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Statistical crop models: predicting the effects of temperature and precipitation changes

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ABSTRACT: Statistical models are common tools for quantifying possible impacts of climate change on crops. Climate change involves shifts in both mean and variability of climate parameters, and experimental results and simulations have shown that both mean and variability can have the same-order effects on crop growth and yield. It is therefore important for impact models to be able to capture the effects of both these aspects. The aim of the present study was to test the ability of statistical crop models to predict the effects of changes in mean and variability of temperature and precipitation on grain yield of maize. Climate variables were aggregated over different time intervals to explore effects of temporal aggregation of predictor variables. To examine the predictive capabilities of statistical crop models beyond the ranges of observed data, we applied the 'perfect model' approach using the process-based crop model CropSyst. Statistical crop models were then fitted based on different sample sizes to explore minimum data requirements for predicting the effects of different synthetic climate scenarios. The analysis revealed that statistical crop models are generally able to quantify the effects of changes in mean and variability of temperature and precipitation with reasonable accuracy, provided that a minimum of 10 to 20 samples per predictor are available for fitting. Also, we can conclude that with total sample sizes of <300 observations, disaggregation of predictor variables increases the risk of model over-fitting. Disaggregation of predictor variables had small beneficial effects, particularly for predicting impacts of changes in climate variability, only with large sample sizes (>300 observations).

KEY WORDS: Statistical crop model · Climate change · Impact assessment · CropSyst · LARS-WG

1. INTRODUCTION

Temperature is expected to increase globally with climate change, while changes in precipitation may differ between regions. As summarized by Christensen et al. (2007), the annual precipitation amount is very likely to increase across most of northern Europe and decrease in the Mediterranean basin. Also, extremes of daily precipitation are very likely to increase in northern Europe. In central Europe, precipitation is likely to increase in winter, but decrease in summer, which, in connection with increased temperatures, could lead to increased risk of summer drought. Especially in southern and central parts of Europe, simulated annual mean warming from 1980–1999 to 2080–2099 varies from 2.2° to 5.3°C under the A1B emission scenario (Christensen et al. 2007), accompanied by a general increase in daily temperature variability during summer months (Schär et al. 2004). In addition, heat waves are likely to increase in frequency, intensity, and duration (Barnett et al. 2006, Clark et al. 2006, Tebaldi et al. 2006). Conversely, the number of frost days is likely to decrease (Tebaldi et al. 2006).

These changes in climatic conditions may significantly affect crop yield and yield variability (Olesen et al. 2011). In general, crop responses to changing conditions are highly non-linear with distinct thresholds in response functions, and changes in growth, development, and yield result from the combined effects of stress factors (Porter & Semenov 2005). With respect to precipitation, both changes in amount

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and seasonal distribution are important (Olesen & Bindi 2002), and experimental results and simulations have shown that altering temperature variability had the same-order effect on the development and growth of wheat as changing the mean value (Porter & Semenov 2005). Accounting for increased variability is therefore essential to predict the impact of climate change on crop development and yield (Semenov & Porter 1995, Rigby & Porporato 2008, Moriondo et al. 2011).

Statistical crop models are often used for climate impact studies (e.g. Lobell et al. 2006, Almaraz et al. 2008, Iglesias et al. 2010, Kristensen et al. 2011). They usually incorporate linear and quadratic effects of radiation, temperature, and precipitation to account for the dependence of primary production on these main climate variables (Olesen & Bindi 2002). Temperature influences plant physiological processes such as photosynthesis and respiration and thus biomass accumulation, and it determines the length of the growing season (Rotter & Van de Geijn 1999). Also, changes in short-term temperature extremes can be critical for crop growth, especially if they coincide with key stages of development (Gornall et al. 2010). Only a few days of extreme temperature (>32°C) around the flowering stage can drastically reduce the yield of many crops (Wheeler et al. 2000, Semenov & Shewry 2011). For example, maize exhibits reduced pollen viability for temperatures >36°C during flowering (Decker et al. 1986), and in wheat, temperatures >34°C during the grain-filling stage accelerate leaf senescence leading to reduced grain yield (Asseng et al. 2011). Rainfall and related soil-water availability may limit photosynthetic efficiency due to stomatal closure and wilting of leaves. To capture climate-yield relationships with greater precision and to account for shifting sensitivity to climatic stress during crop development, many statistical studies have considered climate predictor variables aggregated over monthly or seasonal periods (e.g. Katz 1979, Quiroga & Iglesias 2009, Cabas et al. 2010, Iglesias et al. 2010) or over specific phenological periods (e.g. Peltonen-Sainio et al. 2010, Kristensen et al. 2011). However, such temporal disaggregation of climate predictor variables in statistical models bears the risk of over-fitting if inadequate sample sizes are used for model fitting. A further limitation of studies relying on experimental or census data is that statistical models can only be validated within the range of observed data, while it is unknown how well they can be used to project impacts of climate change (mean and variability) beyond the range of current conditions.

In the present study, we investigated the ability of statistical crop models developed based on current climatic conditions to project impacts of changes in mean and variability of temperature and precipitation with different levels of predictor-variable aggregation and for different sample sizes of simulated data. Our aim was to define minimum data requirements and to formulate recommendations for the development of reliable statistical crop models.

2. METHODS

To overcome the limitations of studies relying on field experimental or census data, we used the 'perfect model' approach proposed by Lobell & Burke (2010) to generate synthetic yield series, assuming that the process-based model reproduces the 'true' yield response to climatic conditions. A statistical model can then be fitted to the simulated 'true' yield and underlying climate data for the current climate. By comparing predictions of climate impacts derived with the statistical model to predictions of the process-based crop model, it is possible to evaluate the ability of the statistical model developed for current climatic conditions to reproduce simulated 'true' yields under climate change. In the present study, the predictive capabilities of statistical models were tested for different levels of aggregation of climate predictor variables and for different sizes of samples used for fitting. The overall approach is shown in Fig. 1.

2.1. Generation of weather data

To develop synthetic daily weather data, we used the stochastic weather generator LARS-WG (Semenov & Barrow 1997), which was conditioned using data from 15 stations distributed across the main agricultural areas of Switzerland (Fig. 2). The choice of stations was motivated by the necessity to provide a sufficiently broad basis for capturing climate-yield relationships. Observed climate data from 1981 to 2009 were obtained from the Federal Office of Meteorology and Climatology (MeteoSwiss) and used as an input to LARS-WG. For each station, 100 yr of synthetic daily weather data were generated for a baseline scenario representing current climate conditions. In addition, 100 yr of data were also generated for 4 synthetic scenarios developed to address changes in mean and variability of temperature and precipitation relative to the baseline:

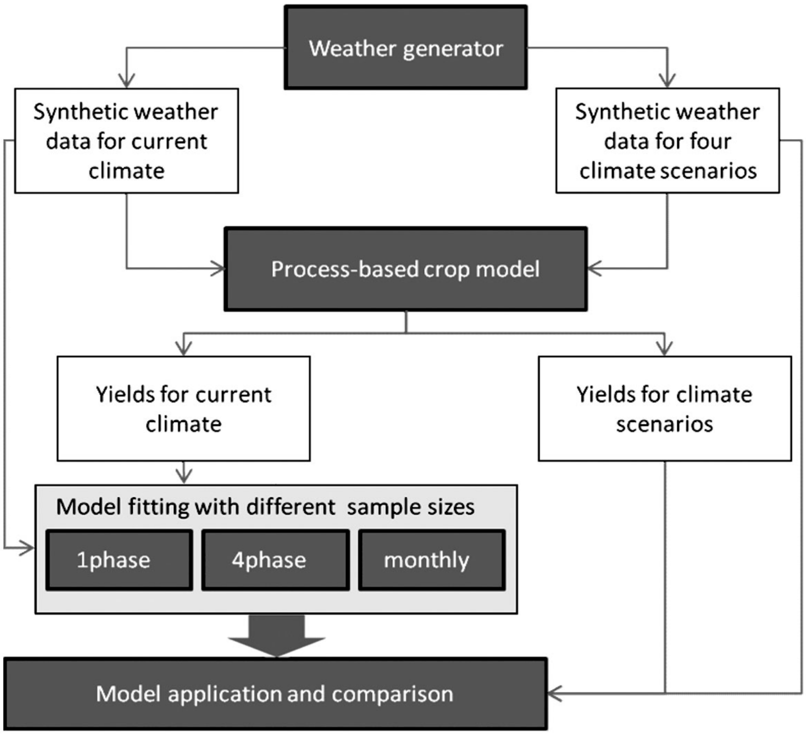

Fig. 1. Overview of the analytical procedure. See Section 2.3 for definitions of the '1phase', '4phase', and 'monthly' aggregation approaches

(1) 4C = constant 4°C increase in daily temperatures,

(2) TempVar = 20% increase in temperature variability,

(3) p20 = constant 20% decrease in daily precipitation,

(4) SpellChange = 20% increase in length of dry spells and 20% decrease in lengths of wet spells.

The synthetic scenarios were used to examine yield sensitivity to different aspects of climate change, and to explore the ability of the models to predict such responses.

2.2. Crop model application

To generate the 'true' yield, we used the process-based crop model CropSyst (version 4.13.09; Stöckle et al. 2003), which has previously been tested under Swiss conditions (Torriani et al. 2007). Despite the fact that CropSyst was previously shown to perform reasonably well under Swiss conditions (Torriani et al. 2007), the model specification used in the present study does not account for all impacts of climate on crop growth. For instance, it does not consider the negative impacts of erosion or extreme heat, nor is it able to account for physical damage to plants due to heavy rainfall or hail. Furthermore, CropSyst, like most process-based crop models, is not able to capture effects of pests and diseases on crop growth.

In our study, CropSyst was applied to simulate maize *Zea mais*. Maize is a typical and important spring-sown crop and as such it is strongly affected by increased temperature and reduced precipitation during the summer months (see e.g. Harrison et al. 2011). For our application, we assumed a fixed planting date (15 May or DOY [day of year] = 130) and a latest possible harvest date (15 November or DOY = 319). As the goal of the study was to investigate only climate impacts on yield, soil conditions were kept constant across all stations and optimal fertilization was assumed to prevent nitrogen limitation. The reference soil had a depth of 3m with a texture of 26% sand, 38% clay, and 36% silt.

2.3. Fitting the statistical models

Multiple regression models were fitted to yields simulated with CropSyst for current climate conditions using 3 different approaches of temporal aggregation of climate predictors:

(1) '1phase', an aggregated approach, where all climate predictor variables were aggregated over the entire growing period of maize (from 15 May to the average harvest date according to CropSyst simulations = 15 November);

(2) '4phase', a 4-phase disaggregated approach, where climate predictors were aggregated over 4 main phenological phases (i.e. sowing to emergence = 15 to 22 May; emergence to the onset of flowering = 23 July; onset of flowering to start of grain filling = 14 August; maturation = to 15 November) defined in accordance with the phenological development simulated with CropSyst;

(3) 'monthly', a monthly disaggregated approach, where climate predictors were aggregated for each individual month between May and November.

Linear effects of radiation as well as linear and quadratic effects of temperature and water deficit (defined as the difference between reference evapotranspiration and precipitation) were selected as cli-

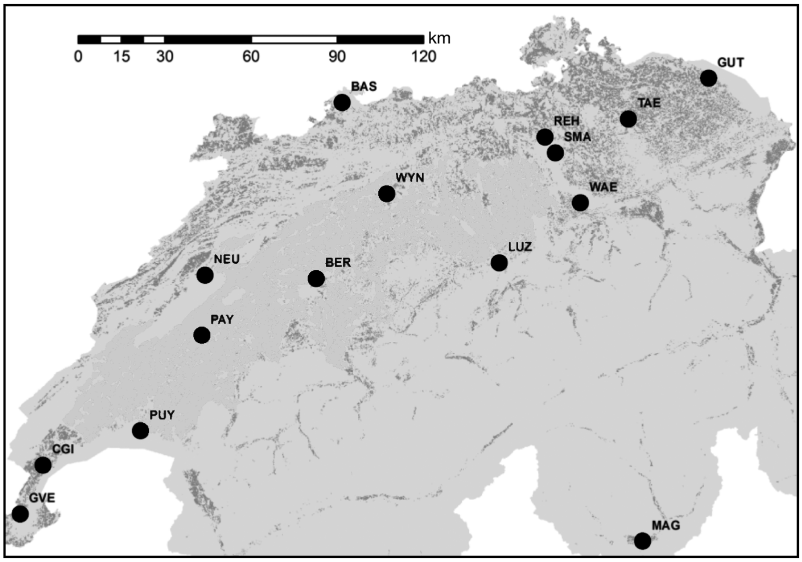

Fig. 2. Locations of stations (●) in Swiss agricultural areas (dark grey zones)

mate predictor variables. Based on randomly drawn samples of different size (10, 50, 100, 150, 300, 400, 600, 1000, 1300), multiple regressions were fitted automatically for all 3 aggregation approaches using the forward and backward stepwise regression procedure in the software package R (R Development Core Team 2010). As model fits can differ substantially depending on the sample that is drawn, fitting was repeated 50 times to derive estimates of sampling uncertainty.

Despite the fact that the data sets used for fitting the models were panel data sets, for which one would usually apply fixed-effects models (e.g. Schlenker & Lobell 2010, Lobell et al. 2011), we used multiple regressions without fixed effects. The integration of fixed effects was not necessary as reference yields simulated with CropSyst did not include any site-specific variation in yield responses to climate (e.g. due to soil conditions).

2.4. Model application and comparison

The statistical models fitted for the reference period were used to predict impacts of the 4 climate-change scenarios (4C, TempVar, p20, SpellChange). The predictions of the statistical models were compared to predictions derived with the process-based crop model for the same scenarios to evaluate predictive capabilities depending on sample size and temporal aggregation of predictor variables.

3. RESULTS

3.1. Properties of generated weather data

Table 1 shows a summary of statistical properties of generated weather data for the baseline and the 4 synthetic climate-change scenarios. The daily average precipitation amount was constant both in the baseline and in the 2 temperature scenarios, but decreased in the p20 scenario, and slightly increased in the SpellChange scenario. The latter was due to the modification of precipitation patterns introduced by LARS-WG to ensure that the same monthly total rainfall amounts were obtained with a reduced number of rain days. Variability of daily precipitation again was constant in the baseline and in the 2 temperature scenarios, decreased in the p20 scenario, and increased in the SpellChange scenario. Average minimum and maximum temperatures were relatively constant in all scenarios but the temperature scenario 4C; and variability of daily temperature was relatively constant in all scenarios except the TempVar scenario. Mean and variability of solar radiation were constant in all scenarios but the SpellChange scenario, where these values were slightly decreased in LARS-WG to keep monthly amounts constant.

3.2. Simulated yield response to synthetic climate scenarios

Yield generally increased in the 4C scenario and decreased with TempVar (Fig. 3). The yield increase in the 4C scenario indicated that under current conditions, maize yield is often temperature-limited, and optimum temperatures for grain maize growth are rarely exceeded with a constant 4°C increase in temperature. However, the increase in temperature variability in the TempVar scenario had negative impacts on yield due to increased occurrence of thermal stress, particularly during early growth after emergence, when temperatures are typically cooler than during mid-season. In this phase, temperature limitations were found to occur more often in CropSyst.

In the p20 scenario, precipitation decrease reduced yield through increased soil-water limitation. An increase in precipitation variability (SpellChange sce-

Table 1. Summary of statistical properties of generated weather data during the growing season (May to October) for all stations and years and the different scenarios. 4C = +4°C scenario, TempVar = increased temperature variability, p20 = 20% decrease in precipitation, SpellChange = increased precipitation variability. Data are mean ± SD of daily data of all stations and years

Scenario	Daily precipitation (mm d^{-1})	Daily minimum temperature (°C)	Daily maximum temperature (°C)	Daily solar radiation (MJ m^{-2})	Wet spell length (d)	Dry spell length (d)
Baseline	3.43 ± 8.40	9.67 ± 4.72	19.00 ± 6.70	14.26 ± 8.12	3.11 ± 2.19	4.00 ± 5.51
4C	3.43 ± 8.40	13.67 ± 4.72	23.00 ± 6.70	14.26 ± 8.12	3.11 ± 2.19	4.00 ± 5.51
TempVar	3.42 ± 8.47	9.61 ± 6.15	19.20 ± 8.51	14.27 ± 8.12	3.09 ± 2.19	4.01 ± 5.75
p20	2.73 ± 6.76	9.66 ± 4.73	18.97 ± 6.71	14.25 ± 8.14	3.09 ± 2.16	4.00 ± 5.46
SpellChange	3.54 ± 9.88	9.67 ± 4.68	18.94 ± 6.70	14.18 ± 7.86	2.65 ± 1.84	4.77 ± 6.28

nario) only slightly reduced yield but increased yield variability. Apparently, more extended dry spells had no considerable negative impact on simulated yield, probably because the overall water availability remained sufficient and the critical threshold for the appearance of significant yield reductions was not reached.

3.3. Model fits

Fig. 4 shows that best model fits were achieved with the most disaggregated approach and with the smallest sample sizes. With the 1phase approach, large error bars were associated with small sample sizes in Fig. 4, indicating that model fits differed greatly depending on the choice of the sample data set. With the most disaggregated approach, error bars for small sample sizes were smallest. This was due to the fact that disaggregation increases the number of possible predictor variables, which allowed for near-perfect model fits with almost any sample data set. Uncertainty of sample choice decreased with increasing sample size, as indicated by the change in the size of the error bars. Also, model fits leveled off with increasing sample size. This effect was most apparent with the 1phase approach, where model fits remained largely the same with sample sizes >50.

3.4. Model predictions

Despite good model fits, prediction results with small sample sizes were very poor, thus indicating model over-fitting (Fig. 5). The over-fitting effect was greatest for the 4phase and monthly approaches, as can be seen from the large discrepancies between model fit and predictive success in all scenarios. Prediction success, as indicated by the correlation between simulated and predicted yield, increased with sample size for the 4 synthetic climate scenarios. This increase was generally steepest with the aggregated approach; the disaggregated approaches (4phase and monthly) showed the smallest increases in model performance with sample size. With a sample size of around 300, predictive success was approximately the same with all aggregation approaches. With this sample size, the 1phase model includes on average 4 predictors, the 4phase model 13 predictors, and the monthly model includes 20 predictors. Beyond 300 samples, disaggregated approaches performed slightly better than the aggregated approach, but for small sample sizes, the

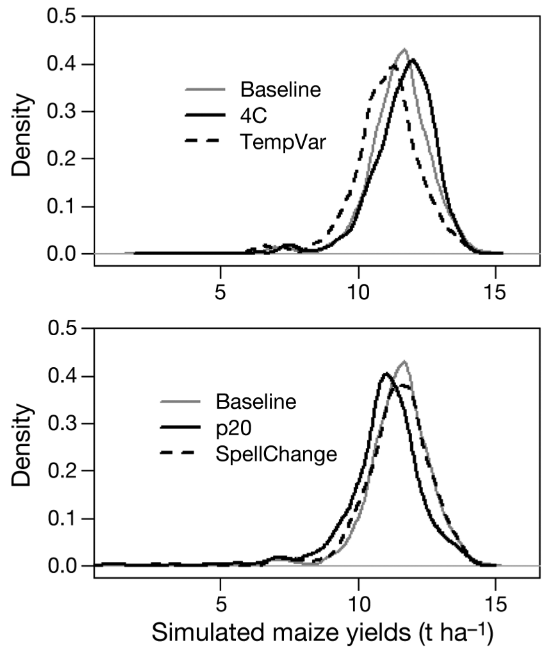

Fig. 3. Probability density distributions of maize yield simulated with CropSyst for all scenarios (top: 4C and TempVar; bottom: p20 and SpellChange). See Section 2.1 for definitions of the 4 scenarios

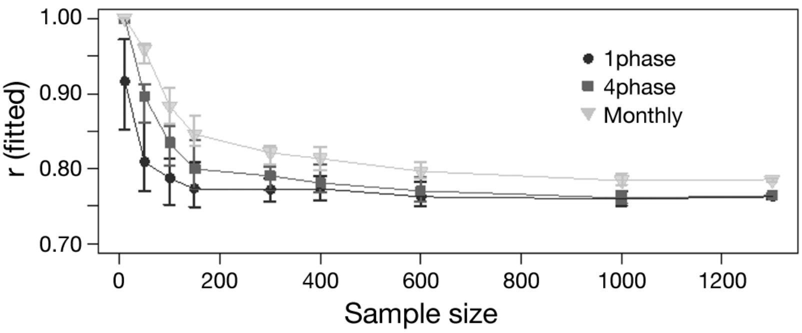

Fig. 4. Spearman rank correlations (r) between simulated and fitted yield depending on aggregation and sample size (data points = median values, error bars indicate 25th and 75th percentiles). See Section 2.3 for definitions of the 3 aggregation approaches

1phase approach was generally the most reliable, as disaggregation promoted over-fitting.

A benefit of disaggregation with larger sample sizes was least apparent for predictions of constant changes in precipitation (p20 scenario) and temperature (4C scenario), respectively. This is not surprising, since the aggregated approach was able to capture such constant changes to the same extent as the disaggregated approach. For the scenarios of increased variability in temperature and precipitation, however, the discrepancy in performance between the aggregated and disaggregated approaches increased with large sample sizes. This indicated that disaggregation was beneficial for capturing impacts of changes in climate variability, provided that the sample size used for fitting was sufficiently large.

Fig. 6 shows the relationships between minimum numbers of samples per predictor and predictive success for the synthetic scenarios and the 3 aggregation approaches. We will use the term 'events per variable' (EPV) to describe the number of samples per predictor (e.g. Peduzzi et al. 1996, Núñez et al. 2011).

In accordance with Fig. 5, Fig. 6 shows that the best possible performance was always achieved with the disaggregated approach. Overall, minimum EPV differed only slightly between scenarios and aggregation approaches. Between 10 and 20 EPV were usually sufficient to achieve reasonable predictive success. With the 1phase approach, the uncertainty of predictions was greater within this range due to the fact that fewer predictors were included in the model and thus the total sample size was still comparatively small (with 10 to 20 EPV, sample sizes ranges from 10 to 100 in the 1phase approach and from 150 to 400 in the monthly approach).

With regard to the climate scenarios, ~10 EPV were already sufficient to predict impacts of a constant precipitation decrease (p20); ~15 to 20 EPV were necessary for both temperature scenarios (4C and TempVar) and for predicting impacts of increased precipitation variability (Spell Change) with reasonable accuracy. These slight differences between synthetic scenarios were in accordance with the general ability of the statistical approach to capture impacts of the different synthetic scenarios: impacts of the p20 scenario could be predicted with greater accuracy than impacts of the other synthetic scenarios.

4. DISCUSSION

The simulation study for 15 stations in Switzerland showed that an increase in temperature led to yield increase, while increase in temperature variability decreased yield; in terms of rainfall, a decrease in precipitation reduced yield considerably, while an increase in precipitation variability (i.e. extension of dry spells, shortening of wet spells) had only small negative effects on simulated yield levels, but increased variability of yield (Fig. 3). These findings apply to the reference climate conditions found in Switzerland today and are generally in line with results from other studies investigating impacts of climate change on agricultural productivity in Europe (Olesen & Bindi 2002, IPCC 2007, Olesen et al. 2007, 2011). In regions with a different climate, the response to the tested climate scenarios might differ. For instance, in warmer regions, a 4°C increase in temperature is more likely to lead to an exceedance of the optimum temperature for growth and a decrease in yield levels (e.g. see Lobell et al. 2011).

The application of the 'perfect model' approach indicates that the capability of statistical crop models to predict impacts of climate change on maize yield in Switzerland is reasonably good, provided that the sample size used for fitting the statistical models is sufficiently large. In general, best fits are achieved with the monthly model and poorest fits with the aggregated approach, as the disaggregated approach allows better adjustment to the data due to the larger number of predictor variables. On the other hand, variable disaggregation increases the risk of overfitting. Results in the present paper suggest that the disaggregation is not beneficial with sample sizes <300. Where sample sizes are sufficiently large

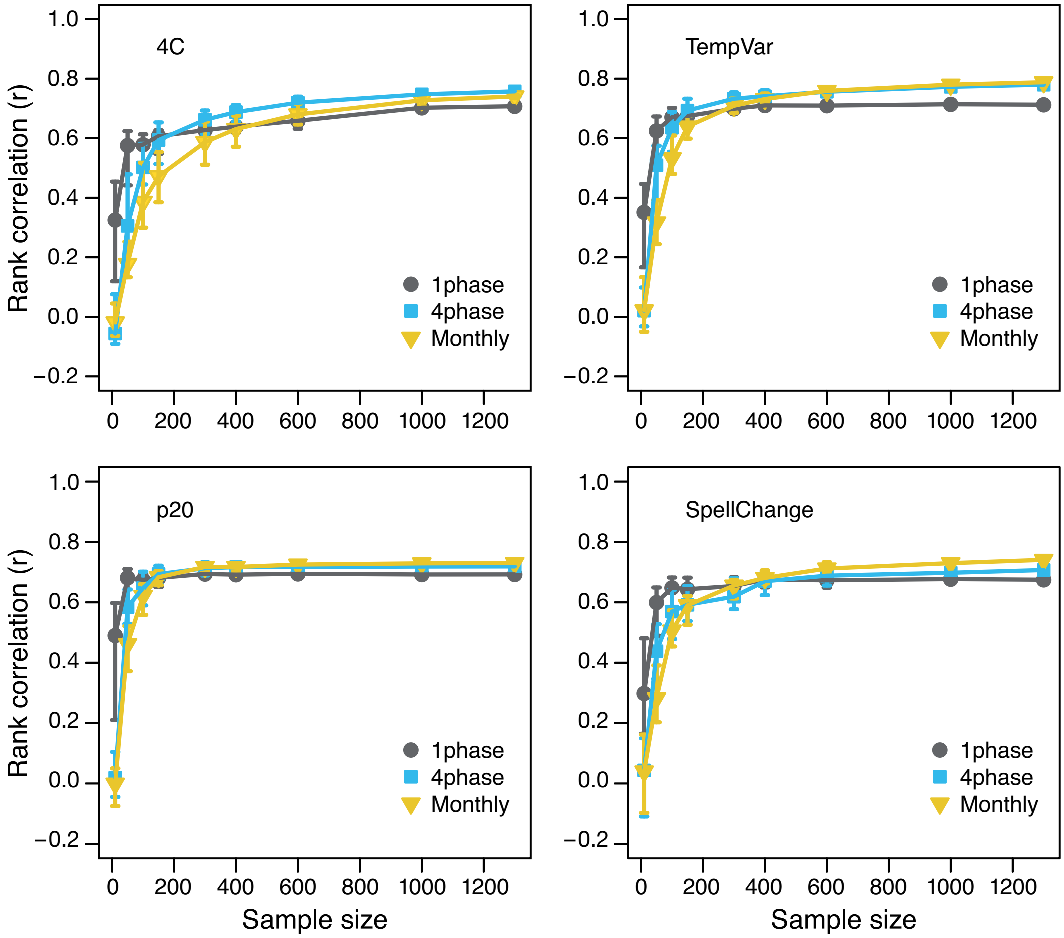

Fig. 5. Spearman rank correlations (r) between simulated and predicted yield for the 4 climate scenarios (see Section 2.1 for definitions) depending on aggregation approach (1phase, 4phase, monthly—see Section 2.3 for definitions) and sample size (data points = median values, error bars indicate 25th and 75th percentiles)

(>300), the beneficial effect of disaggregating predictor variables increases, especially for predicting impacts of changes in climate variability as with the scenarios TempVar and SpellChange. However, the beneficial effect of variable disaggregation up to the monthly time scale is still surprisingly small considering that sub-seasonal variation of climate variables (e.g. long dry spells) is known to be very important for crop development and subsequent yield (Porter & Semenov 2005). According to the results in Lobell & Burke (2008), this finding is not only limited to the specific application in our study (maize in Switzerland), but is also valid with respect to different crops and different geographical regions.

The limited benefit of variable disaggregation found in the present study can probably be attributed to the fact that statistical models are inevitably extremely simplified in comparison to process-based models. Variable disaggregation even to monthly averages does not allow for capturing the effects of climate variability on yield sufficiently; aggregation error is still too large. Also, interactive effects between different climate variables and between climate effects in different phenological phases are not considered in the statistical models investigated here, yet they are very important for crop development and subsequent yield. This may introduce bias in statistical models that cannot be compensated for by disaggregating climate predictor variables. Quite the contrary; model bias can be increased through variable disaggregation due to increased problems of multi-colinearity resulting in biased model coefficients.

However, it should be noted that yield responses to the synthetic climate scenarios were relatively moderate in the present study, due to the prevailing temperate climate conditions in Switzerland and due to the fact that the synthetic scenarios represented only changes in single climate statistics. If changes in temperature and precipitation occur together, overall effects on yields could be greater due to additive and

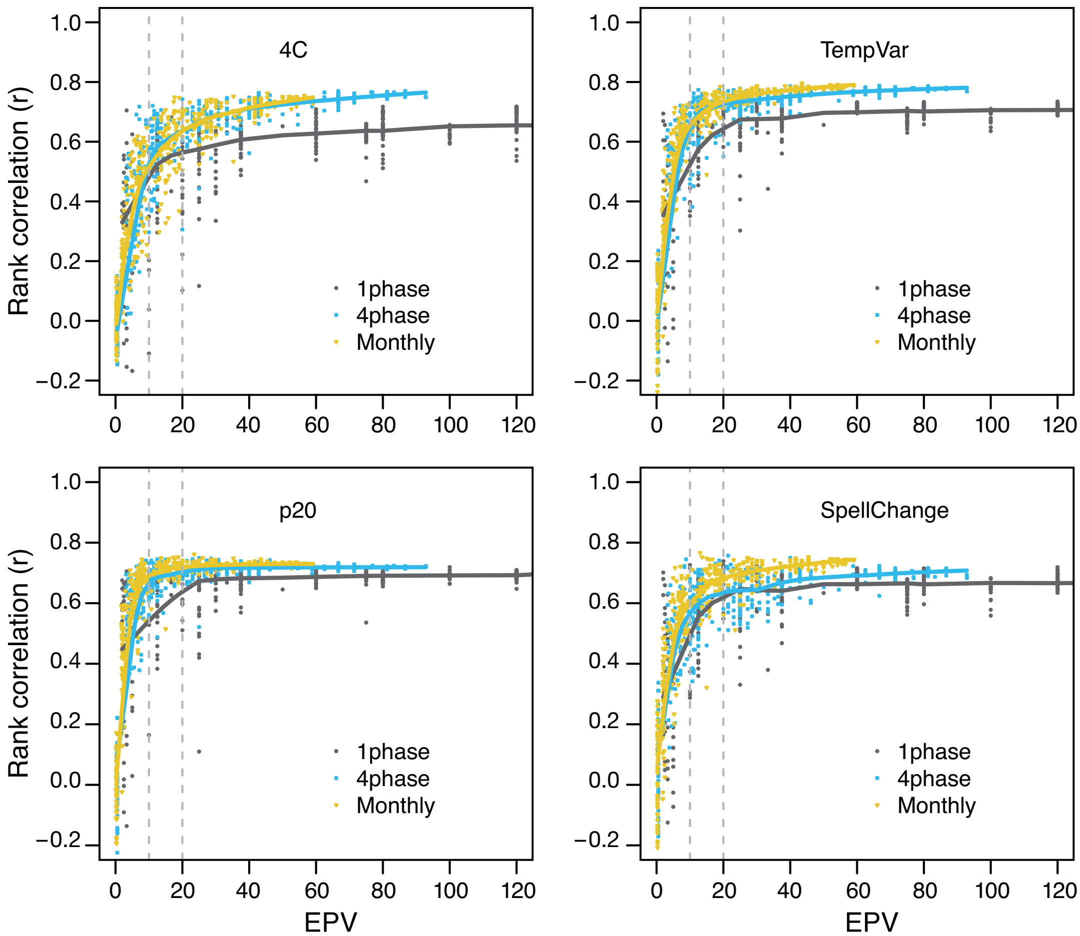

Fig. 6. Spearman rank correlations (r) between simulated and predicted yield for the 4 climate scenarios (see Section 2.1 for definitions) depending on aggregation approach (1phase, 4phase, monthly—see Section 2.3) and events per variable (EPV) (colored lines: locally-weighted polynomial regression lines through points of each aggregation approach; dashed lines: interval of 10 to 20 samples per predictor)

possibly interactive effects between temperature and precipitation. Future research should investigate whether variable disaggregation would have greater beneficial effects for predicting impacts of climate scenarios where changes in temperature and precipitation occur together or in a warmer and drier climate, where climatic changes may have more extreme impacts on yield.

We found that a minimum sample size to obtain a reliable statistical crop model is 10 to 20 EPV, which is only slightly higher than the 10 to 15 EPV suggested as a general rule of thumb to prevent over-fitting in multiple regressions (Harrell et al. 1984, Green 1991, Núñez et al. 2011). This indicates that statistical crop models developed based on 10 to 20 EPV are not subject to over-fitting and should allow for predicting impacts of climate changes with reasonable accuracy within the range of conditions tested in the present study. However, we must also note that the EPV recommendation is not entirely independent of total sample size, as was indicated by the fact that minimum EPV requirements differed slightly with aggregation approach. As aggregated models tend to include less predictor variables, more EPV (~20) are required to sufficiently cover the range of variability in predictor and response variables.

While some authors are aware of the risk of model over-fitting with large numbers of predictor variables and small data sets and have either reduced the number of predictors to a minimum (e.g. Lobell et al. 2007, 2011) or based their statistical models on very large data sets (e.g. Kristensen et al. 2011), others have developed and applied statistical crop models with large numbers of predictor variables that could be prone to over-fitting. For example, Cabas et al. (2010) used 26 yr of data from 8 regions fitting regression models with up to 51 coefficients. Almaraz et al. (2008) fitted multiple regression yield models with 5 predictor variables based on a time series of 33 yr (~7 EPV). Iglesias & Quiroga (2007) have developed multiple regression crop models including monthly climate variables as predictors. Their models were based on ~9 EPV, which suggests that there could be a risk of model over-fitting. Quiroga & Iglesias (2009) developed similar models with 5 to 10 EPV that could at least partly be subject to this risk. In particular, the application of these models for predicting impacts of climate scenarios, as presented in Iglesias et al. (2010), can be problematic. We found that for predicting impacts of moderate changes in climate variables, minimum samples sizes are relatively small. This was shown with the p20 scenario, where the minimum sample size is ~10 EPV due to the fact that the shift in precipitation distribution does not exceed the range of precipitation in the baseline scenario as much as the baseline temperature distribution is exceeded in the 4C scenario. However, for predicting impacts of the 4C, TempVar, and SpellChange scenarios, 15 to 20 EPV were required to fit a reliable model. Impacts of these scenarios were more difficult to predict, because the changes in climate variables are more extreme (4C scenario) and impacts of changes in climate variability (i.e. TempVar and SpellChange scenarios) are more difficult to predict than constant changes in precipitation. The results of the present study can provide some general indications for real-world applications of statistical crop models, bearing in mind that they are bound to the reference climate conditions found in Switzerland today, and to the assumptions made in the process-based crop model. As stated in Section 2.2, negative impacts of extreme heat were not considered in our study, but could be investigated in the future using the modified version of CropSyst including heat-stress effects on harvest index as described by Moriondo et al. (2011) for generating reference yields. There is also a need to examine how well statistical crop models can account for negative effects of heavy rainfall events such as erosion and physical damage to plants or for impacts of pests and diseases. Finally, possible adaptation measures such as shifts in sowing dates and crop varieties may affect true yield responses to future climate change. Such effects could be investigated in the future by testing different assumptions in the process-based crop model. Further, as the present study focused on climate-yield relationships for maize, it should be tested whether the same conclusions can also be derived for other crops and with different models.

5. CONCLUSIONS

In the present study, we investigated the ability of statistical crop models to predict impacts of changes in mean and variability of temperature and precipitation using a 'perfect model' approach based on the generic crop model CropSyst for maize applied at 15 climate stations in Switzerland.

Statistical crop models were fitted with different sample sizes, and it was found that these models are generally able to provide good estimates of impacts of changes in mean and variability of temperature and precipitation when they are fitted based on an adequate sample size. By testing predictive capabilities of statistical models with different levels of predictor variable aggregation and different sample sizes, conclusions could be derived regarding minimum data requirements and ideal predictor variable aggregation. Our findings can be summarized as follows:

(1) A minimum of 10 to 20 EPV is needed to fit a statistical crop model that is capable of predicting impacts of climate change with reasonable accuracy. As the EPV recommendation is not entirely independent of total sample size, it is advisable to use rather more EPV with an aggregated approach than with a disaggregated approach.

(2) With sample sizes <300 observations, the statistical approach based on aggregated climate predictors performed better than the disaggregated approaches, suggesting that it is not advisable to disaggregate predictor variables due to the risk of model over-fitting.

(3) With larger sample sizes (>300 observations), disaggregation of predictor variables has a small beneficial effect, especially for predicting impacts of changed variability.

Further work should investigate whether these conclusions are also valid for other crops, with climate scenarios where changes in mean and variability of temperature and precipitation occur together, or in warmer and drier reference conditions, where climate-change effects on yield may be more pronounced compared to the situation with the present reference climate for Switzerland.

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