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A comparison of methods

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Calculating temperature dependence over long time periods:

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Abstract

Nonlinear temperature dependencies play a major role in a large variety of ecological models. For the sake of simplicity and efficiency, the temperature dependencies in many models are calculated for monthly or yearly time intervals, using temperature means or interpolations between means as input. As a consequence, information about the variability of the temperature input data is lost, which leads to a bias in the temperature dependence function and to errors in the model results. We tested the performance of a range of other methods against this common approach for calculating temperature dependence on a larger time scale, i.e. for a temporal aggregation. The methods estimate the expected value of the dependence function in different ways, using the mean or standard deviation of temperature variables in different temporal resolutions as input. In our tests we used temperature dependence functions from four different ecological fields; hourly temperature data sets from various climatically differing sites were used as input. The precision of the tested methods increased with the resolution of the input data, although computing time increased. The mean errors ranged from less then 1% to about 8% for the aggregation to one month and from about 1% to over 30% for the aggregation to 10 years. The most precise and at the same time efficient method is the explicit calculation of the expected value for the dependence function, which is based on the mean and standard deviation of hourly temperatures. The least precise but most efficient method is the common application of the dependence function to mean values. Condensing available highly resolved input data into means is only appropriate if either the dependence functions are linear in the observed temperature range, or low precision but very high efficiency is required. Given a certain requirement on precision or efficiency, we are now able to indicate for a number of input data resolutions the appropriate method to calculate temperature dependence over long time periods.

Introduction

Many biologically, ecologically, and agriculturally relevant processes are controlled by temperature dependent rates. The functions *dep(T)* with which these rates depend on temperature *T*, usually have a nonlinear shape. The accumulated effect of temperature, e.g. on insect maturity

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or plant phenology, is normally measured by means of the integral

$$M(t,t_0) := \int_{t_0}^{t} dep(T(\tau))\, d\tau \tag{1}$$

over a time interval (t_0, t). This integral is often referred to as “physiological time”, “day-degree-sum”, or “heat-unit-sum”.

Temperature dependence also plays a major role in many ecological simulation models, ranging from pest prognosis models (e.g. BUGOFF2 (Blago & Dickler, 1990) and APFWICK (Lischke & Blago, 1990; Lischke, 1992), and crop phenology models (e.g. BIOTIME (Kirsta & Tarabrin, 1994)), to models examining the sensitivity of ecosystems to a potential climatic change, as e.g. the forest patch models FORSKA (Prentice & Cramer, 1993) and FORCLIM (Bugmann, 1994; Bugmann & Fischlin, 1994; Fischlin *et al.*, 1995), where physiological time determines the growth and thus the competition and succession of trees.

The precision of the temperature dependence function can have a crucial influence on the outcome of such models, depending on the model sensitivity to the regarded temperature dependence function. The most exact approach is to calculate $M(t,t_0)$ by summing the actual values of the dependence function using temperature data in high temporal resolution, which reflect the diel and even more frequent temperature fluctuations.

However, due to practical constraints such as the lack of appropriate input data or long computation times, in many models a larger time step is chosen, and temperature dependence is calculated by applying the temperature dependence function either to mean temperatures, (e.g. monthly temperature means as in FORCLIM) or to an interpolated temperature course (e.g. in FORSKA or in the BIOTIME-model). Yet, monthly or yearly temperature means or interpolations between means do not contain complete information about temperature variability in the considered period, particularly not about the intra daily variability. If the dependence function is nonlinear, which is realistic for many cases, such a simple approach can lead to a loss of precision in the model outcome.

One commonly used approach for calculating temperature dependence over long intervals, i.e. aggregating it, is to replace the nonlinear dependence function by a linear one. But this approximation again can lead to a considerable loss of precision (cf. Blago & Dickler, 1990). Empirical correction functions of the temperature dependence as used by Bugmann (1994) on the other hand confine the model application to the regions where those functions have been estimated.

Thus, there is a need for methods which aggregate temperature dependence functions over long periods in a precise and efficient way. A range of methods for such a temperature dependence aggregation has been compiled and developed anew (cf. Lischke *et al.*, 1996). The common principle of the methods is that they estimate the expected value of the temperature dependence function over the aggregation period. They take into account the information about temperature variability contained in the available input data, are applicable for general, i.e. nonlinear temperature dependence functions, and suitable for input data of different resolution.

In the present paper, we tested the precision and efficiency of these aggregation methods in four case studies against the commonly used application of the dependence function to temperature means and to temperatures approximated by the sine-method of (Allen, 1976). The temperature dependence functions used in the case studies cover different ecological fields and hierarchical levels. As an example for poikilothermic development as insect maturing or plant growth, the development of the codling moth *(Cydia pomonella)* is examined. Temperature dependent timing processes as insect diapause or seed vernalisation are represented by the chilling requirement of the apple tree bud rest break. Tree net photosynthesis is an example for an aggregated physiological process; several species are regarded separately to assess the influence of the temperature dependence aggregation to interspecific competition. With soil respiration an ecosystem process is regarded, which integrates over space and many different organisms.

Tested Methods

The methods tested in this study approximate the integral of Eq. (1) by the expected value E[*dep(T)*] of the hourly dependence function in the aggregation interval (t, t_0), multiplied with its length $t - t_0$ by

$$M(t, t_0) := (t - t_0) \cdot E[dep(T)].$$

The methods differ in the way in which the expected value *E*[*dep(T)*] is calculated or approximated. Table 1 gives an overview of the different methods, which are divided using the following criteria.
Three different types of approaches are used to determine the expected value *E[dep(T)]***.**
(1) The expected value is determined stochastically (type S) by generating 1000 temperature realisations by a Monte Carlo simulation based on mean and standard deviation of the hourly

temperature μ_T and σ_T, calculating the temperature dependence of each and averaging it. **(2)** The dependence function is applied to the mean of the regarded input variable(s) (e.g. hourly temperature) in the aggregation period (type A). **(3)** The expected value of the dependence function *dep* is calculated explicitly (type E), assuming the regarded temperature variable *X* to be normally distributed with the distribution density p_x. For example, in method EDH the expected value is given by

$$E[dep(T)] = \int_{-\infty}^{\infty} dep(x) \cdot p_T(x)\, dx.$$

The input data required by the methods are the statistical parameters mean μ or mean and standard deviation σ of temperature variables, which are given in hourly, daily or monthly resolution. As variables the hourly temperature *T*, the daily temperature extrema $T_{\max}$ and $T_{\min}$, the daily temperature amplitude Δ, the daily temperature mean $\overline{T}$ (either measured or approximated by $\overline{T}_m = \frac{T_{\min} + T_{\max}}{2}$), the monthly mean temperature $\mu_{\overline{T}}$, or the monthly mean of the daily temperature amplitude μ_Δ are used. **(a)** Methods EDH, EDHT1, and EDHT2 determine the expected value of the hourly dependence functions based on the mean and standard deviation of the hourly data. These statistical parameters are either estimated from the input data in method EDH, or derived from the means and standard deviations of the daily temperature mean $\overline{T}$ or $\overline{T}_m$ and daily temperature amplitude Δ (based on the assumption of a triangle shaped daily temperature course (cf. Fig. 1b) in methods EDHT1 and EDHT2. **(b)** Methods EDDT1, EDDT2, and EDM determine the expected value of the daily dependence function $DEP(\overline{T}, \Delta)$. The expected value e.g.of method EDDT1 is

$$E[DEP(\overline{T}, \Delta)] = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} DEP(y,z) \cdot p_{\overline{T}}(y)\, dy\; p_\Delta(z) dz. \tag{2}$$

In method EDM $DEP(\overline{T}, \Delta)$ is obtained by applying the hourly dependence function to the daily mean temperature $\overline{T}$. In methods EDDT1 and EDDT2 $DEP(\overline{T}, \Delta)$ is given by the integral over the daily course of *dep,* which is obtained by a triangle shaped approximation of the daily temperature course, determined by the two variables temperature mean $\overline{T}$ or $\overline{T}_m$ and amplitude Δ.

Table 1: Overview of the temperature dependence aggregation methods: They are divided according to the type of method (explicit **e**xpectation value calculation, **s**tochastic expectation value calculation or dependence function of **a**verage input), the resolution and kind of the input data needed (T hourly temperature, $T_{\min}, T_{\max}$: daily temperature extrema, Δ: daily temperature amplitude, $\overline{T}$: daily temperature mean, $\overline{T}_m$: approximated daily temperature mean, $\mu_{\overline{T}}$: monthly mean temperature, μ_Δ: monthly mean amplitude), the statistical parameters estimated from these data (μ: mean, σ: standarddeviation) and the approximations used (dep: dependence function, TC: daily temperature course, ND: normal distribution).

Method	Abbr.	Type	Temperature input data: Temporal resolution	Temperature input data: Variables	Temperature input data: Stat. param.	Approx.
Stochastic generation of average dependence function	STOCH	S	hours	T	μ_T, σ_T	dep
Expectation value of **d**ependence function of **h**ourly temperatures	EDH	E	hours	T	μ_T, σ_T	dep TC
Expectation value of **d**ependence function of **h**ourly temperatures approx. by **t**riangle of mean and amplitude	EDHT1	E	days	$\overline{T}$, $\Delta = T_{\max} - T_{\min}$	$\mu_{\overline{T}}, \sigma_{\overline{T}}$ $\mu_\Delta, \sigma_\Delta$	dep TC
Expectation value of **d**ependence function of **h**ourly temperatures approx. by **t**riangle based on extrema	EDHT2	E	days	$\overline{T}_m = \frac{T_{\min} + T_{\max}}{2}$ $\Delta = T_{\max} - T_{\min}$	$\mu_{\overline{T}_m}, \sigma_{\overline{T}_m}$ $\mu_\Delta, \sigma_\Delta$	dep TC
Expectation value of **d**ependence function of **d**aily temperature **t**riangle based on mean and amplitude	EDDT1	E	days	$\overline{T}$, $\Delta = T_{\max} - T_{\min}$	$\mu_{\overline{T}}, \sigma_{\overline{T}}$ $\mu_\Delta, \sigma_\Delta$	dep TC ND
Expectation value of **d**ependence function of **d**aily temperature **t**riangle of extrema	EDDT2	E	days	$\overline{T}_m = \frac{T_{\min} + T_{\max}}{2}$ $\Delta = T_{\max} - T_{\min}$	$\mu_{\overline{T}_m}, \sigma_{\overline{T}_m}$ $\mu_\Delta, \sigma_\Delta$	dep TC ND
Expectation value of **d**ependence function of daily temperature **m**ean	EDM	E	days	$\overline{T}$	$\mu_{\overline{T}}, \sigma_{\overline{T}}$	dep
Dependence function of **a**verage daily temperature **t**riangle	DAT	A	months	$\mu_{\overline{T}}$, μ_Δ	$\mu_{\overline{T}}, \mu_\Delta$	dep TC
Sine-sine method of Allen (control)	Allen	-	days	$\overline{T}_m = \frac{T_{\min} + T_{\max}}{2}$ $\Delta = T_{\max} - T_{\min}$	-	-
Dependence function of **a**verage temperature (control)	DA	A	months	$\mu_{\overline{T}} = \mu_T$	$\mu_{\overline{T}}$	dep

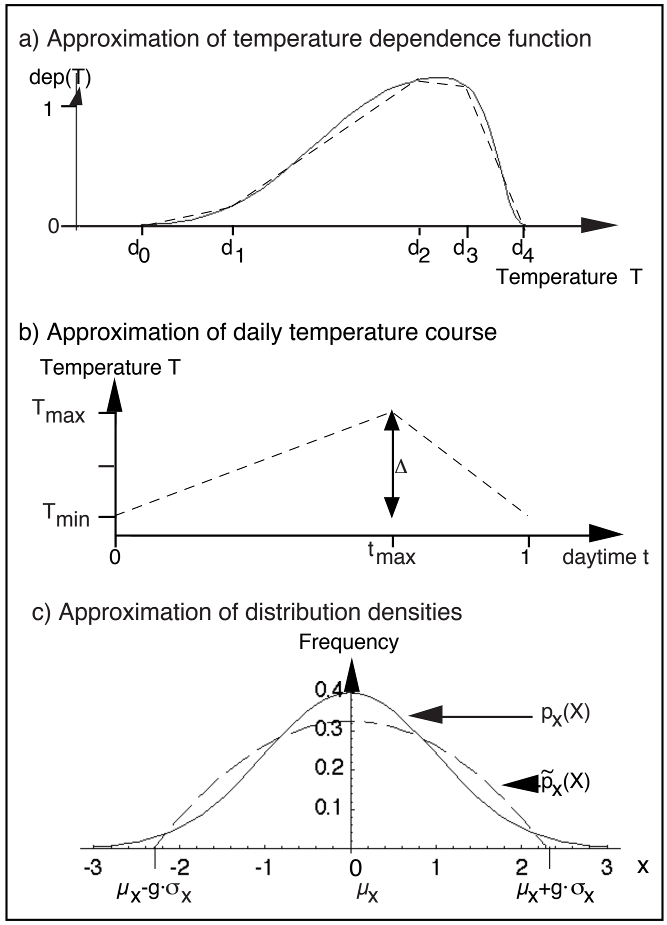

Fig. 1: Approximations (dashed lines) used in aggregation methods.

We used some assumptions and approximations. The random variables daily temperature mean $\overline{T}$ and $\overline{T}_m$ respectively, and the amplitude Δ are assumed to be independent. As approximations we use a piece wise linear function for the nonlinear temperature dependence function *dep(T)*, an asymmetric triangle $\tilde{T}(t)$ with the same minimum temperature at the beginning and end of the day and a variable time point $t_{\max}$ of the maximum temperature for the daily temperature course (TC) (cf. Fig. 1b), and a parabola $\tilde{p}$ (cf. Fig. 1c) for the normal distribution densities (ND) $p_{\overline{T}}(y)$ and $p_{\Delta}(z)$ in Eq. (2).

We used the approximated dependence function applied to the hourly temperature values and averaged over each test period as a reference (exact value) in the case study test. As controls we utilised the commonly used methods of applying the dependence function either to the mean temperature, i.e. method DA, or to hourly temperatures obtained by a sine-wave approximation of the daily temperature course (Allen, 1976) (without empirical correction). The stochastic temperature generator STOCH served as a third control.

Case Study Tests

To test the performance, in terms of precision and efficiency, of the seven new aggregation and three comparison methods DA, STOCH, and Allen, four case study tests with the following temperature dependent processes from different ecological fields were carried out: **a)** Soil respiration (cf. Fig. 2a), modelled with the function used in Parton (1993); **b)** Bud rest break (cf. Fig. 2b) of apple trees, as modelled by del Real-Laborde (1990); **c)** Tree net photosynthesis (cf. Fig. 2c) of the tree species *Pinus cembra, Picea abies, Abies alba, Larix decidua, Betula pendula,* and *Fagus silvatica*, parametrized with the cardinal temperature values documented in Pisek (1969); **d)** Development of the larval and pupal stages of the codling moth *(Cydia pomonella L., (Lepidoptera, Tortricidae))* with the temperature dependence function from Lischke (1990) (cf. Fig. 2d).

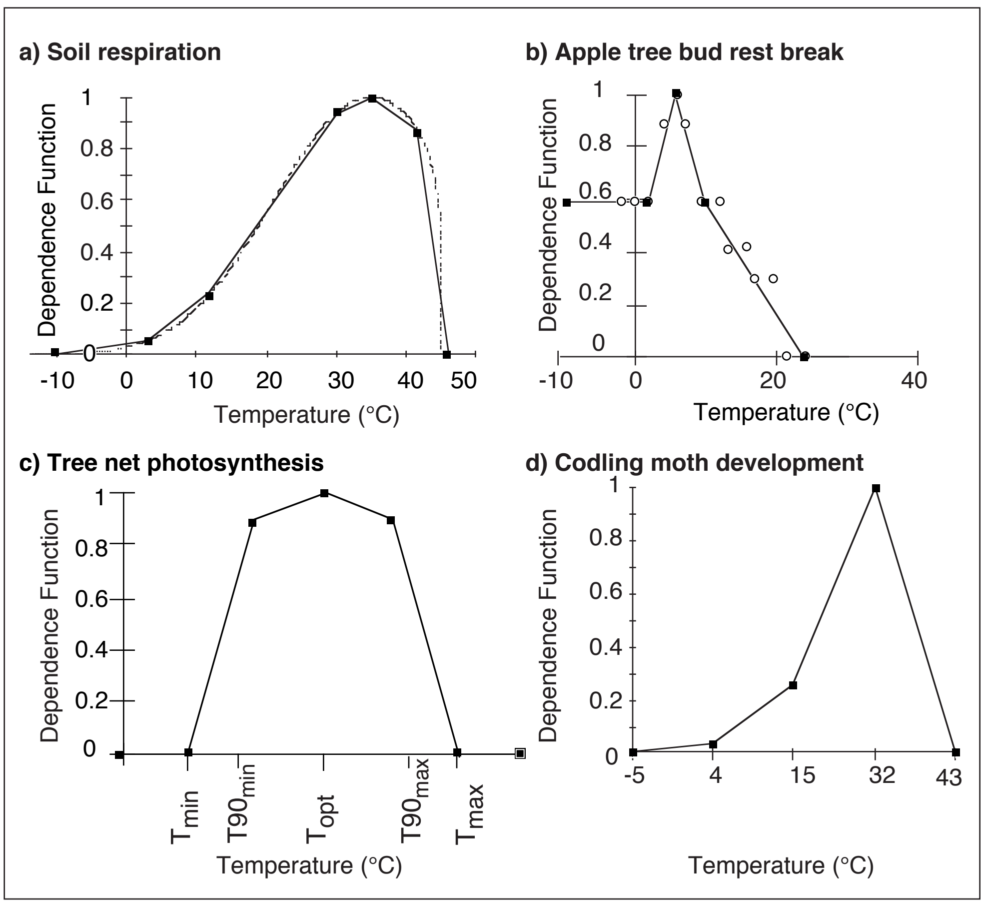

Fig. 2: Temperature dependence functions of the processes tested in the case studies. Dotted line or separate points: dependence function, solid line: approximation, black squares: discretization points of approximation.

For the soil respiration case study a) an 8-month time series (data provided by Richner (1994)) of hourly soil temperatures at 10 cm depth under grass was used as input. As input data for the case studies b), c), and d) served 11 years of hourly air temperature from six climatically differing sites (ranging from dry temperate to boreal climate) in the European Alps. For the bud rest break study b) only temperature data of the winter months (October to April) were included in the analysis.

We calculated the monthly expected values of the dependence functions, i.e. aggregated them from an hourly to a monthly time step in the case studies a), b), and c). To explore the influence of the aggregation period length in case study d) the 2-, 3-, 6- monthly, yearly, and 10-yearly expected values were also calculated.

The performance in terms of precision and efficiency of all methods was determined for each aggregation period P_a at each test site. The precision, i.e. the error due to the aggregation, was measured as percentage difference between exact temperature dependence expected value and the value obtained by the aggregation methods. The efficiency *eff* of the methods is given in percent computing time Δt_{method} of the run-time needed to calculate the exact value, which is given by the P_a fold of the time needed for one day

$$eff = \frac{100 \cdot \Delta t_{method}}{\Delta t_{exact}} = \frac{100 \cdot \Delta t_{method}}{P_a \cdot \Delta t_{exact,day}}.$$

The time for calculation of the statistical parameters of the data was not included in this measurement.

All methods except Allen need only one evaluation regardless of the aggregation period length. The ratio $\Delta t_{method} / \Delta t_{exact,day}$ of the time required for this single evalution to the time required for the exact evaluation for one day then can be determined with

$$\frac{\Delta t_{method}}{\Delta t_{exact,day}} = \frac{eff \cdot P_a}{100}.$$

This ratio yields also the critical aggregation period length $P_{a,crit}$, above which the tested methods starts to be faster than the exact evaluation.

The performance tests were implemented in the programming language Modula-2 using the program library of the Dialog-Machine V2.2 (Fischlin, 1991) and run on a SUN SPARCserver10 with the batch environment RASS (Thöny *et al.*, 1994).

Results

Figs. 3a, b, and c show the errors of the different approaches for the aggregation to one month in three case studies. For the soil respiration the errors are very small, below 0.5%. In contrast to this, the aggregation errors in the case studies apple tree bud rest break and tree net photosynthesis reach up to 30% for method DA, with the mean values ranging from below 1% for method EDH to 12% for method DA. The mean errors and the error variability increase from EDH to DA, same as the differences of the errors between the tree species in the tree net photosynthesis study. The methods which calculate the expected value and include information about the daily temperature variability, by the temperature variance as EDH and STOCH, or by the temperature amplitude as EDHT1, EDHT2, EDDT1, and EDDT2, are of a similar or higher precision than the control, the sine-wave-approximation of Allen (1976).

In Fig. 3d (codling moth case study) the errors for the aggregation to various periods are compared. For the one month aggregation the results are similar to those of the case studies b) and c). As the period length increases, in methods DA and DAT the mean errors increase up to 30%, whereas in the other methods it remains constant. Fig. 4 shows for the same case study the computation time of the different methods measured in percent of the time needed for the exact calculation. The computation time was plotted against the mean percentage aggregation error, which corresponds to the middle line in the box plot in Fig. 3d.

Fig. 5 qualitatively summarises the relationship between precision, efficiency, aggregation period length and input data resolution. The general trend is that precision increases with the information contained in the input data. At the same time efficiency decreases. In Figs. 4 and 5 we can distinguish between three groups of methods.

(1) Methods EDH, EDHT1, EDHT2, Allen, and EDM combine high precision (error < 5.5%) with high efficiency (from below 1% to 30% of the exact computation) for all tested aggregation periods. The use of the Allen method pays off for all aggregation periods longer than one day, the use of the other four methods for aggregation periods longer than 10 days.

(2) Methods EDDT1, EDDT2, and STOCH have mainly the same precision as group 1, however a 9, 9, and 5 times longer computing time, respectively. This means, that these methods start to pay off at aggregation periods of 90, 90, and 50 days, respectively.

(3) Methods DA and DAT are the most efficient (< 1% for all aggregation periods, always faster than exact calculation), but least precise methods. Their precision decreases from > 8% to 30% with the aggregation period length

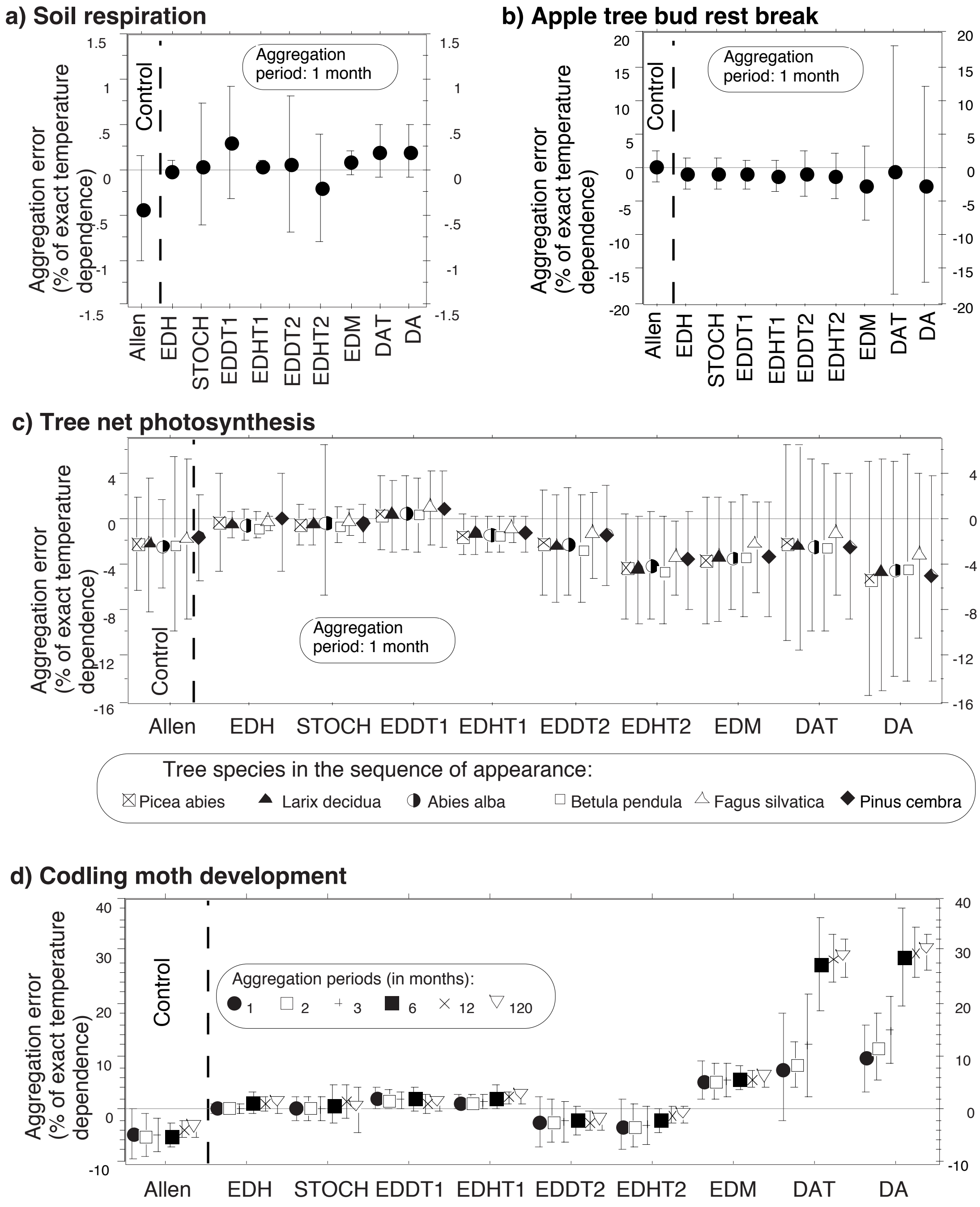

Fig. 3: Aggregation errors: Differences expressed as a percentage of the temperature dependence approximated with several methods to the exact temperature dependence value. Means and standard deviations of the difference distributions are given as point symbols and bars.

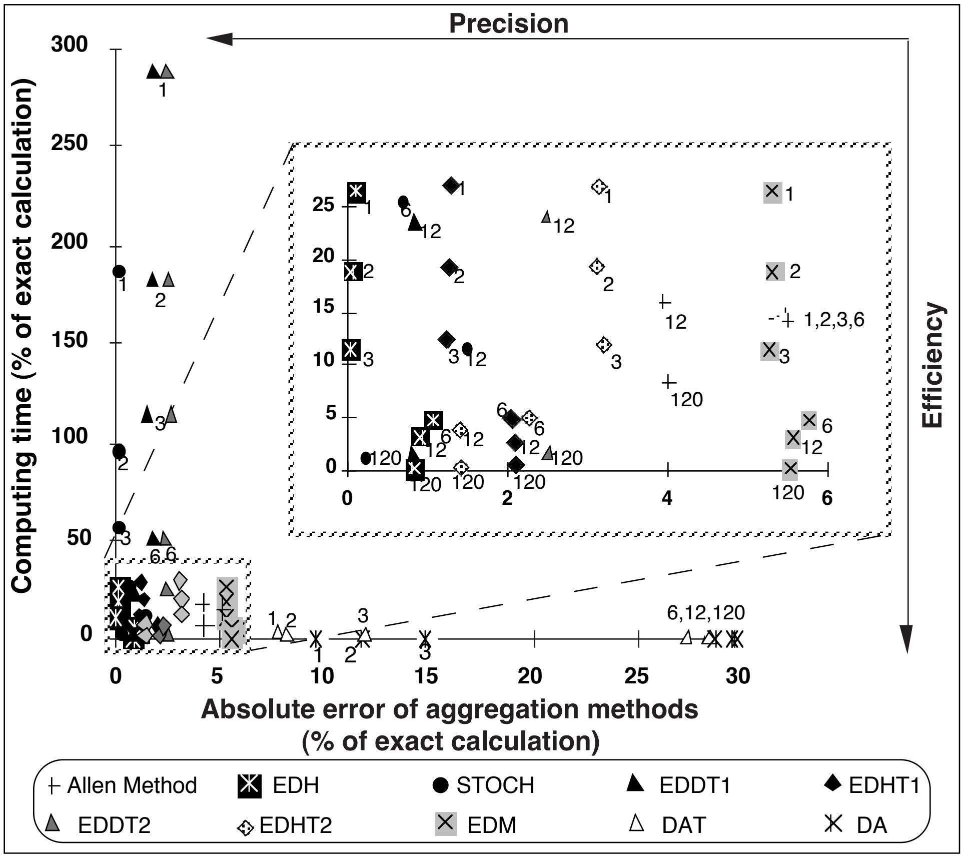

Fig. 4: Efficiency measured as computing time vs. precision measured as mean aggregation error. The small numbers at the symbols refer to the length of the aggregation period.The dotted rectangle zooms into the region near (0,0).

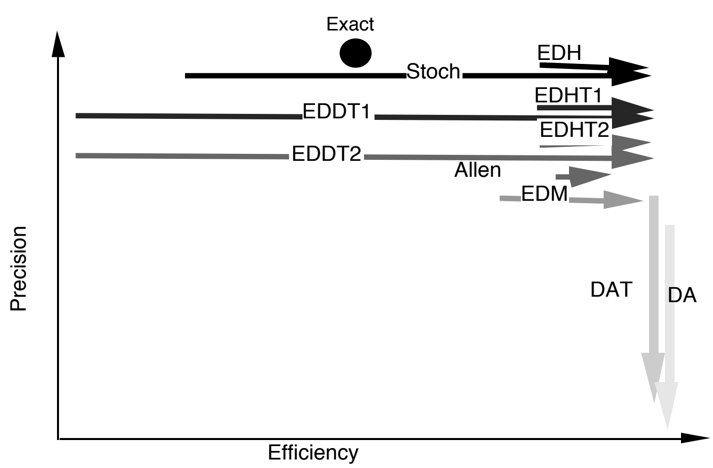

Fig. 5: Qualitative scheme of the precision of the aggregation methods depending on input data resolution, method efficiency and aggregation interval. The arrows symbolize the aggregation interval lengths, with 1 month at the beginning and 10 years at the end of the arrow. The input data resolution is represented as gray scale of the arrows. It ranges from black for the hourly input data to very light gray for the monthly mean input.

Discussion and Conclusions

In this study, a range of approaches for aggregating temperature dependence functions to longer time periods was tested. The aim was to assess the suitability of the methods for a variety of input data resolutions, given certain precision and efficiency requirements.

The most appropriate method for a specific model can be chosen from Figs. 4 and 5, depending on the availability of input data (cf. Table 1), the relative importance of precision and efficiency, and the required aggregation period of the model.

When temperature data in hourly resolution are available, the dependence function can be estimated accurately with EDH, if computing time is limiting and the aggregation period is longer than about 10 days. Otherwise it can also be calculated exactly. The stochastic temperature generator STOCH is generally as precise as method EDH, but less efficient. If daily mean temperatures and extrema are available, EDHT1 is the best choice. If only daily extrema are obtainable and the aggregation period is longer than 3 months, EDHT2, for shorter aggregation periods the Allen method has the best performance. EDM is the only usable method if just the daily temperature means are available. Finally, if only aggregation period means of temperature and daily amplitude respectively only of temperature are obtainable, method DAT respectivley the commonly used method DA are the only possible choices.

Method DA yields the largest mean bias of all methods, 8% respectively 30% (aggregation to one month respectively 10 years). Such an error can influence strongly the outcome of a model. For instance, an 8% respectively 30% bias in the codling moth developmental rate with the parameter values from Lischke (1992) would correspond to 0.2 respectively 0.8 less codling moth generations per year, an intolerable inaccuracy e.g. in a pest prognosis model. The large error variability connected with this high mean error renders the method even less reliable and hinders the use of empirical correction terms.

In the soil respiration case study, the errors of all methods, also of DA, are very small. Here, the temperatures remained mostly in the linear part of the dependence function approximation. This shows that the application of the dependence function to the temperature mean (method DA) is reliable for temperature data remaining in the linear part of the dependence function.

For the case of highly resolved input data, the results suggest to optimize precision and efficiency by the appropriate choice of the aggregation method and throught this by the aggregation level of the input data. This means to use as much information of the input data as available, if precision and not computing time is limiting or the efficiency of several methods is similar, as e.g. for EDH, EDHT1, EDHT2, Allen, and EDM. In cases of low precision or very high efficiency requirements and also for mostly linear dependence functions, a condensation of the input data into means and mean amplitudes and the application of method DAT or DA is reasonable. Finally, a good compromise between precision and efficiency requirements for high input data resolution is method EDH.

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