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

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25 **Abstract**

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

39 The mean yield difference (bias) at regional level was positive due to productive dominant
40 soil at coarser resolution which could potentially be negative bias that would have been non-
41 productive soil aggregated in respective region. In both regions, aggregation effects i.e. errors
42 in simulation of crop yields at coarser spatial resolution due to the combined aggregation of
43 soil and climate input data increased with decreasing resolution for both crops but the
44 aggregation error in Tuscany was larger than in North Rhine Westphalia (NRW). Over
45 Tuscany, the average percentage absolute differences between grid cell yields at the coarsest
46 resolution (100 km) compared to the finest resolution (1 km) were up to 20 % and 30 % for
47 winter wheat and silage maize, respectively. In contrast, in NRW, the average percentage
48 absolute yield differences in the coarsest grid cells were <15 for wheat and <20 % for maize.
49 This implies that for regional yield simulations in temperate humid regions of central Europe

50 coarser resolutions may be sufficient to achieve reliable yield estimations , whereas, in
51 Mediterranean areas higher spatial resolutions are required avoiding prediction errors of the
52 spatially averaged yield of up to 60 % as observed for individual crop models. For
53 generalization of these outcomes, further investigations in other sub-humid or semi-arid
54 regions will be necessary. Additionally, aggregating soil data caused larger aggregation errors
55 in both regions than aggregating climate data.

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

57 **1 Introduction**

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

70 In general, field scale crop models have been validated and applied for multiple locations. The
71 field based crop models are applied for multiple grid cells at different resolution to cover
72 entire area of interest. The spatial distinction among the applied grid cells are characterized by
73 data variability of agro-climatic (such as soil and climate) condition of the studied area.
74 Therefore, these models are also run beyond the scale of development to predict yields at

75 regional to global scale, whereby spatially aggregated input data are used (Rosenzweig et al.,
76 2014; Rosenzweig and Iglesias, 1998; Rosenzweig and Parry, 1994). In climate change
77 studies crop models are applied using climate change data produced by global circulation
78 models (GCMs) at larger scale to assess climate change impacts on crops and environment
79 (Donatelli et al., 2015) and to design comprehensive adaptation strategies such as
80 optimization of sowing date from regional to global level.

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

85 Climate input data from two relatively small regions in Northern and Central Europe
86 aggregated to different resolutions was used in a range of crop models in Angulo et al., 2013
87 to study the characteristics of the response variable (i.e. crop yield distribution) as a result of
88 the input data aggregation (climate data). Further, soil data at different resolutions were used
89 to simulate crop yield and analyze yield distribution from two contrasting sites in Angulo et
90 al. (2014). In these two studies (Angulo et al., 2014, 2013), the impact of input data (soil and
91 climate respectively) aggregation on simulated yield distribution were not different within
92 each model. While, simulated yield distributions ('figureprint') were different for various
93 models. Thus, the authors insist to use a multi-model ensemble (average of all model output)
94 approach to analyze input data aggregation impact on regional crop yield simulation. A
95 multi-model ensemble approach was also used by Zhao et al, (2015a) who quantified the
96 climate data aggregation error for regional simulations of several model output variables such
97 as yield, evapotranspiration, and water use efficiency in North Rhine-Westphalia (NRW) in
98 Central Europe. The authors used aggregated climatic data at different resolutions (10, 25, 50,
99 and 100 km). They concluded that weather data aggregation error was highest for simulated

100 crop yield compared to crop evapotranspiration or water use efficiency, but was below 10% in
101 all cases. In the same region, the characteristics (variability and spatial variance) of climatic
102 data aggregated to coarser resolution was compared to simulated crop yield (winter wheat and
103 silage maize) from an ensemble mean calculated at different aggregation levels in Hoffmann
104 et al, (2015). The aggregation error for simulated crop yield was significantly increasing for
105 decreasing resolution of the climate data The application of simultaneous aggregation of soil
106 and climate data to simulate regional crop yield by different crop models were further
107 investigated by Hoffmann et al, (2016). The results showed, that the aggregation errors were
108 amplified with decreasing resolution of soil and climate data input compared to the
109 aggregation error made by aggregating only one input variable.

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

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

130 **2 Material and Methods**

131 **2.1 Study regions**

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

138 **[Table 1 Here]**

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

143 **[Figure 1 Here]**

144 2.2 Preparation of model input data

145 2.2.1 Soil data

146 • NRW

147 The soil data at 1 km resolution for NRW, Germany was originally already aggregated by
148 dominant soil type from approximately 300 m resolution to grid cells of 1 km resolution
149 (Hoffmann et al., 2016). The soil data source for NRW and the methods to derive several soil
150 properties including topsoil organic carbon, soil texture, soil bulk density, and soil albedo are
151 explained in Hoffmann et al, (2016). In a second step the soil data at 1 km resolution was
152 aggregated to coarser resolution by dominant soil type from the 1 km resolution to 10, 25, 50,
153 100 km as well as to a NRW mean (S_{NRW}). The results of the soil data aggregated from 1 km
154 resolution to 100 km resolution for NRW is shown in Fig. 2. The dominant soil type for NRW
155 (S_{NRW}) was a Cambisol.

156 **[Figure 2 Here]**

157 • Tuscany

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

167 (10 – 100 km). The soil data at a coarser resolution of 10, 25, 50 and 100 km were prepared
168 by selecting the dominant soil texture among the 1 km soil grids (Fig. 3).

169 **[Figure 3 Here]**

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

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

177 The soil depth of the most dominant soil in NRW is about 2.3 (range 0.1 – 2.3 m for soil
178 various layers in 1 km grid cells) m while for Tuscany it is 1.36 (range in 0.18-1.5 for
179 different soil layers in 1 km grid cells) m. The field capacity of the first soil layer for the
180 dominant soils are 0.36 and 0.23 m³ m⁻³ for NRW and Tuscany, respectively. Other soil
181 parameters required to simulate the crop yields are provided in Hoffmann et al. (2016) mainly
182 for NRW region and in the supplementary material (Table S2).

183 **[Table 2 Here]**

184 2.2.2 *Climate data*

- 185 • NRW

186 The climate data set for NRW at 1 km include daily time series of minimum, mean and
187 maximum air temperature, precipitation, global radiation, wind speed and relative humidity
188 for the period 1982 to 2011 and was established by interpolation of measured climate
189 variables at 280 weather stations provided by the German Meteorological Services (DWD).
190 All climate variables were aggregated to coarser resolutions from 1 km resolution data by

191 arithmetic averaging. The climate data source and the aggregation process to coarser
192 resolution for NRW are explained in detail in Hoffmann et al, (2016).

193 • Tuscany

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

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

213 The daily climate variables for each year during the growing period of the respective crop
214 where averaged from 1995 to 2011 (Table 6). The mean temperature during the growing
215 season for silage maize in NRW and Tuscany are respectively 16 and 22 °C while, the

216 average of mean temperature during the growing period of wheat are 8 °C for NRW and 12 °C
217 for Tuscany. The sum of precipitation during growing season of maize in NRW and Tuscany
218 are similar with the approximate value of 350 mm, while, the precipitation sum during
219 growing season of winter wheat in NRW is about 632 and 591 mm for Tuscany Italy. The
220 climate water balance (cwb: $ET_0 - \text{Precipitation}$, mm) for respective crop growing season and
221 regions is higher for Tuscany than for NRW. The summary statistic of the climatic variables
222 for each region for the respective crop during growing period is presented in Table 3 and the
223 soil properties of the dominant soil type in each region is presented in Table S2.

224 **[Figure 4 Here]**

225 **[Table 3 Here]**

226 **2.3 Model setup**

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

236 **[Table 4 Here]**

237 Aggregated soil and climate as well as crop management data were used for the crop model
238 ensemble to simulate the yield of silage maize and winter wheat. The crop management data
239 with respect to tillage, sowing, and fertilizer application (timing and amount) were fixed for

240 both regions while the date of harvest for each crop was either simulated or observed harvest
241 dates were used depending on the requirements of individual models. The detailed crop
242 management data for winter wheat and silage maize in the two regions are shown in Table 5
243 and 6.

244 **[Table 5 Here]**

245 **[Table 6 Here]**

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

253 **[Table 7 Here]**

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

262 **[Figure 5 Here]**

263 2.4 Calculation of the aggregation errors

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

$$272 \quad AbsPD_j = \left(\frac{|YC_j - YF_j|}{YF_j} \right) * 100 \quad (1)$$

273 where, $AbsPD_j$ is the absolute percentage difference with YC_j as the yield simulated at coarser
274 resolution that is disaggregated to 1 km resolution of j^{th} pixel, and YF_j is the simulated yield of
275 respective grid cell at 1 km resolution included by coarser resolution. The mean difference
276 (MD) is calculated as the average difference between the yield YC_i simulated at coarser
277 resolution disaggregated to 1 km resolution of j^{th} pixel and the yield YF_j simulated at finer of
278 1 km resolution (pixel j) $MD = N^{-1} * (\sum_{j=1}^N YC_j - YF_j)$ (2) The mean absolute
279 difference (AMD) is the equivalent to the mean difference (MD) except that the absolute
280 value of the differences between coarser resolution pixel and the 1 km pixel is used:

281

$$282 \quad AMD = N^{-1} * \left(\sum_{j=1}^N |YC_j - YF_j| \right) \quad (3)$$

283

284 $AvgYF$ is the average yield at 1 km resolution, where N is the number of pixels at 1 km
285 resolution, and $rAAD$ is the average absolute yield deviation normalized to the average yield
286 at 1 km resolution.

287

$$288 \quad AvgYF = N^{-1} * \left(\sum_{j=1}^N YF_j \right) \quad (4)$$

$$289 \quad rAAD = \frac{N^{-1} * \left(\sum_{i=1}^N |YC_i - YF_j| \right) * 100}{AvgYF} \quad (5)$$

290

291 **3 Results**

292 **3.1 Spatial pattern of crop yield simulations in NRW and Tuscany**

293 3.1.1 Silage maize yield simulation in NRW and Tuscany

294 The ensemble mean for silage maize across all crop models simulated for different
295 combinations of aggregated soil and climate data under water limited conditions shows a
296 relatively higher silage maize yield simulated for NRW (Fig. 6A) as compared to Tuscany
297 (Fig. 6B). Additionally, spatial variability of silage maize yields are highest when both soil
298 and climate input data at the finest resolution (1 km) were used ($S_1 \times C_1$ in NRW and Tuscany).
299 For both regions, only small changes in the spatial yield patterns are detectable, when the
300 finest soil input data resolution (S_1 = soil at 1 km) is combined with average climate input
301 data over the entire region (C_{NRW} or C_{TUS}) (Fig. 6, 1st column for each panel i.e. $S_1 \times C_{NRW}$ and
302 $S_1 \times C_{TUS}$). On the other hand, combining dominant soil conditions (S_{NRW} or S_{TUS}) with high
303 resolution climate data (C_1 = climate at 1 km) leads to pronounced differences in the predicted

304 silage maize yield compared to the finest resolution $S_1 \times C_1$. The overall range of silage maize
305 yield for NRW is from 10 to 18 t ha⁻¹ while for Tuscany it is from 5 to 18 t ha⁻¹.

306 **[Figure 6 Here]**

307 3.1.2 Winter wheat simulation in NRW and Tuscany

308 The average crop yields for winter wheat in NRW are much higher than in Tuscany regardless
309 of the soil-climate input data combination (Fig. 7). Yield for winter wheat in NRW ranges
310 from 4 to 10 t ha⁻¹ while for Tuscany it is between 0 and 6 t ha⁻¹. The spatial variability of the
311 ensemble mean yield for (winter) wheat across all models is similar to the variability of the
312 ensemble mean of silage maize yield. In both NRW and Tuscany, the spatial variability of the
313 winter wheat yield is highest when the finest resolution of climate and soil input ($S_1 \times C_1$) is
314 used. In Tuscany, the spatial variability of simulated winter wheat yields using the finest
315 resolution of soil and climate input data ($S_1 \times C_1$) is comparable to the spatial variability of
316 yields simulated with the combination of finest soil resolution and average regional climate
317 ($S_1 \times C_{TUS}$) that exhibit slightly higher values in the northern part of the region. The yield
318 pattern in which the finest resolutions of soil and climate input is used ($S_1 \times C_1$ i.e, Fig. 7 1st
319 column of panel B) is comparable with yields produced with the finest climate resolution and
320 the dominant soil type ($S_{TUS} \times C_1$ i.e, Fig. 7, 1st column of Panel B). This is contrast to the
321 spatial variability of winter wheat yields in NRW, where the simulated yields based on the
322 combination of finest climate input resolution with the dominant soil type exhibited a much
323 lower spatial variability as compared to the yield simulated with the highest resolution of both
324 soil and climate input ($S_1 \times C_1$ i.e, Fig. 7, 1st column in panel A).

325 **[Figure 7 Here]**

326 Thus, yield simulations for silage maize and winter wheat at finest resolution of soil and
327 climate input (1 km resolution ($S_1 \times C_1$) (Fig. 6 and 7) have the highest spatial variability
328 compared to all other soil and climate input data combinations. With aggregation of soil and

329 climate input data the spatial variability of simulated crop yields decreases (Fig. 6 and 7).
330 However, in the case of winter wheat, when only climate input data is aggregated and
331 combined with the dominant soil type (3rd row, 7) the spatial variability of simulated yields
332 is much lower in all resolutions. Thus, the aggregation of climate input data has less impact
333 on the spatial variability of simulated wheat yields under water limited conditions than the
334 simultaneous aggregation of soil and climate for both regions.

335 **3.2 Aggregation effects on simulated crop yields**

336 **3.2.1 Aggregation effect on silage maize yield simulations in NRW and Tuscany**

337 In a next step, the aggregation errors were calculated based on Eq. 1-5 for the different
338 regions and combinations of aggregation. Hereby, the finest resolution ($S_1 \times C_1$) was always
339 chosen as the reference simulation in each region. The difference of crop yields when
340 simulated at a coarser resolution of soil and climate input compared to the finest resolution at
341 1 km ($S_1 \times C_1$) is considered as the effect of input data aggregation on yield simulations. The
342 magnitude of yield differences for silage maize ranged from -6 to 6 t ha⁻¹ (Fig. 8) for both
343 regions. In general, the average bias in silage maize yield (MD) due to input data aggregation
344 was always positive, except for the combined aggregation of soil and climate variables in
345 Tuscany. For silage maize simultaneous aggregation of soil and climate to coarser resolution
346 of 50 and 100 km caused lower simulated yield in the North-East of NRW compared to the
347 reference resolution (1 km) as indicated by negative yield differences, while higher yields
348 with positive yield difference are observed towards the southern part (Fig. 8, panel A: $S_{50} \times C_{50}$
349 and $S_{100} \times C_{100}$). A similar pattern can be distinguished when aggregating soil input data to 50
350 and 100 km combined with an average regional climate (Fig. 8, panel A: $S_{50} \times C_{NRW}$ and
351 $S_{100} \times C_{NRW}$). The combination of an average regional climate for NRW with the soil input data
352 at 1 km resolution has almost no yield difference with respect to the simulated maize yields of
353 the reference resolution (Fig. 8, panel A: $S_1 \times C_{NRW}$). The spatial patterns of yield differences

354 for other combinations (Fig. 8, panel A: from $S_{10} \times C_{NRW}$ to $S_{100} \times C_{NRW}$, 2nd row) are similar to
355 the pattern of yield differences that are observed with the simultaneous aggregation of soil
356 and climate data (Fig. 8, panel A: from $S_{10} \times C_{10}$ to $S_{100} \times C_{100}$).

357 A similar observation can be made for the spatial patterns of yield differences in Tuscany for
358 maize under water-limited conditions (Fig. 8, panel B). With decreasing resolution of soil and
359 climate input data, the yield differences are positive towards the northern part and negative
360 towards the southern part of Tuscany (Fig. 8, panel B: $S_{50} \times C_{50}$ and $S_{100} \times C_{100}$). The yield
361 difference for silage maize due to the combination of the average regional climate (C_{TUS}) with
362 soil input at 1 km resolution is zero towards the northern part, while it is positive from the
363 central to the southern part of Tuscany (Fig. 8, panel B: $S_1 \times C_{TUS}$). The pattern of yield
364 differences for silage maize in Tuscany based on simultaneous aggregation of soil and climate
365 input data is similar (Fig. 8, panel B: from $S_{10} \times C_{10}$ to $S_{100} \times C_{100}$, 1st row) to the pattern
366 observed when only soil is aggregated and combined with the average regional climate (Fig.
367 8, panel B: from $S_{10} \times C_{TUS}$ to $S_{100} \times C_{TUS}$, 2nd row). The yield differences are either positive or
368 zero for Tuscany when aggregation of climate input is combined with the dominant soil
369 (S_{TUS}) (Fig. 8, panel B, 3rd row).

370 **[Figure 8 Here]**

371 The aggregation effects on simulated silage maize yields are further analyzed as absolute
372 percentage yield difference (Eq. 1) from the yields simulated on the reference 1 km
373 resolution. The variability of absolute percentage difference for silage maize is presented as
374 box plots and its frequency distribution as violin plot for different aggregation levels for
375 NRW (Fig. 9A) and Tuscany (Fig. 9B). The percentage absolute yield differences (%) for
376 silage maize yield for the ensemble mean for combined soil and climate data aggregation are
377 in general higher for Tuscany than for NRW (Fig. 9). The mean percentage absolute
378 differences are ranging from 5 to 12 % in NRW and from 15 to 35 % in Tuscany. Looking at

379 the histograms it becomes also clear, that the variability of the percentage absolute yield
380 differences in NRW can reach up to 40 % in some grid cells, and that it can be even larger in
381 Tuscany (>40%). On the other hand, lowest values of the percentage absolute difference are
382 between 0 to 5 % in NRW and 0 to 15 % in Tuscany.

383 **[Figure 9 Here]**

384 The aggregation effect at the regional scale quantified as the normalized or relative average
385 absolute yield deviation (rAAD) of silage maize yield in NRW is below 35 % for all crop
386 models regardless of the aggregation level of soil and climate input (Fig. 10, panel $S_y \times C_z$)
387 whereas the rAAD increases with decreasing resolution. The rAAD is highest reaching 30 %
388 for the EPIC model followed by DayCent when soil and climate input is aggregated to 100
389 km ($S_{100} \times C_{100}$) and lowest for MONICA, which is always below 10% while the ensemble
390 mean is about 10%. In contrast, when soil and climate input are aggregated, rAAD for the
391 maize simulations in Tuscany is much higher and reaches for DailyDayCent values of ~60 %.
392 Lowest values were found in Tuscany for Century (<16%), indicating that the overall spread
393 of the model results is much larger compared to NRW. The larger spread but also the higher
394 values of rAAD for some models in Tuscany is also reflected in the rAAD of the ensemble
395 mean, which reaches 30% at the lowest input data resolution ($S_{100} \times C_{100}$). However, the effect
396 of aggregating climate data while keeping the dominant regional soil constant (panels:
397 $S_{NRW} \times C_z$ and $S_{TUS} \times C_z$) shows a completely different picture. In this case, the rAAD seems to
398 be relatively unaffected by the aggregation of climate inputs, and additionally, the spread
399 between models is even larger. When aggregating of soil inputs and combining it with the
400 regional mean climate ($S_y \times C_{NRW}$ and $S_y \times C_{TUS}$), the rAAD shows a similar pattern for
401 respective crop models as in the simultaneous aggregation of soil and climate inputs. Only
402 EPIC and CENTURY predicted decreased rAAD when decreasing soil resolution from 25 to
403 50 km for $S_y \times C_{TUS}$ in Tuscany.

404

[Figure 10 Here]

405 **3.2.2 Aggregation effect on winter wheat yield simulation in NRW and Tuscany**

406 As already shown for silage maize in NRW, the simultaneous aggregation of soil and climate
407 input to coarser resolutions of 50 and 100 km caused lower simulated wheat yields with
408 respect to the reference resolution (1 km). This is indicated by negative winter wheat yield
409 differences towards the North-Eastern part of NRW, while higher simulated yields with
410 positive yield differences are observed toward the South of NRW (Fig. 11, panel A: $S_{50 \times C_{50}}$
411 and $S_{100 \times C_{100}}$). A similar pattern is observed when aggregating soil input to 50 and 100 km
412 and combining it with the mean regional climate (Fig. 11, panel A: $S_{50 \times C_{NRW}}$ and $S_{100 \times C_{NRW}}$).
413 The aggregation of climate data at different resolutions with the dominant regional soil caused
414 higher simulated wheat yields than yield simulations for the reference resolution at 1km (Fig.
415 11, panel A: from $S_{NRW \times C_1}$ to $S_{NRW \times C_{100}}$). The mean yield differences for winter wheat in
416 NRW (Fig. 11, panel A) ranged from 0.01 to 1.0 t ha⁻¹. They increased when climate input
417 was aggregated from 1 to 100 km resolution and combined with the dominant regional soil
418 (Fig. 11, panel A: 3rd row). The mean absolute yield differences for winter wheat (AMD i.e.
419 numbers in each figures) are increasing with decreasing resolution of soil and climate input
420 data. The highest mean yield difference in NRW of 1 t ha⁻¹ is observed for the combination of
421 dominant soil and 100 km climate aggregation ($S_{NRW \times C_{100}}$). Again, the overall findings
422 indicate that the simultaneous aggregation of soil and climate input data has higher impact on
423 the mean yield difference than the aggregation of only soil or climate (Fig. 11 Panel A 1st
424 row).

425

[Figure 11 Here]

426 For Tuscany, the mean yield differences for wheat were at maximum 2 t ha⁻¹, mainly located
427 in the northern part, while for other parts of Tuscany slightly negative differences or no
428 difference occurred (Fig. 11, Panel B). In general, the mean yield difference of simulated

429 wheat yields for Tuscany increased with the combination of aggregated soil or climate input
430 to coarser resolutions (from 10 km to 100 km).

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

444 **[Figure 12 Here]**

445 The aggregation error for simulated wheat yields in NRW quantified at regional level as
446 normalized or relative average absolute yield deviation (rAAD) (Eq. 5) is below 30 % for
447 most of the crop models, while only two models HERMES and DailyDayCent show rAAD
448 values higher than 30 %, when climate input is aggregated and combined with the dominant
449 soil (Fig. 13NRW). For the combined aggregation of soil and climate input data ($S_y \times C_z$), the
450 rAAD increases with decreasing resolution in both regions. However, maximum rAAD values
451 are observed in Tuscany reaching almost 50% with the EPIC model (Fig. 13 TUS). The
452 rAAD values for winter wheat are, in general, larger in Tuscany for the same aggregation
453 levels. The spread between the models is also larger in Tuscany compared to NRW, which

454 had been already observed for maize (Fig. 10). Thus, for simulation of winter wheat under
455 water limited conditions, the aggregation error at regional level shows an increasing trend
456 when soil and climate input data are simultaneously aggregated to the coarser resolutions
457 regardless of the region (Fig. 13: panels $S_{y \times C_z}$). The increase of rAAD is less pronounced in
458 winter wheat simulations, when only climate or soil input is aggregated except for climate
459 input aggregation combined with the dominant soil in Tuscany (Fig 13 TUS).

460 **[Figure 13 Here]**

461

462

463 **4 Discussion**

464 **4.1 Input data aggregation**

465 Crop model simulations depend highly on the availability and reliability of input data for soil
466 parameter and climate variables. As Ewert et al. (2015, 2011) already stated, the spatial
467 aggregation of input data from local to regional scale reduces the variability of these data.
468 Furthermore, the deformation of data for different climatic variables when aggregated from
469 higher resolution of 1 km to coarser resolution of 10 km, 25 km, 50 km and 100 km is
470 evaluated in Hoffmann et al. (2017), indicating that the spatial variability of climatic variables
471 decreases due to data aggregation (1 to 100 km) with similar mean values (Hoffmann et al.,
472 2015). For example, in the mountainous North-Western part of Tuscany, the low values for
473 daily minimum temperature detectable at 1 km resolution are averaged out at coarser
474 resolutions of 100 km (Fig. 4). The same applies to the higher temperatures at 1 km resolution
475 at the southern edge of the region (Fig. 4). This means that the aggregation of data in
476 heterogeneous areas has stronger impacts on the extreme than on the mean values. The same

477 feature of a loss of extreme values has been also reported for temporal aggregation of climatic
478 data by (Weihermuller et al., 2011).

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

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

492 Point 1 to 3 has been already reported for NRW by Hoffmann et al. (2017) but due to the
493 limitation of the study to one region no generalization could be made. By analyzing the
494 aggregation effect for two contrasting regions (NRW and Tuscany) it becomes more evident,
495 that soil aggregation has a stronger impact compared to the aggregation of climatic data, for
496 these areas and environmental conditions simulated. The impact of climatic data aggregation
497 on simulated crop yield has been studied by Zhao et al. (2015b) who related the spatial
498 variability of climatic data on high resolution to topographic features (mainly elevation) in the
499 landscape. Hereby, they found that flat and more homogeneous areas can be aggregated to
500 coarser resolution without increasing the aggregation error, while more heterogeneous

501 landscapes react differently with much larger aggregation errors. The aggregation effect of
502 climate data for winter wheat for a Scandinavian region in Finland was also evaluated by
503 Angulo et al, (2013), who stated that simulated yield distributions are similar and independent
504 of the resolution of the climate input data. As both regions analyzed in our study are rather
505 heterogeneous in terms of elevation and climate, an effect of the aggregation of climate data
506 on the simulated yields is expected.

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

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

531 **4.2 Aggregation error on crop yield simulations**

532 *4.2.1 Winter wheats*

533 The aggregation effect of climate data (Angulo et al., 2013) was evaluated for winter wheat
534 for a Scandinavian region in Finland. The aggregation effect of soil data (Angulo et al., 2014)
535 on crop yield simulation of winter wheat was evaluated for a region with a temperate climate
536 in Germany. Angulo et al. (2014) used the frequency distribution of crop yields as a
537 characteristic finger print to compare the effect of input data aggregation between crop
538 models and input data resolutions. They found that finger prints were similar for the different
539 resolutions of climate input data while they varied across the different models applied. In line
540 with these results, the yield distribution of winter wheat in NRW did not differ much between
541 different resolutions of climate input, however, in Tuscany, the range of the frequency
542 distribution and the mean percentage of absolute yield difference increased with decreasing
543 resolution of climate input data (Fig. 12B, climate aggregation panel). Aggregating soil types
544 at 1 km² resolution to the dominant soil in a coarser grid cell without aggregating the climate
545 variables, tends to cause a positive bias in wheat yields in both regions (Figure 11A and B,
546 row 2). This indicates that in both regions the more productive soils for winter wheat were
547 dominant in most of the grid cells in the different resolutions. However, there were two
548 instances where the positive wheat yield bias decreased when changing from the 10 km
549 resolution ($S_{10} \times C_z$) to the 25 km resolution ($S_{25} \times C_z$) in both regions. Additionally, the
550 combination of dominant soil at regional level with aggregated climate for both regions
551 showed positive yield bias for winter wheat simulation. This indicates the characteristics of

552 aggregated soil at regional level is highly productive and simulate positive yield bias. If the
553 aggregated soil at regional level would have been selected with less productive soil, there is
554 also chance of simulating negative yield bias. However, the study is majorly focuses on
555 quantifying the absolute yield difference as indicator of aggregation error rather than yield
556 bias at different soil and climate resolution.

557

558 In NRW, the range and the mean of the percentage absolute yield difference increased when
559 both soil and climate input data were aggregated while in Tuscany only the mean of
560 percentage absolute yield difference increased but not the range. For winter wheat, the
561 aggregation effect on the ensemble yield due to aggregated climate data (1 to 100 km),
562 quantified as relative average absolute deviation (rAAD), was maximum up to 10 % (Zhao et
563 al., 2015a) with mean of 3-5 % for NRW while we have found maximum rAAD of 38% and
564 50% for NRW and Tuscany respectively and around 15% for the ensemble mean in both
565 regions (Fig. 13). These values did not change when combinations of aggregated soil and
566 climate data were used in the ensemble simulations. Thus, for winter wheat, the average error
567 of climate data aggregation combined with regional soil type over the model ensemble is
568 between 10 and 15 % in both regions. However, the uncertainties in the aggregation error for
569 winter wheat yields are higher in Tuscany as shown in the wider range of the mean absolute
570 yield difference and the relative rAAD in Tuscany (Fig. 12 and 13). Thus, the uncertainty in
571 the aggregation effect for the winter crop in the temperate regions due to input data
572 aggregation (irrespective of climate or soil data) is lower compared to the Mediterranean
573 region probably due to the, on average, positive climatic water balance and the higher water
574 holding capacity (Hoffmann et al., 2015).

575 With respect to the differences in aggregation error for simulated wheat yields between the
576 single models, there is no evident consistency in the obtained results, except that the EPIC

577 model could be classified as more sensitive to soil and climate data aggregation, having both
578 in Tuscany and NRW relative rAADs above the ensemble mean, whereas the STICS model
579 belongs to the less sensitive models with relative rAADs close to the ensemble mean. This
580 may be due to differences in reference evapotranspiration (Penman-Monteith against
581 Priestley- Taylor) and in approaches to calculate light absorption (one leaf versus multi-layer
582 approach) (Brisson et al., 1998).

583 4.2.2 *Silage maize*

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

590 The combined aggregation of soil and climate input data caused an increase in median and
591 average relative yield difference of silage maize with decreasing resolution (Fig. 9). This has
592 been already shown by Hoffman et al. (2016) for NRW. However, in contrast, to the winter
593 crop (wheat), the range and mean relative yield differences due to climate and soil input data
594 aggregation for silage maize was much higher in Tuscany compared to NRW. This
595 observation was also made when only climate input data were aggregated. Thus, irrespective
596 of the kind of input data aggregated, simulated maize yields in the Mediterranean region
597 showed higher relative yield differences compared to the temperate region already at
598 resolutions of 10 km. At a resolution of 100 km, the relative yield differences were higher by
599 a factor of up to 3 compared to the temperate region when both soil and climate data were
600 aggregated (Fig. 9). This has been corroborated by the results published by Folberth et al.
601 (2014) for the US and could be explained by the difference in climate conditions between the

602 temperate and Mediterranean site, which is higher during the vegetation period of the spring
603 crops compared to the winter crop (Table 5). The average precipitation in Tuscany and NRW
604 during the growing period of silage maize is around 350 mm in both regions, whereas the
605 mean temperature is much lower in the temperate region (15.7 and 21.7 °C in NRW and
606 Tuscany respectively). Thus, warmer and drier conditions during the growing period tend to
607 translate into higher aggregation errors in regional crop simulations. These results are
608 confirmed by the higher relative rAAD of ensemble yields of maize compared to winter wheat
609 in both regions (Fig. 10 and 13). With respect to maize yields, relative rAAD in Tuscany
610 increases stronger compared to NRW when the resolution of input data is decreasing (Fig.
611 10). In both regions, the increase in relative rAAD from fine to coarse resolution is strongest
612 when aggregation of climate data is combined with aggregation of soil input data and can
613 reach an average relative rAAD of the ensemble mean of 25%. Extreme model-dependent
614 relative rAAD for maize yields can reach 58% in Tuscany compared 38% in NRW. In the
615 case of the spring crop (maize), the aggregation error of the ensemble mean reaches already
616 20% when a resolution of 10 km for the soil or climate data is used, whereas in NRW such
617 high aggregation errors are never reached with simulated maize yields regardless of the spatial
618 resolution of soil and climate data. These results suggest that reliable regional simulation of
619 spring crop yield in Mediterranean climate conditions requires high spatial resolution of both
620 soil and climate data.

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

628 **4.3 Hotspots of aggregation errors**

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

654 differences because small hilly areas with higher precipitation are averaged out, leading to on
655 average lower precipitation at coarser resolutions.

656 **4.4 Influence of the range in altitude on the magnitude of aggregation errors**

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

667 **5 Conclusion**

668 The aggregation effects of soil and climate data on crop yield simulations in the
669 Mediterranean region are higher than in the temperate region for both winter wheat and silage
670 maize. However, the differences between the Mediterranean and the temperate region are
671 stronger in the case of the spring crop (silage maize). The magnitude of the aggregation effect
672 in Tuscany for silage maize expressed as the percentage absolute yield difference is on
673 average 30% compared to an average of 10 % for winter wheat. Because of the higher
674 aggregation effect on crop yield simulation in the Mediterranean region, it is important in
675 these regions to use input data at a finer resolution for reliable estimation of regional crop
676 yield. Moreover, in each region, there are hot spots with extremely high positive or negative
677 yield differences due to input data aggregation. In these hot spots, a finer resolution of climate
678 and in particular soil information is important to reduce errors in crop yield simulations. For

679 generalization of these outcomes, further investigations in other sub-humid or semi-arid
680 regions will be necessary.

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821 **List of table captions**

822 **Table 1. Main climatic variables for the time period 1995 to 2011 for NRW and TUS. Mean is**
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833 **resolutions.**

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835 **Table 1. Main climatic variables for the time period 1995 to 2011 for NRW and TUS. Mean is**
836 **the arithmetic mean, STD is the standard deviation, and 25, 50, 75 % are the respective**
837 **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

838 *TempMin: Minimum Temperature, TempMean: Mean Temperature, TempMax: Maximum
839 Temperature, ET₀: Reference Evapotranspiration (calculated by using ET₀ equation in FAO 56) , cwb:
840 Climate water balance (ET₀ – Precipitation) and others are as indicated

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

NRW	Number of pixels	mean	std	min	25%	50%	75%	max
Depth [m]		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]	34168	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]		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]	22933	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

847

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

850

Climate variable	Summary statistics for climate variables during maize growing season							
NRW	Mean	STD	Minimum	25 %	50 %	75 %	Maximum	
TempMin (°C)	10.6	0.6	9.5	10.3	10.6	11.0	11.6	
TempMean (°C)	15.7	0.6	14.2	15.3	15.7	15.9	17.2	
TempMax (°C)	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 (°C)	13.1	0.6	12.1	12.6	13.1	13.4	14.4
TempMean (°C)	21.7	0.8	20.4	21.1	21.5	22.1	23.6
TempMax (°C)	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 (°C)	4.4	0.9	2.8	3.9	4.3	5.1	6.3
TempMean (°C)	8.2	0.9	6.5	7.8	8.2	8.6	10.3
TempMax (°C)	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 (°C)	5.7	0.7	4.2	5.3	5.9	6.1	7.3
TempMean (°C)	12.5	0.8	10.6	11.9	12.6	12.8	14.2
TempMax (°C)	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

851 *TempMin: Minimum Temperature, TempMean: Mean Temperature, TempMax: Maximum Temperature, ET₀: Reference

852 Evapotranspiration, cwb: Climate water balance (ET₀ – Precipitation) and others are as indicated

853 **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)

854 ^a only simulated wheat; ^b simulated NRW only

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

Management	Winter wheat	Silage maize	Unit
Residues	cut and incorporated into soil plough in late summer/beginning of autumn (harrowing in the plains)	Cut and incorporated into soil plough in late summer/beginning of autumn (ripping in the plains)	-
Tillage			
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

856

857 **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

858

859 **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 xC _z	soil and climate aggregation
S _{Reg}	z	S _{Reg} xC _z	One dominant regional soil with

climate aggregation
soil aggregation with average regional
climate

y

C_{Reg}

$S_{y \times C_{Reg}}$

860
861
862

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

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

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

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

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

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

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

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

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

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

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

896 **Figure 11.** Average yield difference between coarser resolutions ($S_{y \times C_z}$) and the reference resolution
897 ($S_{1 \times C_1}$) for winter wheat for NRW (A) and winter wheat for Tuscany (B). AMD is the average yield
898 difference

899 **Figure 12.** Percentage absolute yield differences of winter wheat between coarser resolutions ($S_{y \times C_z}$) and
900 the reference resolution ($S_{1 \times C_1}$) for NRW and Tuscany. The violin plots show in the x-dimension the
901 distribution of the probability density of the percentage absolute yield difference values. The box plots
902 show the median (red line), mean (black star), and the upper and lower quartiles (box) and the extreme
903 upper and lower values (black lines)

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