

Methods for Spatial Prediction of Crop Yield Potential

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ABSTRACT

Opportunities for and constraints to crop production can be assessed with crop growth simulation models. Most crop simulation models require daily weather data as input but such data are generally not available at a high spatial resolution. Several approaches have been developed to estimate yield potential (Y_p) at locations without daily weather data (weather stations) but these have not been compared. We used two crop simulation models (WOFOST and LINTUL) to compute Y_p for two crops for the entire world. A global weather database was divided into 856 training and 12,808 testing sites. We predicted Y_p at the testing sites by using five main methods (eight methods if one considers within-method variants): (i) weather interpolation followed by simulation; (ii) nearest neighbor interpolation; (iii) thin plate spline interpolation, either with or without covariates; (iv) Random Forest-based metamodels with either climatic or bioclimatic variables; and (v) weather generation from either climate data or interpolated climate data, followed by simulation. The metamodel with bioclimatic variables performed best [average root mean square error (RMSE) = $667 \pm 111 \text{ kg ha}^{-1}$], followed by weather generation from climate data, weather interpolation, and spatial interpolation of yield with climatic covariables. The most commonly used method, nearest neighbor interpolation, performed worst (RMSE = $1763 \pm 472 \text{ kg ha}^{-1}$). The optimal method for a particular study will depend on the simulation model, the region, weather station density, and other variables but these results suggest that for estimating Y_p , alternatives to nearest neighbor interpolation should be considered.

Core Ideas

- We compared five methods for applying crop models to predict yield potential.
- A global weather database was divided into training and test sites.
- Metamodels and weather generation approaches performed best.
- Nearest neighbor interpolation can be replaced by superior and computationally efficient methods.

CROP GROWTH is strongly dependent on environmental conditions. It is therefore highly site-specific and therefore assessments of agricultural production opportunities and constraints may need to be done at a high spatial resolution. Such assessments often involve the use of mathematical models. These can be statistical models (Neumann et al., 2010; Mueller et al., 2012; Hannah et al., 2013) or mechanistic crop growth simulation models (Hijmans et al., 2003; van Ittersum et al., 2013; Rosenzweig et al., 2014). Crop growth simulation models are a mathematical description of the response of a cultivar to the environment and management that can be used to compute crop yield under different conditions (de Wit and van Keulen, 1987; Fischer et al., 2005; Rabbinge and van Diepen, 2000). They have been used, for example, to evaluate the effect of changing agricultural technologies (Hijmans et al., 2003), to interpret yield variation (Basso et al., 2001), to evaluate the effect of temperature variability on crop phenology and yield (Wheeler et al., 2000), and to evaluate the effect of climate change on production (Hijmans, 2003; Jones and Thornton, 2003; Rosenzweig et al., 2014). Crop growth models are also commonly used to estimate yield gaps (i.e., the difference between attainable and actual crop yield) (Lobell et al., 2009; van Ittersum et al., 2013).

Here, we focus on the spatial estimation of Y_p , defined as the yield that can be obtained with a cultivar at a particular location and time in the absence of biotic (pests, weeds, or diseases) or abiotic stresses not directly caused by temperature or solar radiation (i.e., water or nutrient stress). Yield potential is determined by the amount of incoming solar radiation, ambient temperature, and CO_2 and by cultivar traits that govern length of growing period, light interception by the crop canopy and its conversion to biomass, and partitioning of biomass to the harvestable organs (Evans, 1993; van Ittersum and Rabbinge, 1997). Precipitation and soil data are not required to compute Y_p . The computation of Y_p is useful for evaluating variations in

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Abbreviations: GI_{WTH} , weather generator model with the climate data interpolated from the training to the testing locations; G_{WTH} , weather generator model with the climate data for the testing locations was used; I_{NN} , nearest neighbor yield interpolation; I_{XY} , yield potential interpolated with longitude and latitude as independent variables; I_{XYCLM} , yield potential interpolated with longitude, latitude, and additional climatic predictor variables; M_{BIO} , metamodel with yield potential as function of a set of bioclimatic variables; M_{CLM} , metamodel with yield potential as a function of monthly climate data; RMSE, root mean square error; S_{rad} , solar radiation; TPS, thin plate spline; T_{min} , minimum temperature; T_{max} , maximum temperature; W_{INT} , interpolated weather model; Y_p , yield potential.

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crop yield in the absence of water or nutrient stress, pests, and diseases.

Most crop growth simulation models require detailed environmental input data, notably long-term daily weather data. Such data are available from weather stations but, in most regions, the density of stations with sufficient data quantity and quality is low (Grassini et al., 2015). Several approaches are available to estimate crop yield potential for places where there are no weather stations, across space at a high and consistent spatial resolution, but these have not all been pursued and the methods used have not been described and compared systematically. We provide such a comparison here, albeit only for Y_p , leaving the estimation of water-limited yield for future work.

Approaches that are available include (i) estimation of daily weather data for all sites through spatial interpolation and then computing Y_p . A much simpler approach (ii) is to use nearest neighbor interpolation, which assigns the yield value obtained for the nearest weather station, sometimes to the nearest station within an agro-ecological zone, to all other sites (van Bussel et al., 2015). Although this is a commonly used approach, this method is questionable if weather stations are far apart, particularly in mountainous areas and other areas with steep environmental gradients. An alternative is to use (iii) more refined spatial interpolation methods with or without environmental covariables (Wu et al., 2006). It is also possible (iv) to use metamodels. These are summary models in which the original crop simulation model's output is fitted to aggregated original model input (e.g., mean annual temperature). Since such aggregated variables are available at a high spatial resolution, predictions with these metamodels can then be readily made at this spatial resolution (Sparks et al., 2014; Perlman et al., 2013). Finally, one can use (v) synthetic weather generators to produce daily weather data from data with a lower temporal resolution (e.g., monthly weather or climate data) that are available at a high spatial resolution (Hijmans, 2003; Jones and Thornton, 2003) and run the crop model with the simulated weather data.

The goal of this paper was to compare the performance of these methods that can be used to estimate Y_p in places where there are no weather stations. To do so, we computed Y_p for maize (*Zea mays* L.) and wheat (*Triticum aestivum* L.) via two crop models (WOFOST and LINTUL). We ran the simulation models for all locations in a global weather database to compute Y_p . We refer to these values as "observed Y_p ". We then divided the weather station locations into training and testing locations and made predictions for the testing locations with data from the training locations.

MATERIALS AND METHODS

Crop Growth Simulation Models

Crop yields were simulated for maize and wheat using WOFOST (World Food Studies) (van Diepen et al., 1989) and the current version of LINTUL (Light INTerception and Utilization) (van Oijen and Leffelaar, 2014), which is a modification of the original LINTUL model by Spitters (1990) and Spitters and Schapendonk (1990). The two models have been widely used and they were chosen because of their differences in complexity, and because both models were implemented as R packages (R Core Team, 2017), which facilitates their use for this type of study. Both models operate on a daily time step

and require daily solar radiation (S_{rad}) and maximum temperature (T_{min}) and minimum temperature (T_{max}) to compute Y_p . LINTUL is a relatively simple model that simulates the development of leaf area index as a function of thermal time and then uses a fixed radiation use efficiency to estimate biomass production. WOFOST is a more complex model based on leaf level CO_2 assimilation. In both models, storage organ biomass (grain yield) is calculated as a function of total daily dry matter allocation to different plant organs according to partitioning functions depending on the crops' development stage.

We simulated the growth of a maize and wheat cultivar with both models, applying the default crop parameters: LINTUL-Maize, LINTUL-Wheat, WOFOST-Maize, WOFOST-Wheat for an early (typical) and a late variety.

Weather Data

The Prediction of Worldwide Energy Resource dataset from the National Aeronautics and Space Administration (2018) was used as weather input for the crop models. The Prediction of Worldwide Energy Resource dataset has daily weather data, including incident S_{rad} , T_{max} , and T_{min} , for a 1° by 1° (~100 by 100 km) raster of the entire globe starting in 1983. These data were derived from satellite observations coupled with the Goddard Earth Observing System climate model to obtain complete terrestrial coverage. The quality of the Prediction of Worldwide Energy Resource data as input for crop models has been evaluated, with mixed results (Bai et al., 2010; White et al., 2008, Van Wart et al., 2013b). We note that these evaluations are problematic, as they compared weather station data (at a particular site) with the average values for large grid cells but we do not dispute that the data have some error and bias. Though the quality of these data could be important considerations for a particular study, region, or crop model, this is not a major concern for our study, as our purpose is not to provide the most accurate estimates of Y_p , but rather to compare different spatial estimation methods that all use the same input data. We treated each terrestrial cell ($n = 13,664$) as a weather station. We also computed monthly climate averages from the daily data to use as an input for the metamodel and the weather generator.

Spatial Prediction Methods and Evaluation

We ran the two simulation models for each of the two crops for all 18,398 terrestrial weather stations (excluding Antarctica) using an emergence day on the 15th of each month for each of 30 yr (1985–2014). To select a plausible growing season, we then computed the average yield for each month, then the maximum of the resulting 12 values was used as the observed Y_p for a crop and model combination. In other words, for each weather station, we selected the sowing date that on average, gave the highest Y_p during the 30-yr period. The weather stations were split into a training and testing dataset by taking a spatially regular coordinate sample of 856 weather stations (~6%) via the R package 'geosphere' (Hijmans, 2016). The remaining 12,808 weather stations south of $60^\circ N$ were used for model evaluation. Stations north of $60^\circ N$ were not taken into account for testing because that would have led to inflated confidence in the methods, as it would yield very good but irrelevant predictions of Y_p of (near) zero in the Arctic.

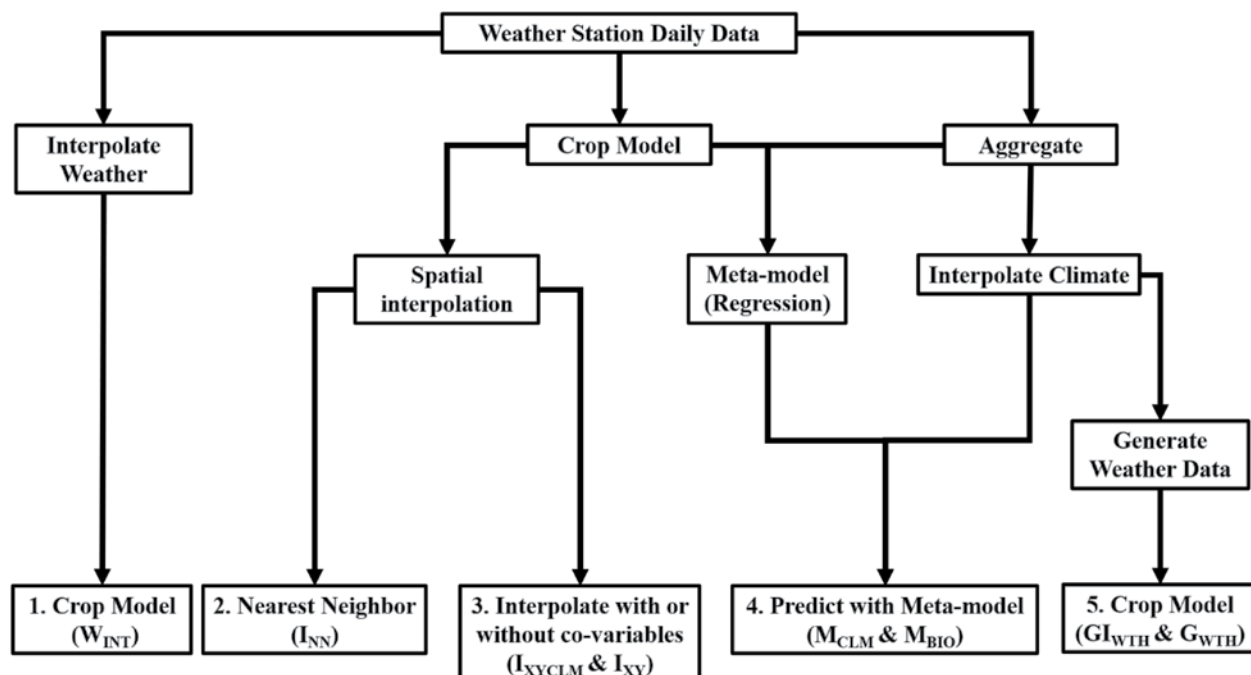


Fig. 1. Flow diagram showing different approaches for creating crop model predictions with high spatial resolution from spatially sparse weather station data.

We evaluated the performance of five main methods to estimate Y_p at the testing locations by comparing the results with observed Y_p , computed with the crop simulation models. We computed the RMSE, Pearson's correlation coefficient between predicted and observed long-term average yield potential at each location, and bias (the average difference between the observed and predicted Y_p values). We also evaluated the effect of distance to the nearest station on RMSE.

Five main spatial estimation methods were used; eight methods one counts the within-method variations (Fig. 1).

1. Interpolated weather (W_{INT}): Daily weather data were interpolated to the testing data sites for which the crop model was run. Interpolation was done via thin plate spline (TPS) models with longitude, latitude, and elevation as independent variables. The TPS model was used here and in the interpolations described below, because of its ease of use and because it has been successfully used for spatial interpolation of climate data (Hutchinson, 1995; Jarvis and Stuart, 2001; Fick and Hijmans 2017). The TPS model was implemented via the 'Tps' function in the R package 'fields' (Nychka et al., 2015).
2. Nearest neighbor yield interpolation (I_{NN}): Y_p values at the testing sites were set to be the same as the values of the nearest neighboring training site via the 'gstat' function in the R package 'gstat' (Pebesma, 2004).
3. Interpolated yield: Simulated Y_p at the training sites was interpolated via TPS to estimate yield at the testing sites. The Y_p was interpolated either with longitude and latitude as independent variables (I_{XY}), or with additional climatic predictor variables (S_{rad} , T_{min} , and T_{max}) (I_{XYCLM}).
4. Metamodel: Simulated Y_p at the training sites was modeled as a function of climate data via the Random Forest algorithm (Breiman, 2001) as implemented in the R package 'randomForest' (Liaw and Wiener, 2002). Random Forest

has the benefit of flexibility for fitting potentially irregular surfaces resulting from complex interactions. Two metamodels were fitted: first, a model in which Y_p was a function of monthly climate data (S_{rad} , T_{min} , and T_{max}) (M_{CLM}) obtained by averaging the weather data; second, a model in which Y_p was a function of a set of 'bioclimatic' variables (M_{BIO}). We used the 'biovars' function in the dismo R-package (Hijmans et al., 2017) to create 19 bioclimatic variables from monthly climate data (S_{rad} , T_{min} , T_{max}). These variables have been shown to be of great practical value in spatial predictive modeling of the distribution of species and in related ecological modeling techniques (Booth et al., 2014; Elith and Leathwick, 2009). The bioclimatic variables represent annual trends (e.g., mean annual temperature and radiation), seasonality (e.g., annual range in temperature and radiation), and extreme or limiting environmental factors (e.g., temperature of the coldest and warmest months).

5. Weather generator: Daily weather data were generated from long-term averages in two ways. In Variation A, the climate data were first interpolated from the training to the testing locations (G_{IWTH}) via TPS with latitude, longitude, and elevation as independent variables. In Variation B, the observed climate data for the testing locations were used (G_{WTH}). Comparing these two variations allows us to separate the effect of the climate interpolation and the weather simulation. The weather generator was extremely simple. Monthly averages were assigned to the 15th of each month (or 14 February) and values for intermediate days were obtained by linear interpolation. These generated values were used to run the crop model.

RESULTS

The results for predicted Y_p at the testing locations were very similar for all crop and models' combinations (WOFOST-Maize, WOFOST-Wheat, LINTUL-Maize, LINTUL-Wheat)

Table 1. Quality of predicted yield potential for nine prediction methods. The numbers are averaged for 12,808 testing sites and four model runs: the combination of two simulation models (LINTUL and WOFOST) and two crops (maize and wheat).

Method†‡	Correlation coefficient (R^2)	RMSE	
		kg ha ⁻¹	
M _{BIO}	0.98	667 ± 111	-27
G _{WTH}	0.98	1141 ± 466	582
W _{INT}	0.96	1167 ± 319	314
I _{XYCLM}	0.95	1124 ± 377	186
GI _{WTH}	0.94	1572 ± 386	205
I _{XY}	0.91	1435 ± 432	18
M _{CLM}	0.90	1522 ± 496	24
I _{NN}	0.87	1763 ± 472	-2

† Rankings were based on Pearson's correlation coefficient.

‡ M_{BIO}, metamodel using bioclimatic factors as independent variables; G_{WTH}, daily weather simulation; W_{INT}, daily weather interpolation; I_{XYCLM}, interpolated simulated yield with latitude, longitude, and environmental covariables; GI_{WTH}, daily weather simulation from interpolated climate data; I_{XY}, interpolated simulated yield without environmental covariables; M_{CLM}, metamodel with solar radiation, maximum, and minimum temperature as independent variables; I_{NN}, simulated Yp interpolated from the nearest neighbor; RMSE, root mean square error.

(Supplemental Table S1). Here, we focus on the average results. The M_{BIO} model performed best by far. It had an average correlation coefficient of 0.98 and a RMSE of 667 kg ha⁻¹ (Table 1) or 8% of the average Yp of 8460 kg ha⁻¹. The next best methods, G_{WTH}, W_{INT}, and I_{XYCLM}, also had high correlation coefficients (³0.95) but their RMSE values were lower than that of M_{BIO} (between 1124 and 1167 kg ha⁻¹) (Table 1). The I_{NN} model was the worst methods with an averaged correlation coefficient of 0.87 and a RMSE of 1763 kg ha⁻¹. The GI_{WTH}, I_{XY}, and M_{CLM} models performed poorly relative to M_{BIO} but better than I_{NN}.

In general, the methods overestimated the observed yield values (Table 1, Supplemental Table S1). Both M_{BIO} and W_{INT} predicted well for both low and high values of Yp. The G_{WTH} model tended towards underestimation for low observed Yps and overestimation for observed Yps higher than about 8000 kg ha⁻¹ (Fig. 2, Supplemental Fig. S1, Supplemental Fig. S4, Supplemental Fig. S7). Poor predictions by I_{XYCLM}, GI_{WTH}, and M_{CLM} were mostly observed for low values of observed Yp. With the I_{XY} method, for low observed Yp values, higher values were often predicted, whereas for high observed values, lower values were often predicted.

There were large differences between the variants within the main methods. For example, although M_{BIO} preformed best, M_{CLM} was one of the poorer performing methods. The choice of predictor variables to fit the Random Forest metamodel clearly made a big difference between these two variants: G_{WTH} performed much better than GI_{WTH}. Thus interpolation of the climate had a negative effect in the performance of the weather generator method. For the TPS-based Yp interpolation methods, the approach that used climatic covariables (I_{XYCLM}) performed much better than interpolation with only geographic coordinates (I_{XY}).

The maps illustrate the major discrepancies with respect to observed Yp for the predictions made via I_{XY}, M_{CLM} and I_{NN} (Fig. 3, Supplemental Fig. S2S, Supplemental Fig. S5, Supplemental Fig. S8). The predictions with I_{XY} are too smooth, whereas those with I_{NN} show sudden jumps. For the

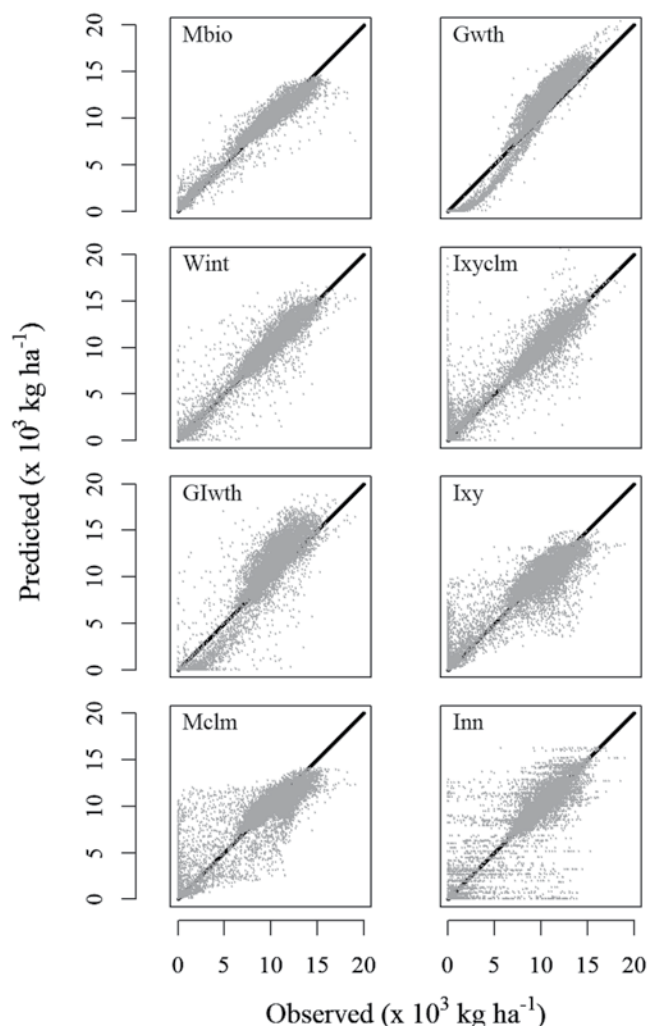


Fig. 2. Correlation between predicted and observed long-term average yield potential at each location for maize and the WOFOST model. M_{BIO}, metamodel with bioclimatic variables; G_{WTH}, weather generator; W_{INT}, interpolation of daily weather data; I_{XYCLM}, interpolation with geographical and environmental covariables; GI_{WTH}, weather generator with interpolated climate data; I_{XY}, interpolation with location data only; M_{CLM}, metamodel with climate averages; I_{NN}, nearest neighbor interpolation.

poorest performing methods (I_{XY}, M_{CLM}, and I_{NN}), the largest differences between the observed and predicted Yp, were found in mountains regions such as the Rocky Mountains, Andes, and Himalayas, as well as in places where there were fewer nearby training sites because of edge effects along the coast (Fig. 4, Supplemental Fig. S3, Supplemental Fig. S6S, Supplemental Fig. S9).

The I_{NN} model was the only method for which there was a clear relationship between RMSE and the distance to the nearest weather station. Unsurprisingly, the performance was better at shorter distances. For example, RMSE was 2150 kg ha⁻¹ at 200 km but 800 kg ha⁻¹ at 50 km and it would be zero at 0 m distance to the nearest weather station. In contrast, the RMSE of M_{BIO} was 500 ton ha⁻¹ at 50 km and 700 ton ha⁻¹ at 200 km. A linear regression model between RMSE and distance to the nearest station for I_{NN} had a slope of 9.2 kg km⁻¹. In other words, for each km increase in the distance from a weather station, the RMSE will increase by 9.2 kg.

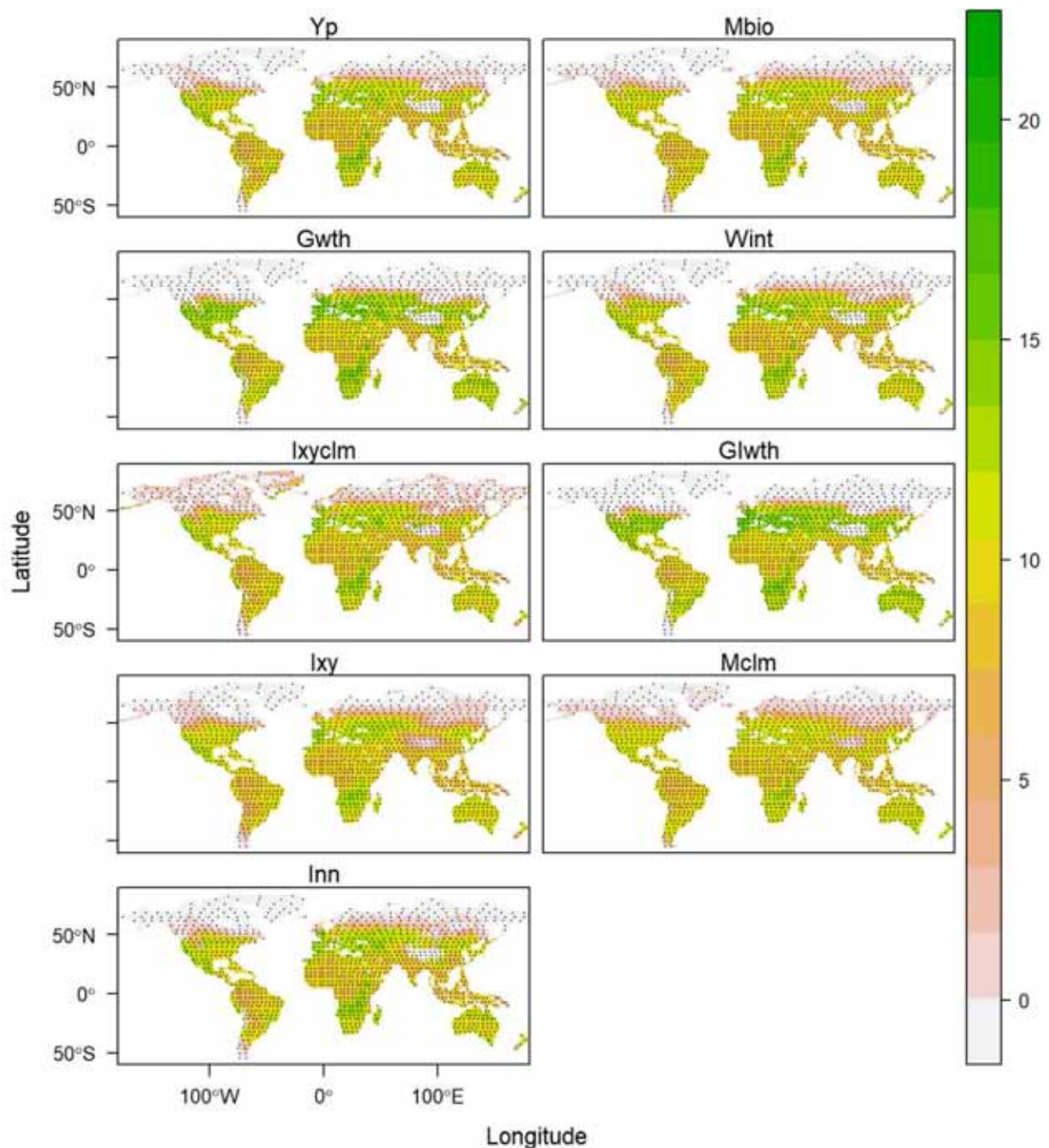


Fig. 3. Maize yield potential (Y_p ; 10^3 kg ha^{-1}) simulated with the WOFOST model and predictions based on 856 training sites (black points on map) via eight methods. M_{BIO} , metamodel with bioclimatic variables; G_{WHT} , weather generator; W_{INT} , interpolation of daily weather data; l_{XYCLM} , Interpolation with geographical and environmental covariables; G_{LWTH} , weather generator with interpolated climate data; l_{XY} , interpolation with location data only; M_{CLM} , metamodel with climate averages; l_{NN} , nearest neighbor interpolation.

DISCUSSION

Most crop simulation models require long-term daily weather data as input but for many regions, weather station data are not available at a high spatial resolution. We compared the performance of five main methods (eight methods if one counts the within-method variants) that can be used to estimate yield potential in places where there are no weather stations. Of the methods considered, the Random-Forest-based metamodel with bioclimatic variables (M_{BIO}) performed best. An advantage of this approach is that such a metamodel is mathematically much simpler than the dynamic crop simulation models and therefore is very fast. This can be an important time-saver when modeling on the global scale and at a high spatial resolution (e.g., 1

km^2 ; Perlman et al., 2013), particularly when many model runs are needed (e.g., to evaluate the effect of many possible future climates). In addition, the quality of the weather input data to the crop model is not that important anymore, as the response to these data is generalized in a new model. A disadvantage of this approach compared with weather generation (G_{WHT}) or weather interpolation (W_{INT}) is that a new metamodel may need to be developed for each change in the simulation's model parameters. The quality of the metamodeling approach depended very much on the predictor variables used. Performance was much better with the bioclimatic variables (M_{BIO}), which have been widely used in ecological modeling (Booth et al., 2014), than with the climate means (M_{CLM}). Metamodels should thus be carefully

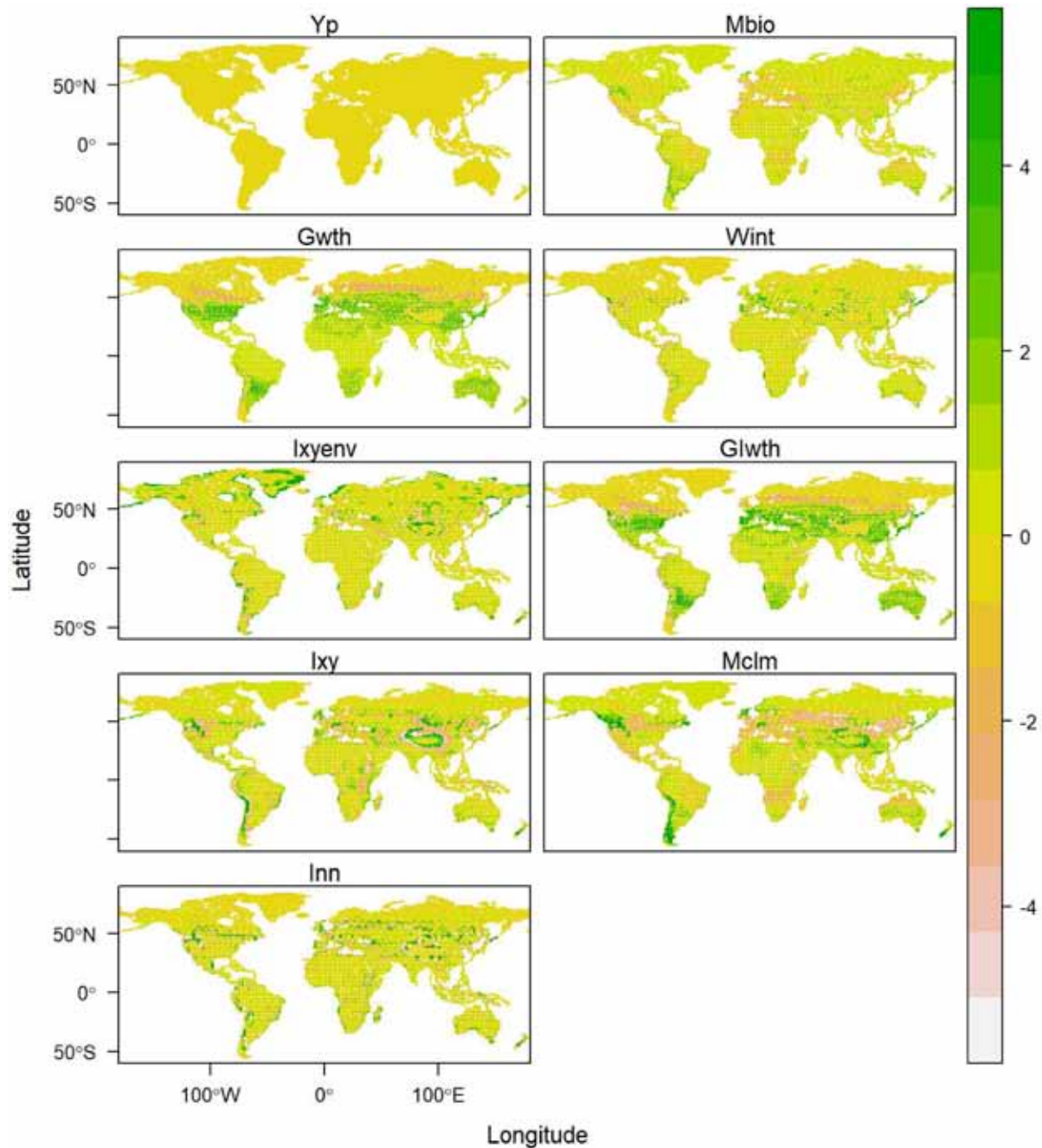


Fig. 4. Differences between maize yield potential (Y_p ; 10^3 kg ha^{-1}) simulated with the WOFOST model and Y_p predicted via eight different spatial methods using 856 training sites (white points on map). M_{BIO} , metamodel with bioclimatic variables; G_{WTH} , weather generator; W_{INT} , interpolation of daily weather data; l_{XYCLM} , interpolation with geographical and environmental covariables; GI_{WTH} , weather generator with interpolated climate data; l_{XY} , interpolation with location data only; M_{CLM} , metamodel with climate averages; l_{NN} , nearest neighbor interpolation.

constructed to assure a good quality model. An alternative to the bioclimatic variables would be to use the average climate data for a number of months following planting. However, reliable crop planting data with a high spatial resolution are not available at the global level. In addition to other predictor variables, alternative algorithmic methods could also be evaluated.

The weather generator method performed well when the effect of the interpolated weather data was not introduced (G_{WTH}). This is despite the fact that the weather generator was extremely simple and extreme temperature events (heat, cold) that could alter the modeled crop phenology and growth, were not considered. This may be because the simulation models used

may not be very sensitive to such extremes. In crop simulation models, yield is strongly affected by changes in phenology. High temperatures increase the rate of crop development, resulting in shorter crop duration, which reduces yield. In addition, temperature also affects radiation use efficiency in the WOFOST model. Better weather generators are available (Richardson, 1981; Verdin et al., 2015; Ailliot et al., 2015), but because of their stochastic nature, they require several models runs for each location. When the effect of interpolating climate data was also considered (GI_{WTH}), the results for the weather generator were not as good. Obviously, errors have been introduced when climate data are interpolated but, in our analysis, this was probably

exaggerated. For methodological consistency, we used an unrealistically low number of weather stations (856 training sites for the whole world). In practice, there are many more stations for which climate data are available than for which long-term daily weather data are available, and we would expect the quality of the interpolated climate data to be better. Therefore, we think that the weather generation method is an attractive option for Yp simulation, as global interpolated climate data are available at high spatial resolution ($\sim 1 \text{ km}^2$; Fick and Hijmans, 2017).

Interpolating daily weather data and then running the crop model did not perform as well as we thought. We expected that W_{INT} would be the most accurate method because this method recreates the 'best' situation (i.e., daily weather data for each cell) to run the crop model. This approach may, nevertheless, be worth pursuing, particularly if a sufficient density of weather stations is available across the study area. The results might also be improved by more refined weather data interpolation techniques (e.g., by using additional high-resolution predictor variables to guide the interpolation). However, a drawback of this method is that it is very computationally intensive, as it involved predicting $30 \text{ yr} \times 365 \text{ d} \times 3 \text{ weather variables} = 32,850 \text{ values}$ for each location. Interpolated weather data with a high spatial resolution are becoming available but their value will depend on the quality of the weather interpolation, which will be variable across the world.

To estimate Yp for locations with weather stations, we compared nonspatial regressionlike methods (Random Forest metamodels: M_{BIO} and M_{CLM}) with spatial interpolation methods (TPS and nearest neighbor interpolation: I_{XY} , I_{XYCLM} , and I_{NN}). In I_{NN} , only one sample point is considered and any other nearby sampled points are ignored in estimating values (Webster and Oliver, 2001). Nearest neighbor approaches should generally only be used to interpolate qualitative data for which other interpolation methods are not applicable (Burrough and McDonnell, 1998). Alternative interpolation methods are available (e.g., inverse distance weighting and kriging) but we would expect the results to be similar irrespective of the interpolation method, as they are data-driven and based on the same principle of computing a local average of sampled data.

Some studies have used interpolation approaches that consider the location of weather stations only, like our I_{XY} model (Wu et al., 2006, 2008; Lu and Fan, 2013). Although this may work in certain regions, our results illustrate that this can be a questionable approach because it ignores the characteristics of the terrain (e.g., the presence of mountains), which can strongly affect Yp in between weather stations. For I_{XY} and I_{NN} , the largest differences were found in mountainous regions. It is more difficult to obtain good estimates for such topographically and climatologically complex areas than it is for plains, which have a simple climate gradient. The I_{XYCLM} method uses climate data and this improved the results in comparison with I_{XY} and I_{NN} . In the regression-like methods (metamodels), we did not explicitly use location. However, it was implicitly considered by use of environmental conditions that were derived from the location. The I_{XYCLM} model combines both explicit (location) and implicit (environmental) spatial data and performed much better than I_{XY} . Interpolation with covariables (I_{XYCLM}) is, in fact, a hybrid between spatial interpolation and regression methods. Other conceptually similar approaches that could be explored are available. For example, regression kriging uses a

nonspatial model to fit the data and then spatial interpolation of residuals, which are then added to the prediction of the nonspatial model. Location data could be added to the Random Forest metamodel (however, in that case, it can no longer be used to predict climate change effects). Spatial interpolation, metamodeling, and their hybrids, are relatively simple to do and they are not very computationally intense. Future work could look for optimal interpolation methods for Yp by using more or better covariates and other interpolation techniques.

To evaluate the performance of the methods, we left out the oceans and extremely cold environments (by restricting simulations to below 60°N). We could have eliminated more areas where climate conditions are marginal for growing crops but estimating low Yp can also be of interest (e.g., to explain why a crop is not grown in a certain place).

In this study, we have only evaluated methods for estimating Yp. Temperature and radiation were the interpolated variables and so differences in Yp were a function of the estimation of these variables. Therefore, future work should compare different estimation techniques of water- and nutrient-limited yield. For water-limited yield, precipitation and soil data are needed, and both of these data types are relatively difficult to work with. Weather generation of realistic precipitation time series is more challenging (Hartkamp et al., 2003; Ailliot et al., 2015) compared with temperature. In the daily weather values, interpolation approach, the number of interpolated values would double, whereas spatial interpolation of precipitation is associated with much larger errors than interpolation of temperature (Fick and Hijmans, 2017).

Several recent studies have used the nearest neighbor interpolation method to estimate water-limited yield (Grassini et al., 2015; van Bussel et al., 2015; van Ittersum et al., 2013; van Wart et al., 2013a, 2013c). These studies assumed that locations up to 100 km away from a weather station are equivalent (unless this is across a "climate zone"). Given the additional spatial variability in rainfall and soil data that affect water-limited yield, alternative methods should be evaluated. Our results suggest that better approaches than nearest neighbor interpolation may be available. With the exception of weather interpolation, such methods are computationally simple and do not require "computing power or sophistication of geostatistical methods running many thousands of simulations" (Grassini et al., 2015).

There was some variation in the results for the different models and crops, and between regions. Although our results provide general guidance, the actual best method will depend on the region, the weather station density, and the model used. For example, I_{NN} could perform well if station density is very high and the climate gradients are relatively shallow, as in the Australian wheatbelt (Hochman et al., 2016) and using it only within agroecological zones may also improve results (Van Wart et al., 2013c; van Bussel et al., 2015). However, it is not guaranteed that the use of predefined climate zones will improve predictions, as the zones may not be very relevant for the crop in question, and because, for any location, the distance to the nearest station will increase, on average.

Thus the best approach for any particular study is difficult to predict. It is clear, however, that metamodels, weather generation, and interpolation with climate predictors can provide good predictions relative to the I_{NN} technique that is commonly used. We suggest using cross-validation to evaluate different approaches

and selecting the method that works best, or to use model averaging to leverage the strengths of the different approaches.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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