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Comparison of Three Modelling Approaches to Simulate Regional Crop Yield: A Case Study of Winter Wheat Yield in Western Germany

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ABSTRACT

The need for more comparisons among models is widely recognized. This study aimed to compare three different modelling approaches for their capability to simulate and predict trends and patterns of winter wheat yield in Western Germany. The three modelling approaches included an empirical model, a process-based model (LINTUL2), and a metamodel derived from the process-based model. The models outcomes were aggregated to general climate zones level of Western Germany to allow for a comparison with agricultural census data for validation purposes. The spatial patterns and temporal trends of winter wheat yield seemed to be better represented by the empirical model (R^2= 70%, RMSE= 0.48 t ha^{-1} yr^{-1}, and CV-RMSE= 8%) than by the LINTUL2 model (R^2= 65%, RMSE= 0.67 t ha^{-1} yr^{-1}, and CV-RMSE=11%) and the metamodel (R^2= 57%, RMSE= 0.77 t ha^{-1} yr^{-1}, and CV-RMSE=13%). All models demonstrated a similar order of magnitude of yield prediction and associated uncertainties. The suitability of the three models is context dependent. Empirical modelling is most suitable to analyze and project past and current crop-yield patterns, while crop growth simulation models are more suited for future projections with climate scenarios. The derived metamodels are fast reliable alternatives for areas with well calibrated crop growth simulation models. A model comparison helps to reveal shortcomings and strengths of the models. In our case, a performance comparison between the three modelling approaches indicated that, for simulating winter wheat growth in Western Germany, higher sensitivity to soil depth and lower sensitivity to drought in the LINTUL2 model would probably lead to better predictions.

Keywords: Crop growth simulation model, Climate change, Metamodel, Regression analysis, LINTUL2.

INTRODUCTION

Process-based Crop Growth Simulation Models (CGSMs) are a commonly used tool for generating future projections of crop yields within climate scenarios (12, 20, 42). These models provide process-based insight in the mechanisms/physiology of crop growth and their responses to changes in the environment (41). These models are mainly developed for the plot and field scale, requiring location-specific, spatially homogenous input data (22, 45, 46). When such models are applied to larger areas (e.g. provinces or countries) and to longer (future) time periods, there is a scaling challenge (32, 41, 45). Required daily weather data is generally not generated by future climate scenarios because they provide coarser time steps (13, 27). Required detailed soil data is often not available for larger areas. One can either mimic the required high resolution data

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by using e.g. weather generators or other downscaling techniques (5, 40), or one can work with coarse data, but then recalibration of the model may be required (15). Furthermore, at a wider range of spatial scales, other factors than those typically used by CGSMs co-determine yield variability (e.g. pests, plagues etc.). Also, at a wider range of temporal scales, new factors may emerge that turn out to be important (e.g. technological development), which are not accounted for in CGSMs (7, 31). That leaves us with the question how to best use data and models at regional scale. Apart from generating the required detailed input data, there are two common solutions for using the coarser input data. One is replacing the CGSM by a metamodel that can deal with less detailed data (10, 30), and the second is deriving a statistical model that relates observed yields to whatever data is available (from now on referred to as empirical model) (49, 34, 51). A metamodel would require similar variables as the original process based CGSM, albeit with coarser resolutions (6). It may turn out, however, that within a certain area and time frame only a limited number of environmental and management factors determine crop growth (e.g. 43). This may save researchers a considerable data collection effort. A disadvantage of metamodels is that, as they mimic the CGSMs, the problem of not including factors that play a role at a wider range of spatial and temporal scales is not solved (14, 18). An empirical model can use all data available, including proxies for factors that are typically not accounted for in CGSMs (e.g. accessibility as a proxy for management intensity). These models are calibrated directly on the aggregated input data, and can include all kinds of factors at any aggregation level. The disadvantage of these models is that extrapolation beyond the calibration range of input variables is illicit, and the relationships used are context dependent and not process based (9).

This study was undertaken to compare the three approaches to simulate and predict crop yields at a wide range of spatial and temporal scales in Western Germany: (1) A CGSM, (2) A metamodel, and (3) An empirical model. All three models are calibrated for a certain time period and validated for a subsequent time period. The spatial extent of the study is Western Germany, and the temporal extent is 1983-2002. Finally, the models are used to make a future projection of crop yields for 2050, which serve to demonstrate the sensitivities of the different modelling approaches to the input variables.

MATERIALS AND METHODS

Study Area

Western Germany, i.e. former West Germany, covers a wide range of agro-ecological conditions. The northwest and the north have a sea climate while the southern part is influenced by the Alpine mountains with a boreal climate. Arable farming is dominated by soft winter wheat (*Triticum aestivum* L.). Temporal averages over the period 1993-2002 of the annual winter wheat yields observed in the individual climate zones varied between approximately 3 t ha^{-1} yr^{-1} in the south and southwest to 9 t ha^{-1} yr^{-1} in the north and northeast (Mean= 6.1 t ha^{-1} yr^{-1}, St dev= 0.9 t ha^{-1} yr^{-1}) (7) (Figure 1-a). A climate zone is defined as a spatial unit that combines NUTS-2 (Nomenclature of Territorial Units for Statistics) regions and Environmental Zones (EnZ) (36).

Data

Weather Data

Weather data were obtained from the SEAMLESS database (47) for 70 climate zones in Western Germany (3, 27) for the period 1983-2002. The database contained daily data on: rainfall (mm d^{-1}), maximum and minimum air temperature (°C), global solar radiation (MJ m^{-2} d^{-1}), wind speed (m s^{-1}), vapor pressure (hPa), and evapotranspiration (mm d^{-1}, calculated with the Penman–

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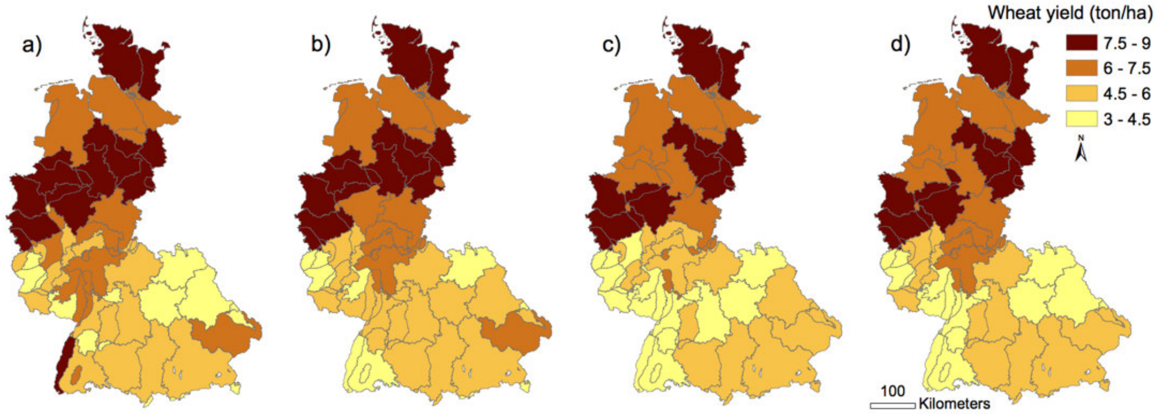

Figure 1. Winter wheat yields averaged over the period 1993-2002 for Western Germany, showing yields per climate zone based on: (a) Agricultural statistics, (b) Empirical model, (c) LINTUL2, and (d) Metamodel. In the figure, each polygon depicts a different climate zone.

Monteith formula as applied by Allen *et al*. (2)). The CO_2 level was considered spatially and temporally invariable (that is, for Western Germany during the period 1983-2002), and one fixed value of 374 ppm was assumed (26).

As a projection of climate change by the mid-21st century, we used the ensemble mean of 15 Global Circulation Models (GCMs) calculated as part of the third Coupled Model Inter-comparison Project (CMIP3) provided by the Intergovernmental Panel on Climate Change (IPCC) Data Distribution Centre (DDC) (13). CMIP3 evaluated a range of different scenarios.

In this study, we used the A1B scenario which corresponds to rapid economic growth in an integrated world where the global population reaches 9.1 billion in 2050.

Soil Data

Soil characteristics at the level of the so-called AgriEnvironmental Zones (25), which are a further refinement of the climatic zones, were obtained from the Pan European SEAMLESS database (3, 47). Data included critical soil water content for transpiration reduction due to water logging, and the water content at field capacity, saturation, wilting point, and air dryness (all in volumetric fraction). In addition, soil depth (in cm) was obtained from the Pan European Soil Erosion Risk Assessment project (39). The soil depth was then used for the application of the metamodel and empirical model.

Management Data

Technological development (TD) has also played an important role in the development of yields over time (12, 20). Here, we used a proxy for technological development as described in Ewert *et al*. (20) to estimate yield increase due to improved varieties and crop management (e.g. pesticides and herbicides). Yield trends were calculated for each climate zone by fitting a linear regression line through the correspondent observed yields. Future trends were obtained by extrapolations of past trends, but were modified depending on scenario-specific assumptions about breeding and crop management. Following this approach, for each climate zone, a trend in technological development was obtained by setting the initial technological development (in our case the year 1983) to e.g. 1.033, and we obtained a value of each subsequent year by adding 0.033. The initial variable is spatially explicit, showing a range between 1.033 and 1.077. The annual increment values (the TD variable) ranged from 0.033 (the lowest value between 1983 and 1984) to 0.66 (the highest value between 2001 and 2002).

Yearly sowing and harvest dates for winter wheat were obtained from the JRC/MARS Crop

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Knowledge Base for 70 climate zones in Western Germany for the period 1983-2002 (28).

Winter Wheat Yields

Time series of winter wheat yields from 1983 to 2002 were obtained from the Statistisches Bundesamt Deutschland (7) at NUTS3 level, which is the finest spatial level at which agricultural statistics are available (approximately 1,155 km^2 in size).

In order to simulate a data-poor environment (needed to evaluate the suitability of the three modelling approaches in such environments), data were spatially aggregated to the level of the climate zone. This resulted in 70 observations on yield, as response variable, and a range of explanatory variables which are listed in Table 1. Weather data were also temporally aggregated to an annual resolution, which were only used by the metamodel and empirical model. Four aggregations were made by taking the: (i) Annual average of daily weather data, (ii) Average over the whole growing season (April-August), (iii) Average over summer (July-September), and (iv) Average over winter (December-March). The winter period is relevant because winter wheat is sown in autumn and has a rest period throughout winter.

Modelling Approaches

Crop Growth Simulation Model

LINTUL2 is a process-based crop growth simulation model made for simulating soft winter wheat (for a comprehensive description: 46). LINTUL2 describes yield under water-limited conditions. Conditions are still optimal with respect to other growth factors, i.e. ample nutrients and a pest-, disease- and weed-free environment (for the model input variables see Table 1). LINTUL2 has been used in numerous climate change studies (e.g. 17, 53).

LINTUL2 is integrated in the so-called Agricultural Production and Externalities Simulator (APES), which is a cropping system modelling framework (1). The model was further extended with various calibration methods valid for European conditions by Angulo *et al*. (4) to allow for the simulation of spatial and temporal yield trends and responses to climate change. The extended method, considering the region-specific calibration of phenology and growth parameters, provided the best agreement between observed and calibrated yields, therefore, was considered to simulate climate change effects on wheat yields in Western Germany. This version of the model includes the effects of technology development (as described by Ewert *et al*. (20)) and CO_2 levels (as described by Angulo *et al*. (4)) on winter wheat yield and it was recalibrated for spatially aggregated input data (4). It was, however, not recalibrated for temporally aggregated weather data, nor did it include factors such as pests and plagues that may become important at a wider range of spatial scales (19, 22). Table 1 lists the total set of variables that were considered in the application of the model. Angulo *et al*. (4) used a simple representation of the effects of increased atmospheric CO_2 level (ppm) on winter wheat yield, using the relationship between CO_2 and Radiation-Use Efficiency (RUE) as proposed by Stockle *et al*. (44). There is a rather strong gradient in *RUE* from northwest to the southeast along which *RUE* increases, due to the gradient in water vapour pressure deficit and global solar radiation. Increased CO_2 also reduces crop transpiration: a linear diminution of transpiration up to 10% for winter wheat was taken into consideration by Angulo *et al*. (4), when the atmospheric CO_2 reaches 700 ppm (18).

Metamodel

A metamodel is considered to be the simplest parsimonious linear regression model that mimics the input–output relationships of the process model. A metamodel was derived from the LINTUL2 model for Western Germany.

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Table 1. The total set of variables used in the particular model approach for Western Germany. [a]

Variables	Description	Empirical model	LINTUL2	Meta-model
Management data				
TD	Technological Development (-)	√	√	√
Sdates	Sowing dates (Day of sowing)	√	√	√
Hdates	Harvest dates (dDay of harvest)	√	√	√
Weather				
Tmax	Mean annual maximum Temperature (°C)	√		√
Tmin	Mean annual minimum Temperature (°C)	√		√
Rain	Mean annual rainfall (mm d^{-1})	√		√
SRAD	Mean annual global Solar Radiation (MJ m^{-2} d^{-1})	√		√
WS	Mean annual Wind Speed (m s^{-1})	√		√
VP	Mean annual Vapor Pressure (hPa)	√		√
ET	Mean annual Evapotranspiration (mm d^{-1})	√		√
GTmax	Mean Growing season maximum Temperature (°C)	√		√
GTmin	Mean Growing season minimum Temperature (°C)	√		√
GRain	Mean Growing season Rainfall (mm d^{-1})	√		√
GSRAD	Mean Growing season global Solar Radiation (MJ m^{-2} d^{-1})	√		√
GWS	Mean Growing season Wind Speed (m s^{-1})	√		√
GVP	Mean Growing season Vapor ressure (hPa)	√		√
GET	Mean Growing season Evapotranspiration (mm d^{-1})	√		√
WTmax	Mean Winter season maximum Temperature (°C)	√		√
WTmin	Mean Winter season minimum Temperature (°C)	√		√
WRain	Mean Winter season Rainfall (mm d^{-1})	√		√
WSRAD	Mean Winter season global Solar Radiation (MJ m^{-2} d^{-1})	√		√
WWS	Mean Winter season Wind Speed (m s^{-1})	√		√
WVP	Mean Winter season Vapor Pressure (hPa)	√		√
WET	Mean Winter season Evapotranspiration (mm d^{-1})	√		√
STmax	Mean Summer season maximum Temperature (°C)	√		√
STmin	Mean Summer season minimum Temperature (°C)	√		√
SRain	Mean Summer season Rainfall (mm d^{-1})	√		√
SSRAD	Mean Summer season global Solar Radiation (MJ m^{-2} d^{-1})	√		√
SWS	Mean Summer season Wind Speed (m s^{-1})	√		√
SVP	MeanS season Vapor Pressure (hPa)	√		√
SET	Mean summer season evapotranspiration (mm d^{-1})	√		√
DTmax	Daily maximum Temperature (°C)		√	
DTmin	Daily Minimum Temperature (°C)		√	
DRain	Daily rainfall (mm d^{-1})		√	
DSRAD	Daily global Solar Radiation (MJ m^{-2} d^{-1})		√	
DWS	Daily Wind Speed (m s^{-1})		√	
DVP	Daily Vapor Pressure (hPa)		√	
DET	Daily Evapotranspiration (mm d^{-1})		√	
CO_2	Atmospheric CO_2 level (ppm)		√	
Soil				
SD	Soil Depth (cm)	√		√
WCFC	Water Content at Field Capacity (%)	√	√	√
WCWP	Water Content at Wilting Point (%)	√	√	√
WCST	Water Content at Saturation (%)	√	√	√
WCAD	Water Content at Air Dryness (%)	√	√	√
WCWET	Critical Soil Water Content to Waterlogging (%)	√	√	√
WHC	Water Holding Capacity (%)	√		√

[a] √ Indicates whether or not the variable is used in the particular model approach for western Germany.

Table 1 continued…

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Continued of Table1.

Variables	Description	Empirical model	LINTUL2	Meta-model
Interactions				
SD×WS	Interaction of SD and WS	√		√
SD×GWS	Interaction of *SD* and *GWS*	√		√
SD×WWS	Interaction of *SD* and *WWS*	√		√
SD×SWS	Interaction of *SD* and *SWS*	√		√
SD×Rain	Interaction of *SD* and Rain	√		√
SD×GRain	Interaction of *SD* and *GRain*	√		√
SD×W.Rain	Interaction of *SD* and *WRain*	√		√
SD×SRain	Interaction of *SD* and *SRain*	√		√
WHC×WS	Interaction of *WHC* and *WS*	√		√
WHC×GWS	Interaction of *WHC* and *GWS*	√		√
WHC×WWS	Interaction of *WHC* and *WWS*	√		√
WHC×SWS	Interaction of *WHC* and *SWS*	√		√
WHC×Rain	Interaction of *WHC* and Rain	√		√
WHC×GRain	Interaction of *WHC* and GRain	√		√
WHC×WRain	Interaction of *WHC* and *WRain*	√		√
WHC×SRain	Interaction of *WHC* and *SRain*	√		√
Rain/ET	Ratio of Rain and ET	√		√
GRain/GET	Ratio of G.Rain and *GET*	√		√
WRai /WET	Ratio of *WRain* and *WET*	√		√
SRai /SET	Ratio of *SRain* and *SET*	√		√
$Tmax^2$	Square of *Tmax*	√		√
$GTmax^2$	Square of *GTmax*	√		√
$WTmax^2$	Square of *WTmax*	√		√
$STmax^2$	Square of *STmax*	√		√
$Tmin^2$	Square of *Tmin*	√		√
$GTmin^2$	Square of *GTmin*	√		√
$WTmin^2$	Square of *WTmin*	√		√
$STmin^2$	Square of *STmin*	√		√
10Log(Rain)	The logarithm of Rain	√		√
10Log(GRain)	The logarithm of *GRain*	√		√
10Log(WRain)	The logarithm of *WRain*	√		√
10Log(SRain)	The logarithm of S*Rain*	√		√

[a] √ Indicates whether or not the variable is used in the particular model approach for western Germany.

LINTUL2 was run for a ten-year period (1983-1992) for the 70 climate zones for the simulation of winter wheat in Western Germany. This way, both spatial and temporal variability was represented in the input and output. The metamodel was obtained by relating model input to model output by means of a multiple linear regression in SPSS. In this case, because our metamodel was meant to be run with coarser data than those required by the LINTUL2 model, we deliberately chose variables that were also available at a wide range of spatial and temporal scales, i.e. soil depth in addition to the detailed variables used by LINTUL2, and annual average of daily weather data instead of daily data (see Table 1). As theory suggests that some variables are non-linearly related to crop yields, we included transformations: (see e.g. 34). Furthermore, we included several interactions (see Table 1). These were included to account for the possibility that, e.g., water holding capacity becomes a more important determinant of crop yield in areas where rainfall is low. A Pearson correlation matrix was calculated to indicate the degrees of collinearity between all explanatory variables (Table 2). The most significant independent variables for predicting winter wheat yields were selected by means of a backward elimination of the

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variables with the lowest statistical significance. The threshold we handled for removing variables was $P \leq 0.001$.

Empirical Model

An empirical model was created for the simulation of winter wheat in Western Germany by regressing 10 years of observed annual winter wheat yields (1983-1992) for 70 climate zones on the various predictor data in Table 1, using SPSS. The most significant independent variables for predicting winter wheat yields were selected by means of a backward elimination of the variables with the lowest statistical significance, so as to obtain the simplest parsimonious model that mimics the yield - predictor relationships. Because we wanted to compare the empirical model to the metamodel, for both models the same set of potentially explanatory variables were used, including transformed predictors and products of predictors. Yearly yields were considered independent events, so we did not correct for temporal autocorrelation.

Validation of the Modelling Approaches

The three modelling approaches were validated for a second 10 year period (1993-2002), for which agricultural yield statistics and predictor data were available. The results of the validation were expressed as a Coefficient of determination (R^2), the Root Mean Squared Error (RMSE), and the Root Mean Squared Error normalized to the Average of the Observed values (CV-RMSE). The coefficient of determination was calculated as *1–SSE/SST*, whereby *SSE* is the sum of squares of residuals, and *SST* is the total sum of squares. The *RMSE* was calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{x}_i - x_i)^2}{n}} \qquad (1)$$

Where, $\hat{x}_i$ is the simulated yield, x_i is observed yield at climate zone i, and n is the number of observations (70 climate zones times 10 years). The *CV-RMSE* was calculated as $RMSE/\bar{x}$, where $\bar{x}$ is the average of the observed yield.

Spatial Patterns and Temporal Trends

Spatial patterns generated by the three modelling approaches were compared. Hereto, we averaged outcomes over the period 1993-2002. The results of comparison were expressed as an R^2, the *RMSE* [same as in Equation (1)], and *CV-RMSE*. Whereas the previous analysis (validation of the modelling approaches) was based on 700 observations (70 climate zones times 10 years), this analysis was based on only 70 observations. Temporal trends were compared as well. Hereto, the spatial dimension was removed by computing the spatial average for the entire study area. We averaged temporal observations for blocks of five years. As this left us with a few observations, we did not apply statistics to compare the trends, but made a visual comparison instead.

Simulation of Future Yields

The three modelling approaches were used to simulate future winter wheat yield for a

Table 2. Pearson correlation coefficient between variables included in the empirical and metamodel approach for Western Germany. [a]

	Rain	Tmax	SRAD	ET	GRain	GTmin	GSRAD	GET	GVP	STmax	SSRAD
GTmax	-0.27	0.90	0.54	0.82	-0.26	0.78	0.66	0.88	0.78	0.79	0.51
SRain	0.81	-0.32	-0.05	-0.23	0.77	-0.06	-0.26	-0.25	-0.08	-0.46	-0.29
SET	-0.32	0.68	0.80	0.91	-0.25	0.39	0.81	0.83	0.43	0.82	0.94

[a] Only those variables are shown that were strongly related (i.e. Pearson correlation coefficient > 0.75) to at least one of the significant variables.

possible future (period 2041-2061), in which climate changes (according to the 15GCM A1B scenario) and technology progresses (according to Ewert *et al*. (20)). The soil variables were considered constant in time. We took the winter wheat yield maps for the period 1993-2002 as the baseline, and compared them with the future maps (centered around 2050) to explore the predicted changes in yields. Although such an analysis bears no value in terms of model-evaluation, it does allow exploring potential over-sensitivity or lack of sensitivity of the different models to changes in climate.

RESULTS

Crop Growth Simulation Model

LINTUL2 outcomes (Mean= 5.7 t ha^{-1} yr^{-1}, SD= 0.7 t ha^{-1} yr^{-1}) explained 58% (= R^2) of the observed winter wheat yield variability for the validation period (1993-2002) with an *RMSE* of 0.73 t ha^{-1} yr^{-1}, and a *CV-RMSE* of 12%. As the model was already calibrated (4), we only present its performance on the validation period.

Metamodel

The best metamodel to emulate the winter wheat yield estimates (in t ha^{-1} yr^{-1}) by the LINTUL2 for the period 1983-1992 was:

Yield= -0.2 + TD - 0.3 W.SRAD + 0.1 SRain/SET

According to this model, yields decrease with increasing global solar radiation during winter, which can probably be ascribed to the fact that rising radiation might have caused additional water stress by affecting the soil water balance (7, 52). Yields increase with increasing the ratio of rainfall and evapotranspiration during summer (from now on referred to as summer drought), which can probably be ascribed to a reduced risk on drought damage (29, 35). Furthermore, with each unit increase in *TD*, yields go up by 1 t $ha^{-1}yr^{-1}$. For instance, if the initial technology development for a climate zone in the base line year has been established at 1.055, the annual increase in productivity is 0.055 (i.e. the TD variable). This comes down to an annual increase of approximately 55 kg ha^{-1} (1 ton times 0.055) in the simulated yield. For the calibration period (1983-1992), the metamodel (Mean= 5.1 t ha^{-1} yr^{-1}, SD= 0.7 t ha^{-1} yr^{-1}) predicted 75% of the simulated winter wheat yield variability with a *RMSE* of 0.43 t ha^{-1} yr^{-1}, and a *CV-RMSE* of 8%. For the validation period (1993-2002) the metamodel (Mean= 5.6 t ha^{-1} yr^{-1}, SD= 0.6 t ha^{-1} yr^{-1}) predicted 66% of the simulated winter wheat yield variability with a *RMSE* of 0.75 t ha^{-1} yr^{-1}, and a *CV-RMSE* of 11%. The metamodel predicted 51% of the observed winter wheat yield variability for the validation period (1993-2002) with a *RMSE* of 0.86 t ha^{-1} yr^{-1}, and a *CV-RMSE* of 14%.

Empirical Model

The best linear multiple regression model to emulate the observed winter wheat yield (in t ha^{-1} yr^{-1}) for the period 1983-1992 was:

Yield= -0.3+1.1TD + 0.2 WSRAD - 0.1 GTmax + 0.01 SD

According to this model, yields are higher on deeper soils being related to rooting depth and plant available water. Yields decrease with increasing maximum temperature during the whole growing season and winter radiation, which can probably be attributed to the fact that increasing temperatures enhance development rate and reduce the growing period (16, 24), which often counteracts the positive effect of temperature on photosynthesis. Additionally, higher radiation and temperatures might have caused additional water stress by affecting the soil water balance, which in turn resulted in reduced yields (7, 52). The empirical model did not contain a precipitation variable. Rainfall was also not strongly correlated to any of the variables that were included, which could account for its absence (Table 2). Indirect negative effect of rainfall on yields, such as

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increasing the risks for pests and diseases, may have counterbalanced the positive effect of rainfall on crop growth (7, 33). For the calibration period (1983-1992), this model (Mean= 5.5 t ha^{-1} yr^{-1}, SD= 0.7 t ha^{-1} yr^{-1}) predicted 87% of the observed winter wheat yield variability with a *RMSE* of 0.34 t ha^{-1} yr^{-1}, and a *CV-RMSE* of 6%. For the validation period (1993-2002), this model (Mean= 6 t ha^{-1} yr^{-1}, SD= 0.7 t ha^{-1} yr^{-1}) predicted 63% of the observed winter wheat yield variability with a *RMSE* of 0.58 t ha^{-1} yr^{-1}, and a *CV-RMSE* of 9%.

Spatial Patterns and Temporal Trends

The observed and modelled winter wheat yield maps for 1993-2002 are presented in Figure 1. The observed yields, obtained at 347 NUTS3-units, were aggregated to the 70 climate zones to allow comparison (Figure 1-a). Figure 1-b shows results from the empirical model, Figure 1-c those of the LINTUL2 model, and Figure 1-d those of the metamodel. All models have a similar order of magnitude of yield prediction and associated uncertainties. They were all capable of reproducing high-productivity regions in the northern part of Western Germany as well as the low-productivity regions in the southern parts. The spatial patterns are better represented by the empirical model (R^2= 70%, RMSE= 0.48 t ha^{-1} yr^{-1}, and CV-RMSE= 8%) than by the LINTUL2 model (R^2= 65%, RMSE= 0.67 t ha^{-1} yr^{-1}, and CV-RMSE=11%) and the metamodel (R^2= 57%, RMSE= 0.77 t ha^{-1} yr^{-1}, and CV-RMSE=13%). This spatial variability must be associated with the spatial variability in soil depth. The absence of any soil variable in the metamodel reveals an overall insensitivity of the LINTUL2 model and metamodel to soil variability for this specific case study. This insensitivity seems to be refuted by the spatial variability in the observed crop yields.

The temporal trends in winter wheat yields, observed as well as predicted by the three models, are plotted in Figure 2. The reported census data demonstrate a major discontinuity around 1990-1995, which is only reproduced by the empirical model. All models simulate a general increase in average yield with time. Based on the small differences between the metamodel and the empirical model, it seems likely that this may be attributed to an overestimation of the drought effect in the metamodel. This overestimation can be expected for models applying the *RUE* concept instead of detailed photosynthesis routines (38), and for the derived metamodels.

Simulation of Potential Climate Change Effects for Western Germany

The difference between simulated future winter wheat yields (2041-2061) and past

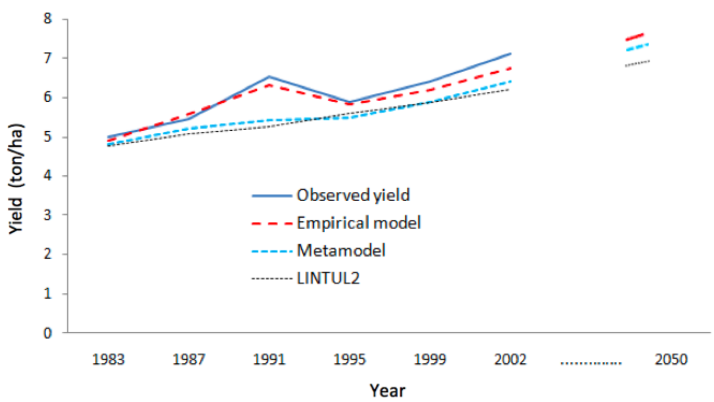

Figure 2. The temporal trends of observed and simulated winter wheat yields from 1983 to 2050 for Western Germany.

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yields (1993-2002) is shown in Figure 3 for the different modelling approaches. Projected future yields were higher than baseline yields for all modelling approaches, although the increase varied considerably per modelling approach and per geographical area. Yield increases were highest for the empirical model, showing an increase in yields between 3 and 58% (on average 27%). The metamodel predicts a yield increase between 7 and 52% (on average 24%). The LINTUL2 model predicts the smallest yield increase, between 5 and 52% (on average 22%). Our results suggest the predictions of future ranges depend on the models' sensitivities to specific changes in input variables. The degree to which the input variables change is, of course, context dependent.

Overall future increases in winter wheat yield (Figures 2 and 3) can obviously be ascribed to technological development, and, for the LINTUL2 projection, also to elevated atmospheric CO_2. It is remarkable that both the metamodel and the empirical model predicted higher future yields than the LINTUL2 model, in spite of not being sensitive to increased CO_2 levels. This could indicate a structural overestimation of a positive effect of one of the other (correlated) variables, such as technological development. Particularly, assumptions about technological development can have substantial impacts on yield prediction. Yield increase due to technology would, between 2002 and 2050, amount to 2 (according to the metamodel) or 2.3 t ha^{-1} (according to the empirical model). This is computed by taking the average *TD* value in 2050 (being 3.1), subtract the average *TD* value in 2002 (being 1.05; the difference is 2.05), and multiply that by the coefficients 1 and 1.1, respectively. Apart from uncertainties in the regression coefficients' estimation (resemblance with past trends indicate that these are relatively small), most uncertainty lies in the estimation of the actual development. Here, we have assumed a linear extrapolation of past trends (20), but many scientists have argued that these increases will gradually decline (see e.g. 11, 21). Obviously, further investigation is required to reduce uncertainty in the assumptions regarding technology development, especially for future projections of crop yields within climate scenarios.

The spatial variability in the changes predicted by the metamodel and the empirical model suggests that changes in yield predictors vary throughout space. This applies to technology development, winter radiation, maximum temperature during the whole growing season, and summer drought. In the center and south (empirical model), and the

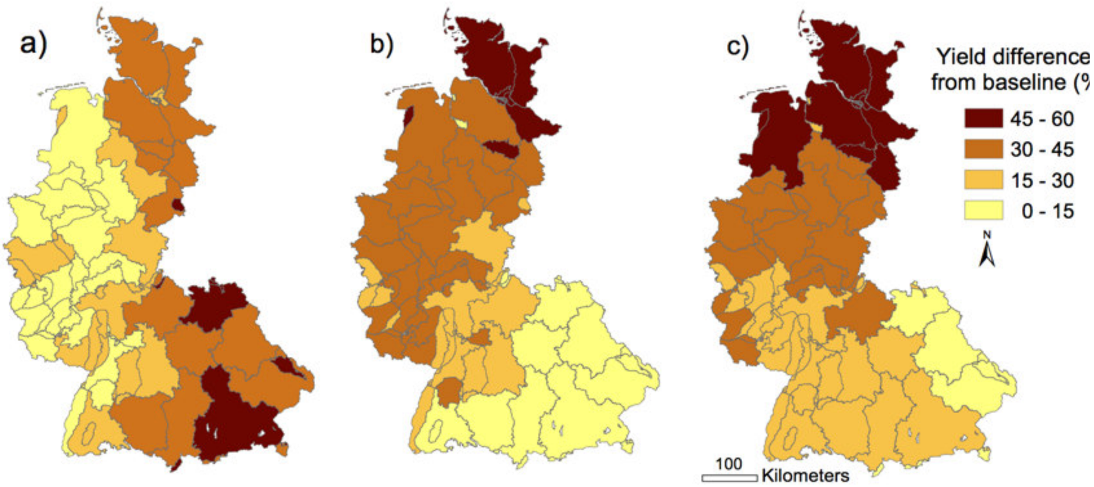

Figure 3. The difference between wheat yields in 1993-2002 and 2041-2061 for Western Germany, simulated by the: (a) LINTUL2, (b) Metamodel, and (c) Empirical model. In the figure, each polygon depicts a different climate zone.

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center east and southeast (metamodel), changes in winter radiation, maximum temperature during the whole growing season, and summer drought have a negative impact on yields, almost offsetting the positive impact of technological development. Looking at Figure 4, it becomes clear that it is especially the increase in maximum temperature during the whole growing season (mostly in the south, used by the empirical model) and decrease in summer drought (mostly in the southeast, used by the metamodel) that causes this relative decline in wheat yields.

Future projections serve the purpose to demonstrate the different sensitivities of the modelling approaches to changes in input variables that are relevant for studying impacts of climate change. According to the LINTUL2 model, the northwest and southeast *RUE* gradient in Western Germany is important for influencing the spatial variability in winter wheat yield under future climate conditions (Figure 3-a). These projected increases in yield can probably be attributed to the presumed lower sensitivity to changes in weather conditions and a much higher sensitivity to elevated atmospheric CO_2 level, as also suggested by Harrison and Butterfield (23). The empirical model, on the other hand, predicts large increases in wheat yields for the northern parts of the region, while the southern parts will only experience small increases in yield (Figure 3-c). These projected increases in yield can probably be attributed to the model's sensitivity of winter wheat to changes in winter radiation and a much higher sensitivity to maximum temperature during the whole growing season. The metamodel predicts large increases in wheat yields for the northWestern parts of the region, while the southeastern parts will only experience small increases in yield (Figure 3-b). These projected increases in yield can probably be attributed to the metamodel's sensitivity of winter wheat to changes in winter radiation and a much higher sensitivity to summer drought.

DISCUSSION

We compared different modelling approaches for simulating and predicting crop yields at a wide range of spatial and temporal scales. Apart from the inherent differences of the proposed models, all three seem reasonably able to predict winter wheat yield level at regional to national scales. The fact that all approaches had similar model performances could be somewhat overestimated due to aggregation effects of the reported yields. The yields were aggregated from NUTS3 to either climate zones (Figure 1)

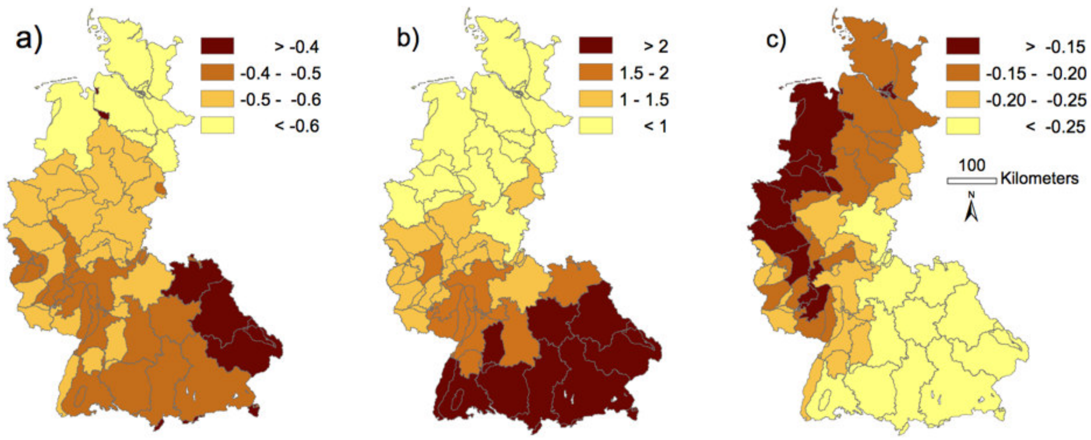

Figure 4. The change in variables included in the metamodel and empirical model between 1993-2002 and 2041-2061 for Western Germany: (a) Winter season global solar radiation (MJ m^{-2} d^{-1}), (b) Growing season maximum temperature (°C), and (c) Ratio of summer season rainfall and evapotranspiration. In the figure, each polygon depicts a different climate zone.

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or the whole of Western Germany (Figure 2). It is known from landscape-scale studies that such aggregation steps can cause a scale-dependent overestimation of model fits (49). Whether this effect has caused some overestimations of model performance or not, is not relevant for the model approach comparison in the sense that it would affect all three models in a similar fashion.

A model comparison helps to reveal shortcomings and strengths of the models. For example, in our study, a performance comparison between the three models indicated that a higher sensitivity to soil depth in the LINTUL2 model would probably lead to better predictions of yield spatial variability. Moreover, a performance comparison between the three modelling approaches indicated that a lower sensitivity to drought in the LINTUL2 model would probably lead to better predictions. The best fit with the observed data is demonstrated by the empirical model, which outperforms the CGSM and its derived metamodel.

However, the fundamental limitation of the empirical model is that it is not valid outside its calibration domain, which severely hampers its usefulness for future predictions (51). When the predicted values of important predictors exceed the range that was used for calibration, the validity of future projections by empirical models is questionable. Future projections of crop yields for climate change scenarios can, therefore, best be made by more mechanistic CGSMs, such as LINTUL2. The added value of the metamodel is that it is much faster to run and it requires far less (detailed) data than the original model. This suggests that such metamodels could be successfully used for quick scan applications of future yield scenarios for areas where the CGSM has been calibrated. The empirical models and the metamodels are easy to drive and require fewer input variables compared to the CGSMs to estimate regional patterns of crop yield. Moreover, the spatial and temporal resolutions can be adjusted to what is available at the spatial and temporal scale and extent in question. In this study, we selected different modelling approaches to assess regional patterns of winter wheat in Western Germany (e.g., CGSM, metamodel of the CGSM, and empirical model). We recognize that there are other approaches available (e.g., 37, 48). Note that we do not give a final preference to one of the approaches. This depends on the specific study aim.

All three modelling approaches are limited by the fact that they do not account for other, mainly socio-economic, factors in driving crop productivity. This could be easily overcome by using such data to derive improved empirical models. The general validity of such simplistic models is questionable because many mechanisms of the complex multi-level land system are still unknown (50). For example, the effect of a shift in the locations where wheat is grown is not taken into account, although recent research suggests that arable cultivation gradually shifts to less favorable soils (8). To investigate this properly, far more advanced statistical analyses are required (9).

CONCLUSIONS

All three explored model options have the capability to simulate and predict crop yields at a wide range of spatial and temporal scales. The suitability of the three modelling approaches used is context dependent. For near-future projections, the empirical model appeared to be most reliable. However, when values of predictors exceed the range that was present in the calibration dataset, the performance of this type of model is questionable (51). For that reason, future projections of crop yields within climate change scenarios can be best made by CGSMs. The derived metamodels can be fast and reliable alternatives for areas with well calibrated CGSMs. The metamodels can easily be made more climate-robust by calibrating them on the future climate variable range, rather than on just the observed one. A model comparison helps to reveal shortcomings and strengths of the models. In our case, a performance comparison between the three modelling approaches indicated that, for simulating winter wheat growth in Western

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Germany, a higher sensitivity to soil depth and a lower sensitivity to drought in the LINTUL2 model would probably lead to better predictions.

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مقایسه سه روش مدلسازی برای شبیه سازی عملکرد منطقه ای محصول: مطالعه موردی عملکرد گندم زمستانه در آلمان غربی

ا. سلطانی، م. م. بیکر، ا. ولدکمپ، و ج. ج.استوروگل

چکیده

مقایسه روشهای مختلف مدلسازی بسیار ضروری می باشد. هدف این تحقیق، مقایسه توانایی سه روش مختلف مدلسازی برای شبیه سازی و پیش بینی الگوی مکانی و زمانی عملکرد گندم زمستانه در آلمان غربی بود. سه روش مدلسازی شامل مدل تجربی، مدل پیشرفته مبتنی بر فرآیند (لینتول۲) و متامدل بدست آمده از لینتول۲ می‌باشد. به منظور ارزیابی نتایج، خروجی مدلها با داده های شاهد منطقه مقایسه شدند. مقیاس خروجی مدل، برای متناسب شدن با مقیاس داده های شاهد، افزایش یافتند. نتایج حاکی از توانایی بیشتر مدل تجربی (R2= 70%, RMSE= 0.48 t ha-1yr-1, CV-RMSE= 8%) نسبت به مدل لینتول۲(R2= 65%, RMSE= 0.67 t ha-1yr-1, CV-RMSE=11%) و متامدل(R2= 57%, RMSE= 0.77 t ha-1yr-1, CV-RMSE=13%) . در شبیه سازی الگوی مکانی و زمانی عملکرد گندم زمستانه در آلمان غربی می باشد. هرسه روش مدلسازی مقادیر نسبتاً مشابهی از برآورد محصول و عدم قطعیت مربوطه را نشان داده اند. مناسب بودن روشهای مدلسازی بستگی به شرایط محیطی و پروژه مطالعاتی دارد. مدلهای تجربی مناسبترین انتخاب برای تجزیه تحلیل گذشته و حال الگوهای عملکرد محصول هستند. در حالیکه مدلهای پیشرفته مناسب‌ترین انتخاب برای پیش بینی الگوهای آینده عملکرد با در نظر گرفتن سناریوهای اقلیم می باشند. متامدل مشتق شده از مدل پیشرفته، جایگزین قابل اعتماد و سریعی از مدلهای پیشرفته است اگر بخوبی برای شرایط منطقه کالیبره شده باشد. مقایسه مدلها، نقاط قوت و ضعف آنها را آشکار می سازد. بطوریکه در این مطالعه موردی مقایسه سه روش مدلسازی نشان داد که برای شبیه سازی عملکرد گندم زمستانه در آلمان غربی، لحاظ کردن حساسیت بیشتر نسبت به عمق خاک و حساسیت کمتر نسبت به خشکسالی در مدل لینتول۲، احتمالاً به پیش بینی دقیقتری از محصول با استفاده از مدل لینتول۲ منجر می شود.