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LINEAR CORRECTION OF MODEL-BASED CROP BIOMASS SIMULATIONS USING INTERMEDIATE FIELD OBSERVATIONS

R. Delecolle[1], *L. Kuchar*[2]

[1]Station de Bioclimatologie, INRA, F-84143 Montfavet, France
[2]Faculty of Land Reclamation and Improvement, Agricultural University, 50-357 Wrocław, Poland

A b s t r a c t. A method of linear correction of above-ground dry matter values, simulated by AFRC-WHEAT, a mechanistic model of wheat crop, is described. It uses values of dry matter and green leaf area index observed at previous crop stages. Correction of current simulation is based upon the differences between observed and simulated values of each or both variables for previous stages. The method is tested on three wheat datasets obtained from two locations in France: Avignon and Mons, with various genotypes, sowing dates and crop conditions. A validation test using a cross validation method shows that the mean square error can be reduced down to 12 % of model error, depending on time stage and predictors. This method can be used to improve the prediction of final yield by plant process models, using remotely sensed information.

INTRODUCTION

Crop simulation models have primarily been designed to synthesize existing knowledge in crop physiology, but lately they have been proposed as tools for crop yield prediction [11], although several later studies have shown them more or less able to predict crop production over large areas [4,5]. Due to their components (large sets of crop state variables updated at short-time steps, genotype- and soil-specific coefficients), they can be adequately calibrated for one precise situation (e.g., one field with one genotype), but their extension to other sites is subject to several sources of error in simulation of final crop production. According to Swaney *et al.* [11], the two main types of error are: error in model structure and error in model parameter values. Each type of error can be addressed separately, first by improving the description of physiological processes and then by estimating site-specific values of parameters. These values may represent local genetic variability not accounted for in the model or highlight the deep statistical nature of parameters (model calibration in a test site partly reflects the particular pattern of environmental variables, very similarly to purely empirical yield models).

Estimating crop model parameters on a site during vegetation growth by using crop data taken at the site has been proposed by Swaney *et al.* [11], in order to improve crop yield predictions. Delecolle and Guerif [2], and Maas [7] have derived calibration methods specifically adapted to the case where crop data are provided by remote sensing. Baret [1] suggests a general scheme for model recalibration using radiometric data. Another way of improving the results in a model is to deal with both error types by using prior knowledge on simulation errors caused by the model. Intermediate crop state variables and/or yield simulated values can be corrected if a correction term is estimated from deviations between simulated and measured intermediate crop variable values and from an empirical relationship between these deviations and the variable to be corrected. This method does not modify any parameter value in the model itself. Faivre *et al.* [3] show how the correction term can be linearly estimated from intermediate errors and solve the problem in a general case where available crop data are randomly distributed over time.

In this paper, we wish to investigate how such a correction method can be applied to simulations of wheat state variable values in a simpler case where available crop data are evenly distributed over a biological time scale.

MATERIALS AND METHODS

Observed data

Experimental data on winter wheats, spring wheats and intermediate types from two locations in France were employed: Avignon (43°54' N, 4°48' E, Mediterranean climate) and Mons (49°48' N, 3°12' E, semi-oceanic climate). Apart from climate and latitude, sources of variation were large ranges of genotypes, sowing dates and years (Table 1). Data were sampled in experimental plots of various sizes, generally 2 m x 10 m, with two replications per treatment and 2 to 4 samples per replication. The samples of 2 m x 1 m on adjacent rows were harvested at various sampling intervals, in order to describe the whole crop cycle. Above-ground dry matter (*dm*) was measured by oven drying at 85 °C for 2 days. In all experiments, global green area index (GAI) was estimated by measuring green area of individual plant organs (leaves, stems, ears) on a subsample with an optical area meter and using the ratio of subsample-to-sample dry weights for each type of organ. Daily weather data (minimum, maximum and wet bulb temperatures, short-wave radiation) were obtained from standard weather stations not more than 500 m from the experimental fields. From the plant information, three datasets have been constructed, in order to validate the method. The first dataset named 'Avignon', includes data from 4 years of experiments in this location. 'Avignon Plus' contains the same data, plus data from experiments where only late observations of GAI and dry matter (GAI>3.5) were available. The mixed 'Avignon-Mons' dataset contains all data from both locations.

Table 1. Location, genotypes and sowing dates of wheat experiments used for linear correction of simulated data

Location	Genotypes	Sowing Dates
Avignon	Arminda (w)	Nov. 28, 1986;
	Fidel (s)	Oct. 1, 1986; Nov. 28, 1986; Feb. 27, 1987*
	Prinqual (s)	Mar. 29, 1988
	Talent (i)	Sept. 27, 1985**; Oct. 25, 1985**; Mar. 10, 1986
	Arcane (i)***	Oct. 25, 1985
	Arminda (i)***	Oct. 25, 1985
	Talent (i)***	Nov. 28, 1984
Mons	Arminda (w)	Oct. 28, 1983; Dec. 10, 1983
	Cappelle (w)	Oct. 28, 1983
	Courtot (i)	Oct. 28, 1983
	Fidel (s)	Sept. 30, 1983; Oct. 28, 1983; Dec. 10. 1983
	Pernel (w)	Sept. 30, 1983; Oct. 10, 1983
	Talent (i)	Sept. 30, 1983; Oct. 28, 1983
	Vuka (w)	Oct. 28, 1983

Explanations: w = winter; s=spring; i=intermediate; * two experiments (irrigated and dry); ** two experiments (two sowing densities); *** these genotypes and sowing dates only belong to Avignon Plus dataset.

Simulated values

Daily simulated values of *drm* and GAI were obtained from AFRCWHEAT [8,12], a mechanistic model of wheat growth and development under optimal conditions. As this model uses a set of genetic coefficients values for sensitivities to vernalization and photoperiod, computed from an independent datatset, were applied to each genotype. Other coefficients, including duration of phenological phases and leaf geometrical properties, were kept constant over the situations (genotype x location x sowing date x year).

Comparing simulated values to observed data

In order to provide a common time scale to all treatments, comparisons between simulated and observed values were conducted for the period from when measured GAI first exceeded 1.0 to the day when GAI first decreased below 1.0 late in the season. Including these two, seven evenly-spaced dates were selected. The seven dates of measurement closest to the evenly-spaced dates were thus used for comparisons between simulated and observed values.

Correction method

Let $drm^{(i)}_{obs}$ (resp. $GAI^{(i)}_{obs}$) be the value of above-ground dry matter (resp. green leaf area index) observed at time (i) and $drm^{(i)}_{mod}$ (resp. $GAI^{(i)}_{mod}$) be the corresponding simulated values.

Assuming that at time k, values of $drm^{(i)}_{obs}$ and $GAI^{(i)}_{obs}$ $(i=1,..,k)$ have been observed, the problem is then to use this information to correct subsequent simulated values of dry matter $drm^{(i)}_{mod}$ $(i=k+1,..,s)$ for which no observed values are available. We suggest using a linear correction term $y^{(i)}$ to obtain more realistic values $drm^{(i)}_{est}$ with:

$$drm^{(I)}_{est} = drm^{(i)}_{mod} + y^{(i)} \qquad (i=k+1,..,s) \qquad (1)$$

The general pattern of term $y^{(i)}$ must be computed from previous experiments (historical datasets of observed and simulated values used as a calibration set) and current values of $y^{(i)}$, estimated for each new experiment. This method can be described as follows: $drm^{(i)} = drm^{(i)}_{mod} - drm^{(i)}_{obs}$ and $GAI^{(i)} = GAI^{(i)}_{mod} - GAI^{(i)}_{obs}$ $(i=1,..,s)$; and $U = (u_1,..,u_k)^T$ (T being the transpose operator) a subvector of vector V of known values:

$$V=(GAI^{(1)}, drm^{(1)}, ..., GAI^{(k)}, drm^{(k)})T$$
$$(\dim(U) \leq \dim(V)).$$

Let $W = (drm^{(k+1)}, ..., drm^{(s)})^T$ be the vector of *drm* deviations for forthcoming periods, known from the calibration dataset and $Y = (y^{(k+1)}, ..., y^{(s)})^T$. Rao [9] suggests a model for correcting current W given current U:

$$Y = E(W) + \mathrm{cov}(W,U)\,[\mathrm{var}(U)]^{-1}\,[U^*-E(U)] \qquad (2)$$

where $E(W)$, E(U) and $\mathrm{cov}(W,U)$ are respectively vectors of means and covariance matrix for variables W and U, and $\mathrm{var}(U)$ is a definite positive dispersion matrix. Equation (2) is computed with the known calibration dataset and for a new experiment where a value U^* of vector U has been observed.

This technique has been applied by Kuchar [6] in the EPM model for anticipating future weather values, and is similar to (although simpler than) the work by Faivre et al. [3] on correction of crop yields simulated by the EPIC model [13].

In order to avoid prediction bias, the correction term Y has been modified as follows:

$$Z = (I - P)\; E(W) + P\,Y \qquad (3)$$

Table 2. Absolute mean square error (MSE) of dry matter prediction by AFRCWHEAT model alone

Dataset	MSE at stage i						
	i = 1	2	3	4	5	6	7
Avignon (N=12)	1 220	13 000	30 830	42 800	24 620	58 610	54 610
Avignon Plus (N=15)	3 480	13 500	25 710	36 450	25 100	48 620	51 210
Avignon and Mons (N=24)	1 210	9 120	26 700	29 690	23 720	56 320	67 750

where I is the identity matrix, P the diagonal matrix of correlation coefficients between variables $drm^{(i)}$ ($i=k+1,...,s$) and u_j ($j=1,..,k$) (Eq.3 minimizes the effect of u_j values that are loosely correlated to $drm^{(i)}$ and gives a higher weight to 'historical' mean drm deviation in this case). The values of $y^{(i)}$ values in Eq.1 were therefore replaced by the elements $z^{(i)}$ of vector Z. As our datasets were too small to be split into one calibration and one validation set, terms $z^{(i)}$ were evaluated by Leave-One-Out (Cross Validation) [10]. In our case, only current simulated dry matters were corrected, assuming that future weather was unknown: vector W thus reduces to ($drm^{(k+1)}$).

RESULTS

The estimation errors on current above-ground dry matter that were obtained by the method described above are displayed in the following Tables 2 and 3. They correspond to the use of one, two or three previous values of GAI and/or previous values of *drm* as predictors ((i) 'predictors' will be used in the following text as a shorter equivalent of variables used in U for estimatig the correction term, (ii) the reader should remember that '*drm*' and 'GAI' refer to differences between observed data and simulated values). Error is computed for each stage as a percentage of the simulation error which is achieved by the uncorrected AFRCWHEAT model.

Table 3. Relative mean square error of dry matter prediction based on simulated and observed values of dry matter

Dataset	Predictors	Relative error on dry matter prediction at stage i					
		i = 2	3	4	5	6	7
Avignon (N=12)	$drm^{(i-1)}$	77.6	11.7	24.8	20.7	66.5	60.4
	$drm^{(i-1)}, drm^{(i-2)}$		23.4	29.4	22.3	76.8	80.7
	$drm^{(i-1)}, drm^{(i-2)}, drm^{(i-3)}$			34.8	26.4	93.0	35.7
Avignon Plus (N=15)	$drm^{(i-1)}$	44.4	16.9	35.7	44.0	72.8	76.2
	$drm^{(i-1)}, drm^{(i-2)}$		14.9	33.8	36.1	93.8	78.1
	$drm^{(i-1)}, drm^{(i-2)}, drm^{(i-3)}$			39.8	41.0	96.7	99.7
Avignon and Mons (N=24)	$drm^{(i-1)}$	69.2	80.5	61.5	59.1	86.3	50.1
	$drm^{(i-1)}, drm^{(i-2)}$		82.4	61.6	59.9	94.1	54.6
	$drm^{(i-1)}, drm^{(i-2)}, drm^{(i-3)}$			67.3	61.2	91.5	42.6

Correction by dry matter

When previous values of *drm* are used as predictors, it appears that the time evolution of error is not monotonic (Table 3). It most often presents a minimum for intermediate phases, which correspond to the almost linear period in the time evolution of dry matter. Errors are globally lower for the first dataset and the results for Avignon Plus show that if only late information is added, the global error is increased. Concerning the mixed dataset Avignon-Mons, the variation of error is less pronounced, but its average level is higher, except for the last stage: globally, it appears that the number of *drm* values used as predictors is less important than the time of correction and that using three previously observed *drm* gives even worse results than using the last (or two last) value(s).

Correction by GAI

Table 4 shows that, when using GAI as a predictor, the error level is comparable with the above situation for the mid-cycle stages in Avignon and Avignon Plus datasets. Most of the time it is worse for the mixed Avignon-Mons dataset. Again, the time variation of error is not monotonic, and error is minimum during stage 3, which corresponds to near-to-linear evolution of *drm* and GAI. It should be noted that, for the last stage in Avignon-Mons, the error is lower than it is in other datasets.

Table 4. Relative mean square error of dry matter prediction based on simulated and observed values of GAI

Dataset	Predictors	Relative error on dry matter prediction at stage i					
		i = 2	3	4	5	6	7
Avignon (N=12)	$GAI^{(i-1)}$	61.5	13.9	18.6	73.1	97.2	98.6
	$GAI^{(i-1)}, GAI^{(i-2)}$		16.9	19.8	17.5	93.8	99.3
	$GAI^{(i-1)}, GAI^{(i-2)}, GAI^{(i-3)}$			14.0	20.3	57.8	99.5
Avignon Plus (N=15)	$GAI^{(i-1)}$	88.6	41.2	30.1	72.2	96.7	99.0
	$GAI^{(i-1)}, GAI^{(i-2)}$		89.8	26.0	24.4	97.3	99.6
	$GAI^{(i-1)}, GAI^{(i-2)}, GAI^{(i-3)}$			44.5	32.6	65.8	100.0
Avignon and Mons (N = 24)	$GAI^{(i-1)}$	65.6	44.9	97.6	98.6	82.1	74.6
	$GAI^{(i-1)}, GAI^{(i-2)}$		52.4	72.1	83.3	80.2	78.3
	$GAI^{(i-1)}, GAI^{(i-2)}, GAI^{(i-3)}$			71.4	63.8	78.5	76.8

Correction by dry matter and GAI

Table 5 displays the results of current *drm* correction when both *drm* and GAI known for previous stages are used as predictors. In this case, only two previous values for each variable were used and we separated the cases when last-but-previous *drm* alone and both *drm* and GAI were involved. The level of estimation error is globally lower than it was in the previous cases. Its evolution still presents a minimum value for stage 3 and it decreases slightly for the last stage in the mixed dataset.

Optimal procedure

From Tables 3 to 5, it appears that an optimal procedure can be found in order to correct current above-ground-matter with minimum error, according to the stage where the correction should be done. For stages 2 to 6, the use of *drm* and GAI (Table 5) leads to better performances. For stage 7, *drm* alone (Table 3) is a better

Table 5. Relative mean square error of dry matter prediction based on simulated and observed values of dry matter and GAI

Dataset	Predictors	Relative error on dry matter prediction at stage i					
		i = 2	3	4	5	6	7
Avignon (N=12)	$drm^{(i-1)}$, $GAI^{(i-1)}$	84.6	12.9	13.9	18.7	54.6	71.4
	$drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$		22.5	17.4	20.3	64.6	98.9
	$drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$, $GAI^{(i-2)}$		12.9	23.2	15.4	61.4	100.0
Avignon Plus (N=15)	$drm^{(i-1)}$, $GAI^{(i-1)}$	42.2	13.1	25.0	39.8	58.4	74.2
	$drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$		17.6	27.7	30.3	76.1	95.7
	$drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$, $GAI^{(i-2)}$		33.7	30.2	18.7	71.4	100.0
Avignon and Mons (N=24)	$drm^{(i-1)}$, $GAI^{(i-1)}$	57.1	45.7	64.6	50.6	60.0	52.9
	$drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$		52.7	67.3	54.9	69.9	56.1
	$drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$, $GAI^{(i-2)}$		48.6	75.4	54.8	74.6	59.1

corrector. We can therefore use the best predictors for each stage (Table 5: predicted by $drm^{(i-1)}$, $GAI^{(i-1)}$; predicted by $drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$; predicted by $drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$, $GAI^{(i-2)}$) in terms of relative mean square error of prediction for the three datasets. It appears that, for both Avignon datasets, the error may be kept low during the phase of linear *drm* evolution, but it increases for the last stages (Table 5: predicted by $drm^{(i-1)}$, $GAI^{(i-1)}$; predicted by $drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$).With the multi-local dataset, the average error level is higher, but almost constant whatever the stage (Table 5: predicted by $drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$, $GAI^{(i-2)}$).

DISCUSSION AND CONCLUSIONS

Using the method described above, the introduction of intermediate data allows us to correct the values of above-ground dry matter simulated by the AFRCWHEAT model. With our highly heterogeneous datasets, the level of improvement largely depends on predictor and stage, ranging from 12 to 100 percent of error level performed by the model alone and it is usually less for intermediate phases. This variation suggests that the linear correction model used by our method is not adequate for some phases of dry matter evolution (namely the phases where dry matter accumulation, rate changes rapidly). This is particulary true when GAI differences are used as predictors, because the evolution of GAI is not monotonic with dry matter.

An optimal choice of correction according to phases allows to minimize the global estimation error, showing a strongly non-linear pattern of relative error evolution for the one-site model (Table 5: predicted by $drm^{(i-1)}$, $GAI^{(i-1)}$; predicted by $drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$) and a relatively stable one for the two sites (Table 5: predicted by $drm^{(i-1)}$, $GAI^{(i-1)}$, $drm^{(i-2)}$, $GAI^{(i-2)}$). It should nevertheless be noticed that these relative values correspond to higher levels of absolute error in the case of two sites. In any case, the use of cross-validation prevents this estimated error from being too optimistic. Improvements may be achieved by using a non-linear correction technique, for instance approximation by polynomial functions.

Results could probably be better if the time axis, which is currently split into classes of equal duration, was replaced by a more biological criterion, like classes of equal thermal duration or possibly phenological phases. Given such improvements, this method can be used to forecast final above-ground dry matter from GAI alone, provided future weather values are simulated from current date to maturity. A major application could be to use estimations of crop state variables derived from satellite information in order to provide local corrections to areal simulations performed by a crop model (theoretically valid over the validity domain of the weather factors and soil maps that are used as inputs). Should 'future' weather data be simulated, one can estimate crop final dry matter (or final yield) by combining model simulations and radiometric data observed from sowing to some 'present' time in the crop cycle. In this case, however, as *drm* estimations by vegetation indices are not reliable [1], only GAI can be used [5,7]. As, in our study, GAI was the less efficient predictor, the above mentioned improvements to the method would likely be essential to obtain acceptable error levels.

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LINIOWA KOREKCJA MODELU DYNAMICZNEGO PLONU BIOMASY W OPARCIU O WYNIKI SYMULACYJNE I OBSERWACJE POLOWE

W pracy przedstawiono metodę liniowych korekcji wartości suchej masy pszenicy, symulowanej przy pomocy modelu AFRCWHEAT, w oparciu o obserwacje polowe. Metoda istotnie wykorzystuje wartości suchej masy (drm) oraz powierzchni zielonej roślin (GAI) obserwowanych we wcześniejszych fazach bieżącej wegetacji, analizowanych na tle danych wieloletnich. Metodę testowano na 3 zbiorach danych doświadczalnych pszenicy, otrzymanych dla dwóch stacji eksperymentalnych Instytutu I.N.R.A. (Mons - Północna Francja oraz Awinion - Południowa Francja) o zróżnicowanych warunkach klimatycznych, dla różnych odmian i agrotechniki. Testy weryfikacyjne (CV - LOO) wykazały znaczną redukcję błędu średniokwadratowego (nawet do 12 % błędu modelu) w zależności od terminu wykonania korekcji oraz użytych zmiennych. W pracy zawarto również sugestie wykorzystania obserwacji satelitarnych.