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Assessing lead-time for predicting wheat growth using a crop simulation model

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Abstract

In order to use crop simulation models to predict crop yield, unobserved daily weather, an important input for crop models, must be forecast in some sense. Due to the chaotic nature of weather and the non-linear response of crop simulation models to weather input, this forecast weather cannot simply be a single weather series (e.g. average historical weather for the upcoming growing season), but must be an ensemble of weather series, incorporating site-specific climatic variability. To capture weather uncertainty, we used the LARS-WG stochastic weather generator to produce a probabilistic ensemble of weather series by mixing observed weather from the beginning of a season with stochastically generated (synthetic) weather for the remainder of the growing season. This ensemble was used with the crop simulation model Sirius to generate distributions of crop characteristics. Progressing through the growing season, as the proportion of synthetic weather in these ensembles decreased, the distribution means converged towards the true values, allowing us to make predictions with a high level of confidence before crop maturity. In this fashion, we analysed six sites with diverse climates in Europe and New Zealand, comparing lead-times for predicting different crop characteristics at various geographic locations. We demonstrated that that there is a large difference between lead-times amongst different crop characteristics at a single location, and that there is a large variation in lead-times for predicting selected crop characteristics between locations. Variation in climates places a quantifiable limit on our ability to make crop predictions using crop simulation models.

Keywords: Crop simulation; Stochastic weather generator; Lead-time; Climate variability; Sirius; LARS-WG; Probabilistic ensembles

1. Introduction

The weather during a plant's growing season affects growth and development and through accumulative dynamic growth, the final value of crop characteristics of interest (e.g. grain yield). As a plant's lifecycle progresses from sowing towards maturity, the degree of uncertainty in the weather, which the plant will experience during its complete lifecycle decreases. This reduction in uncertainty leads to increased confidence in the prediction of crop characteristics. Here we present a method of quantifying how our confidence in predictions increases during the growing season.

The development of a methodology for predicting grain yield in advance, in response to different managements, environments and weathers, is a desirable goal. Such a methodology would assist farm-management decisions by allowing an examination of the trade-off between the value of expected crop yields and the cost of inputs. Examining this trade-off allows optimum decisions to be made. Expected weather has a strong influence on the most suitable crop-type, and to a certain extent the most suitable cultivar at a given site (Jagtap et al., 2002). On the regional scale, such a methodology

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would help to predict the supply of grain to market for a given year, which is an important factor determining expected grain prices. Grain yield depends on weather in the coming season, and on how farmers choose to fertilize and protect their crops. Yield prediction is also important in assessing the trade-off between food security and the environmental impact of agricultural inputs (e.g. N pollution). The timing of certain plant disease epidemics relative to the growth stage of the crop is important. For instance, Fusarium Head Blight is caused when ascospores of the pathogen *Fusarium graminearum* or *F. culmorum* infects wheat ears during anthesis (Pearce et al., 1976). Chemicals applied at anthesis are used to reduce yield losses (Ioos et al., 2005). An ability to predict anthesis date could be useful in predicting damage due to disease, and the optimum timing and magnitude of fungicide applications.

Most yield prediction methods involve the use of quantitative crop models, statistical or process-based, which are capable of estimating crop yield, for example, for a given combination of weather, management and environment. The National Agricultural Statistics Service (N.A.S.S.) of the United States Department of Agriculture uses statistical models linking weather to yields for prediction. The weather data, which they use as input to their statistical models to represent future weather, is the mean of historical weather time-series. This approach has serious limitations. It has been demonstrated (Porter and Semenov, 1999; Porter and Semenov, 2005; Semenov and Porter, 1995) that due to the non-linear response of crops to their environments (in particular, weather) that historical mean weather could be inappropriate for prediction of crop growth.

In this paper we have developed an approach for within-season predictions of yield, based on a process-based crop simulation model and a stochastic weather generator. Having observed weather for the first part of the growing season, we used a stochastic weather generator to produce a probabilistic ensemble of synthetic weather time-series for the remainder of the season, specific to the selected site. Then we used constructed weather-series as an input to a crop simulation model to generate distributions of crop characteristics. Moving through the season, as the amount of observed weather increases, uncertainty in predictions decreases (i.e. the distributions narrow, and their mean and median converge towards values computed with fully observed weather) eventually achieving an acceptable level of predictive accuracy well before the maturity date.

In regions where crop production depends strongly on a single factor, it is possible to develop a simpler method, based on regression between this factor and grain yield. One such region (where crop production is strongly dependent on the amount of rainfall) is southern Africa (Phillips et al., 1998). Rainfall in this region is strongly influenced by the El Niño Southern Oscillation (ENSO). Analysis of the relationship between Pacific sea surface temperatures (SSTs) and national-level maize production in Zimbabwe proved that a large component of the interannual variability in maize production could be explained by them (Cane et al., 1994). Recent advances in ocean climate modelling make it possible to predict ENSO events by as much as 1 year in advance (Chen et al., 2004). This predictability can be used to reduce the risk in agricultural production associated with rainfall variability. Knowledge of the ENSO phase was used in planting date decisions to avoid the worst impact of drought or to take advantage of a good rainy season in Zimbabwe (Phillips et al., 1992). In Europe, however, the ENSO signal is generally too weak to have a noticeable effect on crop growth and development (Cantelaube and Terres, 2005). In another example, a regression relationship was developed between the North Atlantic Oscillation (NAO) and the quality of wheat in the UK (Kettlewell et al., 1999). Kettlewell et al. reported on the correlations between a range of quality parameters for wheat in the UK, including the Hagberg falling number (HFN)[1], specific grain weight and total protein concentration, and an index of the NAO measured 5 months before harvest. Millers often have a specific requirement for grain protein concentration for their products. Multi-national milling companies have access to markets in many different global regions. The ability to assess before harvest the relative likelihood of a given region producing grain of the required quality would allow advance selection of appropriate markets for each year. Unfortunately, the relationship between wheat quality and NAO is not valid for other regions of continental Europe, and if we would like to make predictions about crop growth and development, we are compelled to look for an alternative method.

2. Method

2.1. Overview

Assuming that the Sirius crop simulation model (Jamieson et al., 1998) adequately predicts crop growth given complete input information, we can ask how

[1] HFN for a particular flour is an indication of its α-amylase content and is expressed in seconds.

incomplete weather observations (i.e. lacking future weather data) limit our ability to predict yield accurately in diverse climates.

To use a crop simulation model, weather input must be provided for the whole growing season. To do this in a predictive sense, we combined observed weather with many synthetic weather time-series, generated by a stochastic weather generator and representing samples from the population of possible future outcomes. Stochastic weather generators, calibrated previously for a selected site using historical observed records, are capable of generating synthetic weather statistically similar to observed historical weather, meaning that a range of statistical tests will show no significant difference between observed and synthetic weather. Instead of attempting to forecast future weather at a particular point in the growing season, we generated probabilistic ensembles of likely synthetic weather time-series using the LARS-WG stochastic weather generator (Racsko et al., 1991; Semenov and Barrow, 1997). Using the generated ensemble as an input to Sirius, we simulated the corresponding final grain yields, above ground biomass, etc., and took the average value over the ensemble as our predictor. The variation in simulated yields using fully synthetic weather could be considered as an indication of the effect of climatic uncertainty on yield prediction for a given site (see Figs. 1 and 8).

This process of simulating a distribution of likely yields could be repeated as the season advances and another ensemble of weather series (given the observed data) could be generated for the remainder of the year (see Fig. 4). This produces a narrower distribution of grain yields. As time passes and we increase the amount of observed data available for prediction, the simulated prediction becomes more accurate. The question we are trying to answer is: what amount of observed weather data is required using this method in order to achieve accurate predictions?

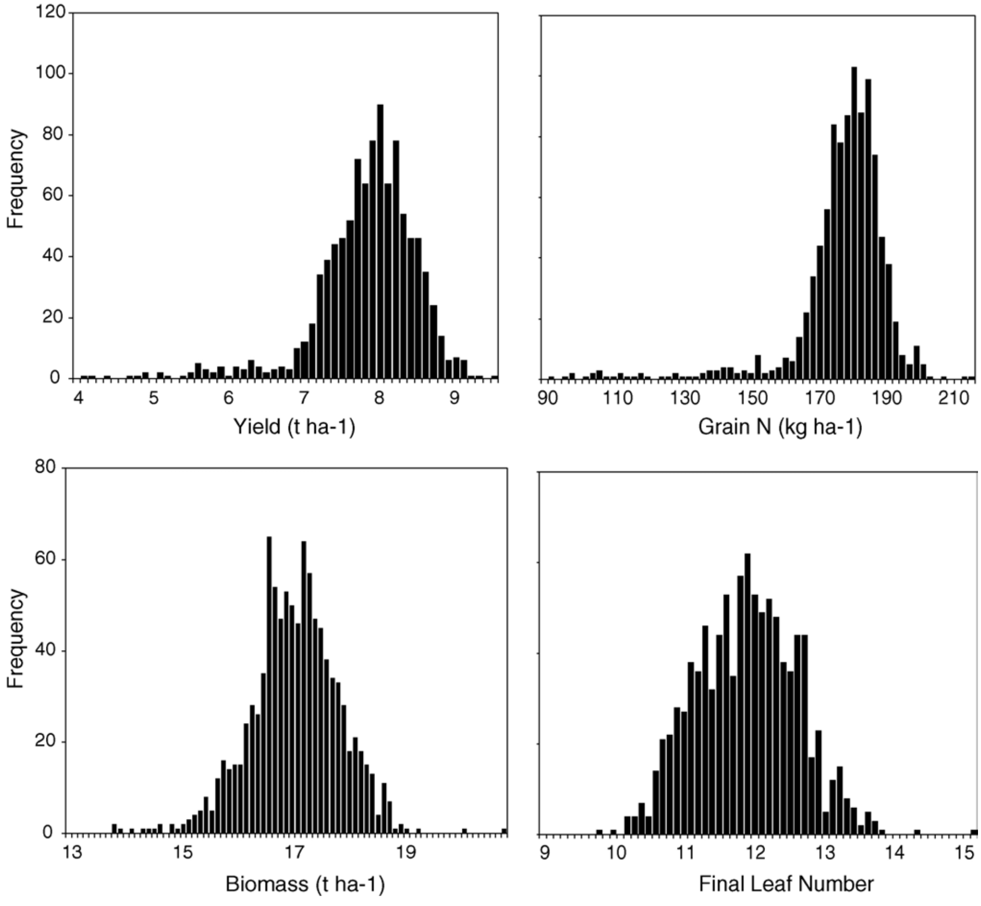

Fig. 1. Frequency distributions for various crop characteristics calculated with 999 years of synthetic weather data generated for Rothamsted (cultivar *Mercia*, Rothamsted soil).

2.2. Cultivar, soil and management input

For consistency and to allow direct comparison across sites, all of the simulations carried out below differ only in weather input. Cultivar, soil and management remain the same and are not varied to reflect differing agronomic practice or actual soil-types. This work is intended as a theoretical exercise, demonstrating the use of a prediction method for a particular site and climate. We also demonstrate the effect of local climate on the forecasting power of this method by artificially isolating the climate effect from interactions with environment and management. This sort of analysis is only possible in simulation context. The methods outlined here can be used as part of a decision-support system, provided that a relevant cultivar, actual soil, management and site-specific historical and real-time weather are used.

2.3. Model description

Sirius is a wheat simulation model, developed in collaboration between Crop & Food Research, NZ and Rothamsted Research, UK (Jamieson et al., 1998). Sirius calculates biomass from intercepted photosynthetically active radiation (PAR) and grain growth from simple partitioning rules. Phenological development is calculated from the mainstem leaf appearance rate and final leaf number, with the latter determined by responses to daylength and vernalisation. Sirius contains a mechanistic model of N uptake and redistribution in wheat crops incorporating the effects of N shortages through variation in leaf area (Jamieson and Semenov, 2000). The predictions of the model were tested against independent data from experiments at environmentally diverse sites, giving good agreement with experimentally observed data (Ewert et al., 2002; Jamieson and Semenov, 2000). The latest development of Sirius was a new canopy model linking a phenological model that depends on the prediction of leaf appearance with a canopy model that assigns a particular area to each cohort of leaves associated with a mainstem leaf (Lawless et al., 2005).

2.4. Model input data

In order to capture the dynamic behaviour of these processes, Sirius requires certain data as input. Obviously, it needs daily weather data (necessary: minimum and maximum temperatures, total radiation and total rainfall; optional: wind run and vapour pressure). It also requires a set of parameters describing the cultivar being grown. Cultivar-specific parameters include: phyllochron, maximum canopy area, vernalisation rate parameters, daylength sensitivity and grainfill kinetic parameters. An important part of the growing environment for a plant is its substrate, the soil. The soil acts as a buffer between weather and plant, acting as a water reservoir. Soil also contains nutrients and determines their availability in the rooting zone (affected by mineral supplements during the growing season, mineralization of organic N and flushing by rainwater). Sirius requires a description of the moisture retention properties of the soil, since they directly affect both water and nitrogen availability.

For these simulations, we used cultivar parameters representing *cv. Mercia* calibrated against agronomic experimental data supplied by Roger Sylvester-Bradley from the UK Agricultural Development and Advisory Service (personal communication) and leaf appearance data supplied by Allan Lock (a consultant agronomist, personal communication). The management description consisted of a sowing date of 10th October with an initial amount of inorganic N in the soil of 100 kg ha^{-1}, a single mineral N application of 130 kg ha^{-1} on 30th April (for the site in NZ the south hemisphere correction of the sowing date has been made). The same soil description was used for all sites, corresponding to a Rothamsted soil. The soil has an available water capacity (AWC) of 240 mm with a percolation constant of 0.3 day^{-1} and saturated moisture content and drained upper and lower limits of 44%, 22% and 6%, respectively, over the whole profile. The initial inorganic N was described as being split over a 1.5 m profile, 50% in the top 0.5 m, 30% in the mid 0.5 m and the remainder in the bottom 0.5 m. Organic N content was 10 t ha^{-1} with a mineralization constant (defined under optimal conditions) of 0.07 (kg mineral N) (t organic N)$^{-1}$ ha^{-1} day^{-1}.

2.5. Synthetic weather

The LARS-WG weather generator[2] (Racsko et al., 1991; Semenov and Barrow, 1997) was used to generate ensembles of synthetic site-specific weather. By using several years of historical observed weather data for a given site, LARS-WG computes a set of model parameters representing the site weather. The number of years of observed daily weather for the six sites used in our study varied from 18 to 37 (see Table 2). Model parameters are used by LARS-WG to generate stochastic

[2] LARS-WG is available from www.rothamsted.bbsrc.ac.uk/mas-models/larswg.php.

synthetic weather time-series for this site. The synthetic weather data conform to the distributions estimated from the observed data and therefore pass a variety of statistical tests, such as the χ^2 goodness-of-fit test for distributions of the lengths of wet and dry series, series of frost days and series of hot days and the *t*-test and *F*-tests for means and variances of weather variables. LARS-WG is not a predictive tool and cannot be used to forecast weather within a single season. Nevertheless, it can generate many years of daily weather suitable for a selected site and these can be used in combination with a crop model for yield predictions and risk assessments. In this way it can be used to generate the distribution of crop yields resulting from probabilistic ensembles of possible future weather series.

2.6. Simulation output distributions

Physical limits to plant growth such as the saturation of light absorption and limitations to the rate of nutrient uptake from the soil, which are incorporated in Sirius, mean that the distributions of final crop characteristics were often asymmetrical (see, for example, grain N and grain yield in Fig. 1). Biomass accumulation, for example, is constrained at an upper limit by the amount of N available in the soil and added during N-management. There is also a maximum rate at which the plant can take up available N. These two effects result in a maximum amount of radiation that can be intercepted, since N is required for the construction of green leaves to intercept radiation. The amount of radiation that can be absorbed by the plant is limited by green area index (GAI). When the crop canopy reaches GAI = 5 it intercepts most of the radiation and further increasing of GAI does not result in a proportional increase of biomass accumulation. This is a consequence of representing radiation interception using the Beer–Lambert law (Jamieson et al., 1998). There are therefore upper constraints on biomass accumulation which are not related to radiation. If the level of incident radiation decreases towards zero, biomass production will fall towards zero, however.

These asymmetrical limits are different for various crop characteristics estimated by Sirius (Fig. 1), and make it difficult to justify making assumptions about distribution types for them. We can avoid this difficulty by analysing the distributions non-parametrically.

2.7. Sampling weather-space

The description of just a few weather variables for each day throughout a growing season (maximum and minimum temperature, rainfall and radiation, for example) defines a formidably high-dimensional weather-space despite the constraints and correlations between variables contained in LARS-WG. Given a set of parameters for a site, LARS-WG could be viewed as a Monte Carlo sampler from ‘‘permitted’’ site specific weather series (actually it generates each sample). Since crop growth is a cumulative process, with grain weight and biomass accumulated as monotonically increasing functions of time within each growing season, the calculation of final grain yield can be thought of as an integration of daily weather effects over the growing season. For this reason, many different possible weathers will give similar final yields. All we need to do is to explore weather-space evenly in some sense, increasing the size of our statistical ensembles of mixed and observed weather until we reach a stage where adding more years to the ensembles provides little extra information about the crop simulation output distribution. The question is: how many ensemble members are necessary to compute crop characteristic predictors accurately? We can see the convergence of mean and median of crop yield with increasing ensemble size in Fig. 2.

From Fig. 2 we can see that for this site, median and mean yields converge so that their confidence intervals lie within model precision (± 500 kg ha^{-1}) with an

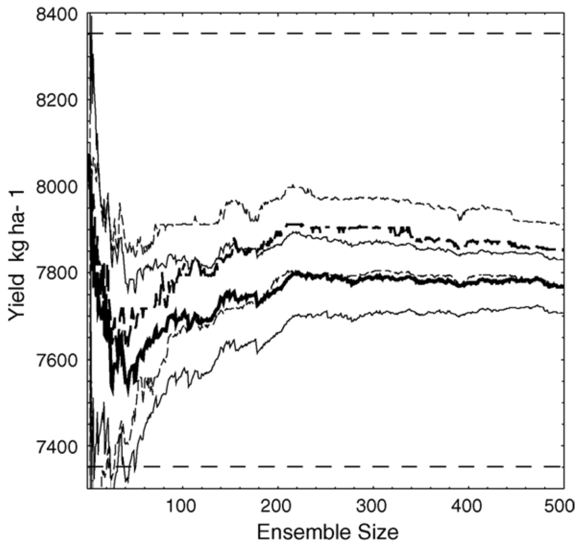

Fig. 2. Mean yield estimate (solid bold) with associated 95% confidence intervals (solid thin), median yield estimate (dashed bold) with associated 95% confidence intervals (Sprent, 1993) (dashed thin) varying with number of samples in the fully synthetic ensemble. Tolerance range representing intrinsic model precision (± 500 kg ha^{-1} as identified in a sensitivity analysis by Brooks et al. (2001) centred on median of 1000 synthetic years, horizontal long-dashed lines).

ensemble size of ~60, suggesting that ensembles containing 300 synthetic weathers are more than adequate for estimating the mean or median of the yield distribution with the required precision. Three hundred samples is an excessive number, but we selected a high number of samples to avoid having to test each site, and each mix of observed and synthetic weather separately for the convergence of mean and median. We can see that the mean and the median lie outside of each of their respective 95% confidence intervals at $N \geq 300$, however, since they both lie well within the range of model precision we consider them interchangeable as predictors. For convenience of calculation, we use the distribution mean as the most suitable predictor of yield, rather than the median.

Since this is a stochastic process, the convergence shown in Fig. 2 could just be a random feature of the ensembles generated. We repeated the process five times (see Fig. 3), and chose the most slowly converging set of ensembles for comparison of mean and median convergence in Fig. 2. Fig. 3 demonstrates that for an ensemble size $\geq$300, grain yield distribution mean

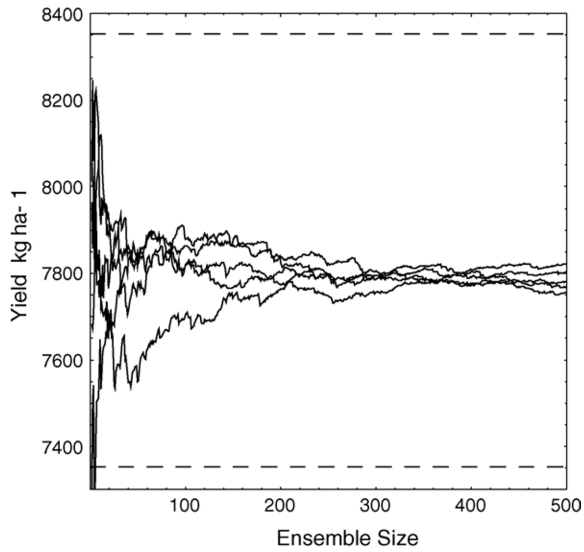

Fig. 3. Mean yield estimates as a function of ensemble size for five different ensembles. Tolerance range, representing intrinsic model precision ($\pm$500 kg ha^{-1}) centred on median of 1000 synthetic years (horizontal dashed lines).

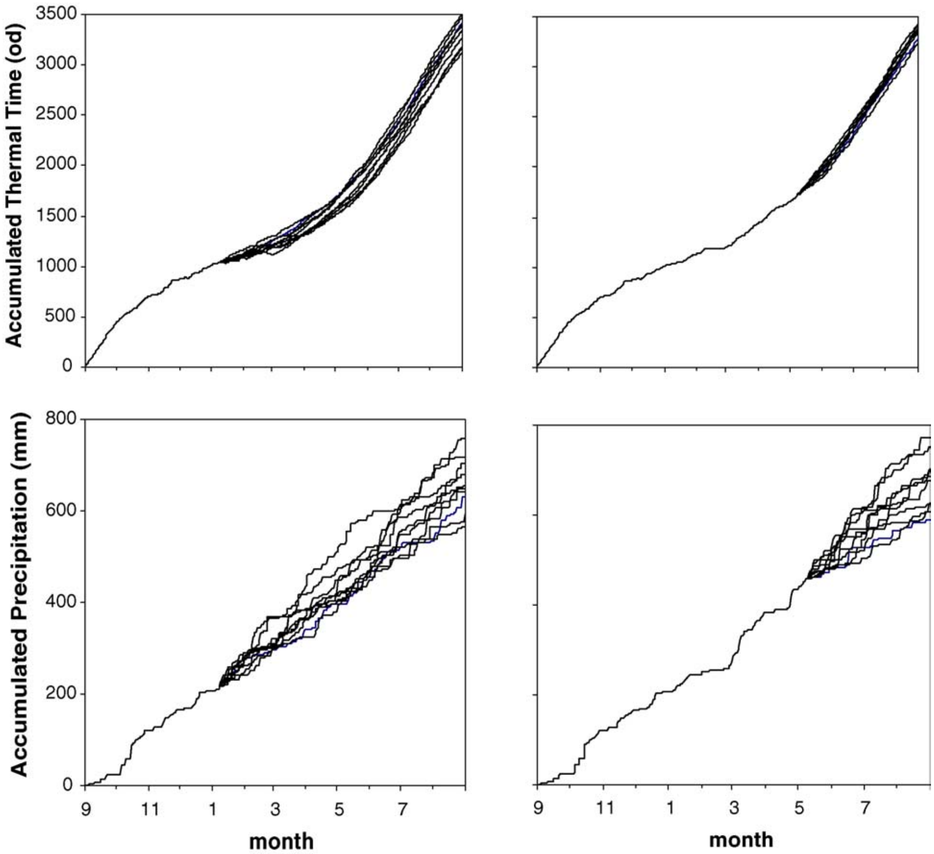

Fig. 4. Ensembles of mixed observed and synthetic accumulated thermal time and accumulated rainfall for Rothamsted, UK. Ten years per ensemble. Observed data from 1980 with 130 and 250 days of observed data from left to right.

depends weakly on the particular ensemble generated, and the difference between ensembles is much smaller than the model precision (±500 kg ha^{-1}).

2.8. Mixing observed and synthetic weather

We assumed that observed daily weather is available for the initial part of the growing season. We used LARS-WG to generate a probabilistic ensemble of synthetic weather for the remainder of the season, given the observed weather. Whole weather time-series for the season, used as input by the crop simulation model, thereby consisted of a period of observed weather, followed by many possible synthetic weather series. By repeating this procedure, gradually increasing the proportion of observed weather data in the mixture ensembles, we produced many weather series, the first parts of which coincide with the observed weather and remaining parts representing many continuations possible for the site. Examples of two weather statistics, accumulated thermal time and accumulated precipitation, for two weather ensembles with increasing periods of observed weather are shown in Fig. 4. Real observed weather for the remaining part of the season will be close to some of these synthetic series. Note that this requires that the synthetic ensembles are constrained to give a smooth switching from observed to synthetic weather. In this way, we were able to generate realistic ensembles of weather varying from fully synthetic to fully observed.

Starting from 10 days before sowing, an ensemble consisting of 300 years of purely synthetic weather was generated. For each year in the ensemble we ran Sirius to calculate yield, biomass, final leaf number and anthesis and maturity dates for the chosen cultivar, soil and management. The mean and standard deviation were calculated for these variables, giving an estimate

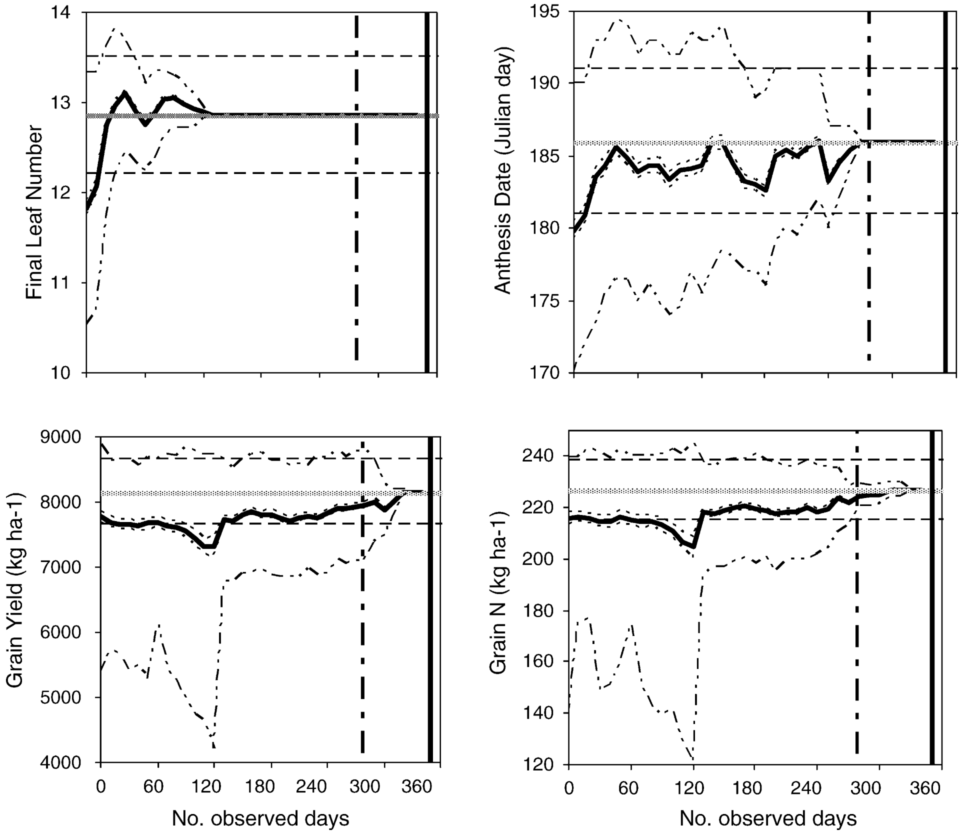

Fig. 5. Variation in mean predicted model outputs (solid black), the 95% confidence intervals associated with the mean (dashed) and the non-parametric two-tail 95-percentile range (dot–dashed) for weather ensembles containing a mix of 300 years of synthetic and observed data. The output predicted with 100% observed weather (solid horizontal) and the tolerance-range (dashed horizontal) are also shown. Tolerances are ±5% of the grain yield with fully observed weather data (or 500 kg, whichever is larger) for grain yield, ±5 days from the estimated dates with fully observed weather data for anthesis date, and ±5% of the estimate with fully observed weather data for all other outputs. Anthesis date (dot–dashed vertical) and maturity date (solid vertical) are shown also. These example plots are for observed weather from Rothamsted 1977. Synthetic weather generated from parameters estimated from Rothamsted weather for the years 1960–1989 using LARS-WG.

of the population mean and its 95% confidence interval. The two-tail 95-percentile range for each distribution was estimated non-parametrically, in order to give an indication of modelled range.

This procedure was repeated with ensembles containing increasing amounts of observed weather data (starting from 10 days before sowing) in 10-day increments. That is, after analysing the ensemble containing 300 years of purely synthetic data, we performed the same analysis with a weather ensemble consisting of 10 days of observed data leading up to sowing and the remainder of the year made up with synthetic data. Then, after that, observed weather data until 10 days after sowing, with the remainder made up of synthetic data, and so on. For each different mix of synthetic and observed data, the mean (and its 95% confidence intervals) and the non-parametric 95-percentile range of the output variables were estimated. These were plotted against the number of days of observed weather (see Fig. 5 above).

We can observe the 95-percentile range for the outputs collapsing as the output variable under consideration approaches its value with completely observed weather as more observed data is supplied to the model. The amount of observed data required for acceptably accurate prediction was estimated as the lowest amount above which the 95% confidence intervals on the mean estimate moved within the tolerance range of the output predicted for the last time. Since the number of observed days was increased in relatively large increments (10 days), the number of observed days at which this occurred was estimated by linear interpolation between the last point to fall outside the range of tolerance, and the point following it. We can see (Fig. 5) that, in this case, 125 days of observed data (starting 10 days before sowing) are required to achieve the required accuracy in final grain yield estimate. On the other hand, only 13 days of observed data were required for the final leaf number prediction.

The 95-percentile range in Fig. 5 represents the likely range of predictions based on a single year of mixed observed and synthetic data. The 95% confidence interval on the mean represents the precision of the prediction if an average output value over an ensemble of 300 mixtures of synthetic and observed data is used as a predictor. This is a sensible approach to prediction, since it incorporates climatic variability into the analysis with an acceptable computational cost.

3. Single-site analysis

As the results from this procedure are strongly dependant on the chosen observed year, this analysis

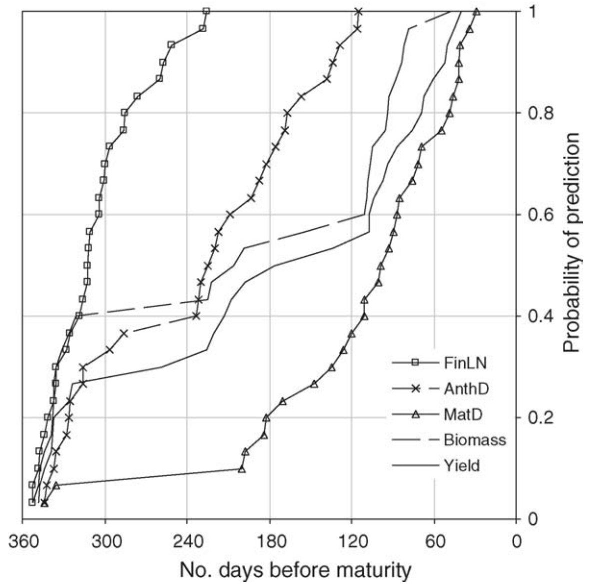

Fig. 6. Cumulative distribution functions of lead-time for Sirius predictions estimated over 30 years of observed weather data (1960–1989) at Rothamsted, UK. Predicted variables shown are: final leaf number (FinLN), anthesis date (AnthD), maturity date (MatD), final above ground biomass (Biomass) and final grain yield (Yield).

was repeated for all available observed years at a single site. In this way, the risk associated with a prediction is estimated on all available observations for this site. For Rothamsted, UK, this procedure was carried out for observed years with sowing dates from 1960 to 1989.

Consider the two extreme outputs in Fig. 6, final leaf number and maturity date. We can see that final leaf number is determined with relatively little observed weather data (all years predicted 225 days before maturity, 75% explained 284 days before maturity, and 35% explained before the sowing date). Maturity date on the other hand was determined for all observed years by 29 days before maturity. These observations are consistent with the mechanisms of the model. Final leaf number is most strongly affected by vernalisation, a process which can commence once the seed imbibes water (well before emergence). Vernalisation saturation is complete very early on in the plant's life cycle, fixing the number of primordia and thereby the final number of leaves. This implies that final leaf number prediction does not require much observed weather data. Maturity date on the other hand, depends on the accumulated effects of the weather experienced at every stage throughout the plant's lifecycle, and so it can be expected to be among the plant characteristics requiring the most observed weather to predict accurately.

There is a lot of variation in the forecasting range behaviour shown in Fig. 6 and Table 1, demonstrating

Table 1
Number of days before maturity at which winter wheat characteristics can be predicted with given probability at Rothamsted, UK

	0.95	0.90	0.85	0.80	0.75
Biomass	80	83	90	94	100
Yield	48	52	64	69	81
Maturity	38	41	44	49	62

that when considering the ability of a model to predict, we must ask ourselves "predict what?", since the answer to this question will impact significantly on the forecasting range. We are usually most interested in predicting grain yield, but it is interesting to note that some other aspects of crop growth and development require less observed weather for prediction.

A diagram like Fig. 6 could be used in a decision support context for a given site (provided this analysis was carried out with sensible, site-specific cultivar, soil and management descriptions and observed weather data for the site). First, it should be decided whether the number of years of observed weather (30 in this case) is a significant sample of the site's climate. Note that historical datasets much longer than 30 years are likely to show trends due to climate change and need to be de-trended before they can be used with LARS-WG. Stationarity of weather is a necessary condition for estimating site parameters from historical data using LARS-WG. Then, it should be decided what the acceptable prediction risk is. Fig. 6 tells us what lead-time is associated with this acceptable level of risk for each output. Obviously, the more risk we are willing to tolerate, the further in advance we can predict, making prediction more valuable. It is important to consider the trade-off of increased risk of inaccurate prediction against the value of longer lead-time.

Table 3
Number of days before maturity at which winter wheat yields can be predicted with given probability

	Probability				
	0.95	0.90	0.85	0.80	0.75
Debrecen	37	40	48	47	49
Lincoln	37	39	48	50	52
Munich	47	58	61	62	66
Rothamsted	48	52	65	69	73
Toulouse	36	38	42	46	48
Tylstrup	49	61	64	65	68

4. Multi-site analysis

To investigate the effect of diverse climates on our ability to predict wheat growth, we selected five sites in Europe and one site in NZ. These sites represent diverse climates with variation in total rainfall from 361 to 1304 mm, accumulated thermal time per year from 2590 to 5019°Cd and potential evapotranspiration from 324 to 629 mm (see Table 2). Wheat is grown at each of these sites.

The procedure described in the previous section was applied to each of six sites and distributions of lead-time for predicting selected crop characteristics were computed (see Fig. 7).

In a similar fashion, we can use Fig. 7 to compare lead-times for predicting wheat growth for different sites. Sites only differ in climate in this analysis, and in this way, we isolate the effect of climate on forecasting range. For grain yield, the differences between the sites diverge as we take a progressively higher risk as being acceptable (see Fig. 7 and Table 3). The lead-times of grain yield vary from 37 to 62 days before maturity with probability of successful prediction 0.9 and between 55 and 180 days before maturity with probability 0.5. This analysis demonstrates that there are large, quantifiable

Table 2
Site weather statistics

Site	Longitude (°)	Latitude (°)	Altitude (m)	Observed years	Accumulated thermal time (° day)	Potential evapotranspiration (mm)	Total rainfall (mm)
Debrecen, Hungary	21.6	47.6	114	1960–1990	3918 (3414–4252)	485 (399–569)	570 (361–934)
Lincoln, NZ	172.0	43.6	11	1960–1996	4148 (3760–4555)	439 (324–537)	658 (372–1010)
Munich, Germany	11.7	48.1	11	1951–1980	3304 (2942–4229)	571 (512–604)	885 (532–1304)
Rothamsted, UK	0.3	51.8	128	1960–1990	3381 (2980–3782)	467 (380–522)	691 (386–872)
Toulouse, France	1.4	43.6	152	1971–1988	4620 (4411–5019)	553 (489–629)	696 (510–981)
Tylstrup, Denmark	9.9	57.2	14	1961–1990	2820 (2590–3286)	471 (413–546)	660 (407–942)

Accumulated thermal time and total rainfall are calculated over a full year. Potential evapotranspiration is accumulated over a growing season at each site with sowing date at 10th October for European sites and at 10th April for NZ (growing season duration depends on the site). Figures quoted are averages over observed years available at each site; figures in brackets are minimum and maximum values of statistics.

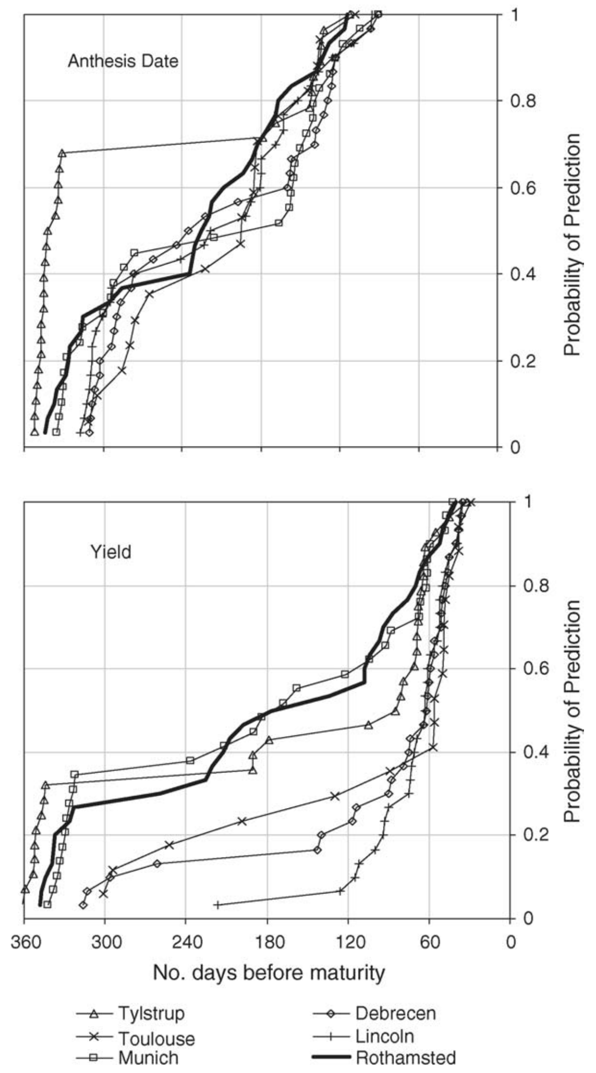

Fig. 7. Cumulative distribution functions of lead-time for various model outputs across sites in Europe and New Zealand.

differences between the prediction lead-times for sites with diverse climates. Climate puts a fundamental limitation on our ability to predict in advance crop characteristics using simulation models. Therefore, when considering the predictive power of a simulation model it is necessary to analyse this with respect to the climate in which it will be used.

We can also compare sites by measuring the intrinsic variability in the climate as seen by the plant. One measure of this is the range of the yield distributions, for example, given an ensemble of purely synthetic weathers for the site (Fig. 8).

Fig. 8 demonstrates the different amounts of climatic variability associated with crop characteristic predictions in each of the sites under consideration. We can see that one of the highest variability in grain yields is at Lincoln, which might explain why the grain yield forecasting range curves differ so much between Lincoln and Rothamsted (Fig. 7), despite the fact that their climate is similar in average terms (see Table 2). The climate variability in Lincoln induces a much greater variability in grain yields than that in Rothamsted, and therefore it is more difficult to predict them.

5. Discussion

We demonstrate that it is possible to predict plant growth in advance with confidence without using weather forecast for the growing season. LARS-WG generates a probabilistic ensemble of weather series based on analysis of observed historical data. Improvement in crop predictions can be expected, if information for the current growing season, which reduces the range of climatic uncertainty, would be made available. One of possibilities is the use of high resolution seasonal climate forecast. Seasonal climate predictions, based on coupled ocean–atmosphere models, are now available at a number of operational meteorological centres around the world. Despite predictable signals arising from atmosphere–ocean coupling, atmospheric processes are intrinsically chaotic and very sensitive to initial conditions (Palmer, 1993). A practical solution is to generate an ensemble with individual members differing by small perturbations to the starting conditions of the atmosphere and oceans (Palmer, 2001). Seasonal weather forecast needs to be downscaled to be suitable for crop models. This could be achieved by using climate statistics from seasonal prediction to alter corresponding parameters of LARS-WG, which will be later used to generate synthetic weather (Meza and Wilks, 2004; Wilks, 2002).

Instead of downscaling output from seasonal weather forecast, using a stochastic weather generator, it is possible to upscale a crop model to one, which can operate on a larger regional scale and can take seasonal predictions from GCM output directly without the need for spatial and temporal downscaling. A general large area model (GLAM) for annual crops has been developed (Challinor et al., 2004), which has been used to predict groundnut yield in India at a $2.5^\circ \times 2.5^\circ$ grid cell resolution. GLAM has been used directly with DEMETER ensembles[3] (Palmer et al., 2004) as its weather input and produces yield estimates on a regional

[3] The DEMETER system constitutes a multi-model ensemble prediction based on seven state-of-the-art global coupled ocean-atmosphere models to produce a series of 6-month multi-model ensembles.

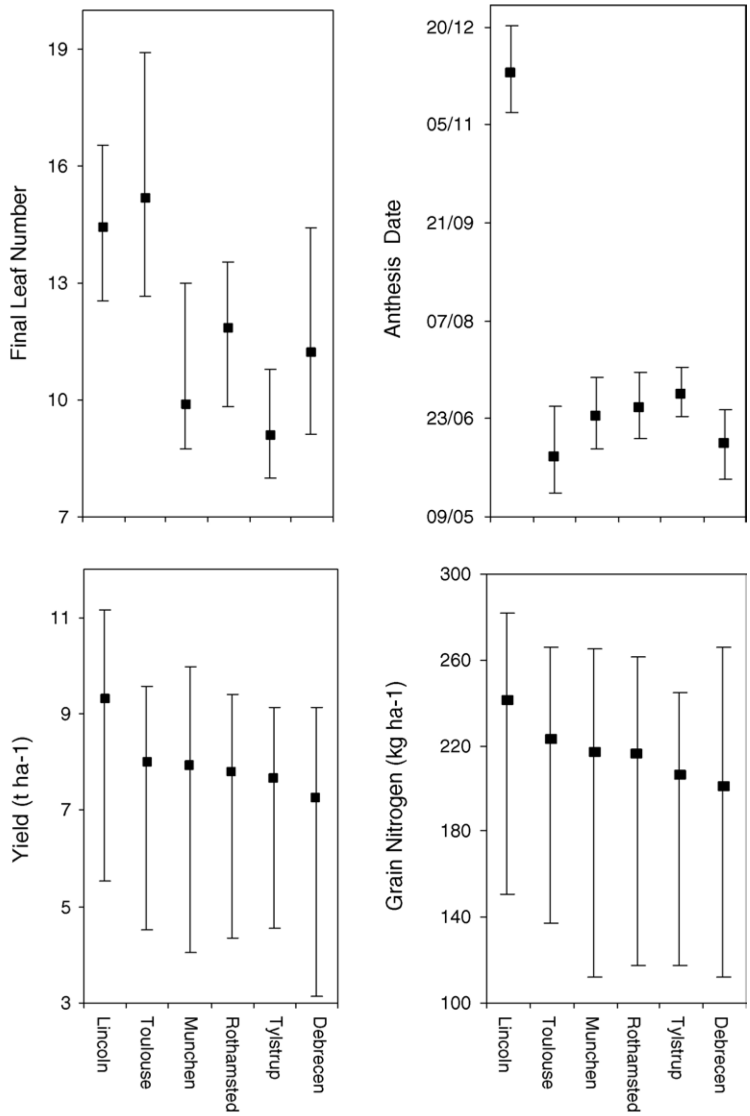

Fig. 8. Non-parametric two-tail 95-percentile range (bars) and means (squares) for different crop characteristics from 300 years of synthetic weather (generated by LARS-WG) for five sites in Europe and one site in New Zealand. Sites listed in decreasing order of mean grain yield from left to right.

scale (Challinor et al., 2005). Regional estimates can be produced using detailed crop simulation models like Sirius, but require adequate detailed description of the distribution of soil-types and climate over the region. Regional yields are often poorly correlated with the yields of individual farms however, and are of less value in a local decision support context (such as for selection of the timing and magnitude of N application and irrigation).

6. Concluding remark

In this paper, we considered how to use an existing crop simulation model (Sirius) to forecast yield, and to analyse how observed variability in climate affects the confidence and lead-time of our prediction. We use a stochastic weather generator (LARS-WG) to generate probabilistic ensembles of weather for a specific site as input to our crop simulation model. Lead-time for wheat growth prediction was calculated and compared for several crop characteristics at five locations in Europe and one in New Zealand. We demonstrated that there is a large variation in lead-time of predictions for selected crop characteristics between locations and that there is a large difference between lead-times amongst different crop characteristics at a single location.

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