Published January, 2003

MODELING

Application of the CERES-Wheat Model for Within-Season Prediction of Winter Wheat Yield in the United Kingdom

M. Bannayan, N. M. J. Crout, and Gerrit Hoogenboom*

ABSTRACT

Mechanistic crop growth models have many potential uses for crop management. These models can aid in preseason and within-season management decisions for cultural practices such as fertilizer and irrigation applications and pest and disease management. When making these management decisions, maximizing yield and net return as a function of inputs and production costs is one of the fundamental goals. Reliable yield forecasting within the growing season would enable improved planning and more efficient management of grain production, handling, and marketing. The objective of this study was to determine if the dynamic simulation model CERES-Wheat could be used to forecast final grain yield and crop biomass within the growing season for environmental and management conditions in the United Kingdom (UK). Experimental data for three seasons and four sites were used for model calibration and evaluation. A stochastic approach was applied, based on multiple years of weather data generated with the weather generator SIMMETEO. Yield forecasts were conducted for five different developmental stages within the growing season. For each forecast date, observed weather data were used up to the forecast date and supplemented with generated weather data until final harvest was predicted. Eighty-nine different sequences of generated weather data were used for each forecast. Predicted grain yield had a root mean square difference (RMSD) ranging from 0.95 t ha^{-1} for the first forecast date to 0.68 t ha^{-1} for the final forecast date while the RMSD for total predicted biomass ranged from 3.59 to 2.09 t ha^{-1}. An analysis of predicted final grain yield and biomass for all forecast dates showed a significant difference for the first three sample dates up to flag leaf appearance. No significant difference was found for the forecasts conducted at the anthesis stage (paired *t* test: $p = 0.73$ for grain yield and $p = 0.32$ for biomass) and milk stage ($p = 0.79$ for grain yield and $p = 0.22$ for biomass). This study showed that using only stochastically generated weather data to substitute measured data could provide a reliable forecast for wheat (*Triticum aestivum* L.) grain yield starting in June until the remainder of the season for conditions in the UK.

Providing accurate estimates of the benefits and risks of alternative crop management systems with knowledge of expected yield before final harvest has placed an increasing demand on crop simulation models. Assisting individual decision-makers to manage production risk in a more effective manner is of utmost importance (Anderson, 1974). To provide such assistance, a detailed quantification of production risks is required. In many cases, quantitative information on production can only be obtained through crop simulation studies and long-term climatic records (MacDonald and Hall, 1980; Matis et al., 1985; Bouman et al., 1995). Understanding the impacts of weather on crop production by applying simulation models provides a credible basis for a quantitative estimate of the range of yields farmers can expect for a given set of management conditions (Arkin and Dugas, 1981, Hammer et al., 1996; Tsuji et al., 1998).

The use of crop simulation models for predicting crop yield as function of weather and climate has been studied extensively (Hoogenboom, 2000). These applications range from predicting yield at a farm level to predicting regional and national yield levels although large-scale predictions are normally more common (Travasso and Delecolle, 1995; Supit, 1997). Most of these prediction applications include forecasts that are conducted before planting while some simulations are conducted during the growing season. The improved understanding of El Nino and the Southern Oscillation phenomenon has especially led to many applications that are based on seasonal climate forecasts (Hammer et al., 1996; Meinke and Hammer, 1997; Meinke and Stone, 1997; Mjelde and Hill, 1999; Hammer et al., 2000; Jones et al., 2000; Royce et al., 2001). However, not much progress has been made in yield forecasting for tactical applications at a field level that directly benefits the farmer (McKinion et al., 1989; Jacobson et al., 1997; Reddy et al., 1997).

Recently, there has been an increased interest in the use of crop simulation models in association with spatial variability and precision farming (Sadler et al., 2000; Paz et al., 2001). The application of crop models to optimize in-season management for spatially variable fields in particular provides farmers with options to reduce inputs and increase net returns (Booltink et al., 2001). However, these applications require accurate crop models in concert with historical and current weather data. Obviously, more accurate weather forecasts would benefit the accuracy of yield forecasting, but this is an issue for meteorologists. However, a high accuracy of the yield forecast would attract more farmers and others associated with agribusiness. Weather forecast services tailored for the specific needs of the farming community

M. Bannayan, School of Agric., Ferdowsi Univ. of Mashhad, P.O. Box 91775-1163, Mashhad, Iran; N.M.J. Crout, School of Biol. Sci., Univ. of Nottingham, Sutton Bonington, LE 12 5RD, UK; and G. Hoogenboom, Dep. of Biol. and Agric. Eng., Univ. of Georgia, Griffin, GA 30223. Received 7 Mar. 2000. *Corresponding author (Gerrit@griffin.peachnet.edu).

Published in Agron. J. 95:114–125 (2003).

Abbreviations: DSSAT, Decision Support System for Agrotechnology Transfer; LAI, leaf area index; MBE, mean bias error; MPE, mean percentage error; RMSD, root mean square difference; UK, United Kingdom.

Table 1. Environmental, soil, and crop management summary for the evaluation sites.

Site	Institute	Latitude	Longitude	Soil series and description	Sowing date
Sutton Bonington (SB)	Nottingham University	52°50′	1°15′	Hodnot series (Sandy clay loam over loamy sand over clay)	7 Oct. 1992 2 Nov. 1993 6 Oct. 1994
Boxworth (BX)	ADAS†	52°15′	0°02′	Hanslope series (chalky boulder clay/calcareous clay topsoil with few flints, chalk increases at 40-50 cm depth)	1 Oct. 1992 18 Oct. 1993 6 Oct. 1994
Gleadthorpe (GL)	ADAS	53°13′	1°07′	Wick series (medium sandy loam over medium sand)	17 Oct. 1992 28 Oct. 1993 30 Sept. 1994
Rosemaund (RM)	ADAS	52°07′	2°39′	Bromyard series (silty clay loam)	16 Oct. 1992 23 Oct. 1993 23 Sept. 1994

† ADAS, Agricultural Development and Advisory Service.

are now becoming more readily available around the world (Georgiev and Hoogenboom, 1998; Fox et al., 1999). Evaluation of these services to farmers is increasingly important to help set budget priorities. If crop models would be able to predict final yield with reasonable accuracy within the growing season, it might justify the cost of supplying weather forecasts in a competitive market. As a further extension of this approach, stochastic modeling can be used to determine the probability distribution of yield and the risks associated with certain management decisions. This is in contrast to deterministic models where the predicted values are computed without consideration of their variability.

The objective of this study was to evaluate the application of the dynamic crop process model CERES-Wheat for forecasting final crop biomass and grain yield for wheat under growing conditions in the UK.

MATERIALS AND METHODS

Experimental Data

Field data were obtained from a previous study that has been fully described by Gillett et al. (1999). Winter wheat ('Mercia') was sown during the autumn of 1992, 1993, and 1994 at four sites representing the varied weather conditions and soil types of the UK. These four sites included Sutton Bonington, Boxworth, Gleadthorpe, and Rosemaund. Additional site and experimental information, including participating institutions, latitude, longitude, sowing date, descriptions of the soil series, the number of collected samples taken, and climate information are presented in Tables 1 and 2. The objective of the field trial was to provide a high quality reference data set that could be used as an aid for developing the predictive scheme for the growth and development of winter wheat. The same variety of winter wheat (Mercia) was sown at each of the four sites. Disease, weed, and pest infestation were controlled to achieve full expression of yield potential. In each trial, a standardized sampling procedure was used during the growing season. The experiments conducted during the 1992–1993 and 1993–1994 growing seasons were used to calibrate the model, and the experiments conducted during the 1994–1995 growing season were used for model evaluation.

Standard meteorological data were obtained for each site using the nearest weather station. Each station provided daily values of the maximum and minimum air temperature (°C), wet and dry bulb temperatures (°C), rainfall (mm), sunshine hours (h), and total wind run (m s^{-1}). Sunshine hours were converted to daily total radiation (MJ m^{-2}) using the method of Rietveld (1978). Eighty-nine years of daily weather data (minimum and maximum temperature, °C; total daily radiation, MJ m^{-2}; daily precipitation, mm) were generated with the weather generator SIMMETEO (Simulation of Meteorological Variables) (Geng et al., 1986) and used as an input for CERES-Wheat. The key components of both CERES-Wheat and SIMMETEO are outlined below.

The model was run 89 times from different forecasting dates within the growing season using the seasonal analysis option of the Decision Support System for Agrotechnology Transfer (DSSAT) Version 3 (Thornton and Hoogenboom, 1994; Tsuji et al., 1994). This is the maximum number of years that the seasonal analysis option of DSSAT allows for multiple simulations that include the weather generator. The forecasting dates were three- to five-leaf stage [67–76 day of year (DOY) or 132–166 days after sowing (DAS)], the third sampling date

Table 2. Climate summary for the evaluation sites.†

Period	Boxworth	Sutton Bonington	Rosemaund	Gleadthorpe	Mean (UK)
			Temperature, °C		
Season‡	9.6	9.3	9.2	9.0	9.0
Oct.–Feb.	5.7	5.7	5.5	5.3	5.3
Mar.–May	8.3	8.1	8.1	7.9	7.8
June–Aug.	15.7	15.1	15.0	14.8	14.8
			Rain, mm		
Season	563	604	663	628	662
Oct.–Feb.	228	250	301	268	284
Mar.–May	140	138	150	152	154
June–Aug.	152	166	155	155	167
			Radiation, MJ m^{-2} d^{-1}		
Season	9.4	9.0	9.4	9.0	9.0
Oct.–Feb.	3.7	3.4	3.5	3.3	3.3
Mar.-May	12.3	11.7	12.2	11.7	11.7
June–Aug.	15.7	15.4	16.0	15.4	15.3

† Climatological data are based on the period from 1961 to 1990.
‡ Season includes the weather data for the entire wheat growing season, starting in October and ending in August.

(74–89 DOY or 146–179 DAS), tip of flag leaf appearance (130–158 DOY or 193–249 DAS), anthesis (158–171 DOY or 229–250 DAS), and milk stage (179–187 DOY or 244–270 DAS). Third sampling is the next field measurement after three- to five-leaf stage across all sites and years but does not exactly coincide with a specific development stage. At each of these dates, the simulated weather data were updated with the observed weather data to provide weather data for the complete growing season. This process was undertaken for each of the first 2 yr (1992–1993 and 1993–1994) of the experiments conducted at the four sites (Table 1). In addition to the frequency distribution of yield, the mean and median of multiple simulations for both grain yield and crop biomass were calculated and compared with measured final yield and crop biomass. A comprehensive statistical analysis was also conducted across all sites.

CERES-Wheat Model

CERES-Wheat is a yield simulation model that was originally developed under the auspices of the USDA-ARS Wheat Yield Project and the U.S. government multiagency AGRISTARS program (Ritchie and Otter, 1985). The model is also one of the main models that have been incorporated in DSSAT (Hoogenboom et al., 1994). The CERES-Wheat model simulates the impacts of the main environmental factors, such as weather, soil type, and major soil characteristics, and crop management on wheat growth, development, and yield (Ritchie et al., 1998).

Input requirements for CERES-Wheat include weather and soil conditions, plant characteristics, and crop management (Hunt et al., 2001). The minimum weather input requirements of the model are daily solar radiation, maximum and minimum air temperature, and precipitation. These values are usually available at many locations with the exception of solar radiation. However, solar radiation can be approximated from other observations, such as the number of sunshine hours, which is sometimes more readily available. Soil inputs include drainage and runoff coefficients, first-stage evaporation and soil albedo, water-holding characteristics for each individual soil layer, and rooting preference coefficients at several depth increments. The model also requires saturated soil water content and initial soil water content for the first day of simulation. Required crop genetic inputs are coefficients related to photoperiod sensitivity, duration of grain filling, conversion of mass to grain number, grain-filling rates, vernalization requirements, stem size, and cold hardiness (Hunt et al., 1993). Check management input information includes plant population, planting depth, and date of planting. If the crop is irrigated, the date of application and amount is required. Latitude is required for calculating daylength. The model can use different weather, soils, genetic, and management information within a growing season or for different seasons in a single model execution. The model simulates phenological development; biomass accumulation and partitioning; leaf area index (LAI); root, stem, leaf, and grain growth; and the soil and plant water and N balance from planting until harvest maturity based on daily time steps (Godwin and Singh, 1998; Ritchie, 1998; Ritchie et al., 1998).

Cultivar Calibration

When using a crop model for any application, one first has to estimate the cultivar characteristics if they have not been previously determined. To calculate the seven cultivar coefficients required by the CERES-Wheat model, DSSAT includes a program called the Genotype Coefficient Calculator (GENCALC). This program estimates the coefficients for a genotype by iteratively running the crop model with an approximate value of the coefficients concerned, comparing the simulated and measured data, and then automatically altering the cultivar coefficient until the simulated and measured values match or are within predefined error limits. The required crop measurements are the key phenological dates, such as anthesis and harvest maturity, and yield and yield components (Hunt et al., 1993). To estimate the genotype coefficients for the cultivar Mercia, measured data for 2 yr of experiments across the four sites were used. The available data included emergence date, anthesis date, maturity date, grain yield, aboveground crop biomass, grain number per unit of ground area, individual grain weight, maximum LAI, and final grain yield. GENCALC was applied for these eight data sets to determine the optimal genetic coefficient values for the cultivar Mercia (Table 3).

Model Evaluation

To achieve our research objective, the first step was to assess the accuracy of the model simulation compared with the observations. Therefore, observed weather data for the two growing seasons (1992–1993 and 1993–1994) used for calibrating the cultivar coefficients were applied to run the model for all sites. Then, to evaluate the prediction capabilities of the model, a separate, independent set of experimental data (1994–1995) not used for model calibration was used for model evaluation.

SIMMETEO Model

Stochastic weather generators (Richardson, 1981; Geng et al., 1986; Hutchinson, 1991; Racsko et al., 1991) can use climate data from a site to provide daily sequences of the main weather parameters that are statistically similar to the observed data from which they were derived. The generated data can then be used as weather input for crop growth models (Semenov et al., 1993). The program WeatherMan (Pickering et al., 1994) was used in this study to generate 89 yr of daily weather data for each site. The daily weather variables that were generated included minimum and maximum temperature, total solar radiation, and precipitation. WeatherMan is also part of the DSSAT system (Tsuji et al., 1994; Hoogenboom et al., 1999) and contains two different weather generator methods, i.e., WGEN and SIMMETEO. WGEN is based on daily historical weather data to determine its input coefficients while SIMMETEO is based on monthly data.

Historical weather data were used to provide the monthly mean data required by WeatherMan. The number of years

Table 3. Genetic coefficients for the cultivar Mercia.

P1V†	P1D‡	P5§	G1¶	G2#	G3††	PHINT‡‡
3.00	4.67	5.17	4.91	1.83	2.24	95.00

† P1V, relative amount that development is slowed for each day of unfulfilled vernalization, assuming that 50 d of vernalization is sufficient for all cultivars.
‡ P1D, relative amount that development is slowed when plants are grown in a photoperiod 1 h shorter than the optimum (which is considered to be 20 h).
§ P5, relative grain-filling duration based on thermal time (degree days above a base temperature of 1°C) where each unit increase above zero adds 20 degree days to an initial value of 430 degree days.
¶ G1, kernel number per unit weight of stem (less leaf blades and sheaths) plus spike at anthesis (1/g).
# G2, kernel-filling rate under optimum conditions (mg/d).
†† G3, nonstressed dry weight of a single stem (excluding leaf blades and sheaths) and spike when elongation ceases (g).
‡‡ PHINT, phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances.

that were available ranged from 10 to 19 yr (10 for Sutton Bonington, 11 for Gleadthorpe, 16 for Boxworth, and 19 for Rosemaund). A summary of the climatic conditions for each site is shown in Table 2. The generated daily weather values showed reasonably good agreement with the observed weather data, and there were no significant differences (maximum temperature, $P = 0.45$; minimum temperature, $P = 0.36$; solar radiation, $P = 0.88$) between generated and observed values for Sutton Bonington. A similar level of agreement was obtained for the other sites.

Forecasting Approach

The accuracy of a crop growth and development prediction can be improved by updating the model within the growing season with measured data as they are being recorded during the growing season, a so-called real-time simulation approach. This concept has been applied to sorghum [*Sorghum bicolor* (L.) Moench] yield prediction by Arkin and Dugas (1981), for maize by Duchon (1986) and many others. An online version for yield forecasting based on the DSSAT crop simulation models was presented by Georgiev and Hoogenboom (1999). In this study, a similar approach was used. For the first set of simulations, the crop model was provided with observed weather data up to the three- to five-leaf stage and supplemented with generated weather data from that date up to harvest maturity. The above procedure was repeated for the other four forecast dates, which included the third sampling date, tip of flag leaf appearance, anthesis, and milk stage. The model was run 89 times for each forecast date within the growing season. To be able to manage this large data set, a software application was developed to supplement observed weather data with generated data from any required day of year. This process was undertaken for two growing seasons of the field experiment, i.e., 1992 to 1993 and 1993 to 1994, at the four sites.

For each site-year combination, the 89 yr of crop model outputs were used to determine the frequency distributions, median and mean values for each of the five forecast dates. The median values for predicted yield and total aboveground biomass were compared with observed values. Forecasting performance was evaluated by calculating the mean percentage error (MPE), RMSD, and mean bias error (MBE) across all sites and seasons for each forecast date. These measures of model deviation are defined as follows:

$$\mathrm{MPE} = \left[\sum_{i=1}^{n}\left(\frac{|\mathrm{data}_i - \mathrm{model}_i|}{\mathrm{data}_i}\right)100\right]/n \qquad [1]$$

$$\mathrm{RMSD} = \left[\left(\sum_{i=1}^{n}(\mathrm{model}_i - \mathrm{data}_i)^2\right)/n\right]^{0.5} \qquad [2]$$

$$\mathrm{MBE} = \left[\sum_{i=1}^{n}(\mathrm{model}_i - \mathrm{data}_i)\right]/n \qquad [3]$$

where model_i is the ith forecast median value, data_i is the ith measured value, and n is the number of observations.

The standard deviation of model forecasts was also calculated for each forecast date.

RESULTS AND DISCUSSION

Model Evaluation

In general, the CERES-Wheat model performed very well in simulating development, biomass, and final grain yield for all four sites, as shown by the results based on the estimation of the cultivar coefficients (Table 4). The model predicted anthesis date reasonably well with a RMSD value of 7.1. The only large discrepancy is Rosemaund for the 1994 growing season. Deleting this site-season from the calculation reduced the RMSD to 3.7 d. The RMSD for the final maturity date is 10 d with a MPE of 2.4%, which is <10% of the mean of observed

Table 4. Summary of the simulation results for the 1992–1993 and 1993–1994 growing seasons used for determination of the genetic coefficients.

Site† and year	Anthesis Obs.‡	Anthesis Sim.§	Maturity Obs.	Maturity Sim.	Grain yield Obs.	Grain yield Sim.	Crop biomass Obs.	Crop biomass Sim.
	DAS¶				t ha^{-1}			
SB 1993	249	252	305	299	8.57	8.47	18.60	20.89
SB 1994	230	233	279	273	9.47	7.36	18.64	19.35
GL 1993	245	245	296	294	8.64	8.77	17.06	20.60
GL 1994	235	239	270	280	8.07	7.83	16.09	20.41
RM 1993	241	245	290	293	7.58	8.31	18.08	20.02
RM 1994	238	218	282	265	8.78	8.65	18.98	18.00
BX 1993	249	256	305	303	7.85	8.27	19.42	21.58
BX 1994	245	246	280	285	8.45	7.84	20.31	19.75
RMSD#	7.1		10.0		0.93		3.2	
MBE††	0.0		−2.8		−0.03		2.5	
MPE‡‡	2.0		2.4		8.70		16.8	

† See Table 1 for site definitions.
‡ Obs., observed.
§ Sim., simulated.
¶ DAS, days after sowing.
# RMSD, root mean square difference.
†† MBE, mean bias error.
‡‡ MPE, mean percentage error.

Table 5. Wheat production statistics for the United Kingdom from 1990 through 2001.†

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
Area ('000 ha)	2013	1981	2067	1759	1811	1859	1976	2036	2045	1847	2086	1635
Yield (t/ha)	6.97	7.25	6.82	7.33	7.27	7.70	8.15	7.38	7.56	8.51	8.06	7.77
Production ('000 t)	1403	1436	1409	1289	1316	1431	1610	1502	1547	1487	1670	1157

† Adapted from statistics published by the Food and Agricultural Organization of the United Nations (www.fao.org; verified 4 Oct. 2002).

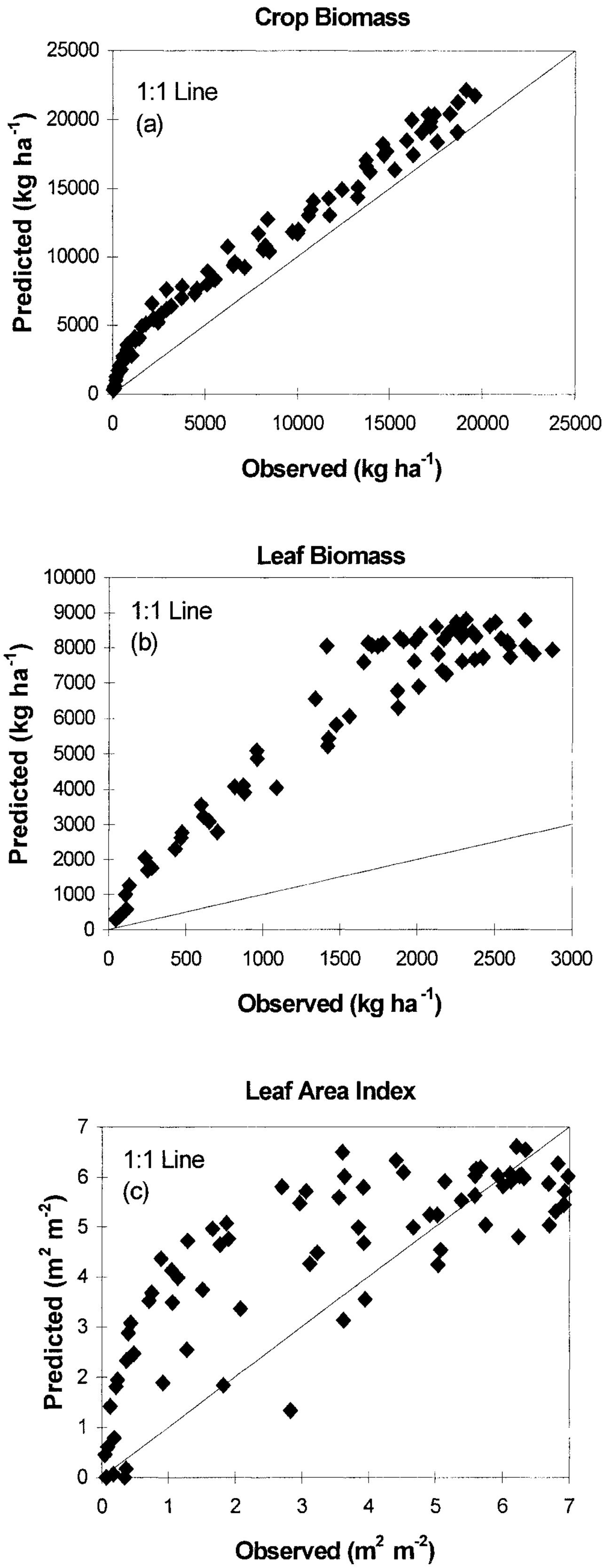

Fig. 1. A comparison of predicted and observed crop and leaf biomass and leaf area index for Sutton Bonington and Gleadthorpe for the 1992–1993 and 1993–1994 growing seasons.

value (2.9 d) for maturity date. The model slightly underestimated grain yield with a MBE of −0.03. Overall simulation of grain yield was quite acceptable with a RMSD of 0.93. However, the model overestimated the crop biomass with a MBE of 2.5 and a RMSD of 3.2, which is about 20% of the mean observed crop biomass (1.76 t ha^{-1}) across all site-years.

Using the independent experimental data for the 1995 growing season, the corresponding simulation results are shown in Table 5. The RMSD was 5.7 for the anthesis date and 6.0 for the maturity date, which was much less than the RMSD for the 1993 and 1994 growing seasons. Overall, the model was very robust in its estimation of critical phenological dates. Grain yield simulations across all sites were also very good with a RMSD of 0.28. The model only overestimated crop biomass (MBE = 3.39) with a RMSD of 4.15. These evaluation results showed that, once the model was calibrated for a cultivar, its accuracy when applied to the independent data sets was comparable to the accuracy of the calibrated data sets. The predictions of the CERES-Wheat model were also consistent with the range of long-term average observed wheat yield in the UK (Table 5).

The above results indicated a good accuracy for simulated grain yield, but there was a large error for simulated biomass production. Jamieson et al. (1998) found similar results when they compared five different wheat models, including CERES-Wheat. In explaining the higher error of biomass prediction compared with grain yield simulation, they concluded that there was no close link in the model between its ability to predict grain yield and biomass. They did not investigate the underlying assumptions and instead proposed another assessment after close examination of the models' dynamic performances. To help interpret the overestimation of crop biomass, the growth analysis data of the individual crop components were analyzed. These included aboveground biomass, LAI, and leaf weight for 2 yr for Sutton Bonington and Gleadthorpe (Fig. 1). The model clearly overpredicted leaf weight as well as LAI while the model adequately simulated the trend of biomass production. However, there were some discrepancies, and these were more obvious earlier within the growing season when biomass values were small. Leaf dry matter simulation again showed a large overestimation for the two sites. Due to the underestimation of stem dry weight, the overall biomass simulation was approximately balanced. Leaf area index was overestimated early in the growing season when LAI values were small and thus might have contributed to a higher overall biomass simulation. Despite these problems associated with biomass partitioning, the simulation of grain yield and total crop biomass was quite accurate (Tables 4 and 6). Therefore, it appeared reasonable to apply the model to predict grain yield for within-season forecasts.

Grain Yield and Biomass Forecast

For most forecasts, the observed grain yield was within the forecasted range, except for Sutton Bonington in the 1993 growing season (Table 7). For each

Table 6. Summary of the simulation results for the 1994–1995 growing season used for independent model evaluation.

Site† and year	Anthesis		Maturity		Grain yield		Crop biomass	
	Obs.‡	Sim.§	Obs.	Sim.	Obs.	Sim.	Obs.	Sim.
	DAS¶				t ha^{-1}			
SB 1995	255	255	290	294	NA#	6.73	19.71	18.82
GL 1995	260	254	295	293	7.40	7.11	14.78	20.92
RM 1995	255	265	295	305	7.46	7.26	19.11	22.13
BX 1995	251	253	288	292	7.35	7.28	17.11	20.80
RMSD††	5.7		6.0		0.28		4.15	
MBE‡‡	2.2		4.6		0.14		3.39	
MPE§§	1.12		1.15		1.90		14.19	

† See Table 1 for site definitions.
‡ Obs., observed.
§ Sim., simulated.
¶ DAS, days after sowing.
# NA, not available.
†† RMSD, root mean square difference.
‡‡ MBE, mean bias error.
§§ MPE, mean percentage error.

update step toward the end of growing season, the frequency distribution became narrower (Fig. 2). The precision of the grain yield prediction would be acceptable when its frequency distribution is sufficiently narrow. Qualitatively, this occurred for forecasts conducted at the anthesis and milk stages (Fig. 2 and 3).

The field trials exhibited a significantly different pattern and amount of biomass accumulation for the two growing seasons and between sites. Similar to the grain yield predictions, the variability of biomass predictions became narrower for the later forecasts across all sites and years (Fig. 3). However, observed crop biomass for most sites and years did not fall within the predicted ranges for the early forecasts during the growing season

Table 7. Range, mean, median, and standard deviation (SD) for predicted grain yield for the 1992–1993 and 1993–1994 growing seasons.

Site† and year	Forecast date		Minimum yield	Maximum yield	Median yield	Mean yield	SD	Observed yield
	DOY‡	DAS§	t ha^{-1}					
SB 1993	75	160	5.10	9.96	8.06	7.86	1.14	
	88	173	5.21	9.68	7.91	7.79	1.11	
	130	215	5.03	9.74	8.06	7.93	1.08	8.57
	165	250	7.39	9.01	8.25	8.25	0.32	
	179	264	8.52	8.76	8.61	8.61	0.06	
SB 1994	73	132	4.93	10.08	7.77	7.62	1.18	
	87	146	4.80	10.21	7.68	7.59	1.20	
	136	195	4.78	10.39	7.78	7.68	1.16	9.47
	171	230	6.65	10.11	8.41	8.37	0.72	
	185	244	7.41	9.59	8.21	8.20	0.31	
BX 1993	75	166	4.30	9.64	7.41	7.44	1.00	
	88	179	4.75	9.52	7.48	7.49	0.94	
	130	221	6.12	9.72	7.71	7.85	0.82	7.85
	158	249	7.61	9.59	8.68	8.70	0.42	
	179	270	8.97	9.03	8.99	8.99	0.14	
BX 1994	73	147	4.54	9.67	7.38	7.41	1.00	
	88	162	4.79	9.61	7.27	7.34	0.98	
	136	210	5.74	9.68	7.75	7.73	0.95	8.45
	171	245	7.51	9.85	8.77	8.75	0.51	
	185	259	8.59	9.21	8.85	8.88	0.14	
RM 1993	67	143	4.47	10.57	7.87	7.82	1.32	
	74	150	4.45	11.06	7.83	7.80	1.32	
	130	206	4.95	9.89	7.89	7.69	1.00	7.58
	165	241	6.27	8.78	7.79	7.79	0.45	
	196	262	7.82	8.39	8.21	8.20	0.11	
RM 1994	73	142	4.40	11.05	7.84	7.69	1.36	
	87	156	4.45	10.78	7.77	7.63	1.31	
	142	211	4.58	10.03	8.00	7.85	1.05	8.78
	169	238	7.02	9.78	8.65	8.62	0.58	
	192	261	8.56	8.68	8.63	8.22	0.26	
GL 1993	76	138	4.25	10.25	7.80	7.76	1.22	
	89	151	3.73	10.01	7.69	7.66	1.20	
	131	193	4.00	10.05	7.67	7.68	1.14	8.64
	167	229	6.58	8.97	7.90	7.87	0.56	
	187	249	8.12	8.54	8.35	8.35	0.93	
GL 1994	74	138	3.89	10.27	7.68	7.65	1.18	
	88	152	3.72	10.35	7.65	7.60	1.19	
	136	200	3.86	9.97	7.64	7.51	1.11	8.07
	171	235	6.63	9.63	8.48	8.42	0.72	
	185	249	7.60	9.29	8.56	8.55	0.39	

† See Table 1 for site definitions.
‡ DOY, day of year.
§ DAS, days after sowing.

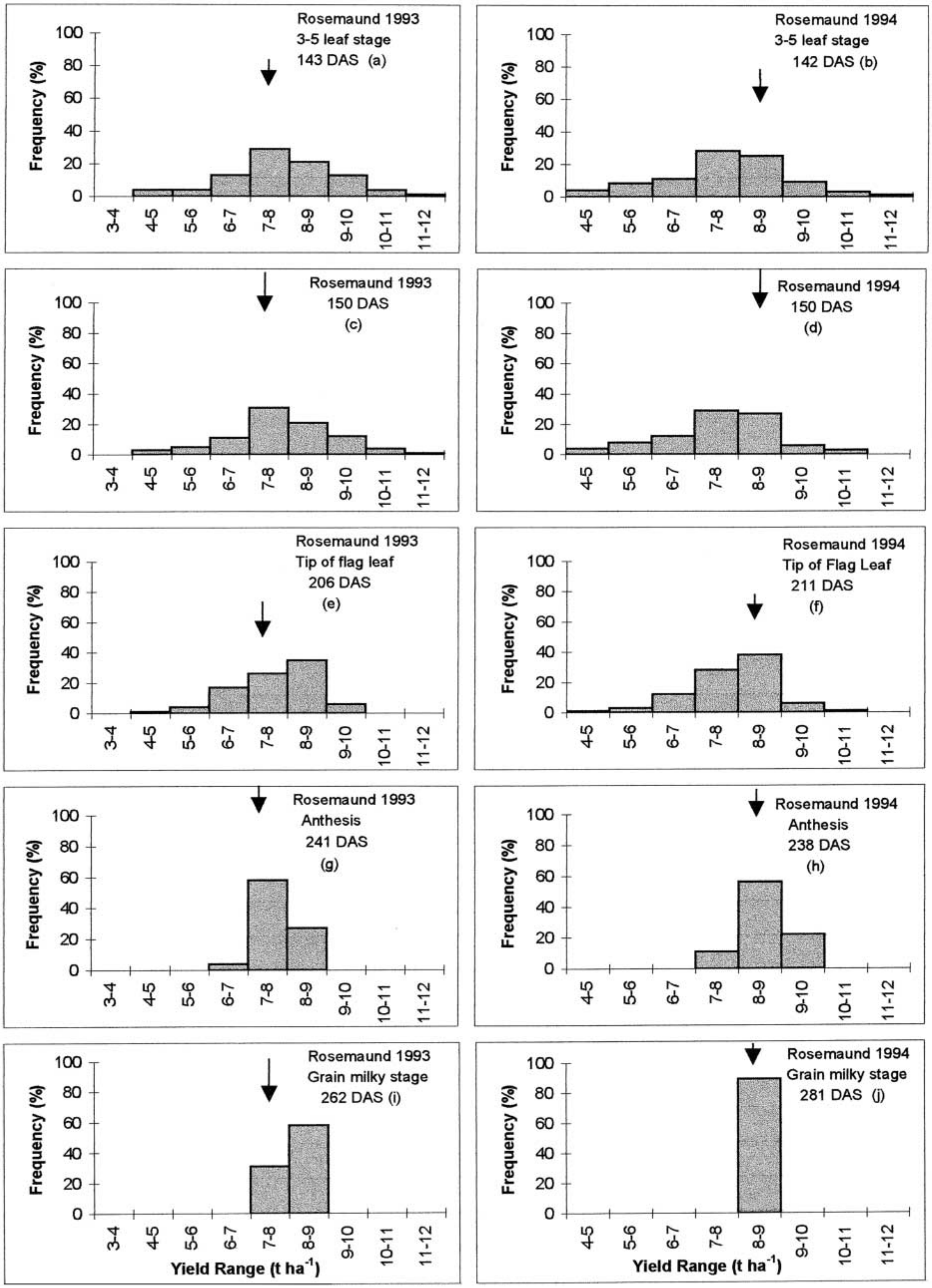

Fig. 2. Frequency distribution of predicted grain yield for the (a, c, e, g, and i) 1992–1993 and (b, d, f, h, and j) 1993–1994 growing seasons for Rosemaund for yield forecasts conducted at five different growth stages. DAS, days after sowing.

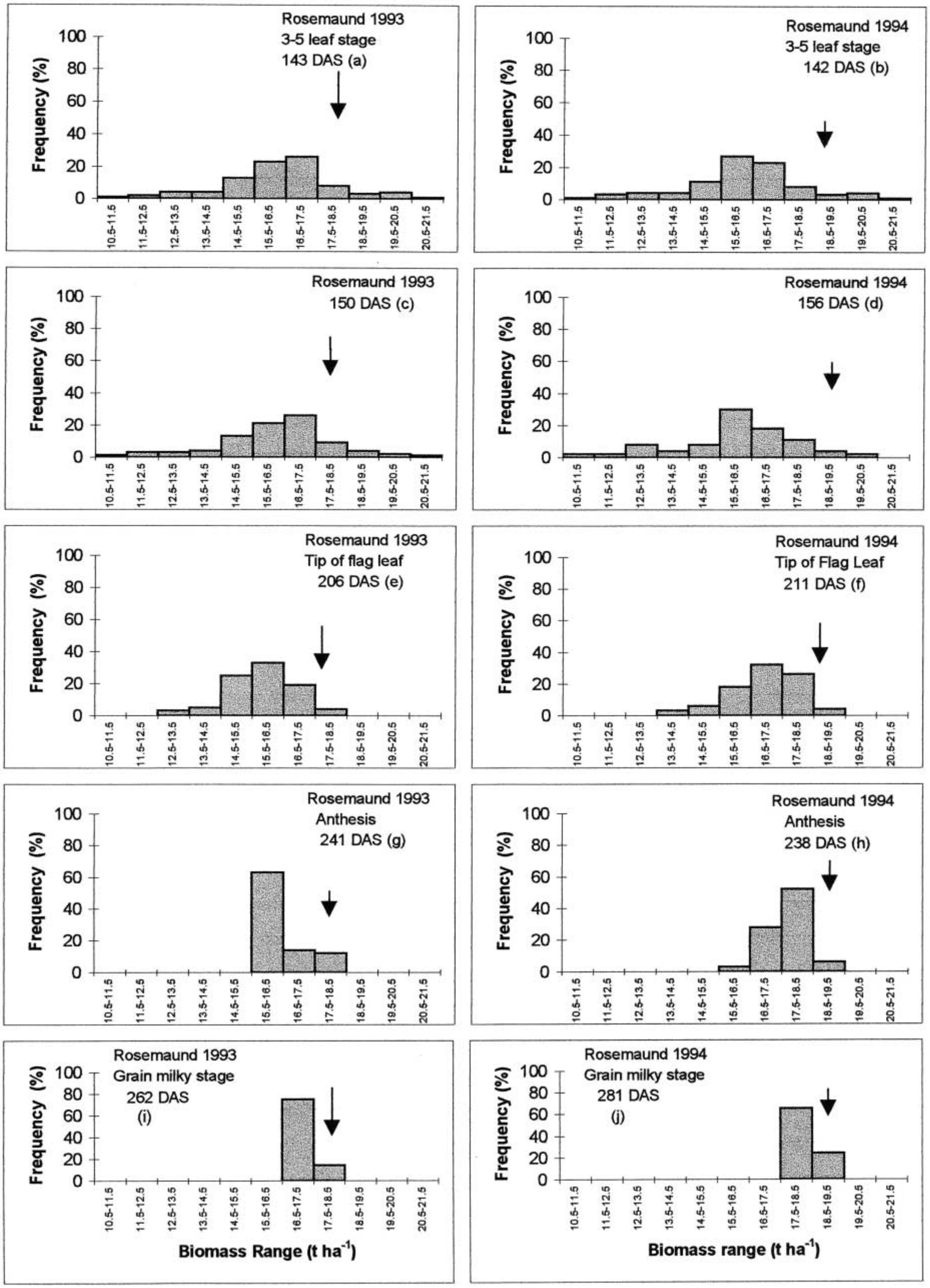

Fig. 3. Frequency distribution of predicted crop biomass for the 1992–1993 (a, c, e, g, i) and 1993–1994 (b, d, f, h, j)) growing seasons for Rosemaund for yield forecasts conducted at five different growth stages.

Table 8. Range, mean, median, and standard deviation (SD) for predicted biomass for the 1992–1993 and 1993–1994 growing seasons.

Site† and year	Forecast date		Minimum biomass	Maximum biomass	Median biomass	Mean biomass	SD	Observed biomass
	DOY‡	DAS§	t ha^{-1}					
SB 1993	75	160	11.90	18.40	15.97	15.63	1.62	
	88	173	12.09	18.05	15.72	15.50	1.51	
	130	215	12.84	18.67	15.94	15.81	1.07	18.60
	165	250	15.59	18.93	16.12	16.12	0.32	
	179	264	16.56	18.65	16.91	16.98	0.32	
SB 1994	73	132	12.86	19.89	17.02	16.78	1.67	
	87	146	12.80	19.70	16.76	16.63	1.64	
	136	195	13.56	19.86	17.27	17.13	1.33	18.64
	171	230	16.39	19.79	18.07	18.04	0.70	
	185	244	17.50	19.72	17.90	17.90	0.31	
BX 1993	75	166	10.59	17.94	15.80	15.70	1.53	
	88	179	11.44	19.69	15.96	15.87	1.40	
	130	221	15.55	19.87	17.80	17.72	0.81	19.42
	158	249	17.56	19.89	18.67	18.63	0.41	
	179	270	18.77	20.51	18.91	18.87	0.12	
BX 1994	73	147	11.27	18.95	16.24	16.22	1.60	
	88	162	11.11	19.19	16.14	16.10	1.54	
	136	210	15.86	19.89	17.81	17.82	0.99	20.31
	171	245	17.70	19.98	18.93	18.89	0.5	
	185	259	18.82	19.72	19.05	19.05	0.12	
RM 1993	67	143	10.93	21.13	16.44	16.32	1.78	
	74	150	11.11	20.67	16.39	16.23	1.76	
	130	206	13.22	18.13	15.99	15.82	1.03	18.08
	165	241	15.50	17.94	16.98	16.98	0.44	
	196	262	16.60	18.12	17.60	17.59	0.28	
RM 1994	73	142	11.14	21.19	16.38	16.22	1.83	
	87	156	10.68	20.91	17.17	16.02	1.80	
	142	211	13.58	19.03	17.05	16.91	1.02	18.98
	169	238	15.97	18.80	17.67	17.64	0.58	
	192	261	17.60	19.10	17.96	17.96	0.25	
GL 1993	76	138	11.95	20.11	16.59	16.46	1.63	
	89	151	11.75	19.98	16.28	16.17	1.60	
	131	193	14.16	20.16	17.43	17.40	1.28	17.06
	167	229	15.52	19.81	17.73	17.70	0.55	
	187	249	17.09	19.51	17.31	17.31	0.11	
GL 1994	74	138	12.76	20.63	17.44	17.14	1.60	
	88	152	12.58	20.39	17.26	16.98	1.56	
	136	200	13.60	19.90	17.67	17.71	1.41	16.19
	171	235	15.57	20.35	18.71	18.70	0.72	
	185	249	16.11	19.50	17.80	17.79	0.38	

† See Table 1 for site definitions.
‡ DOY, day of year.
§ DAS, days after sowing.

(Table 8). This improved for later forecasts. In most cases, mean predicted biomass was lower than the observed final biomass (Fig. 3 and Table 8).

Assessment of Forecast Accuracy

The RMSD values for predicted grain yield for all forecast dates was <1 t ha^{-1}, re-emphasizing the capability of the CERES-Wheat model for grain yield prediction (Table 9). The RMSD value of 0.95 t ha^{-1} for the first forecast date was reduced to 0.59 t ha^{-1} by anthesis. For the earlier forecast dates, the model tended to underestimate yield although the underestimation at three- to five-leaf stage was just 0.76 t ha^{-1} (MBE), which is <10% of the mean observed final grain yield. The maximum standard deviation between sites and seasons was found for the forecast conducted at the three- to five-leaf stage and was reduced for later forecasts.

In general, we found that the larger the proportion of observed weather data used in simulation, the greater the agreement. This was similar to observations of other studies (Thornton et al., 1997). As Semenov et al. (1993) stated, the dynamic growth and development processes of crop models are connected to the environment via a combination of linear and nonlinear responses. In other words, many plant processes such as radiation interception are curvilinearly related to environmental variables. Assuming a linear relation between canopy net photosynthesis and intercepted radiation (Monteith, 1977), not much error will be introduced in crop growth rate in northwest Europe because the crop remains on the linear portion of the response curve for most of the growing season. When thresholds of environmental variables are used as conditional switches of plant responses, e.g., reduction of grain-filling rate at a super optimal temperature, then weather variability can introduce yield variability into models and thus cause a discrepancy between simulation and observation. Reducing weather variability by increasing the proportion of observed weather reduces the forecasted yield variability.

A comparison of predicted final crop grain yield (mean) with observed data for the forecast dates up to flag leaf appearance showed a significant difference (paired t test: $p < 0.01$). However, for the last two forecast dates at anthesis and milk stage, no significant difference was found (paired t test: $p = 0.73$ for anthesis and $p = 0.79$ for milk stage).

Table 9. Measures of model deviation between predicted and observed grain yield and crop biomass for the 1994–1995 growing season for all sites.

Growth stage	Forecast date		RMSD†	MPE‡	MBE§
	DOY¶	DAS#	t ha^{-1}	%	t ha^{-1}
				Grain yield	
Three- to five-leaf stage	67–76	132–166	0.95	9.5	−0.76
Third sampling	74–81	146–179	0.88	8.9	−0.70
Tip of flag leaf App.	130–158	193–249	0.82	7.9	−0.61
Anthesis	158–171	229–250	0.59	5.9	−0.06
Milk stage	179–187	244–270	0.68	6.5	0.12
				Crop biomass	
Three- to five-leaf stage	67–76	132–166	3.59	13.48	−2.06
Third sampling	74–81	146–179	3.51	12.92	−1.91
Tip of flag leaf App.	130–158	193–249	2.89	10.50	−1.28
Anthesis	158–171	229–250	2.55	8.53	−0.54
Milk stage	179–187	244–270	2.09	6.25	−0.47

† RMSD, root mean square difference.
‡ MPE, mean percentage error.
§ MBE, mean bias error.
¶ DOY, day of year.
# DAS, days after sowing.

In Table 9, the deviation for each forecast date for simulated final crop biomass is summarized. The maximum standard deviation for biomass forecasts was obtained at the first forecast date (three- to five-leaf stage) and was reduced for the later forecast dates. The standard deviation at the three- to five-leaf stage across sites-years was about 1.66 t ha^{-1} while the standard error of observed biomass was 1.30 t ha^{-1}. As shown in Fig. 3, the agreement between observed and predicted biomass improved for later forecasts during the growing season and showed less variability. The MPE of crop biomass (Table 9) predictions was approximately twice the MPE of the grain yield predictions. This indicated that in contrast to the prediction of grain yield, the model was weak in prediction of crop biomass. Generally, the model tended to underestimate crop biomass (Table 9). This underestimation (MBE) at three- to five-leaf stage was about 2.06 t ha^{-1} and decreased to 0.47 t ha^{-1} at anthesis.

A comparison of predicted final crop biomass (mean) with observed data for the forecast dates up to flag leaf appearance showed a significant difference ($P < 0.05$). However, for the final two forecasts dates at anthesis and milk stage, there was no significant difference ($p = 0.32$ for anthesis and $p = 0.22$ for milk stage) across all sites and years.

Rank Correlation Test

Spearman's rank correlation was applied to CERES-Wheat predictions to investigate whether the ranking of mean final crop biomass and grain yield between sites and seasons were correctly predicted. Comparing the observed production of each site-year combination with forecasts for crop biomass showed that across all sites-years, a significant correlation was found for forecasts made at the milk stage ($r_s = 0.44$, $n = 8$, $\alpha < 5\%$). However, it was not significant for forecasts made at anthesis ($r_s = 3.8$, $n = 8$, $\alpha > 5\%$) or earlier stages. For final grain yield, there was a highly significant correlation across all sites and years for the forecast made at the milk stage ($r_s = 0.91$, $n = 8$, $\alpha < 1\%$). For the forecast made at the anthesis date, this was only significant after eliminating the high yield of Sutton Bonington for the 1993 to 1994 growing season ($r_s = 0.93$, $n = 7$, $\alpha = 1\%$).

Confidence Interval

Confidence intervals for both predicted grain yield and crop biomass for the last three forecast dates are shown in Table 10. In the case of grain yield, the model generally gave a good response for all site and year combinations although the yield range was closer to the target yield toward the end of growing season. At the tip of flag leaf appearance stage and at the anthesis stage, five out of eight of the observed values for grain yield were within the predicted range of simulated yield. For the 1992 to 1993 growing seasons for Sutton Bonington and Gleadthorpe, the 75% confidence interval did not include the observed yield at the anthesis stage although the difference from the upper limit of the simulated range was negligible. Only the grain yield for the 1993 to 1994 growing season for Sutton Bonington was significantly underestimated (Table 10).

The CERES-Wheat prediction for crop biomass showed an underestimation for all site-year combinations, except for one site for the last two forecast dates. Underestimation of crop biomass by CERES-Wheat may be due to unsuitable canopy production parameter values, such as the leaf area/weight ratio, the partitioning coefficients for biomass, the green area senescence rate, or the canopy radiation absorption for potential wheat production in the UK.

SUMMARY AND CONCLUSIONS

The results from this study show that the forecast accuracy for wheat grain yield for the environmental conditions of the UK improved with later forecasts during the growing season. There was no significant difference between the predicted yields across all site and year combinations for forecasts made at the anthesis and milk stages. However, there could be a difference if economic factors are taken into consideration. For

Table 10. The range of grain yield and crop biomass predicted with 75% certainty when forecasts were conducted at Tip of flag leaf appearance, anthesis, and milk stage for the 1992–1993 and 1993–1994 growing seasons.

Site† and year	Forecast dates: Tip of flag leaf appearance	Anthesis stage	Milk stage	
	Predicted range for grain yield			Observed yield
	t ha^{-1}			
SB 1993	5.03–8.70	7.40–8.48	8.52–8.64	8.57
SB 1994	4.78–8.42	6.66–8.85	7.42–8.40	9.47
BX 1993	5.03–8.70	7.62–9.04	8.97–9.01	7.85
BX 1994	5.74–8.57	7.52–9.11	8.59–8.98	8.45
GL 1993	4.01–8.41	6.58–8.15	8.12–8.42	8.64
GL 1994	3.87–8.31	6.64–8.95	7.61–8.86	8.07
RM 1993	4.96–8.41	6.27–8.05	7.82–8.06	7.58
RM 1994	4.58–8.62	7.03–9.00	8.57–8.65	8.78
	Predicted range for crop biomass			Observed biomass
	t ha^{-1}			
SB 1993	14.43–16.80	15.32–16.31	16.46–16.54	18.60
SB 1994	13.56–17.98	16.39–18.51	17.15–18.08	18.64
BX 1993	12.84–16.58	15.98–17.31	17.27–17.30	19.42
BX 1994	15.86–18.55	17.70–19.23	18.82–19.12	20.31
GL 1993	11.97–17.32	15.43–17.00	17.09–17.37	17.06
GL 1994	13.60–18.72	16.87–19.19	17.92–19.07	16.19
RM 1993	13.22–16.50	14.50–16.25	16.60–18.05	18.08
RM 1994	13.58–17.61	15.97–18.00	17.60–17.68	18.98

† See Table 1 for site definitions.

example, the RMSD of crop biomass is about 0.46 t ha^{-1} greater at anthesis than at milk stage, which may be a significant error when considering a large area. The results from the Spearman's rank correlation showed that the CERES-Wheat model was able to predict both the upper and lower limit of observed yield across all sites and years with a significant correlation at milk stage. This could be useful information for farmers to schedule final harvest or for marketing applications. This indicates the reliability of the model to at least provide an accurate range for grain yield at different sites in the UK where weather and soil conditions might be different. Updating the model with the plant variables in addition to the weather data might provide more accurate forecasts with the CERES-Wheat model. In fact, it is believed that the model has some major deficiencies that limit its utility for yield forecasts, unless an updating system is incorporated into the model to correct variables during the simulation. However, changing the model structure to enable updating of plant variables during the growing season would require a major restructuring of the code. It also might not address any inherent problems with the model. In addition, there are other possibilities, such as in-season modification of external variables. Recent studies have also explored using data collected through remote sensing to address similar yield-forecasting issues (Guerif and Duke, 1998, 2000).

Although this analysis was conducted for four specific locations in the UK, the approach that was used is generally applicable to other locations, provided that long-term weather data are available. The information obtained in these yield predictions can be used directly in decision support systems, provided that an updating system is incorporated in the model, allowing for an effective yield forecast especially during the second part of the growing season to assist farm managers in making more informed decisions. Including an economic analysis will provide a means to further advise policy makers and managers.

REFERENCES

Anderson, J.R. 1974. Risk efficiency in the interpretation of agricultural production research. Rev. Mark. Agric. Econ. 42:131–148.

Arkin, G.F., and W.A. Dugas. 1981. Making weather and climate dependent crop management decisions. p. 223–237. *In* A. Weiss (ed.) Proc. Workshop Comput. Tech. and Meteorol. Data Appl. to Problems of Agric. and Forestry, Anaheim, CA. 30–31 Mar. 1981. Am. Meteorol. Soc., Boston.

Booltink, H.W.G., B.J. van Alphen, W.D. Batchelor, J.O. Paz, J.J. Stoorvogel, and R. Vargas. 2001. Tools for optimizing management of spatially-variable fields. Agric. Syst. 70(2–3):445–476.

Bouman, B.A.M., C.A. van Diepen, P. Vosen, and T. van Der Wal. 1995. Simulation and system analysis tools for crop yield forecasting. p. 325–340. *In* (ed.) Application of systems approaches at the farm and regional levels. Volume 1. Kluwer Academic Publ., Dordrecht, the Netherlands.

Duchon, C.E. 1986. Corn yield prediction using climatology. J. Clim. Appl. Meteorol. 25(5):581–590.

Fox, G., J. Turner, and T. Gillespie. 1999. The value of precipitation forecast information in winter wheat production. Agric. For. Meteorol. 95:99–111.

Geng, S., F.W.T. Penning de Vries, and I. Supit. 1986. A simple method for generating daily rainfall data. Agric. For. Meteorol. 36:363–376.

Georgiev, G., and G. Hoogenboom. 1998. Crop growth and yield estimation using current weather forecasts and weather observations. p. 69–72. *In* Preprints Conference on Agricultural and Forest Meteorology, 23rd. Am. Meteorol. Soc., Boston.

Georgiev, G.A., and G. Hoogenboom. 1999. Near real-time agricultural simulations on the web. Simulation 73(1):22–28.

Gillett, A., N.M.J. Crout, D.T. Stokes, R. Sylvester-Bradley, and R.K. Scott. 1999. Simple winter wheat green area index model under UK conditions. J. Agric. Sci. 132:263–271.

Godwin, D.C., and U. Singh. 1998. Nitrogen balance and crop response to nitrogen in upland and lowland cropping systems. p. 41–54. *In* G.Y. Tsuji, G. Hoogenboom, and P.K. Thornton (ed.) Understanding options for agricultural production. Systems approaches for sustainable agricultural development. Kluwer Academic Publ., Dordrecht, the Netherlands.

Guerif, M., and C.L. Duke. 1998. Calibration of the SUCROS emergence and early growth module for sugar beet using optical remote sensing data assimilation. Eur. J. Agron. 9:127–136.

Guerif, M., and C.L. Duke. 2000. Adjustment procedures of a crop model to the site specific characteristics of soil and crop using remote sensing data assimilation. Agric. Ecosyst. Environ. 81:57–69.

Hammer, G.L., D.P. Holzworth, and R.C. Stone. 1996. The value of skill in seasonal climate forecasting to wheat crop management in a region with high climatic variability. Aust. J. Agric. Res. 47:717–737.

Hammer, G.L., N. Nicholls, and C. Mitchell (ed.) 2000. Application of seasonal climate forecasting in agricultural and natural ecosystems. The Australian experience. Kluwer Academic Publ., Dordrecht, the Netherlands.

Hoogenboom, G. 2000. Contribution of agrometeorology to the simulation of crop production and its applications. Agric. For. Meteorol. 103(1–2):137–157.

Hoogenboom, G., J.W. Jones, P.W. Wilkens, W.D. Batchelor, W.T. Bowen, L.A. Hunt, N.B. Pickering, U. Singh, D.C. Godwin, B. Baer, K.J. Boote, J.T. Ritchie, and J.W. White. 1994. Crop models. p. 95–244. *In* G.Y. Tsuji, G. Uehara, and S. Balas (ed.) DSSAT version 3. Volume 2. Univ. of Hawaii, Honolulu.

Hoogenboom, G., P.W. Wilkens, and G.Y. Tsuji (ed.) 1999. DSSAT version 3. Volume 4. Univ. of Hawaii, Honolulu.

Hunt, L.A., S. Pararajasingham, J.W. Jones, G. Hoogenboom, D.T. Imamura, and R.M. Ogoshi. 1993. Gencalc: Software to facilitate the use of crop models for analyzing field experiments. Agron. J. 85:1090–1094.

Hunt, L.A., J.W. White, and G. Hoogenboom. 2001. Agronomic data: Advances in documentation and protocols for exchange and use. Agric. Syst. 70:477–492.

Hutchinson, M.F. 1991. Climatic analysis in data sparse regions. p. 55–73. *In* R.C. Muchow and J.A. Bellamy (ed.) Climatic risk in crop production: Models and measurement for the semiarid tropics and arid subtropics. CAB Int., Wallingford, UK.

Jacobson, B.M., J.W. Jones, and S.M. Welch. 1997. PCYield: A decision support system with real-time soybean yield. p. 16. *In* 1997 agronomy abstracts. ASA, CSSA, and SSSA, Madison, WI.

Jamieson, P.D., J.R. Porter, J. Goudriaan, J.T. Ritchie, H. van Keulen, and W. Stol. 1998. A comparison of models AFRCWHEAT2, CERES-Wheat, Sirius, SUCROS2 and SWHEAT with measurements from wheat grown under drought. Field Crops Res. 55:23–44.

Jones, J.W., J.W. Hansen, F.S. Royce, and C.D. Messina. 2000. Potential benefits of climate forecasting to agriculture. Agric. Ecosyst. Environ. 82:169–184.

MacDonald, R.B., and F.G. Hall. 1980. Global crop forecasting. Science 208:670.

Matis, J.H., T. Saito, W.E. Grant, W.C. Iwig, and J.T. Ritchie. 1985. A Markov chain approach to crop yield forecasting. Agric. Syst. 18:171–187.

McKinion, J.M., D.N. Baker, F.D. Whisler, and J.R. Lambert. 1989. Application of the GOSSYM/COMAX system to cotton crop management. Agric. Syst. 31:55–65.

Meinke, H., and G.L. Hammer. 1997. Forecasting regional crop production using SOI phases: An example for the Australian peanut industry. Aust. J. Agric. Res. 48:789–793.

Meinke, H., and R.C. Stone. 1997. On tactical crop management using seasonal climate forecasts and simulation modelling—a case study for wheat. Sci. Agric. (Piracicaba, Braz.) 54:121–129.

Mjelde, J.W., and H.S.J. Hill. 1999. The effect of the use of improved climate forecasts on variable costs, input usage, and production. Agric. Syst. 60:213–225.

Monteith, J.L. 1977. Climate and the efficiency of crop production in Britain. Philos. Trans. R. Soc. London, Ser. B 281:277–294.

Paz, J.O., W.D. Batchelor, and G.L. Tylka. 2001. Method to use crop growth models to estimate potential return for variable-rate management in soybeans. Trans. ASAE 44(5):1335–1341.

Pickering, N.B., J.W. Hansen, J.W. Jones, C.M. Wells, and V. Chan. 1994. WeatherMan—a utility for managing and generating weather data. Agron. J. 86:332–337.

Racsko, P., L. Szeidel, and M.A. Semenov. 1991. A serial approach to local stochastic weather models. Ecol. Modell. 57:27–41.

Reddy, K.R., H.F. Hodges, and J.M. McKinion. 1997. Crop modeling and applications: A cotton example. Adv. Agron. 59:225–290.

Richardson, C.W. 1981. Stochastic simulation of daily precipitation, temperature and solar radiation. Water Resour. Res. 17:182–190.

Rietveld, M.R. 1978. A new method for estimating the regression coefficients in the formula relating solar radiation to sunshine. Agric. Meteorol. 19:243–251.

Ritchie, J.T. 1998. Soil water balance and plant water stress. p. 41–54. *In* G.Y. Tsuji, G. Hoogenboom, and P.K. Thornton (ed.) Understanding options for agricultural production. Kluwer Academic Publ., Dordrecht, the Netherlands.

Ritchie, J.T., and P.T. Dyke. 1984. Using crop models to evaluate yield probabilities related to weather, soils, and agrotechnology. p. 17. *In* 1984 agronomy abstracts. ASA, CSSA, and SSSA, Madison, WI.

Ritchie, J.T., and S. Otter. 1985. Description and performance of CERES-Wheat: A user-oriented wheat yield model. p. 159–175. *In* ARS wheat yield project. ARS-38. Natl. Tech. Inf. Serv., Springfield, VA.

Ritchie, J.T., U. Singh, D.C. Godwin, and W.T. Bowen. 1998. Cereal growth, development and yield. p. 79–97. *In* G.Y. Tsuji, G. Hoogenboom, and P.K. Thornton (ed.) Understanding options for agricultural production. Kluwer Academic Publ., Dordrecht, the Netherlands.

Royce, F.S., J.W. Jones, and J.W. Hansen. 2001. Model-based optimization of crop management for climate forecast applications. Trans. ASAE 44(5):1319–1327.

Sadler, E.J., B.K. Gerwig, D.E. Evans, W.J. Busscher, and P.J. Bauer. 2000. Site-specific modeling of corn yield in the SE coastal plain. Agric. Syst. 64:189–207.

Semenov, M.A., J.R. Porter, and R. Delécole. 1993. Climatic change and the growth and development of wheat in the UK and France. Eur. J. Agron. 2(4):293–304.

Supit, I. 1997. Predicting national wheat yields using a crop simulation and trend models. Agric. For. Meteorol. 88:199–214.

Thornton, P.K., W.T. Bowen, A.C. Ravelo, P.W. Wilkens, G. Farmer, J. Brock, and J.E. Brink. 1997. Estimating millet production for famine early warning: An application of crop simulation modelling using satellite and ground-based data in Burkina Faso. Agric. For. Meteorol. 83:95–112.

Thornton, P.K., and G. Hoogenboom. 1994. A computer program to analyze single-season crop model outputs. Agron. J. 86:860–868.

Travasso, M.I., and R. Delecolle. 1995. Adaptation of the CERES-Wheat model for large area yield estimation in Argentina. Eur. J. Agron. 4(3):347–353.

Tsuji, G.Y., G. Hoogenboom, and P.K. Thornton (ed.) 1998. Understanding options for agricultural production. Kluwer Academic Publ., Dordrecht, the Netherlands.

Tsuji, G.Y., G. Uehara, and S. Balas (ed.) 1994. DSSAT version 3. A decision support system for agrotechnology transfer. Volumes 1–3. Univ. of Hawaii, Honolulu.