

Spring frost risk in a changing climate

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[1] While both the mean and variance of daily temperature are forecasted to increase in future climate scenarios, studies of spring frost risk to vegetation have relied on changes in mean temperature to understand frost risk in these scenarios. We present a probabilistic model of spring frost risk based on the stochastic-crossing properties of a coupled temperature-phenology model in which the mean, variance, and autocorrelation structure of spring temperature may be controlled through independent parameters. The model results show that frost risk to vegetation is as sensitive to increases in daily temperature variance (which increases frost risk) as to increases in the mean temperature (which decreases frost risk). **Citation:** Rigby, J. R., and A. Porporato (2008), Spring frost risk in a changing climate, *Geophys. Res. Lett.*, 35, L12703, doi:10.1029/2008GL033955.

1. Introduction

[2] Spring frost damage to vegetation is determined by the relative timing of the opening of vegetation buds (hereafter “budbreak”) and freezing temperatures. While frost risk to trees has received significant attention in the literature [Hänninen, 1991; Kramer *et al.*, 1996; Linkosalo *et al.*, 2000], the emphasis has been on improving the phenology component of the model for more accurate prediction of budbreak. Under current climatic conditions the emphasis on developing the phenological model rightly reflects the goal of understanding the processes involved in phenological development. However, inquiry into the likely effects of changing climate (i.e., changes in the temperature process) on frost risk in these studies has relied predominantly on simple increases in monthly mean temperatures to represent future temperature scenarios [Hänninen, 1991, 1995; Kramer *et al.*, 1996, 2000; Linkosalo *et al.*, 2000; Hänninen, 2006; Sherry *et al.*, 2007]. The drawback of this approach is that climatic change probably will not result in a simple translation of mean daily temperature and that vegetation development as a dynamical phenomenon will be sensitive to other statistical characteristics of daily temperature besides the mean. We may assume that vegetation is adapted to a particular risk environment (i.e., to the particular character of spring temperature fluctuations) and that subtle changes in the statistical character of daily temperature might still produce noticeable effects in vegetation.

[3] Heuristically, frost risk may be thought of as a two-stage problem. There is first the early spring, temperature-dependent development of vegetation up to the point of

budbreak. Following budbreak there is then the risk of temperature dropping below a damaging threshold. By responding to warmer temperatures in early spring, plants face a risk of damaging fluctuations after budbreak. As an example of such events Figure 1 shows NDVI data for Walker Branch, TN for 2006 and early 2007 along with minimum temperature data from Durham, NC. The damaging frost indicated by the NDVI was a widespread, abnormally warm period in March followed by almost a week of temperatures well below freezing in early April which affected much of the southeastern and central United States with devastating effects for several agricultural crops (see Gu *et al.* [2008] for detailed description). Notice from Figure 1 that freezes of similar character occurred almost symmetrically around the mean date of last spring frost [Dorn, 2005] in 2007 with only the later one causing damage, thereby highlighting the threshold-like dependence on temperature characterized by budbreak.

[4] Our approach begins with a theoretical analysis using a stochastic temperature process. Assuming that the rate of bud development prior to budbreak is a function of temperature, we treat the time of budbreak as the stochastic-crossing of a threshold in the development variable. The risk of damaging frost then becomes a second crossing problem, this time concerning the crossing of a low-temperature threshold *after budbreak*. We then illustrate the general theory with a particular model of temperature and phenology, using temperature data from Durham, NC to calibrate the temperature process, in order to quantify potential changes in risk due to these statistical aspects of daily temperature.

2. Theory

2.1. Timing of Budbreak

[5] The development of vegetation buds is generally a function of many environmental variables with the strongest contribution typically coming from temperature [Chuine *et al.*, 2003]. Following the approach of so called “Thermal Time” models of plant phenology, budbreak may be modeled as a threshold, D_* , in the development process $D(t)$, such that the rate of development is a function of some representative temperature [Hänninen, 1991; Linkosalo *et al.*, 2000]. The corresponding time of budbreak, t_b , at which $D(t_b) = D_*$ will have probability density function (pdf) $p_{t_b}(t_b)$ which is determined by the particular species and its adaptation to the local climate. Thus $p_{t_b}(t_b)$ is the solution to the first-passage time of the biological development driven by the stochastic temperature process.

[6] For the purposes of determining subsequent frost risk the variable of interest is clearly daily minimum temperature. The representative temperature used for modeling the rate of bud development is, however, generally the daily average temperature. We will assume that driving phenol-

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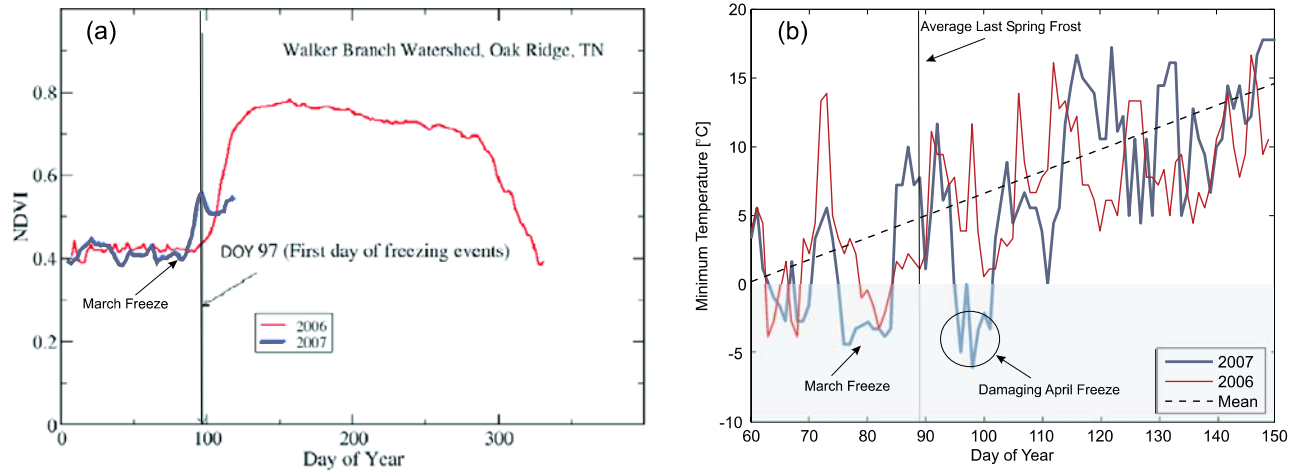


Figure 1. (a) NDVI observed at Walker's Branch Watershed, Oak Ridge, TN for all of 2006 and January–May 2007 (from <http://www.ncdc.noaa.gov/oa/climate/research/2007/apr/apr-cold-event.php>, reprinted with permission of Tilden Meyers). Both the warm March and the April freeze show clear signatures in the 2007 trace in comparison with 2006. (b) Minimum temperature time series for Durham, NC for the spring of 2006 and 2007.

ogy with daily minimum temperature (as opposed to daily average temperature, for example) results only in a change in the parameter values of the plant phenology model and does not qualitatively change the statistical characteristics of development. The daily minimum temperature will be modeled as a stochastic process with parameters $\mathbf{k} = \{k_0, \dots, k_n\}$ (corresponding to mean, variance, etc.) and probability distribution, $p_T(T; t)$, which represents the probability density at time t (interpreted at the daily scale) for the stochastic temperature process.

2.2. Frost Risk

[7] To characterize the risk of frost we consider the problem of temperature dropping below some threshold T_* (such as freezing) *after budbreak*. If we assume that any damaging event is a killing event (i.e., there is no variation in the degree of damage with temperature), such that no open vegetation buds survive the freeze, then we are most interested in the pdf of the time between budbreak and the first subsequent freeze, $\tau = t_f - t_b$, where t_f is the time of first freeze after budbreak. This distribution may be expressed as $p_{\tau|t_b}(\tau|t_b)$. Note that τ , t_b and t_f are clearly dependent variables. Note also that since it is not certain that a damaging frost will occur in spring, the pdf's of τ and t_f will generally have an atom of probability at infinity corresponding to the probability that no damaging frost occurs. As the probability of an infinite τ is not of practical use, we will use $f_{\tau|t_b}(\tau|t_b)$ and $f_{t_f|t_b}(t_f|t_b)$ to denote these densities without the atom at infinity. In this case, rather than integrating to unity, the distribution functions integrate to the probability of a freezing event occurring after t_b in spring.

[8] The distribution of times of first freeze after budbreak is given by,

$$f_{\tau}(\tau) = \int_0^{\infty} f_{\tau|t_b}(\tau|t_b) p_{t_b}(t_b) dt_b \quad (1)$$

and reflects the distribution of times to first frost after budbreak for an ensemble of years. From the distribution

of τ we may derive the distribution of the date of first frost as the distribution of the sum of two random variables $t_f = \tau + t_b$ where the joint probability of τ and t_b is given by $f_{\tau, t_b}(\tau, t_b) = f_{\tau|t_b}(\tau|t_b) p_{t_b}(t_b)$. Then,

$$f_{t_f}(t_f) = \int_0^{\infty} f_{\tau|t_b}(\tau|t_b) p_{t_b}(t_b) p_{\tau}(t_f - \tau) d\tau. \quad (2)$$

From equation (2) we can define a “survivor function” of time [Cox, 1962],

$$F(t) = 1 - \int_0^t f_{t_f}(u) du \quad (3)$$

which represents the probability that a plant survives at least to time t . From the survivor function the ensemble “age-specific failure rate” [Cox, 1962], or “hazard rate function” [Aalen and Gjessing, 2004] may be defined as,

$$\lambda(t) = -\frac{F'(t)}{F(t)} \quad (4)$$

which gives the conditional rate of damaging events occurring at time t given no previous freezing event. It can be shown [Cox, 1962] that the age-specific failure rate completely determines $f_{t_f}(t)$ with the relationship,

$$f_{t_f}(t) = \lambda(t) e^{-\int_0^t \lambda(u) du}, \quad (5)$$

which formally corresponds to the distribution of time between hypothetical Poisson events with an inhomogeneous rate, $\lambda(t)$. From the formal analogy there is a direct relationship between the integral of $\lambda(t)$ and the survivor function,

$$F(t) = e^{-\int_0^t \lambda(u) du}, \quad (6)$$

so that clearly there is a one-to-one relationship between the probability of survival and the area under $\lambda(t)$. Thus, $\lambda(t)$

indicates the temporal distribution of the risk of mortality due to low temperatures, thus the name “hazard rate”.

3. Data and Model

3.1. Temperature Data From Durham, NC

[9] As a guide for developing a temperature model, we used daily minimum temperature data for Durham, NC, from 1919 to 2007. The data set is available from the National Climate Data Center (NCDC), station number 312515.

[10] The average spring trend (March–May) was found to be linear. For each year we then performed a linear least-squares fit to the spring temperatures, removed the trend and calculated the autocorrelation of detrended process. The resulting (average) autocorrelation was found to be approximately exponential (rate given in Table 1). The residuals from the linear fits were also approximately Gaussian.

3.2. Temperature Model

[11] The logical choice of model for the Durham data is an Ornstein-Uhlenbeck process with an added linearly increasing trend [see, e.g., *Kiraly and Janosi*, 2002]. The Langevin equation for the standard Ornstein-Uhlenbeck process is

$$\frac{dx}{dt} = -k_1x + \sqrt{k_3}\eta_t, \quad (7)$$

where x is the state variable and k_1 and k_3 are the drift and diffusion parameters, respectively, and η_t is a delta correlated Gaussian noise with unit variance. For our purposes we consider x to be the “detrended” temperature, such that $x = T - T_\mu(t)$. For the specifics of our case we treat the spring daily mean temperature as increasing linearly during the months of March through May with trend $T_\mu(t) = k_0 + k_2t$. Making the substitution gives us the final equation,

$$\frac{dT}{dt} = k_2 - k_1(T - k_0 - k_2t) + \sqrt{k_3}\eta_t \quad (8)$$

where $\mathbf{k} = \{k_0, k_1, k_2, k_3\}$ are the parameters of the temperature process. The expected value of the temperature process can be checked easily by integration to arrive again at T_μ . Our temperature process is then Gaussian with mean $T_\mu = k_0 + k_2t$, variance $\sigma^2 = k_3/2k_1$, and autocorrelation function (of the detrended process) $\rho(\tau) = e^{-k_1\tau}$.

3.3. Phenology Model

[12] We used a simple Thermal Time (or Degree Day) model for the phenology of budbreak [see, e.g., *Chuine*, 2000, 2003]. Let the rate of daily ontogenetic development [*Hänninen*, 1995] be a function of temperature given by,

$$\frac{dD_o}{dt} = 0, \quad T < T_{th}, \quad (9)$$

$$\frac{dD_o}{dt} = \alpha(T(t) - T_{th}), \quad T \geq T_{th}, \quad (10)$$

where D_o is the level of ontogenetic development, α is a rate constant (which may more generally be a function of other environmental variables) and T_{th} is a threshold temperature above which ontogenetic development proceeds. It is further assumed that degree days begin to accumulate on an arbitrary date, t_0 (here March 1), and that the time of budbreak, t_b , is defined arbitrarily as $D^* = 100$. Parameters of the phenology model were chosen to give a date of budbreak in early April for the mean temperature process (see Table 1 for values).

3.4. Simulation

[13] For each parameter set, 10^5 realizations of temperature and phenology were generated. Each realization represents a simulation of a single spring season from March 1 for 120 days or until a damaging frost, whichever occurred first. From these iterations we constructed the pdf of the day of budbreak and the distribution of times of damaging frost, as well as the survivor function and the frost hazard rate.

4. Results

[14] We simulated temperature and time of budbreak with a simple, coupled stochastic model containing 8 parameters (see Table 1), four each pertaining to the temperature and phenology components. The four temperature parameters correspond to the mean temperature on March 1 (k_0), the decay rate of the autocorrelation function for the detrended temperature process (k_1), the mean linear temperature trend (k_2), and the variance ($k_3 = 2\sigma^2k_1$). The four phenology parameters are the date on which ontogenetic development begins to accumulate ($t_0 = \text{March 1}$), the arbitrary level of development at which budbreak occurs ($D^* = 100$), the rate of development (α), and the temperature threshold above which development accumulates (T_{th}). Of the phenology parameters, t_0 is of little importance as it is largely controlled by photoperiod and will therefore not vary with climate. Thus, as long as we choose t_0 reasonably, it is of little consequence what the exact value is [*Linkosalo et al.*, 2000]. Similarly, D^* is an arbitrary level the effect of which may be absorbed into the rate and threshold parameters. Therefore, our analysis will focus on the effect of six parameters: the four temperature parameters, $\{k_0, k_1, k_2, k_3\}$, and the two phenology parameters, $\{\alpha, T_{th}\}$.

[15] Figure 2 shows the effect of parameter variability on the temperature and phenology models. Each plot shows the effect on the survivor function’s value at the end of spring (representing the probability of a plant surviving spring temperatures), $F(\infty)$, and the most probable date of budbreak. Each plot was generated by varying a single parameter while the remaining parameters were held fixed at their mean values (see Table 1). The vertical line in each plot shows the sample mean from the Durham data. Notice that the greatest changes in both survival probability and date of budbreak are induced by changing the mean daily temperature, k_0 . An increase in mean daily temperature (k_0) of a single degree, with all other parameters held constant,

Table 1. Summary of Parameter Values

Parameter	k_0 (°C)	k_1 (day ^{−1})	k_2 (°C day ^{−1})	k_3 (°C ² day ^{−1})	α (°C ^{−1} day ^{−1})	T_{th} (°C)	t_0	D^*
μ	0.78	0.81	0.16	32.6	1.62	2.8	March 1	100
σ	4.7	0.38	0.05	17	n/a	n/a	n/a	n/a

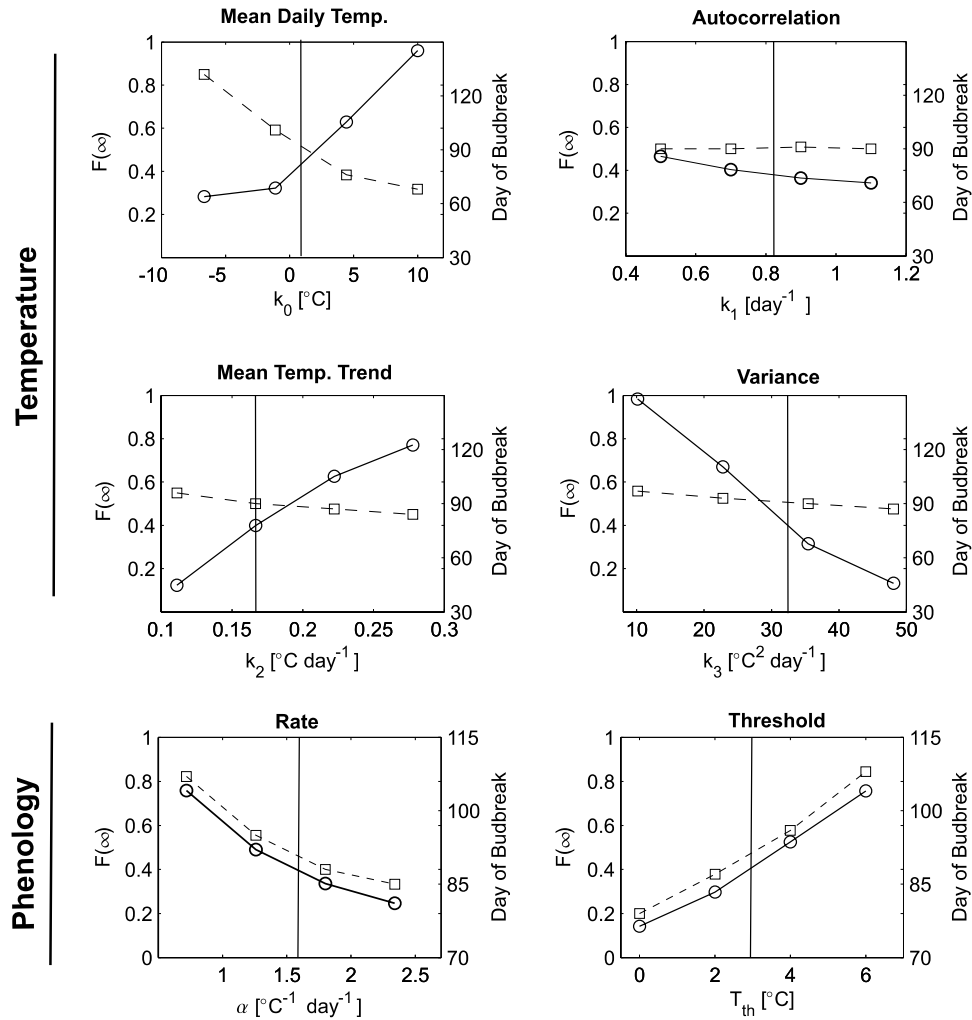


Figure 2. Sensitivity of the probability of survival, $F(\infty)$, (circles) and the most probable date of budbreak (squares) to parameters of the temperature and phenology models. Each plot was generated by varying a single parameter while holding the others at their mean value (see Table 1). The vertical line on each plot represents the mean value of the varied parameter as estimated from the Durham, NC data set.

would result in roughly a 0.05 increase in probability of survival. Changes in both mean slope (k_2) and variance (k_3) have significant effects on the probability of survival but significantly less influence on the date of budbreak, such that a 10% change in either parameter results in an approximate change in probability of survival of 0.05. Finally, changes in autocorrelation (k_1) tend to have almost no effect on the date of budbreak and only a change in survival probability of 0.1 for the range $\pm 35\%$ of the estimated mean value of k_1 at Durham, NC. Note that the low probability of survival predicted under current climate ($F(\infty) \approx 0.4$) is a result both of model assumptions (i.e., all buds open simultaneously and any damaging event results in complete mortality) and the fact that the phenology parameters have not been estimated here against data as they would be in practice.

[16] With regard to the phenology parameters (α and T_{th}), as one might expect, increasing the rate of development advances the date of budbreak and increases the risk of frost damage. Conversely, increasing the threshold for development has the opposite effect. Thus the phenology parameters

have a straight forward effect on the probability of survival by adjusting the date of budbreak.

5. Discussion and Conclusions

[17] In this paper we have presented a theory for characterizing the probabilistic risk of spring frost to vegetation based on the date of budbreak. Spring bud phenology is characterized by two stochastic crossing problems, one of ontogenetic development up to budbreak which is driven by temperature and the other concerning the probability of temperature down-crossing a minima threshold representing frost damage. Using a stochastic process to simulate temperature that in turn forced a simple Degree Day model of plant phenology we have shown that noticeable changes to the risk of frost may be effected by changes in any of the parameters controlling the temperature process (Figure 2). Furthermore, the sensitivity of spring frost risk (represented by $F(\infty)$) to a changing temperature regime is not necessarily concentrated in the parameters defining mean temperature behavior (k_0 and k_2). That is, judging by the change in $F(\infty)$ induced by a given percentage change in each

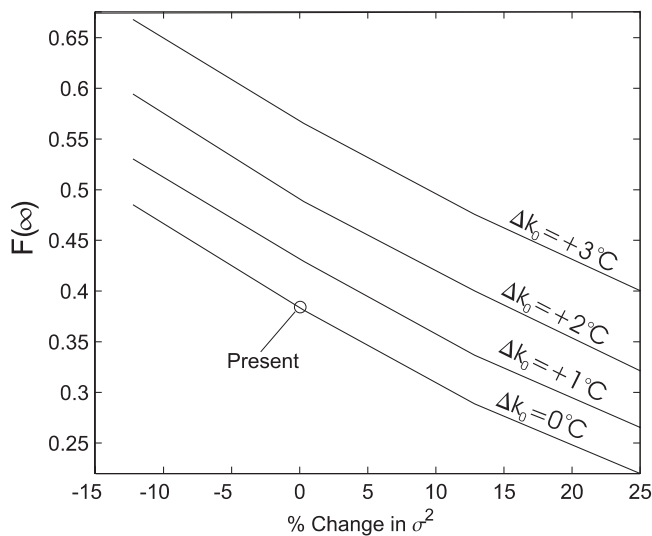


Figure 3. Survival probability as a function of the percent change to the current values of variance (k_3) shown for multiple increases in mean daily temperature (k_0). Notice that an increase in mean temperature of 1°C accompanied by an 6% increase in variance would result in the same value of $F(\infty)$.

parameter, the variance (not the mean) appears to be the strongest determinant. Specifically, an increase in k_0 of a few degrees would increase the probability of survival by about 0.1, a gain which could be lost through a concomitant 10% increase in the variance. Figure 3 shows the relationship between survival probability and temperature variance for multiple increases in k_0 (corresponding to daily mean temperature increases).

[18] In our analysis we have shown that changes in daily temperature correlation and variance must be taken into account in any analysis of projected effects of climate change on frost risk. More subtly, the results shown in Figure 2 suggest that a diagnostic phenological study (e.g., one focused on detecting evidence of changing climate via changes in date of budbreak) may overlook linkages between phenology dynamics and changing climate driven by other statistical characteristics of temperature. For example, changes in species composition driven by changes in risk of spring frost damage (and thus survival probability) may not necessarily be accompanied by, nor be caused by, significant changes in date of budbreak. Such might be the case if the daily temperature displayed a subtle “whitening” (that is, faster decay in temporal autocorrelation, see Figure 2).

[19] Gu *et al.* [2008] have recently shown through a detailed characterization of the April 2007 freeze event that spring frost events can have extreme short-term biological effects, and may yet have important long-term effects, for both natural and agricultural systems over a wide areal extent. Our study highlights the delicate balance of risk for vegetation in spring by which vegetation seeks to avoid frost damage. It is thus important for climate change research to address the sensitivity of biological systems to

subtle changes in spring climate as this linkage may lead to unexpectedly strong responses in ecosystems. We have approached the problem of “extreme spring temperatures” from the plant’s point of view by setting the problem in terms of stochastic environmental variables and associated biological response. This is in line with Gutschick and BassiriRad [2003], who outlined a need for understanding “how extreme events shape individuals, communities, and ecosystems” by, in part, seeking to define environmental extremes relative to the biological adaptation of a community. We believe that in such a way the framework of coupled stochastic crossing properties may be of use in quantitative analysis of “biologically-defined” extremes in a variety of biological settings. This research represents only a first step in providing a quantitative approach to understanding “biologically-defined” extreme climatic events.

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