution that is disaggregated to 1 km resoluton of j^{th} pixel, and YF_j is the simulated yield of respective grid cell at 1 km resolution included by coarser resolution. The mean difference (MD) is calculated as the average difference between the yield YC_i simulated at coarser resolution disaggregated to 1 km resolution ofj^{th} pixel and the yield YF_j simulated at finar of 1 km resolution (pixel j)$MD = N^{-1} * \left(\sum_{j=1}^{N} YC_j - YF_j\right)$ (2)The mean absolute difference (AMD) is the equivalent to the mean difference (MD) except that the absolute value of the differences between coarser resolution pixel and the 1 km pixel is used:

$$AMD = N^{-1} * \left(\sum_{j=1}^{N} |YC_j - YF_j|\right) \qquad (3)$$

$AvgYF$ is the average yield at 1 km resolution, where *N* is the number of pixels at 1 km resolution, and *rAAD* is the average absolute yield deviation normalized to the average yield at 1 km resolution.

$$AvgYF = N^{-1} * \left(\sum_{j=1}^{N} YF_j\right) \qquad (4)$$

$$rAAD = \frac{N^{-1} * \left(\sum_{i=1}^{N} \left|YC_i - YF_j\right|\right) * 100}{AvgYF} \qquad (5)$$

3 Results

3.1 Spatial pattern of crop yield simulations in NRW and Tuscany

3.1.1 Silage maize yield simulation in NRW and Tuscany

The ensemble mean for silage maize across all crop models simulated for different combinations of aggregated soil and climate data under water limited conditions shows a relatively higher silage maize yield simulated for NRW (Fig. 6A) as compared to Tuscany (Fig. 6B). Additionally, spatial variability of silage maize yields are highest when both soil and climate input data at the finest resolution (1 km) were used (S_1xC_1 in NRW and Tuscany). For both regions, only small changes in the spatial yield patterns are detectable, when the finest soil input data resolution (S_1 = soil at 1 km) is combined with average climate input data over the entire region (C_{NRW} or C_{Tus}) (Fig. 6, 1[st]column for each panel i.e. S_1xC_{NRW} and S_1xC_{TUS}). On the other hand, combining dominant soil conditions (S_{NRW} or S_{TUS}) with high resolution climate data (C_1 = climate at 1 km) leads to pronounced differences in the predicted silage maize yield compared to the finest resolution S_1xC_1. The overall range of silage maize yield for NRW is from 10 to 18 t ha^{-1} while for Tuscany it is from 5 to 18 t ha^{-1}.

[Figure 6 Here]

3.1.2 Winter wheat simulation in NRW and Tuscany

The average crop yields for winter wheat in NRW are much higher than in Tuscany regardless of the soil-climate input data combination (Fig. 7). Yield for winter wheat in NRW ranges from 4 to 10 t ha^{-1} while for Tuscany it is between 0 and 6 t ha^{-1}. The spatial variability of the ensemble mean yield for (winter) wheat across all models is similar to the variability of the ensemble mean of silage maize yield. In both NRW and Tuscany, the spatial variability of the winter wheat yield is highest when the finest resolution of climate and soil input (S_1xC_1) is used. In Tuscany, the spatial variability of simulated winter wheat yields using the finest resolution of soil and climate input data (S_1xC_1) is comparable to the spatial variability of yields simulated with the combination of finest soil resolution and average regional climate (S_1xC_{TUS}) that exhibit slightly higher values in the northern part of the region. The yield pattern in which the finest resolutions of soil and climate input is used (S_1xC_1 i.e, Fig. 7 1st column of panel B) is comparable with yields produced with the finest climate resolution and the dominant soil type ($S_{TUS}xC_1$ i.e, Fig. 7, 1st column of Panel B). This is contrast to the spatial variability of winter wheat yields in NRW, where the simulated yields based on the combination of finest climate input resolution with the dominant soil type exhibited a much lower spatial variability as compared to the yield simulated with the highest resolution of both soil and climate input (S_1xC_1 i.e,Fig. 7, 1st column in panel A).

[Figure 7 Here]

Thus, yield simulations for silage maize and winter wheat at finest resolution of soil and climate input (1 km resolution (S_1xC_1) (Fig. 6 and 7) have the highest spatial variability compared to all other soil and climate input data combinations. With aggregation of soil and climate input data the spatial variability of simulated crop yields decreases (Fig. 6 and 7). However, in the case of winter wheat, when only climate input data is aggregated and combined with the dominant soil type (3rd row, 7) the spatial variability of simulated yields is much lower in all resolutions. Thus, the aggregation of climate input data has less impact on the spatial variability of simulated wheat yields under water limited conditions than the simultaneous aggregation of soil and climate for both regions.

3.2 Aggregation effects on simulated crop yields

3.2.1 Aggregation effect on silage maize yield simulations in NRW and Tuscany

In a next step, the aggregation errors were calculated based on Eq. 1-5 for the different regions and combinations of aggregation. Hereby, the finest resolution (S_1xC_1) was always chosen as the reference simulation in each region. The difference of crop yields when simulated at a coarser resolution of soil and climate input compared to the finest resolution at 1 km (S_1xC_1) is considered as the effect of input data aggregation on yield simulations. The magnitude of yield differences for silage maize ranged from -6 to 6 t ha^{-1} (Fig. 8) for both regions. In general, the average bias in silage maize yield (MD) due to input data aggregation was always positive, except for the combined aggregation of soil and climate variables in Tuscany. For silage maize simultaneous aggregation of soil and climate to coarser resolution of 50 and 100 km caused lower simulated yield in the North-East of NRW compared to the reference resolution (1 km) as indicated by negative yield differences, while higher yields with positive yield difference are observed towards the southern part (Fig. 8, panel A: $S_{50}xC_{50}$ and $S_{100}xC_{100}$). A similar pattern can be distinguished when aggregating soil input data to 50 and 100 km combined with an average regional climate (Fig. 8, panel A: $S_{50}xC_{NRW}$ and $S_{100}xC_{NRW}$). The combination of an average regional climate for NRW with the soil input data at 1 km resolution has almost no yield difference with respect to the simulated maize yields of the reference resolution (Fig. 8, panel A: S_1xC_{NRW}).The spatial patterns of yield differences for other combinations (Fig. 8, panel A: from $S_{10}xC_{NRW}$ to $S_{100}xC_{NRW}$, 2nd row) are similar to the pattern of yield differences that are observed with the simultaneous aggregation of soil and climate data (Fig. 8, panel A: from $S_{10}xC_{10}$ to $S_{100}xC_{100}$).

A similar observation can be made for the spatial patterns of yield differences in Tuscany for maize under water-limited conditions (Fig. 8, panel B). With decreasing resolution of soil and climate input data, the yield differences are positive towards the northern part and negative towards the southern part of Tuscany (Fig. 8, panel B: $S_{50}xC_{50}$ and $S_{100}xC_{100}$). The yield difference for silage maize due to the combination of the average regional climate (C_{TUS}) with soil input at 1 km resolution is zero towards the northern part, while it is positive from the central to the southern part of Tuscany (Fig. 8, panel B: $S_{1}xC_{Tus}$). The pattern of yield differences for silage maize in Tuscany based on simultaneous aggregation of soil and climate input data is similar (Fig. 8, panel B: from $S_{10}xC_{10}$ to $S_{100}xC_{100}$, 1st row) to the pattern observed when only soil is aggregated and combined with the average regional climate (Fig. 8, panel B: from $S_{10}xC_{Tus}$ to $S_{100}xC_{Tus}$, 2nd row). The yield differences are either positive or zero for Tuscany when aggregation of climate input is combined with the dominant soil (S_{TUS}) (Fig. 8, panel B, 3rd row).

[Figure 8 Here]

The aggregation effects on simulated silage maize yields are further analyzed as absolute percentage yield difference (Eq. 1) from the yields simulated on the reference 1 km resolution. The variability of absolute percentage difference for silage maize is presented as box plots and its frequency distribution as violin plot for different aggregation levels for NRW (Fig. 9A) and Tuscany (Fig. 9B). The percentage absolute yield differences (%) for silage maize yield for the ensemble mean for combined soil and climate data aggregation are in general higher for Tuscany than for NRW (Fig. 9). The mean percentage absolute differences are ranging from 5 to 12 % in NRW and from 15 to 35 % in Tuscany. Looking at the histograms it becomes also clear, that the variability of the percentage absolute yield differences in NRW can reach up to 40 % in some grid cells, and that it can be even larger in Tuscany (>40%). On the other hand, lowest values of the percentage absolute difference are between 0 to 5 % in NRW and 0 to 15 % in Tuscany.

[Figure 9 Here]

The aggregation effect at the regional scale quantified as the normalized or relative average absolute yield deviation (rAAD) of silage maize yield in NRW is below 35 % for all crop models regardless of the aggregation level of soil and climate input (Fig. 10, panel $S_y x C_z$) whereas the rAAD increases with decreasing resolution. The rAAD is highest reaching 30 % for the EPIC model followed by DayCent when soil and climate input is aggregated to 100 km ($S_{100} x C_{100}$) and lowest for MONICA, which is always below 10% while the ensemble mean is about 10%. In contrast, when soil and climate input are aggregated, rAAD for the maize simulations in Tuscany is much higher and reaches for DailyDayCent values of ~60 %. Lowest values were found in Tuscany for Century (<16%), indicating that the overall spread of the model results is much larger compared to NRW. The larger spread but also the higher values of rAAD for some models in Tuscany is also reflected in the rAAD of the ensemble mean, which reaches 30% at the lowest input data resolution ($S_{100} x C_{100}$). However, the effect of aggregating climate data while keeping the dominant regional soil constant (panels: $S_{NRW} x C_z$ and $S_{TUS} x C_z$) shows a completely different picture. In this case, the rAAD seems to be relatively unaffected by the aggregation of climate inputs, and additionally, the spread between models is even larger. When aggregating of soil inputs and combining it with the regional mean climate ($S_y x C_{NRW}$ and $S_y x C_{TUS}$), the rAAD shows a similar pattern for respective crop models as in the simultaneous aggregation of soil and climate inputs. Only EPIC and CENTURY predicted decreased rAAD when decreasing soil resolution from 25 to 50 km for $S_y x C_{TUS}$ in Tuscany.

[Figure 10 Here]

3.2.2 Aggregation effect on winter wheat yield simulation in NRW and Tuscany

As already shown for silage maize in NRW, the simultaneous aggregation of soil and climate input to coarser resolutions of 50 and 100 km caused lower simulated wheat yields with respect to the reference resolution (1 km). This is indicated by negative winter wheat yield differences towards the North-Eastern part of NRW, while higher simulated yields with positive yield differences are observed toward the South of NRW (Fig. 11, panel A: $S_{50}xC_{50}$ and $S_{100}xC_{100}$). A similar pattern is observed when aggregating soil input to 50 and 100 km and combining it with the mean regional climate (Fig. 11, panel A: $S_{50}xC_{NRW}$ and $S_{100}xC_{NRW}$). The aggregation of climate data at different resolutions with the dominant regional soil caused higher simulated wheat yields than yield simulations for the reference resolution at 1km (Fig. 11, panel A: from $S_{NRW}xC_{1}$ to $S_{NRW}xC_{100}$). The mean yield differences for winter wheat in NRW (Fig. 11, panel A) ranged from 0.01 to 1.0 t ha^{-1}. They increased when climate input was aggregated from 1 to 100 km resolution and combined with the dominant regional soil (Fig. 11, panel A: 3rd row). The mean absolute yield differences for winter wheat (AMD i.e. numbers in each figures) are increasing with decreasing resolution of soil and climate input data. The highest mean yield difference in NRW of 1 t ha^{-1} is observed for the combination of dominant soil and 100 km climate aggregation ($S_{NRW}xC_{100}$). Again, the overall findings indicate that the simultaneous aggregation of soil and climate input data has higher impact on the mean yield difference than the aggregation of only soil or climate (Fig. 11 Panel A 1st row).

[Figure 11 Here]

For Tuscany, the mean yield differences for wheat were at maximum 2 t ha^{-1}, mainly located in the northern part, while for other parts of Tuscany slightly negative differences or no difference occurred (Fig. 11, Panel B). In general, the mean yield difference of simulated wheat yields for Tuscany increased with the combination of aggregated soil or climate input to coarser resolutions (from 10 km to 100 km).

In comparison to NRW, the percentage absolute yield differences for winter wheat in Tuscany has higher values, which range from 10 to 15 % when aggregating soil and climate input simultaneously to coarser resolutions (Fig. 12). Additionally to the larger mean error, the spread of the percentage absolute yield differences is also larger for Tuscany compared to NRW. Aggregating soil input data while keeping the climate input constant over the region (C_{NRW} or C_{TUS}) indicates also an increasing trend of percentage absolute yield difference for NRW. For Tuscany the percentage absolute yield differences increased with climate resolution of 10 and 25 km and slightly decreased for resolutions of 50 and 100 km. Looking at the histograms it becomes also visible that the aggregation of soil input data combined with the dominant climate leads to large absolute percentage yield spreads between the grid-cells. In both regions, the shape of the violin plots are similar, indicating that the lower absolute percentage yield differences are found in a higher number of pixels while only few pixels have very high percentage absolute yield differences (Fig. 12).

[Figure 12 Here]

The aggregation error for simulated wheat yields in NRW quantified at regional level as normalized or relative average absolute yield deviation (rAAD) (Eq. 5) is below 30 % for most of the crop models, while only two models HERMES and DailyDayCent show rAAD values higher than 30 %, when climate input is aggregated and combined with the dominant soil (Fig. 13NRW). For the combined aggregation of soil and climate input data ($S_y x C_z$), the rAAD increases with decreasing resolution in both regions. However, maximum rAAD values are observed in Tuscany reaching almost 50% with the EPIC model (Fig. 13 TUS). The rAAD values for winter wheat are, in general, larger in Tuscany for the same aggregation levels. The spread between the models is also larger in Tuscany compared to NRW, which had been already observed for maize (Fig. 10). Thus, for simulation of winter wheat under water limited conditions, the aggregation error at regional level shows an increasing trend when soil and climate input data are simultaneously aggregated to the coarser resolutions regardless of the region (Fig. 13: panels S_yxC_z). The increase of rAAD is less pronounced in winter wheat simulations, when only climate or soil input is aggregated except for climate input aggregation combined with the dominant soil in Tuscany (Fig 13 TUS).

[Figure 13 Here]

4 Discussion

4.1 Input data aggregation

Crop model simulations depend highly on the availability and reliability of input data for soil parameter and climate variables. As Ewert et al. (2015, 2011) already stated, the spatial aggregation of input data from local to regional scale reduces the variability of these data. Furthermore, the deformation of data for different climatic variables when aggregated from higher resolution of 1 km to coarser resolution of 10 km, 25 km, 50 km and 100 km is evaluated in Hoffmann et al. (2017), indicating that the spatial variability of climatic variables decreases due to data aggregation (1 to 100 km) with similar mean values (Hoffmann et al., 2015). For example, in the mountainous North-Western part of Tuscany, the low values for daily minimum temperature detectable at 1 km resolution are averaged out at coarser resolutions of 100 km (Fig. 4). The same applies to the higher temperatures at 1 km resolution at the southern edge of the region (Fig. 4). This means that the aggregation of data in heterogeneous areas has stronger impacts on the extreme than on the mean values. The same feature of a loss of extreme values has been also reported for temporal aggregation of climatic data by (Weihermuller et al., 2011).

As shown in the results there are common trends in the simulated yields as a function of input data aggregation in NRW and Tuscany but also differences are detectable between the two study regions:

1. Combined aggregation of soil and climate will lead to an increase of the error in simulated yields with decreasing resolution for both winter and spring crop.
2. Aggregation of soil data inputs, while keeping the mean regional climate, shows comparable effects on the error in simulated yields as a combined aggregation of soil and climate for both winter and spring crop for both study regions.
3. Aggregation of climate data inputs, while keeping the dominant regional soils, shows only little effects on the error in simulated yields for both winter and spring crop (wheat and maize) for both study regions.
4. The Mediterranean region (Tuscany) indicate larger spread between the models and larger aggregation errors.

Point 1 to 3 has been already reported for NRW by Hoffmann et al. (2017) but due to the limitation of the study to one region no generalization could be made. By analyzing the aggregation effect for two contrasting regions (NRW and Tuscany) it becomes more evident, that soil aggregation has a stronger impact compared to the aggregation of climatic data, for these areas and environmental conditions simulated. The impact of climatic data aggregation on simulated crop yield has been studied by Zhao et al. (2015b) who related the spatial variability of climatic data on high resolution to topographic features (mainly elevation) in the landscape. Hereby, they found that flat and more homogeneous areas can be aggregated to coarser resolution without increasing the aggregation error, while more heterogeneous landscapes react differently with much larger aggregation errors. The aggregation effect of climate data for winter wheat for a Scandinavian region in Finland was also evaluated by Angulo et al, (2013), who stated that simulated yield distributions are similar and independent of the resolution of the climate input data. As both regions analyzed in our study are rather heterogeneous in terms of elevation and climate, an effect of the aggregation of climate data on the simulated yields is expected.

Depending on the extent of heterogeneity in topographic and climatic features, the threshold of the data resolution needs to minimize the data aggregation effect on model simulation error. This has been investigated in Zhao et al, (2015b), defining the requirement of data at high resolution in topographically heterogeneous regions compared to plain areas. For the aggregation of soils, the soil properties at the field level are aggregated to the regional level. The aggregation of soil properties from fine to coarser resolution is classically done by selecting the dominant soil type with a corresponding reference soil profile rather than averaging soil properties. The reasons not to use spatial averaging is quite obvious, because averaging e.g. soil texture is associated with considerable problems. For example, a grid cell containing an entirely sandy soil for half of its area with the other half a clayey textured soil throughout the rooting zone would provide a sandy clay on average, which neither adequately reflects neither the physical properties of sandy soil material nor those of clayey soilmaterial. On the other hand, aggregation by dominant soil type will lead to a loss of information in the simulated outputs because non-dominant but physically very differently behaving soils will not be taken into account during the model runs (Coucheney et al., 2018). In consequence, model responses (in our case yield) from non-dominant areas of the grid cell will not be reproduced at large scale. The effect of different aggregation or scaling approaches on soil hydraulic properties has been studied by Montzka et al. (2017) but the propagation of the different outputs through non-linear models such as crop growth models has not been analyzed.

The application of soil data aggregation to coarser resolution has considerable impact on simulated crop yields and induces biased results at the regional scale at coarser resolutions. Therefore, in the next chapter, the quantification of the aggregation error in simulated crop yields for maize (spring crop) and winter wheat (winter crop) will be discussed.

4.2 Aggregation error on crop yield simulations

4.2.1 Winter wheats

The aggregation effect of climate data (Angulo et al., 2013) was evaluated for winter wheat for a Scandinavian region in Finland. The aggregation effect of soil data (Angulo et al., 2014) on crop yield simulation of winter wheat was evaluated for a region with a temperate climate in Germany. Angulo et al. (2014) used the frequency distribution of crop yields as a characteristic finger print to compare the effect of input data aggregation between crop models and input data resolutions. They found that finger prints were similar for the different resolutions of climate input data while they varied across the different models applied. In line with these results, the yield distribution of winter wheat in NRW did not differ much between different resolutions of climate input, however, in Tuscany, the range of the frequency distribution and the mean percentage of absolute yield difference increased with decreasing resolution of climate input data (Fig. 12B, climate aggregation panel). Aggregating soil types at 1 km^2 resolution to the dominant soil in a coarser grid cell without aggregating the climate variables, tends to cause a positive bias in wheat yields in both regions (Figure 11A and B, row 2). This indicates that in both regions the more productive soils for winter wheat were dominant in most of the grid cells in the different resolutions. However, there were two instances where the positive wheat yield bias decreased when changing from the 10 km resolution (S_{10} x C_z) to the 25 km resolution (S_{25} x C_z) in both regions. Additionally, the combination of dominant soil at regional level with aggregated climate for both regions showed positive yield bias for winter wheat simulation. This indicates the characteristics of aggregated soil at regional level is highly productive and simulate positive yield bias. If the aggregated soil at regional level would have been selected with less productive soil, there is also chance of simulating negative yield bias. However, the study is majorly focuses on quantifying the absolute yield difference as indicator of aggregation error rather than yield bias at different soil and climate resolution.

In NRW, the range and the mean of the percentage absolute yield difference increased when both soil and climate input data were aggregated while in Tuscany only the mean of percentage absolute yield difference increased but not the range. For winter wheat, the aggregation effect on the ensemble yield due to aggregated climate data (1 to 100 km), quantified as relative average absolute deviation (rAAD), was maximum up to 10 % (Zhao et al., 2015a) with mean of 3-5 % for NRW while we have found maximum rAAD of 38% and 50% for NRW and Tuscany respectively and around 15% for the ensemble mean in both regions (Fig. 13). These values did not change when combinations of aggregated soil and climate data were used in the ensemble simulations. Thus, for winter wheat, the average error of climate data aggregation combined with regional soil type over the model ensemble is between 10 and 15 % in both regions. However, the uncertainties in the aggregation error for winter wheat yields are higher in Tuscany as shown in the wider range of the mean absolute yield difference and the relative rAAD in Tuscany (Fig. 12 and 13). Thus, the uncertainty in the aggregation effect for the winter crop in the temperate regions due to input data aggregation (irrespective of climate or soil data) is lower compared to the Mediterranean region probably due to the, on average, positive climatic water balance and the higher water holding capacity (Hoffmann et al., 2015).

With respect to the differences in aggregation error for simulated wheat yields between the single models, there is no evident consistency in the obtained results, except that the EPIC model could be classified as more sensitive to soil and climate data aggregation, having both in Tuscany and NRW relative rAADs above the ensemble mean, whereas the STICS model belongs to the less sensitive models with relative rAADs close to the ensemble mean. This may be due to differences in reference evapotranspiration (Penman-Monteith against Priestley- Taylor) and in approaches to calculate light absorption (one leaf versus multi-layer approach) (Brisson et al., 1998).

4.2.2 Silage maize

The mere aggregation of the soil types according to the dominant soil in the coarser grid cell, caused a positive bias in silage maize yields in both regions (Figure 8A and B, row 2) as previously observed for wheat yields. In both regions, the more productive soils seem to be dominant in most of the grid cells, although the positive bias strongly decreased in Tuscany from a mean yield difference of 1.24 t ha^{-1} to 0.43 t ha^{-1} when changing from the 1 km resolution (S_1 x C_{TUS}) to the 25 km resolution (S_{25} x C_{TUS}).

The combined aggregation of soil and climate input data caused an increase in median and average relative yield difference of silage maize with decreasing resolution (Fig. 9). This has been already shown by Hoffman et al. (2016) for NRW. However, in contrast, to the winter crop (wheat), the range and mean relative yield differences due to climate and soil input data aggregation for silage maize was much higher in Tuscany compared to NRW. This observation was also made when only climate input data were aggregated. Thus, irrespective of the kind of input data aggregated, simulated maize yields in the Mediterranean region showed higher relative yield differences compared to the temperate region already at resolutions of 10 km. At a resolution of 100 km, the relative yield differences were higher by a factor of up to 3 compared to the temperate region when both soil and climate data were aggregated (Fig. 9). This has been corroborated by the results published by Folberth et al. (2014) for the US and could be explained by the difference in climate conditions between the temperate and Mediterranean site, which is higher during the vegetation period of the spring crops compared to the winter crop (Table 5). The average precipitation in Tuscany and NRW during the growing period of silage maize is around 350 mm in both regions, whereas the mean temperature is much lower in the temperate region (15.7 and 21.7 °C in NRW and Tuscany respectively). Thus, warmer and drier conditions during the growing period tend to translate into higher aggregation errors in regional crop simulations. These results are confirmed by the higher relative rAAD of ensemble yields of maize compared to winter wheat in both regions (Fig. 10 and 13). With respect to maize yields, relative rAAD in Tuscany increases stronger compared to NRW when the resolution of input data is decreasing (Fig. 10). In both regions, the increase in relative rAAD from fine to coarse resolution is strongest when aggregation of climate data is combined with aggregation of soil input data and can reach an average relative rAAD of the ensemble mean of 25%. Extreme model-dependent relative rAAD for maize yields can reach 58% in Tuscany compared 38% in NRW. In the case of the spring crop (maize), the aggregation error of the ensemble mean reaches already 20% when a resolution of 10 km for the soil or climate data is used, whereas in NRW such high aggregation errors are never reached with simulated maize yields regardless of the spatial resolution of soil and climate data. These results suggest that reliable regional simulation of spring crop yield in Mediterranean climate conditions requires high spatial resolution of both soil and climate data.

Looking at the differences between the individual models in the aggregation error for simulated maize yields, DailyDayCent seems to be most sensitive to soil aggregation or the combined aggregation of soil and climate input data both in NRW (together with EPIC) and in Tuscany (Fig. 13). In NRW, this is consistent with the findings for maize yield simulations (Fig. 10). Thus, there is no single explanation which can explain the differences in sensitivity to input data aggregation among the individual models. This may require further analysis of relationships between aggregation errors and modeling approaches of certain processes.

4.3 Hotspots of aggregation errors

Looking at the spatial variability of the average yield differences (Fig. 8 and 11), we were able to identify several hotspots where the simulated yields of both crops were very sensitive to data aggregation by producing large in yield differences (-6 to 6 t ha^{-1} for silage maize, -2 to 2 t ha^{-1} for winter wheat) (Fig. 8 and 11). In NRW, the spatial patterns of yield differences due to the simultaneous aggregation of soil and climate input data (Fig. 8 and 11 Panel A, first row) and due to aggregation of soil input data only (Fig. 8 and 11 Panel A, second row) are similar for both crops. The largest wheat and maize yield differences in NRW due to aggregation of soil are found in the Northeast and in two smaller areas in the Northwest and Central-South with average yield difference of more than 3 t ha^{-1} in the case of maize. This indicates that aggregation of soil data is the main driver to induce aggregation errors in NRW. In Tuscany, a similar trend is observed with stronger spatial differentiation of yield differences due to aggregation of soil input data or the combination of soil and climate input data (Fig. 8 and 11 Panel B, first and second row). However, in Tuscany, the hot spots with highest yield differences for maize depend on the resolution, with underestimations being concentrated in the Center and Northwest of Tuscany for resolutions of 10 and 25 km and with underestimations in the Central and Southern part of Tuscany and overestimations in the North for resolutions of 50 and 100 km. In the case of winter wheat, the location of hot spots is similar, but overestimations with strongly positive yield differences are more prominent in the Northern part of Tuscany toward the Northern mountain ranges. In the Northern mountain region with sharp spatial gradients of temperature, the aggregation of climate input data by the average method eliminates the extreme values which exist at 1 km resolution (Hoffmann et al., 2015) and results in on average moderate temperature for coarser resolutions. Thus, aggregation in the mountain regions produces more favourable environmental conditions in the input data set of the coarser resolutions leading to higher simulated crop yields. While in the central and Southern part of Tuscany, aggregation of climate data causes negative yield differences because small hilly areas with higher precipitation are averaged out, leading to on average lower precipitation at coarser resolutions.

4.4 Influence of the range in altitude on the magnitude of aggregation errors

As the effects of climate input data aggregation on aggregation errors in crop yields is obviously stronger in Tuscany, it could be argued that this is due the topographically stronger climatic gradient within Tuscany. The range in altitude is larger in Tuscany (0-1875 m) compared to NRW (0-845). However, if we eliminate the grid cells in Tuscany which have an elevation above 845 m, to have a comparable range of altitude in both regions, the aggregation effects of soil and climate input on crop yields are still significantly different between the two regions (Fig. S1, 10 and 13). For simulated wheat yields, the rAADs in the coarser resolutions (50 and 100 km) even increase when eliminating grids with altitudes greater than 845 m. This supports our findings that the higher aggregation effects in Tuscany compared to NRW are mainly due to the differences in climatic conditions.

5 Conclusion

The aggregation effects of soil and climate data on crop yield simulations in the Mediterranean region are higher than in the temperate region for both winter wheat and silage maize. However, the differences between the Mediterranean and the temperate region are stronger in the case of the spring crop (silage maize). The magnitude of the aggregation effect in Tuscany for silage maize expressed as the percentage absolute yield difference is on average 30% compared to an average of 10 % for winter wheat. Because of the higher aggregation effect on crop yield simulation in the Mediterranean region, it is important in these regions to use input data at a finer resolution for reliable estimation of regional crop yield. Moreover, in each region, there are hot spots with extremely high positive or negative yield differences due to input data aggregation. In these hot spots, a finer resolution of climate and in particular soil information is important to reduce errors in crop yield simulations. For generalization of these outcomes, further investigations in other sub-humid or semi-arid regions will be necessary.

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Table 1. Main climatic variables for the time period 1995 to 2011 for NRW and TUS. Mean is the arithmetic mean, STD is the standard deviation, and 25, 50, 75 % are the respective percentiles (Mean annual values and temporal variability)

Climate variable*	Summary statistics for climate variables						
NRW	Mean	STD	Minimum	25 %	50 %	75 %	Maximum
TempMin (°C)	5.6	0.7	3.9	5.4	5.6	6.0	6.7
TempMean (°C)	9.6	0.7	7.6	9.4	9.6	10.1	10.3
TempMax (°C)	13.7	0.8	11.5	13.5	13.9	14.2	14.7
Radiation(MJ m^{-2} d^{-1})	10.4	0.4	9.6	10.1	10.4	10.6	11.5
Windspeed (m s^{-1})	2.6	0.1	2.4	2.5	2.6	2.7	2.8
Precipitation (mm y^{-1})	821.1	117.3	659.1	752.3	801.3	861.7	1022.5
ET_0	986.6	56.3	875.7	947.7	986.4	1019.2	1100.2
cwb	165	147	-122	101	197	231	425
Tuscany	Mean	STD	Minimum	25 %	50 %	75 %	Maximum
TempMin (°C)	8.8	0.4	8.0	8.7	8.8	9.1	9.3
TempMean (°C)	16.1	0.5	15.1	15.8	16.2	16.5	16.8
TempMax (°C)	18.6	0.6	17.4	18.1	18.7	19.0	19.4
Radiation(MJ m^{-2} d^{-1})	14.2	0.5	12.8	14.0	14.3	14.5	15.1
Windspeed (m s^{-1})	2.0	0.1	1.7	1.9	2.0	2.1	2.3
Precipitation (mm y^{-1})	949.4	192.5	667.8	809.1	967.8	1035.6	1424.8
ET_0 (mm y^{-1})	1495.8	64.3	1335.3	1460.8	1524.3	1531.8	1626.1
cwb (mm y^{-1})	546	244	-89	441	527	733	858

*TempMin: Minimum Temperature, TempMean: Mean Temperature, TempMax: Maximum Temperature, ET_0: Reference Evapotranspiration (calculated by using ET_0 equation in FAO 56) , cwb: Climate water balance (ET_0 − Precipitation) and others are as indicated

Table: 2. Total soil depth and soil properties of the top soil layer in NRW and Tuscany at 1x1 km resolution

NRW	Number of pixels	mean	std	min	25%	50%	75%	max
Depth [m]	34168	0.29	0.03	0.10	0.30	0.30	0.30	0.30
Sand [%]		37.66	29.76	5.00	15.00	18.00	64.00	92.00
BD [g cm-3]		1.40	0.02	0.56	1.40	1.40	1.40	1.40
Wilting point [m3 m-3]		0.14	0.06	0.04	0.09	0.16	0.18	0.29
Field capacity [m3 m-3]		0.26	0.08	0.12	0.20	0.29	0.33	0.39

TUS	Number of pixels	mean	std	min	25%	50%	75%	max
Depth [m]	22933	0.49	0.04	0.18	0.50	0.50	0.50	0.50
Sand [%]		33.27	16.51	2.00	22.25	30.75	46.80	89.75
BD [g cm-3]		1.38	0.12	0.73	1.34	1.40	1.46	1.71
Wilting point [m3 m-3]		0.10	0.02	0.05	0.08	0.10	0.12	0.20
Field capacity [m3 m-3]		0.26	0.04	0.06	0.24	0.27	0.28	0.38

Table 3: Summary of climatic condition during the growing period of silage maize and winter wheat for NRW and Tuscany (1995-2011)

Climate variable	Summary statistics for climate variables during maize growing season						
NRW	Mean	STD	Minimum	25 %	50 %	75 %	Maximum
TempMin (ºC)	10.6	0.6	9.5	10.3	10.6	11.0	11.6
TempMean (ºC)	15.7	0.6	14.2	15.3	15.7	15.9	17.2
TempMax (ºC)	20.9	0.8	19.2	20.5	20.8	21.2	22.9
Radiation(MJ m^{-2} d^{-1})	16.8	0.7	15.4	16.3	16.8	17.2	18.1
Windspeed (m s^{-1})	2.3	0.1	2.1	2.2	2.3	2.4	2.6
Precipitation (mm y^{-1})	357.6	56.3	276.2	316.4	356.3	378.2	496.2
ET_0	686.0	40.2	616.3	670.8	685.7	708.0	770.0

cwb	328.4	85.8	174.7	286.2	324.3	385.4	469.8

Tuscany	Mean	STD	Minimum	25 %	50 %	75 %	Maximum
TempMin (ºC)	13.1	0.6	12.1	12.6	13.1	13.4	14.4
TempMean (ºC)	21.7	0.8	20.4	21.1	21.5	22.1	23.6
TempMax (ºC)	24.6	0.9	23.2	23.8	24.5	24.9	26.6
Radiation(MJ m^{-2} d^{-1})	21.2	0.6	19.5	20.8	21.3	21.6	22.2
Windspeed (m s^{-1})	1.9	0.1	1.7	1.8	1.9	2.0	2.1
Precipitation (mm y^{-1})	354.3	88.7	219.4	315.3	323.9	397.1	531.7
ET_0 (mm y^{-1})	1130.3	47.2	1033.7	1098.6	1141.3	1156.6	1237.8
cwb (mm y^{-1})	776.0	130.0	502.0	721.7	785.5	838.3	1018.4

Climate variable	Summary statistics for climate variables during wheat growing season						
NRW	**Mean**	**STD**	**Minimum**	**25 %**	**50 %**	**75 %**	**Maximum**
TempMin (ºC)	4.4	0.9	2.8	3.9	4.3	5.1	6.3
TempMean (ºC)	8.2	0.9	6.5	7.8	8.2	8.6	10.3
TempMax (ºC)	12.1	0.9	10.3	11.8	12.2	12.5	14.3
Radiation(MJ m^{-2} d^{-1})	9.6	1.4	4.6	9.5	9.8	10.0	12.2
Windspeed (m s^{-1})	2.7	0.2	2.4	2.6	2.7	2.8	3.0
Precipitation (mm y^{-1})	632.0	151.4	194.0	587.5	674.8	692.3	801.0
ET_0 (mm y^{-1})	710.0	151.7	133.3	710.5	739.7	779.5	825.8
cwb (mm y^{-1})	78.0	106.7	-69.7	12.3	65.6	148.3	292.3
Tuscany	**Mean**	**STD**	**Minimum**	**25 %**	**50 %**	**75 %**	**Maximum**
TempMin (ºC)	5.7	0.7	4.2	5.3	5.9	6.1	7.3
TempMean (ºC)	12.5	0.8	10.6	11.9	12.6	12.8	14.2
TempMax (ºC)	14.7	0.9	12.7	14.1	14.9	15.2	16.4
Radiation(MJ m^{-2} d^{-1})	11.9	1.9	5.3	11.8	12.1	12.6	14.4
Windspeed (m s^{-1})	2.1	0.2	1.8	2.0	2.1	2.2	2.4
Precipitation (mm y^{-1})	591.7	188.3	104.4	506.6	566.5	683.1	901.9
ET_0 (mm y^{-1})	697.9	164.6	83.5	696.1	739.8	768.0	810.5
cwb (mm y^{-1})	106.2	163.5	-252.5	10.6	89.4	255.7	358.0

*TempMin: Minimum Temperature, TempMean: Mean Temperature, TempMax: Maximum Temperature, ET_0: Reference Evapotranspiration, cwb: Climate water balance (ET_0 − Precipitation) and others are as indicated

Table 4. List of crop models used in the model ensemble

No.	Model	Model abbreviation in text and figures	References
1	AgroC [b]	AGROC	(Herbst et al., 2008, Klosterhalfen et al., 2017)
2	Century	CENT	(Parton et al. 1992)

3	CoupModel [ab]	COUP	(Janssen 2012, Conrad and Fohrer, 2009)
4	DailyDayCent	DayC	(Del Grosso et al., 2001, 2006)
9	EPIC v. 0810	EPIC	(Williams 1995)
6	HERMES [b]	HERM	(Kersebaum, 2007, 2011)
7	MONICA [b]	MONI	(Nendel et al., 2011; Specka et al., 2015)
8	SIMPLACE<LINTUL5;SLIM>	LINT	(Gaiser et al., 2013; Shibu et al., 2010)
9	STICS	STIC	(Bergez et al., 2013; Brisson et al., 2009, 1998)

[a] only simulated wheat; [b] simulated NRW only

Table 5. Crop management of winter wheat and silage maize in Tuscany.

Management	Winter wheat	Silage maize	Unit	
Residues	cut and incorporated into soil	Cut and incorporated into soil	-	
Tillage	plough in late summer/beginning of autumn (harrowing in the plains)	plough in late summer/beginning of autumn (ripping in the plains)	-	
Sowing date	10-Nov	03-Apr	date	
Harvest date	25-Jun	03-Oct	date	
Plant density	400	8	m^{-2}	emerging plants
Sowing depth	3	3	cm	

Table 6. Crop management of winter wheat and silage maize in NRW

Management	Winter wheat	Silage maize	Unit	
Residues	straw is removed, stubbles are left on the field (10% of the above ground total biomass and the roots)	straw is removed, stubbles are left on the field (10% of the above ground total biomass and the roots)	-	
Tillage	ploughing in autumn	ploughing in autumn	-	
Sowing date	Oct-01	Apr-20	date	
Harvest date	Aug-01	Sep-20	date	
Plant density	400	10	$1/m^2$	emerging plants
Sowing depth	4	6	cm	

Table 7. The abbreviation for input data combination of soil and climate data at different resolutions.

*Soil resolution km	*Climate resolution km	SoilxClimate	Remarks
y	z	$S_y x C_z$	soil and climate aggregation
S_{Reg}	z	$S_{Reg} x C_z$	One dominant regional soil with

			climate aggregation
y	C_{Reg}	S_yxC_{Reg}	soil aggregation with average regional climate

* the subscripts y and z represents the resolution for soil and climate at 1, 10, 25, 50 and 100 km, S_{Reg} and C_{Reg} are symbols to represents regional soil and climate (eg. S_{Tus} and C_{Tus} to represent for regional soil and regional climate for Tuscany).

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Figure 1. Geographic location of the study regions and the elevation variability for NRW, (Germany) and Tuscany (Italy).

Figure 2. Soil type for NRW aggregated according to dominant soil types for resolutions from 1 km to 100 km (Hoffmann et al., 2016).

Figure 3. USDA soil texture class of the topsoil aggregated by dominant soil type from 1 km resolution.

Figure 4. Average minimum, mean and maximum temperature in Tuscany for the time period 1995-2013 at spatial resolutions from 1 km to 100 km

Figure 5. Sketch of the modelling framework used in this study. Combination of soil and climate data at different aggregation level are distributed to the model ensemble. The collected outputs of all models were averaged to obtain the model ensemble mean.

Figure 6. Ensemble mean crop yields for silage maize for NRW (A) and for Tuscany (B) under water-limited conditions for different levels of aggregation of soil and climate data. In each panel, the 1st row represents the ensemble mean yield for simultaneous aggregation of soil and climate data ($S_y x C_z$), 2nd row for aggregation of soil input data with the same regional mean climate data as $S_y x C_{Reg}$ and 3rd row for the aggregation of climate data with regional dominant soil type as $S_{Reg} x C_z$.

Figure 7. Ensemble mean crop yields for for winter wheat for NRW (A) and for Tuscany (B) for different levels of aggregation of soil and climate data. In each panel, the 1st row represent the ensemble mean yields for simultaneous aggregation of soil and climate input data ($S_y x C_z$), 2nd row for aggregation of soil with with constant regional mean climate ($S_y x C_{Reg}$) and 3rd row aggregation of climate input data with regional dominant soil type as ($S_{Reg} x C_z$).

Figure 8. Average yield difference between coarser resolutions ($S_y x C_z$) and the reference resolution ($S_1 x C_1$) for silage maize for NRW (A) and for Tuscany (B).

Figure 9. Percentage absolute difference for silage maize yields comparing coarser resolutions ($S_y x C_z$) with the reference resolution ($S_1 x C_1$) for NRW and Tuscany. The violin plots show in the x-dimension the distribution of the probability density of the percentage absolute yield difference values. The box plots

show the median (red line), mean (black star), and the upper and lower quartiles (box) and the extreme upper and lower values (black lines)

Figure 10. The relative average absolute yield deviation (rAAD) as indicator for the impact of soil and climate input data aggregation on silage maize yield simulations by different crop models as well as for the model ensemble mean (ESMB)

Figure 11. Average yield difference between coarser resolutions (S_yxC_z) and the reference resolution (S_1xC_1) for winter wheat for NRW (A) and winter wheat for Tuscany (B). AMD is the average yield difference

Figure 12. Percentage absolute yield differences of winter wheat between coarser resolutions (S_yxC_z) and the reference resolution (S_1xC_1) for NRW and Tuscany. The violin plots show in the x-dimension the distribution of the probability density of the percentage absolute yield difference values. The box plots show the median (red line), mean (black star), and the upper and lower quartiles (box) and the extreme upper and lower values (black lines)

Figure 13. The relative average absolute yield deviation (rAAD) as indicator for the impact of soil and climate input data aggregation on winter wheat yield simulations by different crop models as well as for the model ensemble mean (ESMB).