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Evaluation of crop yield simulations of an eco-hydrological model at different scales for Germany

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Abstract

A prerequisite for integrated crop model applications is the evaluation at the desired spatial and temporal scale. Here, we analysed the eco-hydrological model SWIM simulating crop yields. Historic simulations for winter wheat and silage maize from 1991-2010 were used to examine the model performance at the county level in reproducing the county statistics for crop yields. The focus laid on the replication of mean yield levels and interannual crop yield variability. Simulations of silage maize performed better than simulations of winter wheat with R^2-values for interannual yield variability of 0.72 and 0.26 respectively at the national level. In particular, silage maize showed a tendency to perform better in areas of lower soil water availability. The reasons for the clear superiority of silage maize were supposedly the short growing season, the lower susceptibility to pests and diseases and, hence, the direct translation of water stress into yield reductions. This signal was less evident for winter wheat and was additionally superposed of climate induced biotic and abiotic stresses – primarily originating in the cold season - which were not implemented in the model. Overall, the simulation bias seemed to originate rather from unconsidered processes than from uncertainties of input data or in model parameterisation.

Key words

SWIM, EPIC, eco-hydrological modelling, regional crop modelling, silage maize, winter wheat, Germany

1. Introduction

High-yielding high-input systems (e.g. Germany) were identified as regions where weather variability has a relatively high explanatory power for yield volatility (Reidsma and Ewert, 2008; Ray et al., 2015; Conradt et al., 2016). To understand and assess the complex interactions between biophysical and human induced crop growth factors or to predict the response of crop growth to climate change, mechanistic crop models are employed which are run independently or embedded in more complex modelling frameworks such as eco hydrological models (e.g. SWIM, Krysanova et al. (1998)) or integrated assessment models (Ewert et al., 2015).

Originally, such crop models had been developed for plot scale applications assuming homogeneous environmental conditions (Hansen and Jones, 2000; van Ittersum et al., 2003; Challinor et al., 2009). However, the application spectrum of crop models has expanded substantially ever since (Ewert et al., 2015), accompanied by the increased computational capacities. Crop models are now employed at all scales, at the field and farm level, at regional, national and global scale (Tan and Shibasaki, 2003; Stehfest et al., 2007; Srinivasan et al., 2010; Balkovič et al., 2013; Nendel et al., 2013; Rosenzweig et al., 2014; Hoffmann et al., 2015; Zhao et al., 2015b; Soltani et al., 2016; Müller et al., 2017). Crop model estimations are used as inputs to economic agricultural models (Adams et al., 1990; Bowes and Crosson, 1993; Rosenzweig and Parry, 1994; Parry et al., 2005; Rosenzweig et al., 2013), form an integral part of Integrated Assessment Models (Ewert et al., 2015) and support decision makers who require crop simulations at the regional scale (Hansen and Jones, 2000; Priya and Shibasaki, 2001; Rötter et al., 2011) to design spatially explicit integrated policies (Ewert et al., 2011; Ewert et al., 2015). Nevertheless, despite this wide application range, plot scale crop models still form the basis of all simulation exercises (Dhakhwa et al., 1997; Izaurralde et al., 1999; Saarikko, 2000; Priya and Shibasaki, 2001; Tan and Shibasaki, 2003; Parry et al., 2005; Liu et al., 2007). A major challenge is ensuring the representativeness of plot scale results for larger regions either by the extrapolation and upscaling of parameters and model assumptions (Müller et al., 2017) or the aggregation of input data (Hansen and Jones, 2000; Hoffmann et al., 2015; Zhao et al., 2015a; Zhao et al., 2015b). “Gridded” model applications run crop models at a defined raster of points for which input data are provided (Hoffmann et al., 2015; Müller et al., 2017). These rasters usually reflect data availability rather than the actual mosaic landscape heterogeneity. Moreover, the lateral hydrological fluxes of surface and subsurface runoff which form an integrative ecosystem component and impact on the soil water availability of the vegetation are missed out. Eco-hydrological models are designed to overcome this deficit. They integrate regional scale water processes with soil characteristics and plant dynamics at the catchment scale.

The integration of crop simulation approaches into hydrological models has frequently been reported (Arnold et al., 1998; Krysanova et al., 1998; Klocking et al., 2003; Liu et al., 2009; Albano et al., 2017). However, only a few studies have addressed multi-criteria model evaluation, and simultaneously addressed crop yields and hydrological aspects (Krysanova et al., 1999; Huang et al., 2006; Luo et al., 2008; Srinivasan et al., 2010). Vegetation dynamics induce an essential feedback-mechanism for hydrological fluxes in terms of root water uptake and subsequent transpiration. And although the overarching importance of vegetation dynamics on water circulation (modelling) has widely been recognised (Chen, 2015) the multiple range of evaluation criteria of eco-hydrological models have not been exploited yet. An explicit evaluation of crop yield dynamics adds an extra dimension of evaluation aspects to constrain overall model performance. However, in respect to the fundamental importance of vegetation dynamics for evapotranspiration and the latter being one of the most uncertain factors in spatial hydrological modelling (Conradt et al., 2012) and crop modelling (Cammarano et al., 2016), the explicit evaluation of the performance of vegetation dynamics within hydrological models has been widely neglected.

In this study, we used a simplified version of the well-established crop modelling approach of the Erosion Productivity Impact Calculator (EPIC) (Williams et al., 1989) embedded in the spatially explicit Soil Water Integrated Model (SWIM) (Krysanova et al., 1998) to simulate regional crop yields for Germany. In contrast to other crop modelling studies, we use a model here that was pre-calibrated and evaluated at hydrological gauge stations for all main catchments of Germany (Huang et al., 2010). By using a hydrologically calibrated model, the degrees of freedom for additional parameter changes are restricted to those with minor effects on hydrological processes.

We explored simulated inter-annual yield fluctuations for the 20-year period of 1991 to 2010 for a representative winter crop, namely winter wheat (WW) *Triticum aestivum L.*, and a representative summer crop, namely silage maize (SM), *Zea mays L.*. WW and SM are the main winter and summer crops grown in Germany in terms of area coverage and gross yields (Statistisches Bundesamt, 2012). We deliberately chose two crops with different growing seasons also to rationalise model performance based on the comparison between the respective simulations.

Just recently, several crop modelling studies for Germany were published (Nendel et al., 2013; Kersebaum and Nendel, 2014; Hoffmann et al., 2015; Zhao et al., 2015b; Soltani et al., 2016). These studies presented the evaluation of interannual yield variability simulations as a precondition for the assessment of, e.g., scaling issues, but, apart from Nendel et al. (2013), omitted a thorough discussion on the performance of the applied crop models at the regional scale.

Previous studies with SWIM have only peripherally addressed the performance of integrated vegetation dynamics at the regional scale and only for selected regions (Krysanova et al., 1998; Krysanova et al., 1999). Post (2006) evaluated the yield simulations of SWIM at three long-term sites in Germany. Mean yields were met quite satisfactorily but the simulation of a winter wheat long-term trial (1954 – 2002) revealed problems matching interannual yield variability. A number of studies used various versions of EPIC around the globe simulating mean yields and year-to-year yield variability of different crops (Kiniry et al., 1990; Rosenberg et al., 1992; Moulin and Beckie, 1993; Easterling et al., 1996; Roloff et al., 1998; Brown and Rosenberg, 1999; Izaurralde et al., 1999; Huang et al., 2006; Luo et al., 2008; Srinivasan et al., 2010). Overall, these studies agreed that EPIC is well suited to simulate mean crop yields, however, it has difficulties in replicating interannual yield variability.

The aim of our study is to provide a comprehensive and transparent evaluation of crop yield simulations for the whole territory of Germany within the framework of an eco-hydrological model, thereby establishing a reference for modelling efforts to consider crop yields and water household at the water shed scale under German conditions (food-water-nexus).

2. Data and Methods

2.1 The eco-hydrological model SWIM

SWIM is a process-based, time continuous, semi-distributed watershed model which describes the impact of land use and land management on hydrological fluxes at the landscape scale in conjunction with plant growth dynamics and soil organic carbon and nitrogen turnover. It can be regarded as robust and well evaluated for hydrological conditions of German river-catchments (Krysanova et al., 1998; Krysanova et al., 1999; Hattermann et al., 2005a; Hattermann et al., 2005b; Huang et al., 2010). SWIM integrates the heterogeneous landscape by simulating homogeneous landscape units (i.e. hydrotops) of up to several hectare sizes at which site-scale crop growth processes and yields are simulated.

2.2 The plant growth module of SWIM

The plant growth module of SWIM is essentially based on the EPIC crop model (Williams et al., 1984), similar to SWAT (Arnold et al., 1998). The main features are the description of potential plant biomass growth using the Beer's law equation (Monsi and Saeki, 1953) in conjunction with Monteith's approach (Monteith, 1977) of photosynthetic active radiation and plant specific biomass-energy conversion factors. Plant water uptake (and evaporation) is driven by the potential atmospheric demand (Ritchie, 1972). This was calculated by the Turc/Ivanov approach which was adapted for Germany following DVWK (1996) with the monthly adjustments suggested by Glugla and König (1989) and land use adjustment factors taken from ATV-DVWK (2002). Potential transpiration rates depend on the LAI and the overall atmospheric demand while actual soil water supply in the active rooting zone determines and limits actual transpiration. Daily potential biomass growth and LAI development are limited by factoring in the minimum stress factor (ranging from zero to one with one expressing no stress) of water and temperature. Water stress is the proportion of potential atmospheric demand and actual plant-available water in the rooting zone. The temperature stress factor is a function of the crop specific base and optimum temperature, and daily mean temperature

(Krysanova et al., 1998). It approaches one at optimum temperature and decreases rapidly above this temperature. Yield is the product of aboveground biomass and a plant specific harvest index.

In contrast to previous SWIM applications, we slightly modified the standard crop growth calculations as described by Krysanova et al. (1998) by (i) introducing hydrotop-specific dynamic harvest dates, (ii) including a modification factor for potential plant biomass increase depending on day length and (iii) coupling phenology dynamics, i.e. leaf-area-index (LAI) with the biomass development via the plant specific leaf area and the respective biomass allocation fraction into leaves (for more details refer to S1).

2.3 Input data

The general soil map of Germany "BÜK 1000" with a resolution of 1:1 000 000 (Hartwich et al., 1995), the digital elevation model provided by the NASA Shuttle Radar Topography Mission (SRTM), the CORINE 2000 land cover map (CEC, 1995; Bossard et al., 2000), and the standard subbasin map of the Federal Environmental Agency (Umweltbundesamt) were used as spatial input data. Daily weather data for each subbasin were generated from the climate and precipitation station network of the National Meteorological Service of Germany (DWD). For more details on the input data set, hydrological model calibration and evaluation procedures, we refer to Huang et al. (2010).

Some of the "BÜK 1000" soil types were adjusted for plant-available water. Previous studies with SWIM (not shown here) have shown that yield overestimations in the federal state of Brandenburg were related to overestimations of plant-available water (soil parameter). According to a region-specific soil characterisation of typical central eastern soil types (MLUR, 2013) respective "BÜK 1000"-soils overestimate plant-available water. We thus lowered this parameter for respective soil types. This adjustment was applied uniformly across all catchments (see S0).

2.4 SWIM-crop-simulations

The model was applied at the five main river basins of Germany (Elbe, Danube, Rhine, Weser, Ems) plus bordering catchments of Maas, Oder and the coast of the North and Baltic Sea (Fig.1). Crop yield simulations were carried out for the historical period of 1991 to 2010. SWIM simulated mono-cultures, i.e. one model run assumed one crop type across the whole cropland area continuously in time. Between harvests and the next sowing a standard cover crop was planted. We did not distinguish region specific crop cultivars, so only one set of crop parameters of WW and SM was used (Tab. 1). Mean sowing and harvest dates for WW and SM were delineated from the phenology data base of the German Weather Service (DWD, 2017) (for data processing details see S2). Aggregated at county level over 20 years (1991-2010) and across all counties, the mean sowing data for WW and SM was 10th October and 28th April with a standard deviation of +/-5 and +/-2 days respectively. The growth routines of EPIC require the estimation of potential heat units (PHUs; °C) accumulated by a crop from sowing to maturity. They were calculated based on the crop specific base temperature, the mean sowing and harvest dates and mean daily temperature of Germany from 1990-2010 and adjusted for day length (see 1.1.2 in S1). Optimum nutrient supply was assumed. This is a common assumption in crop modelling studies (Brown and Rosenberg, 1999; Izaurralde et al., 1999; Luo et al., 2008; Zhao et al., 2015b; Soltani et al., 2016) and justified for a high yielding cropping area such as Germany. German farmers usually apply fertilisers according to crop demand (Boogaard et al., 2013; Conradt et al., 2016), and Balkovič et al. (2013) identified Germany as a region with almost no N stress.

Management operations such as plant protection measures, plant growth enhancement treatments, soil management, or carry-over effects of crop rotations were not included in the simulations. This was justified since Reidsma and Ewert (2008) identified Germany as a region in which impacts of climate factors on crop yields dominate over management effects (in contrast to other regions in Europe). This is further supported by the study of Conradt et al. (2016) who used different statistical modelling approaches to replicate interannual yield variability across Germany. Yield variability was best explained by climatic explanatory variables and could not be improved by the inclusion of non-climatic variables.

Tab. 1 Key crop parameters. * In case temperature sums are not accumulated over the growing season and thus the dynamic harvest date is not reached SM and WW were harvested at these fixed dates.

2.5 Yield data

Yield data at county level (NUTS3) were collected using reports from the various statistical authorities of the federal states of Germany (Lüttger, A., pers. comm.). The yield statistics generally result from a Germany-wide applied uniform sampling procedure. At the basic level, yields are surveyed from randomly selected fields. In the second step, these basic yields are area-weighted and directly up-scaled to the federal country and the national level. County level yields are derived only in a subsequent third step from the federal country yields by multiplying their value with a county-specific factor resulting from a separate yield reporting (pers. comm., Troegel, T., Statistics Office Berlin-Brandenburg, 2017).

All original yield data are reported in reference to fresh matter. We converted these values from fresh to dry matter (DM) yields using conversion factors of 0.86 and 0.35 for WW grain yield and SM aboveground biomass, respectively (per. comm., Kurz, R., Statistics Office Berlin-Brandenburg, 2011).

Nendel et al. (2013) and Hoffmann et al. (2015) discuss the necessary caution when statistical yield data are used as described. Nevertheless, these data are currently the best available quantitative information on yields at the county, federal state and national scale.

2.6 Evaluation of yield simulations

The performance of yield simulations was assessed in respect of their means and their interannual variability. van Ittersum et al. (2013) recommended a period of at least 15 years to capture the interannual water-limited yield variability, and 10 years for capturing observed yields in high-yielding environments. We regarded statistical measures of yield time series to be robust when they were calculated for a time span of 20 years. We used time series of observed years for the period 1991-2010 reported for German counties and carried out simulations for the same period addressing the same scale. Counties in which the cropland area was less than 10% of the total county area were excluded. This left 264 out of 402 (status 2011) counties in total for the analyses.

Simulated and reported yields were evaluated at the county, basin, federal state and national scale (by cropping area-weight averaging. Equivalent averages from the statistical data for the basin and county level data were area-weighted according to the area of simulated cropland within the part of the counties which overlap with the catchment area.

Fig. 1)in respect of their temporal means and their interannual variability. The interannual variability was analysed using the first-differences approach. It minimises the effect of systematic trends in time series such as slowly changing crop management (Lobell and Field, 2007).

Simulated yields at hydrotop level were aggregated to the county, basin, federal state and national level by cropping area-weight averaging. Equivalent averages from the statistical data for the basin and county level data were area-weighted according to the area of simulated cropland within the part of the counties which overlap with the catchment area.

Fig. 1 Map of spatial aggregation levels

The analysis was limited to yields on soil types suitable for WW and SM cropping. This information was delineated from the soil quality map for Germany (Müller et al., 2007). For WW and SM, only soils with soil quality rating scores of above 50 and 20 respectively qualified for analysis.

Since observed mean yields at county level reflect an unknown distribution of cropping areas and respective simulated values are based on a static selection of hydrotops limited to distinct soil quality levels, we calculated the difference between simulated and statistical cropping areas and tested for the explanatory power of such spatial differences for mean yields and interannual variability of yields. Results were further evaluated for their sensitivity to soil parameters and their spatial distribution, and to terrain altitude and heterogeneity.

2.7 Statistical measures and software

The systematic bias was accessed using the relative error E (Addiscott and Whitmore, 1987; Smith et al., 1996). Positive values of E denote that the model tends to underestimate mean yields while negative values denote a systematic overestimation of mean yield simulations. We also used the relative root mean square error (rRMSE) as a measure of coincidence. It indicates the mean deviation of the simulated data from the statistical data relative to the statistical data and is given in %.

The association between simulated and statistical yearly yield fluctuations was quantified using the the coefficient of determination R^2. R^2 quantifies how much of the variability in the statistical data is described by the model.

All statistical analyses were carried out with R using the standard “stats” package (R Core Team, 2016).

3. Results

3.1 Mean patterns at county level

The mean statistical WW yields increased from lowest values (<5 t ha^{-1}) in the central eastern part to highest levels in the north-western edge (up to >8 t ha^{-1}) of Germany. The central western area and the south part of Germany were characterised by medium to high yields (6-8 t ha^{-1}) (Fig. 2a). The simulated WW yields revealed a similar pattern with a tendency to underestimate yields in the north-western part and to overestimate yields towards the mountainous regions in the east and south (Fig. 2b & c).

Fig. 2 Comparison of statistical and simulated mean winter wheat yields.

Statistical mean yields of SM were lowest (less than 14 t ha^{-1}) in the central eastern part of Germany similar to WW. From there, positive gradientsoccured towards the central west and the south reaching values of around 17 t ha^{-1} (Fig.3a). Simulated SM yields showed a similar pattern, with a tendency for overestimations at the coastal zones and some mountainous regions. Underestimations scattered in the middle of western Germany (Fig. 3 b & c).

Figure 3: Comparison of statistical and simulated mean silage maize yields.

The spatial pattern of under- and overestimation became more clear when we distinguished between counties where statistical mean yields fell within the range envelop of simulated minimum and maximum yields per county and those areas where statistical mean yields left that envelope (Fig. 4).

Out-of-the-envelope overestimations of WW occurred often in the mountainous regions of the south east, with no continuous pattern. Underestimations of WW are mainly located in the lowlands of north-western Germany. SM yields showed the same spatial pattern but with a much lower extend of over- and underestimations.

Figure 4 Consistency between observed county yields and simulated yields at the hydrotop level.

Statistical analysis corroborated the association of WW yield overestimations with higher altitudes. There was a strong negative correlation ($r= -0.7$, $p<=0.05$) between E and the mean altitude per county. In contrast, the rRMSE decreased with increasing altitude for SM resulting in a slight negative correlation between rRMSE and the mean county altitude (spearman's correlation: -0.23, $p<=0.05$).

Under- and overestimation were partly affected by the discrepancy between the mean total simulated area and the mean reported area use for WW and SM cropping in the counties.

The proportion of the actually cropped area covered by the simulations is shown in Fig. 5. The actual WW cropping amounted to less than 50% of the simulated while the actual cropping areas of SM often fell below 25% of the simulated area. The distribution of area discrepancies did not show a distinct pattern across Germany, neither for WW nor SM, such as altitude effects.

Fig. 5 Proportion of mean actual cropland to simulated cropland for WW and SM.

The difference between real and simulated crop coverage had no significant influence on the simulated mean WW yields. In contrast, the simulated mean SM yields decreased with the extent of the SM cropping area discrepancy (spearman's correlation: -0.28, $p<=0.05$).

In respect of the relative error, overestimations of WW and SM yields increased slightly with the increasing discrepancy in cropping area. This correlation was stronger for SM (-0.28, $p<=0.05$) than for WW (-0.13, $p>=0.05$).

Soil characteristics affected the mean yield levels and the bias of simulated yields. Correlations differed by soil depth. The soil water holding capacity (WHC) of the first two soil layers with a mean depth of 28 cm showed the highest positive impact on mean yields while the saturated conductivity (SC) of the third layer (ca. 28 – 52 cm) for WW, and the third and fourth layer (ca. 53 - 91 cm) for SM, showed the highest negative impact. Here, "negative" implied that with decreasing conductivity more water is actually stored in the soil and the two soil parameters complement each other in terms of total available soil water.

At county level, a negative correlation (-0.2, p<=0.05) between WW relative errors and the mean WHC values indicated a tendency to underestimate yields in counties with relatively drier soil conditions and to overestimate yields in counties with relatively wetter soil conditions. A slightly positive correlation (0.2, p<=0.05) between E and the absolute range of WHC showed a tendency to underestimate in counties where the variability of cropped soils is higher and to overestimate in counties where the variability of soils is lower. No correlations for the rRMSE were found.

For SM, deviations (rRMSE) decreased with increasing WHC at county level (-0.19, p<=0.05) and overestimations increased with the range of WHC (E~range WHC, -0.19,p<=0.05).

3.2 Interannual variability of crop yields

3.2.1 County level

Interannual yield variability (expressed as standard deviation from 1991-2010) of statistical yield for WW and SM increased with the extent of the cropping areas. It decreased with mean altitude or altitude's standard deviation which reflected the decreasing cropping area with higher altitudes.

The association between statistical and simulated relative interannual changes was quantified by the R^2 associated with their linear relationship. The spatial distribution of this correlation with the county as basic unit is shown for both crops in Fig. 6.

Fig. 6 R^2-values between simulated and statistical relative interannual yield changes for winter wheat and silage maize

The R^2-values of SM were generally higher than those of WW with no consistency between their spatial patterns. About 7% of the WW cropping area had R^2-values higher than 0.5 and ca. 52% of the WW cropping area had R^2-values lower than 0.25. The respective values for SM were 35% and 41%.

We tested the association between R^2-values and the discrepancy between observed and simulated cropping area, topographic characteristics and soil parameters.

There was no correlation between the R^2-values and the deviation between observed and simulated cropping area (-0.12, p>=0.05). The R^2-values for WW, but not for SM, were slightly negatively correlated with the mean county altitude (-0.13, p<=0.05) but not with the altitude's standard deviation (-0.1, p>=0.05), the latter a measure of relief energy.

The R^2-values showed low negative correlations with WHC (county mean of simulated hydrotops) of the first two layers for both crops (WW: -0.16, p<=0.05, SM: -0.24, p<=0.05), indicating a tendency to better associations at soils with lower water holding capacity and thus higher susceptibility to water stress. Furthermore, R^2-values were often better (WW: 0.25, p<=0.05, SM: 0.22, p<=0.05) in areas of higher soil variability, i.e. higher absolute range of WHC for WW and higher standard deviation of WHC for SM within a county.

Additionally, we tested for a relationship between R^2-values and the mean simulated yield level. For WW, there was only a very slight negative correlation of -0.14 (p<=0.05). SM showed a stronger negative correlation of -0.36 (p<=0.05). This indicated a better model performance at lower yield levels which again suggested that simulations results were better in areas of higher soil water restrictions.

3.2.2 At federal state and catchment level

The aggregation from smaller to larger spatial units was expected to increase statistical quality measures by levelling out random simulation errors. Table 2 presents the improvement of R^2-values from county to federal state, catchment and national level. The aggregation effect was larger for SM than WW and slightly larger for the aggregation at catchment level than at federal state level for both crops. The aggregation to the largest unit, i.e. national level, only showed an improvement for SM but not for WW.

Table 2: The aggregation effect expressed as the difference between the R^2-values between the area-weighted yields at the different aggregation levels (federal country, basin, state) and the arithmetic mean R^2-values averaged from the single R^2-values received for the individual counties within a spatial level.

Improvements of the two crops were spatially not consistent. At catchment level, WW mostly profited in the Ems catchment from the aggregation while SM showed the largest improvements in the Rhine, Elbe and Weser catchment. At federal state level, the association improved slightly in Lower Saxony for WW. Aggregated SM results improved most in North Rhine-Westphalia, Baden-Wuerttemberg, Hessen and Mecklenburg-Vorpommern.

Inspecting our results of interannual yield variability at catchment and federal state level graphically, (Figs. 7-10) we noticed that some years systematically appeared to show opposing trends. Most notably were the years 2007/2008 of the WW simulations. While statistical WW yields decreased in 2007 and increased in 2008, the opposite is true for simulated yields. This was not the case for SM simulations.

Figure 7 Simulated and statistical interannual variability of WW at catchment scale

Figure 8 Simulated and statistical interannual variability of WW at federal state scale

Figure 9 Simulated and statistical interannual variability of SM at catchment scale

Figure 10 Simulated and statistical interannual variability of SM at federal state scale

Statistical WW and SM yields showed opposing trends in 2007 and 2008 while model simulations of WW and SM yields exhibited similar trends. This led to the fact that SM simulations followed the interannual variability as opposed to the WW simulations.

4. Discussion

4.1 Mean yields

The model showed the capacity to reflect the spatial yield variability across the given range of soil and climate combinations with one set of parameters for each crop. At least for wheat, several European modelling studies also indicated that a homogeneous crop parameterisation was sufficient to capture the mean spatial yield pattern of WW across Germany (Therond et al., 2011; van Bussel et al., 2011; Angulo et al., 2013; Balkovič et al., 2013).

Sources of divergences, though, were manifold: simulated mean yields were calculated against the unknown number of actually cropped fields, yield relevant factors might not have been sufficiently included, the spatial heterogeneity of climate and soil conditions was not sufficiently represented to the model or translated by the model. Over- and underestimations of the mean yield level by the modelling approach used were the consequence.

Generally, overestimations can be explained by the negligence of stress factors other than water limitations, such as frost damage in winter, pests, diseases, weeds, extreme events or local nutrient stress. All of these possible yield reductions, either directly or indirectly climate related, were more likely to occur in mountainous regions where cropping areas are exposed to high relief changes and thus more extreme weather conditions, especially in winter. These circumstances probably explain the presented trend of yield overestimations, especially of WW, in higher altitudes. This is also consistent with the lower relevance of other growth factors than water stress for the crop yield of SM compared to WW (Roßberg, 2016).

Underestimations seemed to correlate with relatively lower WHCs for both crops, overestimations vice versa respectively. The model might have underestimated the soil water budget. One clustered area of underestimations in the north-western centre lied within the Weser catchment. While WHC values for the first 28 cm were above 60%, saturated conductivity of the third layer was relatively high (up to 145 mm h^{-1}), which caused fast soil water drainage. Additionally, during the calibration process of the hydrological fluxes for the Weser, SC values were universally calibrated fourfold higher than the values given in the "BÜK 1000". This might explain the underestimations of yields in the Weser catchment by routing the water too quickly out of the landscape into the rivers. It also indicated a trade-off between optimum parameter settings of hydrological fluxes on the one hand and plant growth processes on the other. It definitely highlighted the importance of soil parameterisation for the quality of crop model results.

The importance of reliable soil parameters was also shown in the crop modelling study by Nendel et al. (2013) in which the accuracy of mean WW yield predictions by the agro-ecosystem model MONICA (Nendel et al., 2011) for the federal state of Thuringia (Germany) improved more using additional soil information than higher resolution climate data. Zhao et al. (2015b) generally overestimated WW yield levels for Germany (Fig.4b & c in Zhao et al. (2015b)). Noticeably, their single soil parameter of plant available water was set to 21% which is similar to the value which we had found to be too high for some light soils in the eastern and northern part of Germany (see 2.3).

In addition to the biophysical factors that cause over- and underestimations, there are others that can lead to miss-estimations towards both sides of the tolerance envelope.

The share of different hydrotops assumed for the calculation of county yields was uncertain and might have created local under- and overestimation. A more guided selection of hydrotops could probably decrease this deviation

Similarly, the resolution of climate data can create biases in crop yield simulations. Zhao et al. (2015a) showed that the influence of the climate input data resolution on the quality of yield simulations depended highly on the heterogeneity of the terrain. A heterogeneous landscape required higher resolution input data to reflect yield differences. The density of German weather stations generally increases in the western and southern parts of Germany (Fig. 2 of Huang et al. (2010)) which seems to reflect the more heterogeneous terrain compared to the northern lowlands. However, the resolution might not be sufficient for the simulation of crop yields to match observed yields in mountainous regions.

Some of the mountainous regions are also border regions of Germany (Huang et al., 2010). So, missing data from outside Germany might lead to an interpolation error that can be confused with other errors specific for the mountain regions.

Noteably, the replication of mean yields was generally better for SM than WW across all Germany. The differences between the two crops in respect to the main drivers of the simulations were the different lengths of the growing seasons, different soil coverage and different crop parameter settings. In reality, the difference in their photosynthetic pathways as C3- and C4-plants constitutes an additional factor which could explain model discrepancy because this is considered only very simplistically in the model by different biomass-energy ratios.

The relatively short growing season of SM significantly reduces the complex impact of growth drivers in conjunction with a lower susceptibility of SM to diseases. WW also possess a range of compensation mechanism which are not implemented in the model, neither are growth reducing pests and diseases. The more robust nature of SM was also reflected in its lower sensitivity to soil quality changes. It can be cropped on marginal lands because of its higher water use efficiency (Sadras et al., 2007) as long as this efficiency advantage is not compensated by too densely planted SM. This would make SM populations more susceptible to water scarcity due to a high transpiration demand on relatively lower quality soils. Taking all these aspects together, mechanistic EPIC-type crop models might be still better suited to simulate SM growth and development than WW.

4.2 *Interannual variability of crop yields*

The modelling framework (input data, parameterisation, process resolution) generally better captured the SM than the WW interannual yield variability in conjunction with a trend to perform better in areas with lower plant available water in terms of soil parameterisation.

The advantage of SM simulations can be attributed to the direct effect of weather patterns on plant growth of SM than WW due to the shorter growing season and less mechanism for compensation during the growth period. The current model structure seemed to be better suited for SM than for WW in this respect.

Technically, the simulations of both crops only differed in their individual crop parameter settings, soil coverage and the extend of growing season but not in process resolution. The model does not distinguish between C3 and C4 plant physiology and their different responses to drought stress. Maize has recently been shown to be more sensitive to drought stress than wheat (Daryanto et al., 2016; Fahad et al., 2017). Since model results, especially SM results, were better in areas with relatively lower soil water availability we hypothesise that the response to water stress is the decisive factor for SM yield variability and is reflected realistically by the model – not least due to its simple causal relationship and the absence of other growth reducing factors. Additionally, dense cropping of SM on marginal land might produce a stronger response to drought due to a higher absolute water demand per unit area than WW.

The better modelling performance for SM could again be explained also by a relatively lower pest and disease susceptibility indicated by the generally lower plant protection treatment intensity of SM than of WW (Roßberg, 2016). WW growth has a higher dependency on indirect, weather induced biotic stresses which are not implemented in the model. For example, Jahn et al. (2012) reported mean yield losses of WW due to the main fungal diseases in Germany of up to 0.7 t ha^{-1} with a high interannual and spatial variability. WW plants are exposed to the cold winter season and transition seasons which prolongs the time of potential stress impacts relative to SM. Bare frost damage for example can have wide spread impacts on plant development (e.g. Landwirtschaftskammer Niedersachsen, 2007, Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie, 2009) and influence regional-scale yield fluctuations but are not implemented in the growth module employed here.

In some years, the discrepancies between simulated and reported years between WW and SM were particularly peculiar as for example in 2007 and 2008. In both years the simulations indicated opposite interannual changes compared to the statistical yields for wheat, but not for maize. This could be the impact of a widespread outbreak of the yellow barley dwarf virus during the relatively warm and wet spring 2007 (Amann and Ott, 2007) which was frequently reported in agricultural news reports across Germany and might have affected the health of young wheat plants as well. However, the given weather conditions were interpreted by the model as optimal growing conditions for WW without water or temperature stress and thus led to higher yields. On the contrary, in 2008 temperatures were lower compared to 2007 and the WW model simulated lower yields accordingly (water stress is not apparent in both years). In reality, lower temperatures reduced the risk of the outbreak of crop diseases and provide better crop growth conditions than warm plus wet conditions.

Better predictions of yield variability in areas with lower soil water holding capacities could indicate an overriding effect of limited water supply on plant development over other growth determining factors. In areas of higher water supply, a conglomerate of indirect climate-induced stress factors or management interventions tune the interannual yield changes but cannot be disentangled by SWIM.

An additional source of uncertainty is induced by the model parameters describing crop growth. On the one hand, there is the intrinsic uncertainty of the real value of a crop parameter, for example the biomass-energy ratio. On the other hand, there is the uncertainty due to regional differences of crop varieties such as PHUs, sowing and harvest dates. In some of our preliminary simulations, we analysed the impact of county-scale adjusted crop biomass-energy ratios and PHUs. The impact on interannual yield predictions was negligible although they could be used to tune yield levels.

The difference between simulated and statistical cropping area had no explanatory power for the model accuracy of interannual yield variability. Conradt et al. (2016) as well showed that the actual cropping area of WW and SM in Germany had no explanatory weight for interannual yield volatility.

The aggregation to larger scales generally improved the R^2-values as expected. The improvement was noticeably larger for SM than WW. SM generally showed a more robust and spatially homogeneous pattern of interannual yield changes with random errors cancelling out at larger scale. This is also reflected by the highest improvements in the largest catchments. The course of WW yield changes, especially for the years 2007/2008, showed opposing trends among the simulations, i.e. counties, and did not cancel each other out via aggregation. This again indicated rather systematic than random simulation errors due to missing growth decisive processes.

5. Conclusions

Our main conclusion is the attribution of the systematic difference in the quality of simulations between a winter and a summer grown crop to the model's lack of sensitivity to some real crop growth limitations particularly during winter time. Missing crop growth response to biotic disturbances is a typical phenomenon of winter crop simulations and has been reported in other studies (Brown and Rosenberg, 1999; Izaurralde et al., 1999; Nendel et al., 2013). Simulations of silage maize clearly performed better than winter wheat. Additionally, silage maize showed a tendency to perform better in areas of lower soil water availability. In summary, the reasons for the clear superiority of silage maize simulations were the short growing season, the lower susceptibility to pests and diseases and, hence, the direct translation of water stress into yield reductions which also explained the better performance in drier areas. This signal was less pronounced for winter wheat and was additionally superposed with climate induced biotic and abiotic stresses – primarily originating in the cold season - which were not implemented in the model. Overall, modelling deficiencies seemed to originate rather in unconsidered processes than in uncertainties of input data and in model parameterisation.

We recommend a complementary study which quantifies the errors introduced by the missing plant growth processes, by the false estimation of cropping area of individual crops, and by the universal tuning of soil parameters on the hydrological fluxes to give a better estimate of the propagation of these uncertainties on hydrological model results.

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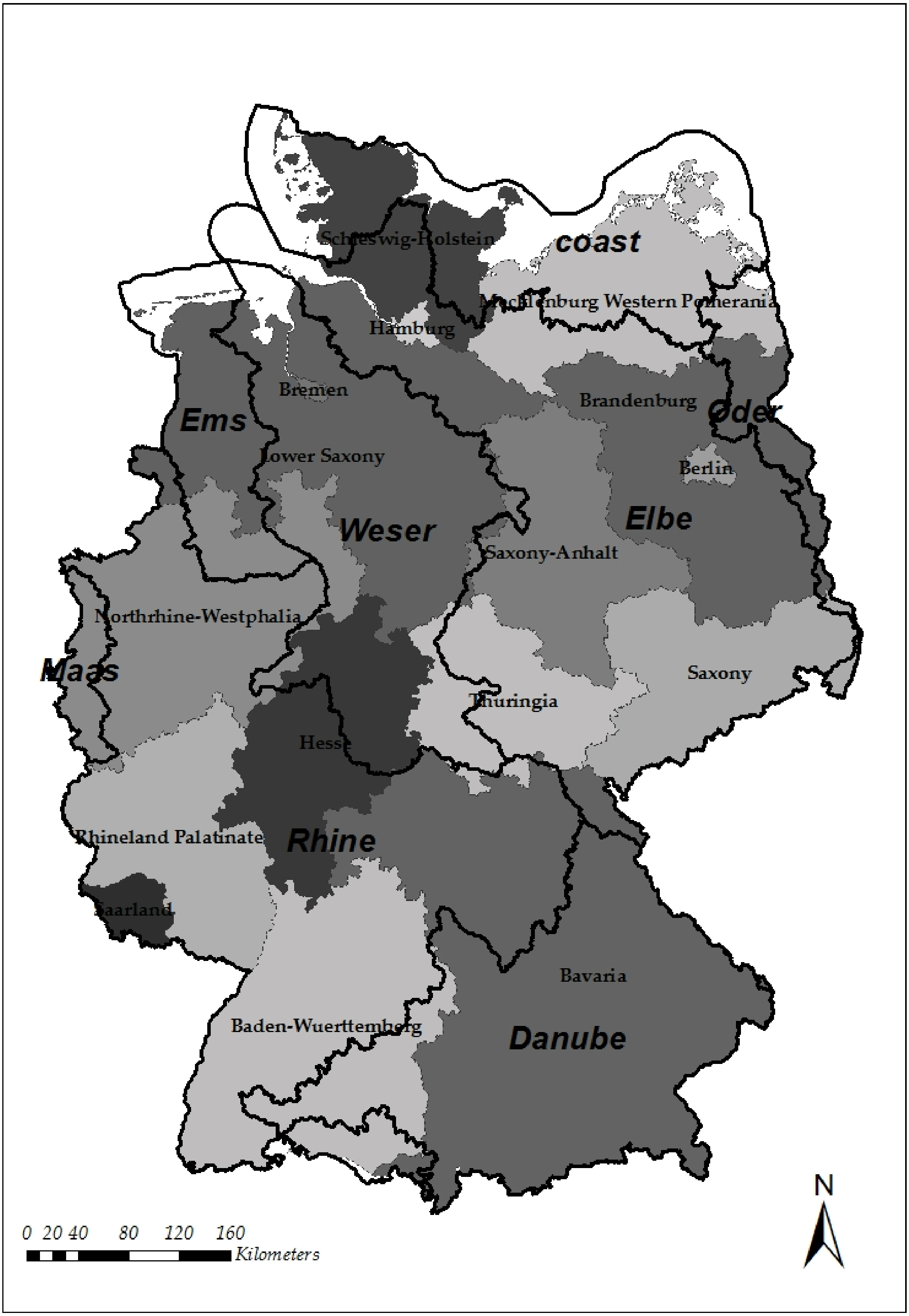

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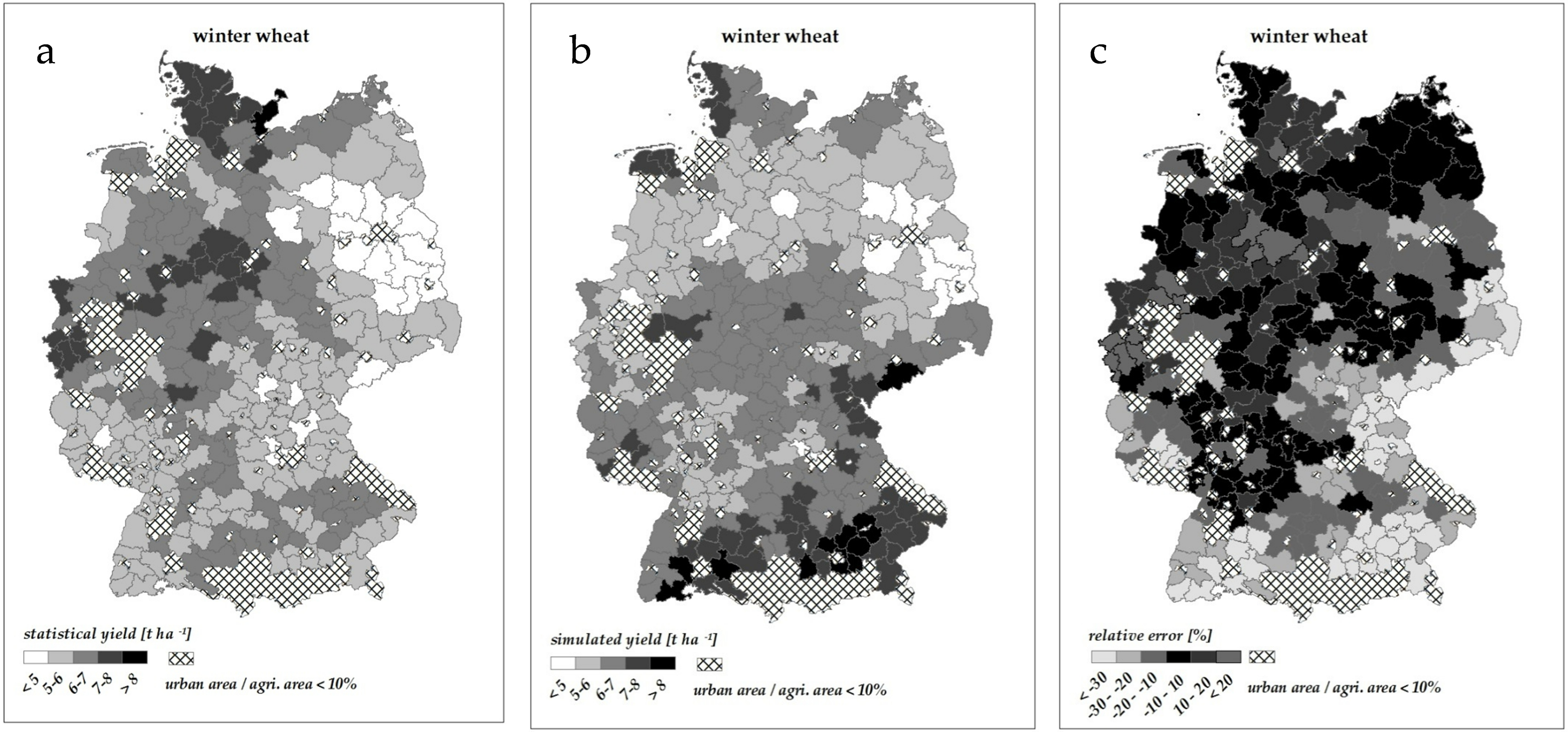
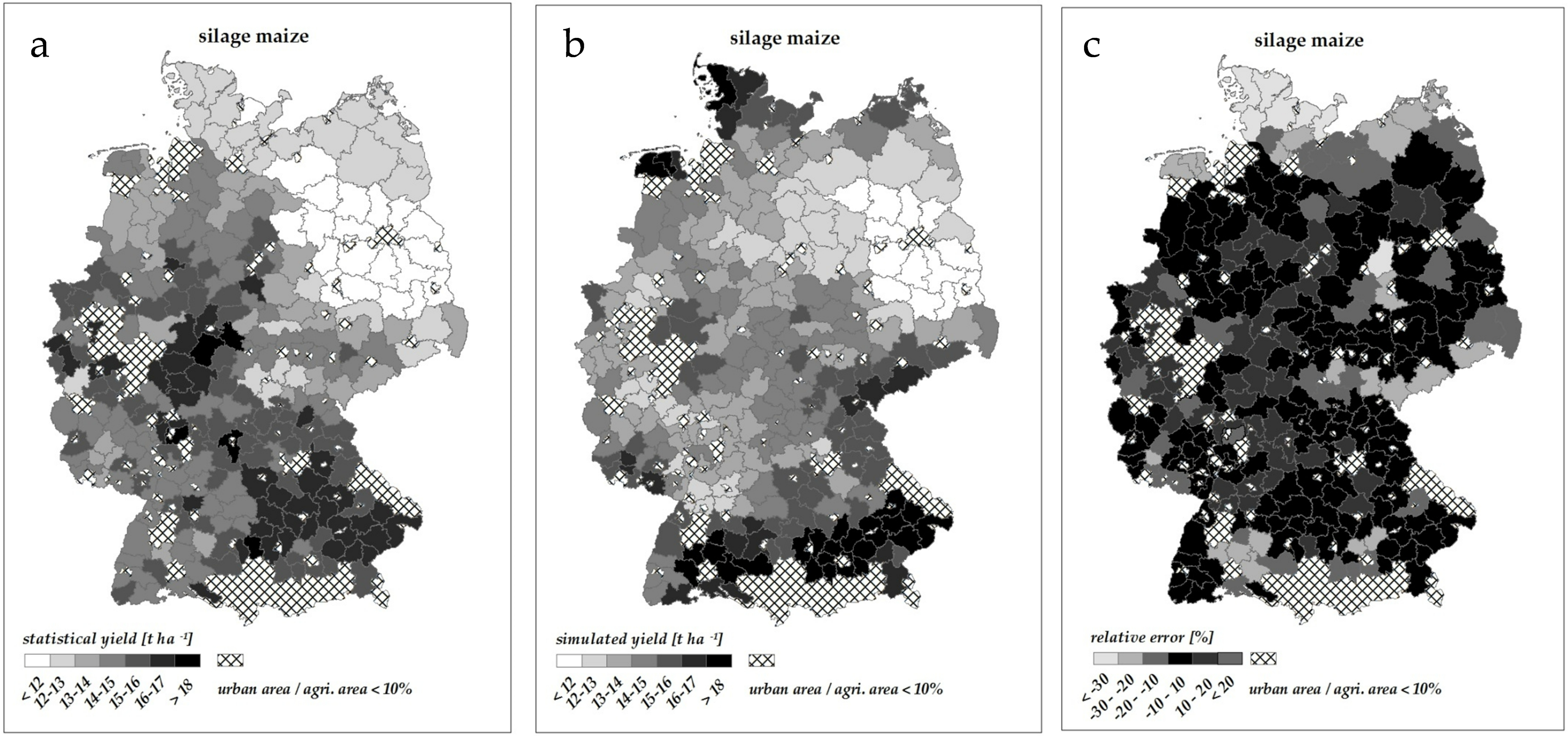
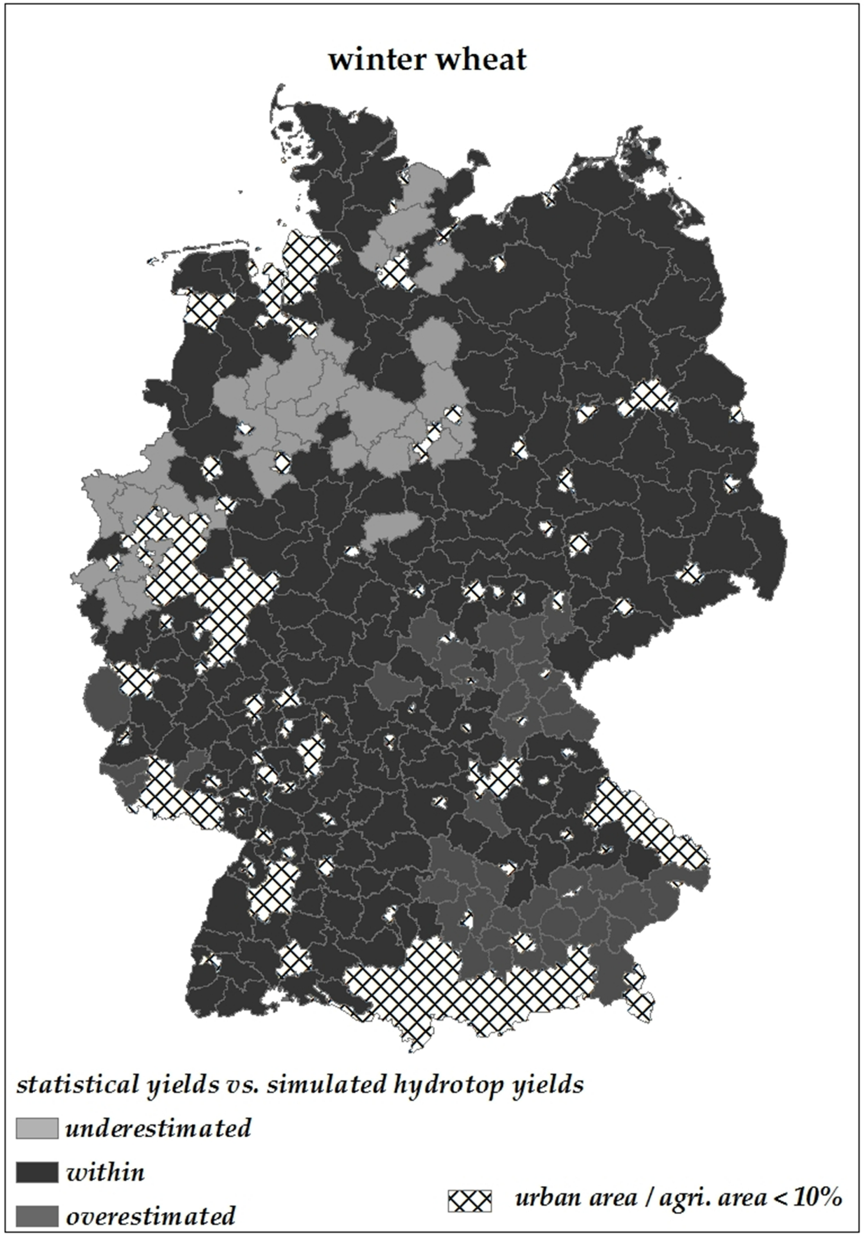
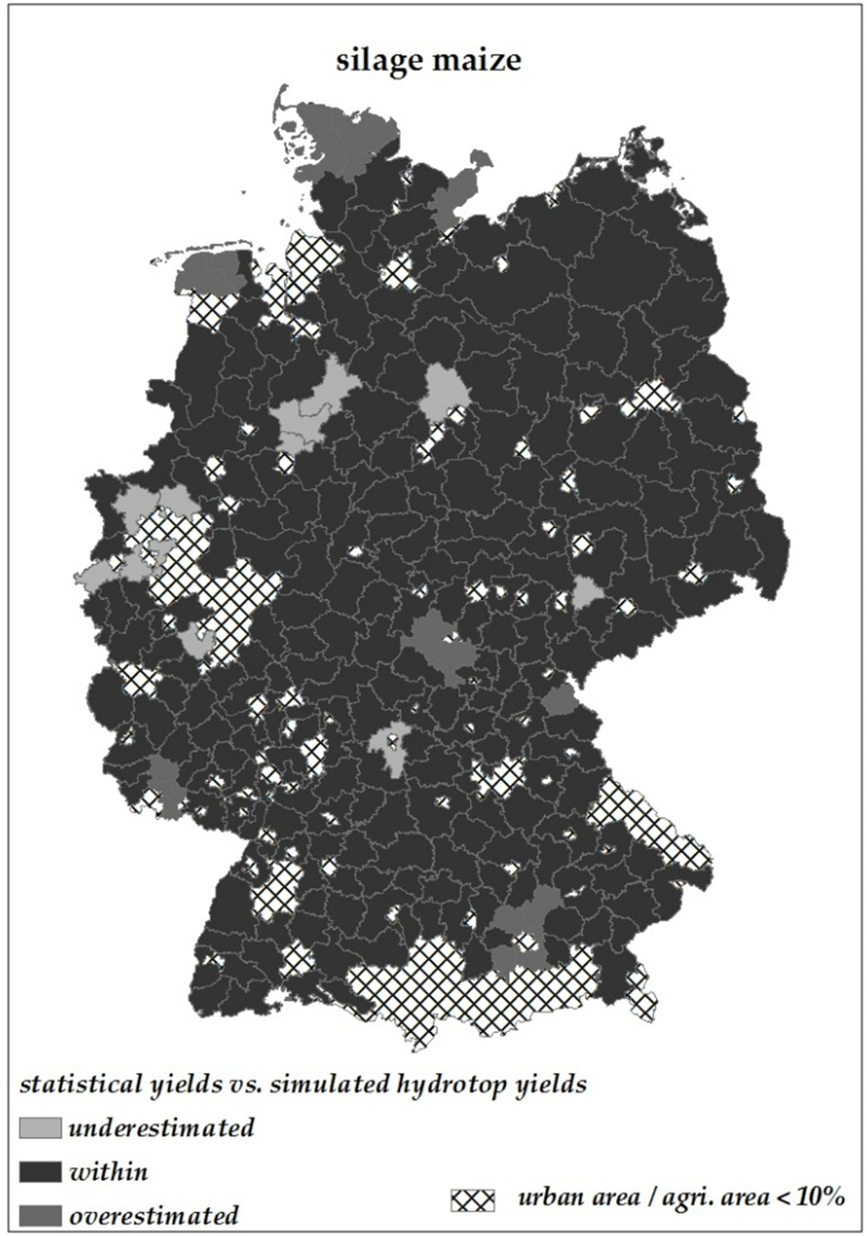
0 20 40 80 120 160
Kilometers


a
winter wheat
statistical yield [t ha -1]
<5
5-6
6-7
7-8
>8
urban area / agri. area < 10%
b
winter wheat
simulated yield [t ha -1]
<5
5-6
6-7
7-8
>8
urban area / agri. area < 10%
c
winter wheat
relative error [%]
< -30
-30 - -20
-20 - -10
-10 - 10
10 - 20
< 20
urban area / agri. area < 10%

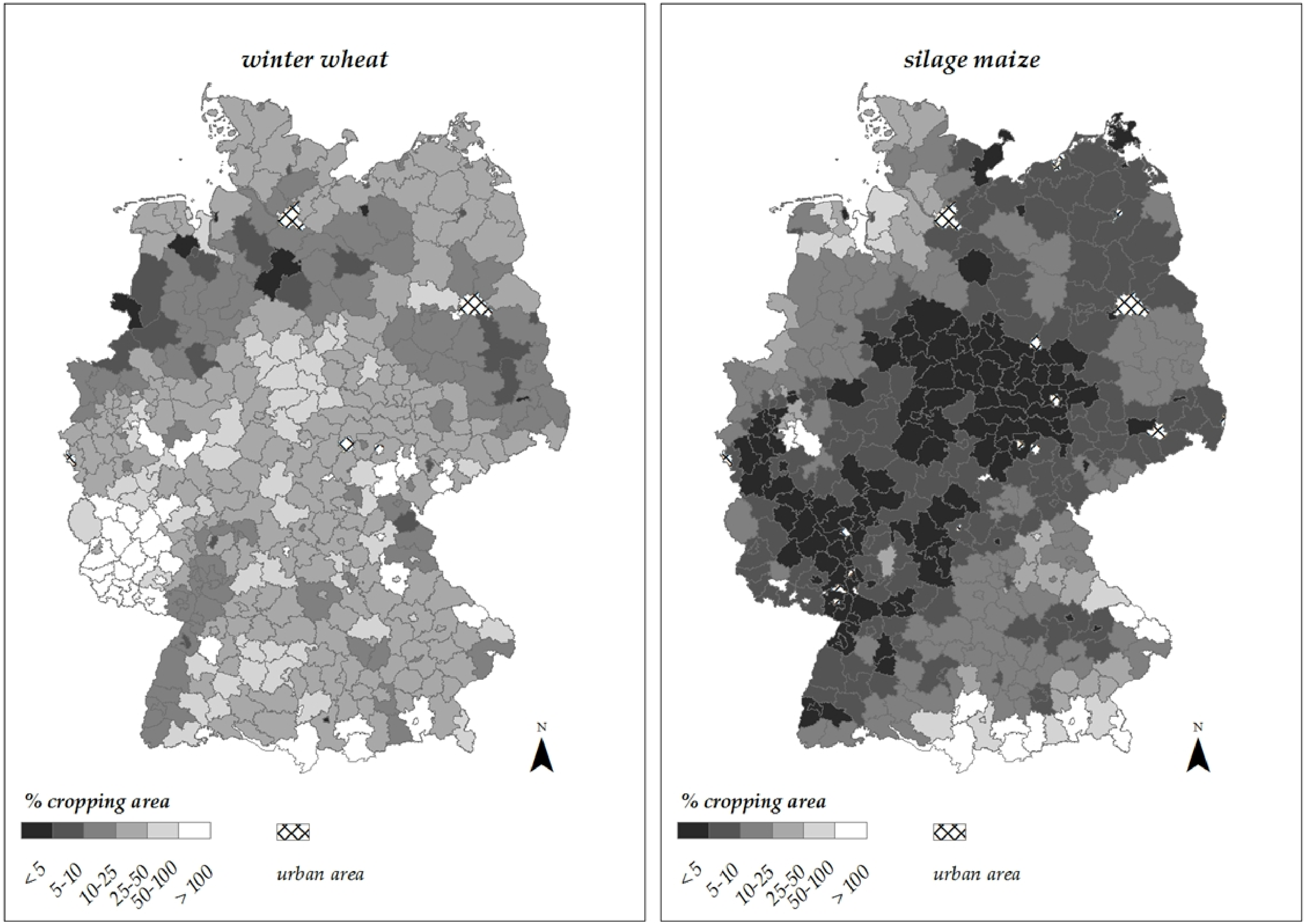

a
silage maize
statistical yield [t ha -1]
< 12
12-13
13-14
14-15
15-16
16-17
> 18
urban area / agri. area < 10%
b
silage maize
simulated yield [t ha -1]
< 12
12-13
13-14
14-15
15-16
16-17
> 18
urban area / agri. area < 10%
c
silage maize
relative error [%]
< -30
-30 - -20
-20 - -10
-10 - 10
10 - 20
< 20
urban area / agri. area < 10%

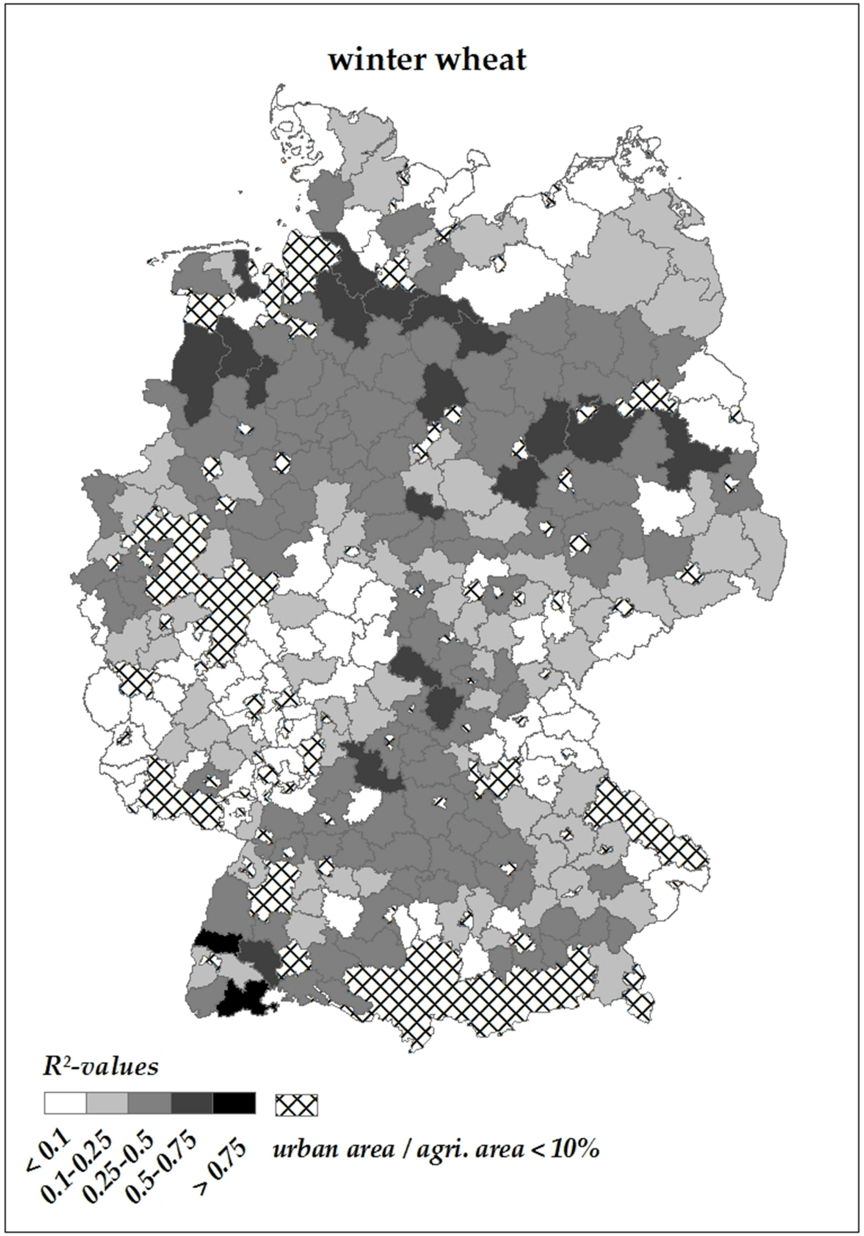


winter wheat
statistical yields vs. simulated hydrotop yields
underestimated
within
overestimated
urban area / agri. area < 10%

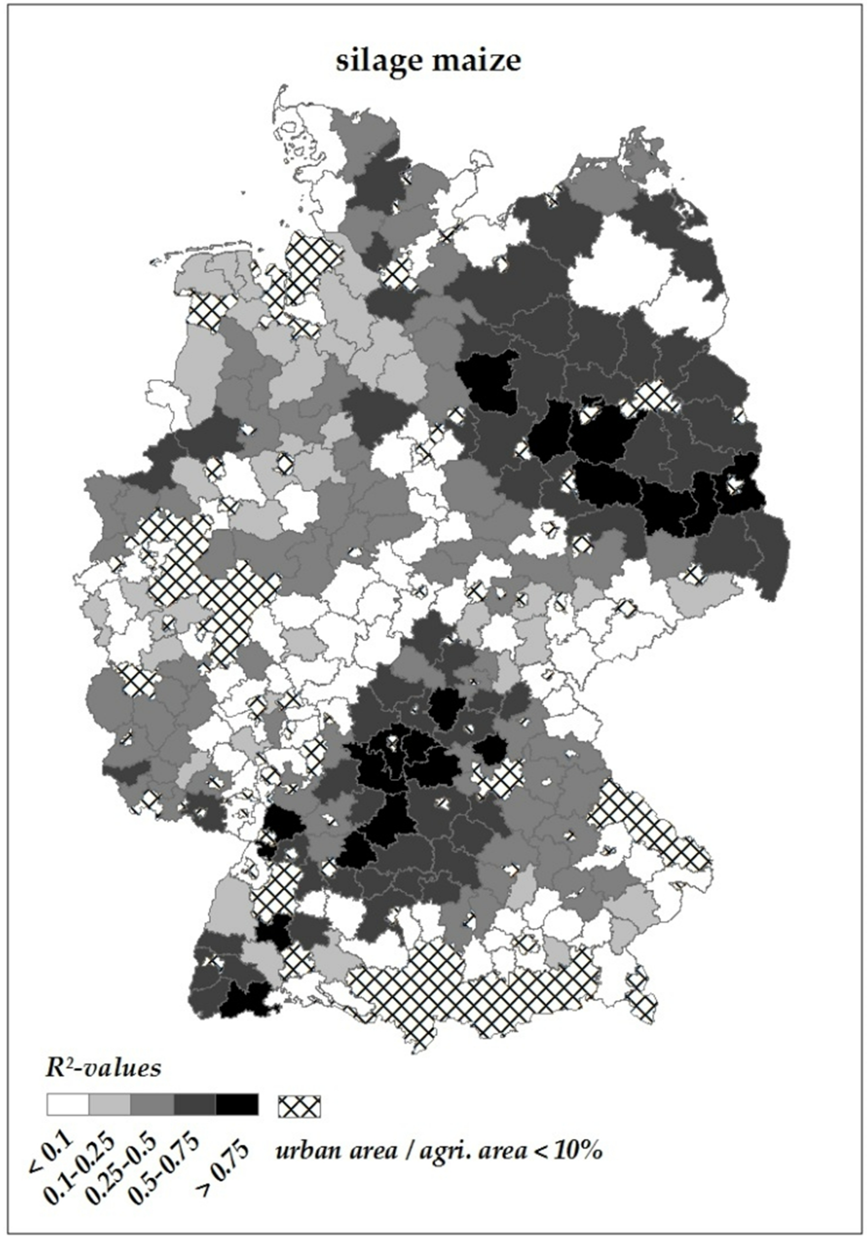


silage maize
statistical yields vs. simulated hydrotop yields
underestimated
within
overestimated
urban area / agri. area < 10%

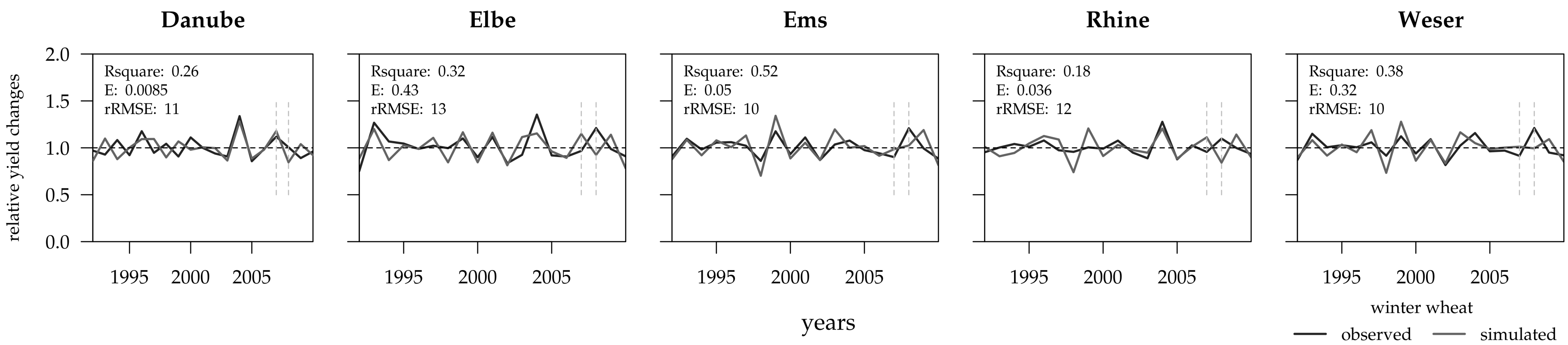

winter wheat
N
% cropping area
<5
5-10
10-25
25-50
50-100
> 100
urban area
silage maize
N
% cropping area
<5
5-10
10-25
25-50
50-100
> 100
urban area

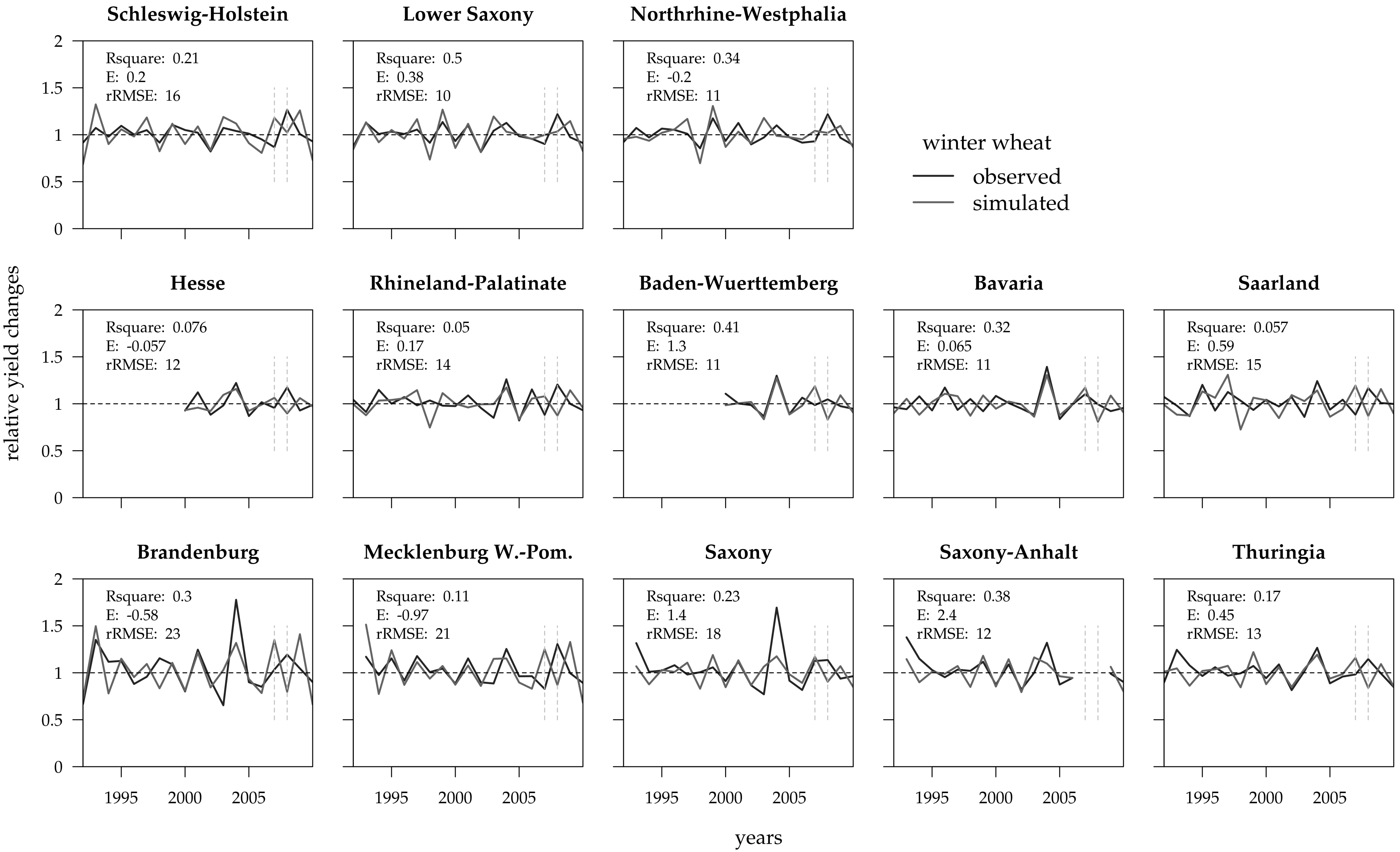


winter wheat
R²-values
< 0.1
0.1-0.25
0.25-0.5
0.5-0.75
> 0.75
urban area / agri. area < 10%

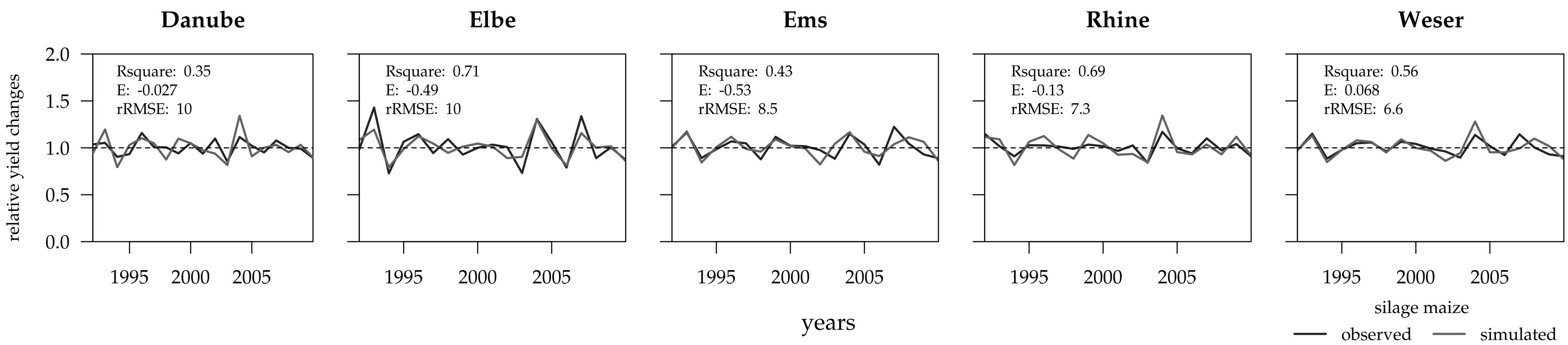


silage maize
R²-values
< 0.1
0.1-0.25
0.25-0.5
0.5-0.75
> 0.75
urban area / agri. area < 10%

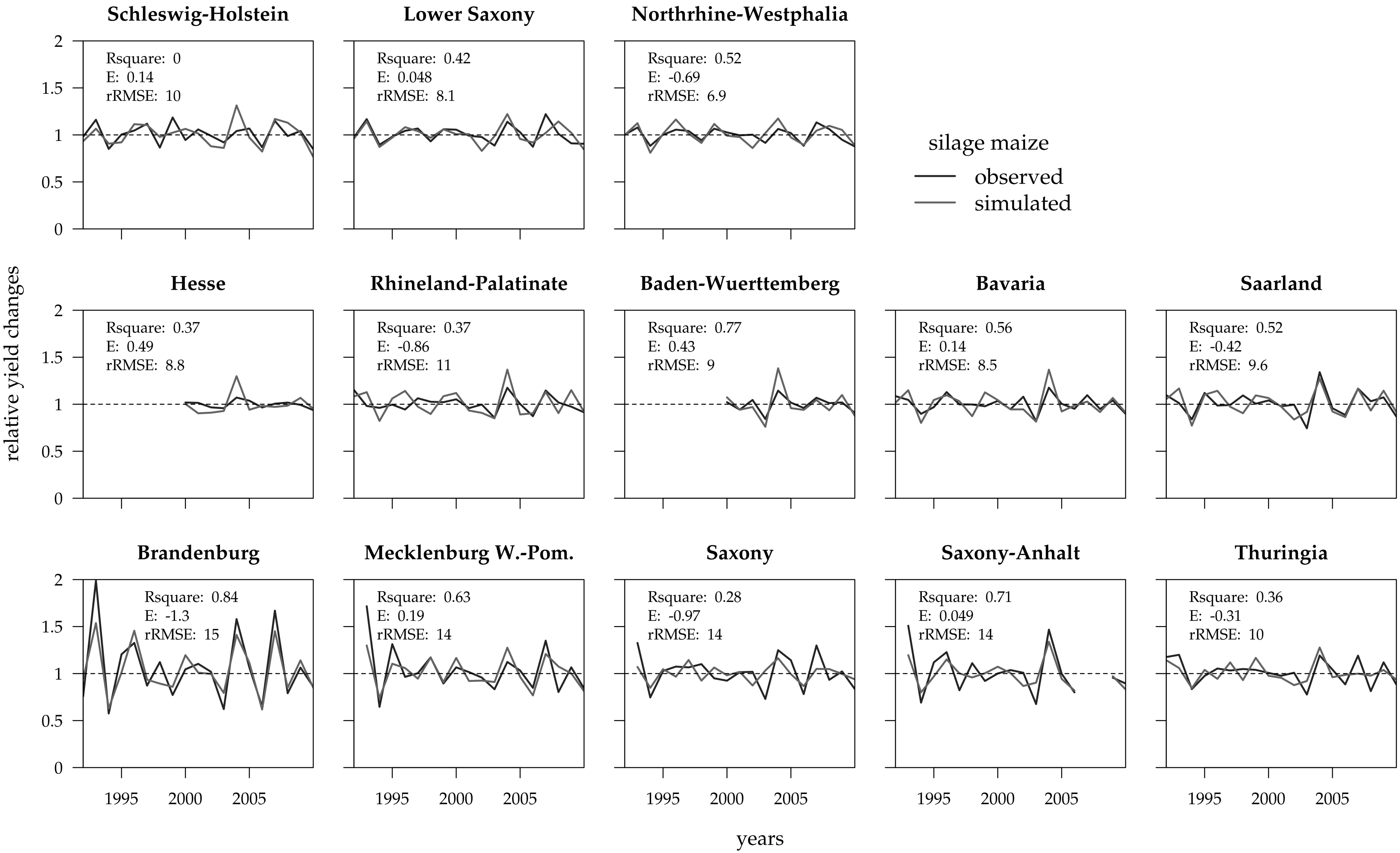

Danube
Elbe
Ems
Rhine
Weser
Rsquare: 0.26
E: 0.0085
rRMSE: 11
Rsquare: 0.32
E: 0.43
rRMSE: 13
Rsquare: 0.52
E: 0.05
rRMSE: 10
Rsquare: 0.18
E: 0.036
rRMSE: 12
Rsquare: 0.38
E: 0.32
rRMSE: 10
relative yield changes
2.0
1.5
1.0
0.5
0.0
1995
2000
2005
years
winter wheat
observed
simulated



Schleswig-Holstein
Rsquare: 0.21
E: 0.2
rRMSE: 16
Lower Saxony
Rsquare: 0.5
E: 0.38
rRMSE: 10
Northrhine-Westphalia
Rsquare: 0.34
E: -0.2
rRMSE: 11
winter wheat
observed
simulated
Hesse
Rsquare: 0.076
E: -0.057
rRMSE: 12
Rhineland-Palatinate
Rsquare: 0.05
E: 0.17
rRMSE: 14
Baden-Wuerttemberg
Rsquare: 0.41
E: 1.3
rRMSE: 11
Bavaria
Rsquare: 0.32
E: 0.065
rRMSE: 11
Saarland
Rsquare: 0.057
E: 0.59
rRMSE: 15
Brandenburg
Rsquare: 0.3
E: -0.58
rRMSE: 23
Mecklenburg W.-Pom.
Rsquare: 0.11
E: -0.97
rRMSE: 21
Saxony
Rsquare: 0.23
E: 1.4
rRMSE: 18
Saxony-Anhalt
Rsquare: 0.38
E: 2.4
rRMSE: 12
Thuringia
Rsquare: 0.17
E: 0.45
rRMSE: 13
relative yield changes
0
0.5
1
1.5
2
1995
2000
2005
years



Danube
Elbe
Ems
Rhine
Weser
relative yield changes
2.0
1.5
1.0
0.5
0.0
Rsquare: 0.35
E: -0.027
rRMSE: 10
Rsquare: 0.71
E: -0.49
rRMSE: 10
Rsquare: 0.43
E: -0.53
rRMSE: 8.5
Rsquare: 0.69
E: -0.13
rRMSE: 7.3
Rsquare: 0.56
E: 0.068
rRMSE: 6.6
1995
2000
2005
years
silage maize
observed
simulated


Schleswig-Holstein
Rsquare: 0
E: 0.14
rRMSE: 10
Lower Saxony
Rsquare: 0.42
E: 0.048
rRMSE: 8.1
Northrhine-Westphalia
Rsquare: 0.52
E: -0.69
rRMSE: 6.9
silage maize
observed
simulated
Hesse
Rsquare: 0.37
E: 0.49
rRMSE: 8.8
Rhineland-Palatinate
Rsquare: 0.37
E: -0.86
rRMSE: 11
Baden-Wuerttemberg
Rsquare: 0.77
E: 0.43
rRMSE: 9
Bavaria
Rsquare: 0.56
E: 0.14
rRMSE: 8.5
Saarland
Rsquare: 0.52
E: -0.42
rRMSE: 9.6
Brandenburg
Rsquare: 0.84
E: -1.3
rRMSE: 15
Mecklenburg W.-Pom.
Rsquare: 0.63
E: 0.19
rRMSE: 14
Saxony
Rsquare: 0.28
E: -0.97
rRMSE: 14
Saxony-Anhalt
Rsquare: 0.71
E: 0.049
rRMSE: 14
Thuringia
Rsquare: 0.36
E: -0.31
rRMSE: 10
relative yield changes
0
0.5
1
1.5
2
1995
2000
2005
years

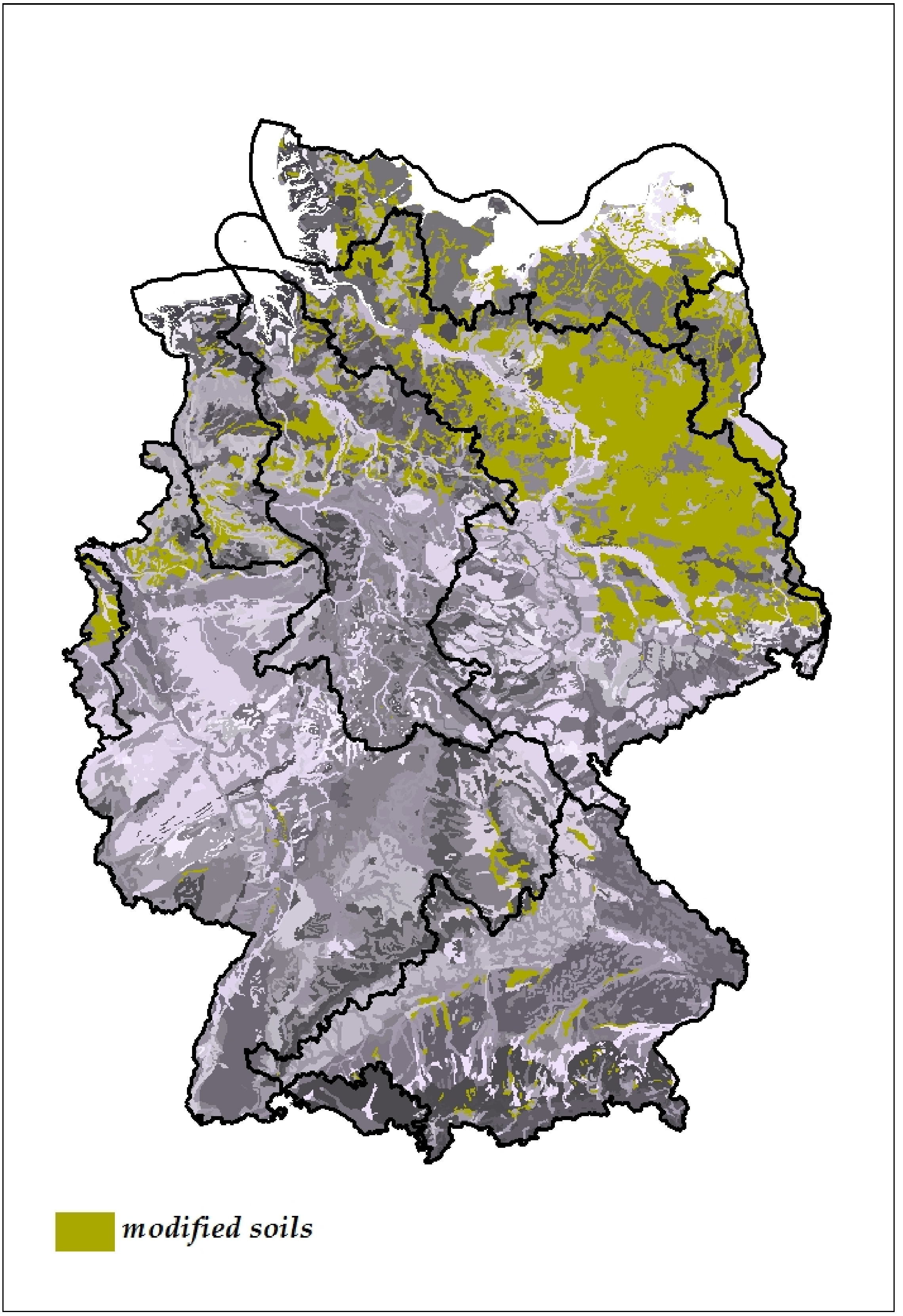

modified soils

Table 1

parameter	winter wheat	silage maize
sowing date	10/10	28/04
harvest date*	21/09	31/10
accumulated heat units at maturity [°C]	1424	936
harvest index	0.42	1
biomass-energy ratio [kg m^2 MJ^{-1} ha^{-1} d^{-1}]	0.3	0.33
optimum growth temperature [°C]	15	20
base temperature[°C]	0	6
maximum LAI	6	8
maximum rooting depth [m]	1.2	1
biomass allocation fraction to leaves	0.2	0.2
Specific leaf area [cm^2 g^{-1}]	161	220

Table 2

spatial unit	r^2-values		delta r^2-values	
	winter wheat	silage maize	winter wheat	silage maize
Danube	0.26	0.35	0.04	0.07
Elbe	0.32	0.71	0.05	0.34
Ems	0.52	0.43	0.15	0.20
Rhine	0.18	0.69	-0.03	0.35
Weser	0.38	0.56	0.06	0.30
average (river basins)	**0.33**	**0.55**	**0.05**	**0.25**
Schleswig-Holstein	0.21	0.00	0.03	-0.27
Saxony	0.23	0.28	0.04	-0.01
Saarland	0.06	0.52	0.01	0.09
Thuringia	0.17	0.36	-0.05	0.14
Saxony-Anhalt	0.38	0.71	0.03	0.15
Rhineland Palatinate	0.05	0.37	-0.03	0.15
Lower Saxony	0.50	0.42	0.10	0.16
Brandenburg	0.30	0.84	0.00	0.17
Bavaria	0.32	0.56	0.08	0.23
Mecklenburg Western Pomerania	0.11	0.63	0.00	0.26
Hesse	0.08	0.37	0.03	0.27
Baden-Wuerttemberg	0.41	0.77	0.06	0.29
Northrhine-Westphalia	0.34	0.52	0.07	0.31
average (federal countries)	**0.24**	**0.49**	**0.03**	**0.15**
Germany	**0.26**	**0.72**	**0.01**	**0.4**