C.A. Cenci · M. Ceschia

Forecasting of the flowering time for wild species observed at Guidonia, central Italy

Received: 4 November 1999 / Revised: 10 May 2000 / Accepted: 10 May 2000

Abstract It is well known that forecasting the flowering time of wild vegetation is useful for various sectors of human activity, particularly for all agricultural practices. Therefore, continuing previous work by Cenci et al., we will present here three new phenoclimatic models of the flowering time for a set of wild species, based on an original data sample of flowering dates for more than 500 species, observed at Guidonia (42° N in central Italy) by Montelucci in the period 1960–1982. However, on applying the bootstrap technique to each species sample to check its basic statistical parameters, we found only about 200 to have data samples with an approximately Gaussian distribution. Eventually only 57 species (subdivided into eight monthly subsets from February to September) were used to formulate the models satisfactorily. The flowering date (represented by the *z* variable), is expressed in terms of two variables *x* and *y* by a nonlinear equation of the form $z = \alpha x^{\beta} + \gamma y$. The *x* variable represents either the degree-day sum (in model 1), or the dailymaximum-temperature sum (in model 2), or the dailyglobal-insolation sum (in model 3), while *y* for all three models corresponds to the rainy-day sum. Note that all summations involved in the computation of the variables *x* and *y* take place over a certain period of time (preceding the flowering phase), which is a parameter to be determined by the fitting procedure. This parameter, together with the threshold temperature (needed to compute the degree-days in model 1), represents the two implicit parameters of the process, thus the total number of parameters (including these last two) becomes respectively, five for model 1, and four for the other two models. The preliminary results of this work were reported at the XVI International Botanical Congress (1–7 August 1999, St. Louis, Missouri USA).

C.A. Cenci Department BEA, University of Udine, Italy

M. Ceschia (\mathbb{R}) Department of Physics, University of Udine, Italy e-mail: ceschia@fisica.uniud.it

Introduction

Early forecasting of the phenological phases of plant species is of great support to various sectors of human activity: agriculture (use of pesticide, choice of varieties), public health (allergies), tourism, the environment and monitoring climate changes. But the timely forecasting of the phenological stages of crops is mainly used for the rationalization of pesticide and fertilizer applications in relation to plant development and growth rate, thus allowing the environmental pollution resulting from agricultural practices to be reduced.

An evident limitation to this approach is the difficulty in finding a reference species close to the crops for which the phenological development has to be predicted; as reported by Robertson (1983), many factors, such as soil fertility, plant population, soil type, soil temperature and soil moisture, influence plant development.

Among the various phenological phases, the flowering time is the one most often considered, because it is easier to record and the ecological and physiological implications are simpler to interpret. Moreover, the environmental conditions during the flowering period of the plant and its sensitivity often have a considerable impact on the final yield of a crop; in fact, the quantity of pollen dispersed into the atmosphere during the flowering period of certain crops is a good indicator of the potential yield (Vossen 1994).

The flowering period is determined by complex interactions between genetic and environmental factors, the latter including rainfall, temperature and solar radiation, which exert a stronger effect than any other on vegetation development, especially the flowering phase, determining the most important year-to-year variations.

According to input data, the forecasting mathematical models can be distinguished as *phenological* or *phenoclimatic*.

The *phenological* models are based on the possible correlations between the phenophases of species other than that under consideration. These models are rather empirical and their construction requires a statistical

Table 1 Basic statistics (including bootstrap estimates of means, standard deviations and sample size) of the eight sub-samples (one for each month from February to September) of the beginning of flowering dates of the plant species used for determining the models. Note that the main sample includes more than 500 plant species observed at Guidonia (near Rome) in the period from 1960 to 1982. Only species with data having either an approximately normal distribution and bootstrap standard deviation less than an appropriate upper limit (which in general may be different according to the month) were taken into account. *ONo* order number in the main sample, *MFD* mean flowering dates, *BMFD* bootstrap mean of flowering dates, *SD* standard deviation, *BSD* bootstrap standard deviation, *MxFD* maximum flowering date, *MnFD* minimum flowering date, *SNo* number of sample data

analysis of long series of observational data to identify the marker species (Lieth 1974; White 1979; Marletto and Sirotti 1993). The appearance of a given event in one or more marker species is used as an index (or evidence) for its appearance in the objective species also.

On the other hand, the *phenoclimatic* models are based on the assumed relationships between the phenological phases of the involved species and the behaviour of the various meteo-climatological quantities, such as rainfall, temperature, humidity, insolation, etc. (White 1979; Castonguay et al. 1984; Oger and Glibert 1989; Marletto et al. 1992; Cenci et al. 1997).

Within this context, we will introduce three new phenoclimatic models involving the forecasting of the flowering dates of 57 wild species living at Guidonia near Rome (Italy).

Data and methods

The data base includes the dates for the beginning of flowering of more than 500 wild species observed at Guidonia near Rome (42° N in central Italy) between 1960 and 1982 by the late Prof. G. Montelucci (1899–1983), a naturalist and geobotanic in Rome.

All the meteorological data for the entire period (including the daily maximum and minimum temperature, daily rainfall, relative humidity and daily global insolation) come from the meteorological station of Guidonia.

In order to build the statistical models properly, for each species of the whole data sample, the main statistic (including the mean and standard deviation) was first checked by applying the bootstrap statistical technique. Owing to the brevity of the time series (only series involving up to 23 years of observations for each species were available), to satisfy the essential requirements of the statistical procedure involved in the analysis we could employ only a selected sample of about 200 species series, each having an approximately Gaussian distribution for their yearly flowering dates. Of these, only 57 species were effectively extracted pertaining to the eight monthly samples. Each has been interpreted by the three phenoclimatic models reported in this paper and critically discussed. The terminology of the species is that adopted by Pignatti (1982).

All such models could be expressed by the same formal equation $z = \alpha x^{\beta} + \gamma y$, i.e. the independent *z* variable (representing the flowering time) has been simply expressed in terms of a power relationship to the variable *x* and a linear dependence on the variable *y*. However, while for all three models the *y* variable is the rainyday sum, the *x* variable represents the degree-day sum in model 1, or the maximum-daily-temperature sum in model 2, and finally the daily-insolation sum in model 3. Moreover, since for all three models both the *x* (it should also be noted that each term of the *x* variable in model 1 has to be over a certain threshold) and *y* variables involve a sum to be computed, starting from a certain date to be determined, the beginning date and the threshold temperature (this last only for model 1) were taken as two implicit parameters to be fitted. In order to represent the process mathematically with a sufficient degree of accuracy, an overall linear dependence on rainy days and a power explicit dependence on the thermal sums (degree-days or maximum daily temperatures for the model 1 or 2 respectively) or on the insolation sum (model 3) was required. However, we would like to point out remark that the flowering process is highly non-linear largely because of its implicit dependence either on the starting date (for models 2 and 3) or peculiarly on both the threshold temperature and the starting date (for model 1). Notwithstanding the brevity of the observational time series available for the analysis, the most relevant result of this work is the automatic estimate (with a determination of the statistical errors) of all fitted model parameters (including the implicit parameters also, i.e. the threshold temperature for model 1 and the starting date for the other models) by a maximum-likelihood method.

The best-fit parameter values and their uncertainties have been determined by the CERN (Geneva, Switzerland) MINUIT libraries. MINUIT is a system for minimizing a function of *n* parameters and computing the parameter errors and correlations. The errors (standard deviations) were determined by MINOS, a routine for non-linear error analysis of MINUIT. MINOS errors may be expensive to calculate, but are very reliable since they take into account both parameter correlations and non-linearities in the problem, and are in general asymmetric. As far as the final error in mean flowering date (*z* variable) is concerned, for each model we may consider the normalized frequency distribution of all its possible values, which can be computed by varying, in every possible way, the parameters of the model around their best estimates, within the standard error interval. The width of the best-fitted Gaussian curve of their distribution or its width at half height may be assumed as a reasonable estimate of the propagation error. But this procedure, in spite of its accuracy, is much time-consuming, therefore in common practice a good estimate of the RMS error of

Table 1 (continued)

Table 2 Comparison between the mean observed flowering dates (*MFD*) and those predicted (*z* variable) from each model. The estimated mean, *x*, and *y* values for various species are also displayed for each month. Model 1 (besides the starting date, STD) also involves a fourth parameter, the threshold temperature (T_{Thr}) , which is shown. While the equation of the model takes the same form in all three cases, i.e. $z = \alpha x^{\beta} + \gamma y$, the *x* variable represents a different quantity depending on the model involved. For model 1 the *x* variable represents the thermal summation (degree-days) counted from a starting date and only including those days with mean daily temperatures above a given threshold. Analogously, for model 2 the *x* variable represents the maximum-daily-temperature summation (°C), while in model 3 it represents the global-insolation summation (langley-day), for both cases computed from a determinated date. For all three models the *y* variable represents the number of days with a precipitation greater than 1 mm, counted from the same starting date as for the *x* variable. Note that the starting dates and the threshold temperature (this last only enters into model 1) are implicit parameters of the models, which have to be determined for each sample considered

February

the *z* variable can be made in terms of the model-parameter standard errors by the quadratic formula of error propagation (neglecting correlations).

3. Results

The spatial plots were performed by the Microcal (California, USA) ORIGIN package.

For each month, the type and species examined were selected according to the sample sizes available in that month and the behaviour of their basic statistical param-

Table 2 (continued)

^a Mean of the two MINOS errors (positive and negative)

^b Parabolic error (MINOS failed to determine errors)

^c Note the existence in this case of another candidate solution with similar probability that could be still taken into account and has

eters. For the monthly sample data involved, together with the order number in the main sample and the family and species names, some details of the basic statistical parameters are displayed in Table 1. A detailed comparison between the mean observed flowering dates (MFD) and those determined (*z* variable) from the three models developed for each monthly subset (from February to September) is reported in Table 2. For an overall view of the results, some pictorial spatial plots of the analyses of some monthly data samples (as a more significant example, the months of March, May and September are presented here) are shown in Figs. 1–3 respectively. In the captions of each figure, some more details of the sample data involved and the models' best-fitted parameters, together with their standard errors, are also reported.

As far as the model errors in the flowering time (*z* variable) are concerned, these are of the same order of magnitude as those of the original observational sample. As an example, Table 3 reports, for comparison, the results of the error computation for the data samples of March (model 1), May (model 1) and September (model 3) (Figs. 1–3), which were determined by applying both the more accurate procedure (including the three parameters α , β , and γ) and the more simplified procedure involving the quadratic formula for error propagation.

the following parameters: STD=213 \pm 2 days, α =34.60 \pm 7.50, $\beta=0.200\pm0.002$, $\gamma=0.22\pm0.10$

Notwithstanding the brevity the available time series and the high non-linearity of the flowering process (at least as far as the meteorological parameters involved in the models are concerned, mainly the starting date and threshold temperature (T_{Thr}) in model 1 or the starting date parameter by itself in models 2 and 3), all three models for each examined month (from February to September) achieved an overall best agreement with the observational data. The merits of these findings result from the robustness of the statistical method employed, together with the accurate selection of samples for the analyses of the monthly data, according to whether or not they assumed an approximately Gaussian distribution with a standard error possibly less than 10 days. The drastic cut of the initial sample size enabled all the statistical procedures to be applied correctly to determine the models, ensuring the accuracy of the results. The automatic estimate of all the involved parameters, including the beginning date and the best temperature threshold (needed for computing the degree-day sums in model 1), is noteworthy.

As far as the results for the different months and their respective models are concerned, the following may be observed. (a) In general, all three models fit reasonably well for all months. However, while models 1 or 2 are

Fig. 1 Analysis of a data sample of flowering dates for 10 wild species observed at Guidonia (Italy) in the period from 1960 to 1982 (mean flowering date between 11 and 23 March and standard deviation <11 days), by using the model represented by equation $z = \alpha x \beta + \gamma y$, where *x* is the thermal summations, *y* the number of rainy days and *z* the mean flowering date (model 1). The best model has the following parameter values: $\alpha = 33.19 \pm 2.50$, $β=0.150±0.010, γ=0.76±0.14, T_{Thr}=2°C$ and beginning date 52± 1 days from 1 January. The *bold dots* on the surface represent the observed mean flowering dates plotted against the *x* and *y* values, which were determined according to the beginning date estimated from the model

Fig. 2 Analysis of a data sample of flowering dates for 10 wild species observed at Guidonia (Italy) in the period from 1960 to 1982 (mean flowering date between 10 and 22 May and standard deviation <11 days), by using the model represented by the equation $z = \alpha x^{\beta} + \gamma y$, where *x* is the thermal summations, *y* the number of rainy days and *z* the mean flowering date (model 1). The best model has the following parameter values: $\alpha=47.60\pm2.13$, β=0.171±0.009, γ=0.43±0.09, *T*Thr=2°C and beginning date 104± 2 days from 1 January. The *bold dots* on the surface represent the observed mean flowering dates plotted against the *x* and *y* values, which were determined according to the beginning date estimated from the model

Fig. 3 Analysis of a data sample of flowering dates for 5 wild species observed at Guidonia (Italy) in the period from 1960 to 1982 (mean flowering date between 12 and 22 September and standard deviation <10 days), by using the model represented by equation $z = \alpha x^{\beta} + \gamma y$, where *x* is the global insolation summation, *y* the number of rainy days and *z* the mean flowering date (model 3). The best model has the following parameter values: α =13.23 ± 0.10 , $\beta = 0.290 \pm 0.001$, $\gamma = 0.19 \pm 0.16$ and beginning date 196 ± 1 days from 1st January. The *bold dots* on the surface represent the observed mean flowering dates plotted against the *x* and *y* values, which were determined according to the beginning date estimated from the model

more accurate than model 3 from February to May, their behaviour appears less satisfactory for the period from June to September, in which it seems that global insolation dominates the process. (b) As far as the threshold temperatures are concerned (model 1), they are 1°C for February, and 2°C otherwise. (c) The length of the development process (only small differences between the various models were found) for the species studied is of about 1 month in the period between February and May, and of more or less than 2 months from June to September. (d) The rainy days appear important in all the models for the months from February (where their contribution reaches the maximum) to June, but become irrelevant during July and August, particularly in model 3; in September they become relevant again for models 1 and 2, remaining irrelevant for model 3.

Conclusion

Finally, one may conclude that noticeable progress has been made in analysing the data and understanding the flowering process, building on previous work by Cenci et al. (1997), not only by the introduction of the bootstrap technique to check the main data-sample statistic, but chiefly by the completely automatic estimation of all the model parameters and their respective statistical errors, together with an initial attempt to estimate their specific relevance for determining the process during the different seasons.

Table 3 Comparison between the bootstrap observational errors and three different estimates of the propagated errors determined by the model equation. As an example, the three cases (plotted in Figs. $1-3$) of model 1 (March and May) and of model 3 (September) are shown, where ∆'*z*, ∆*z*'', and ∆*z*''' represent the width of the fitted Gaussian curve of the error frequency distribution (determined by varying in every possible way the model parameters around their best estimates, within the standard error interval), its width at half height, and the error determined by the quadratic law of propagation respectively

Finally, it should be noted that the formal equation explored in this work to represent the flowering process of a particular set of wild species observed at Guidonia (central Italy), could be powerfully extended and applied to other places and plant species, provided that a sufficiently long time series of flowering dates and the main meteorological parameters (temperature, insolation, rainy days, etc.) of the area involved were available.

References

- Bassi G, Cenci CA, Olivieri AM (1996) A new classification of 91 species based on the beginning of flowering observed during 11 years. In: Phenology and seasonality, vol I, no 1. SPB Academic Publishing, Amsterdam, pp 37–45
- Castonguay Y, Boisvert J, Dubè PA (1984) Comparaison de techniques statistiques utilisées dans l'élaboration de modèles prévisionnels phénoclimatiques. Agric For Meteorol 31:273– 288
- Cenci CA, Pitzalis M, Lorenzetti MC (1997) Forecasting anthesis dates of wild vegetation on the basis of thermal and photothermal indices. In: Lieth H, Schwartz MD (eds) Phenology in seasonal climates, vol I. Backhuys, Leiden, pp 93–104
- Leith H (ed) (1974) Phenology and seasonality modeling. Ecological studies, 8. Springer, New York Berlin Heidelberg
- Lorenzoni GG (1988) Cento anni di fenologia in Italia, vol II. Edizioni Societá Botanica Italia, Firenze, pp 809–820
- Marletto V, Puppi Branzi G, Sirotti M (1992) Forecasting flowering dates of lawn species with air temperaturc: application boundaries of the linear approach. Aerobiologia 8:75–83
- Marletto V, Sirotti M (1993) Modelli fenologici e loro limiti previsionali. AER 3:4–10
- Oger R, Glibert L (1989) Une échelle de temps biométéorologique pour l'estimation du degré de précocité de la végétation. Agric For Meteorol 46:245–258
- Pignatti S (1982) Flora d'Italia. Edizioni Agricole, Bologna
- Robertson GW (1983) Weather-based mathematical models for estimating development and ripening of crops. Technical note no 180. WMO no 620. World Meteorological Organization, Geneva
- Vossen P (1994) Importance of the knowledge of the flowering period of cultivated plants for the forecasting of national crop yields in the European Union. G Bot Ital 128:183–194
- White LM (1979) Relationship between meteorological measurements and flowering of index species to flowering of 53 plant species. Agric Meteorol 20:189–204