Predicting the time of green up in temperate and boreal Biomes

Jörg D. Kaduk (1), Sietse O. Los (2)

(1) Department of Geography

University of Leicester

University Road

Leicester, LE1 7RH

United Kingdom

10

(2) Department of Geography

Swansea University

Singleton Park

Swansea, SA2 8PP

United Kingdom

16

17

18

Keywords: Phenology, Phenological models, budburst, climate change, boreal and temperate

biomes, vegetation modelling

21

22

Corresponding author:

Jörg D. Kaduk

j.kaduk@leicester.ac.uk / Phone: +44 (0) 116 252 3848 / FAX: +44 (0) 116 252 3852

26

Predicting the time of green up in temperate and boreal Biomes determined from NDVI

3

Abstract

5 Normalized Difference Vegetation Index (NDV) data from satellites and ground observations have
6 shown earlier leaf appearance in the northern hemisphere, which is believed to result from climate
7 warming. The advance of leaf out to earlier times in the year could be limited or even reversed,
8 however, as temperate and boreal trees require a certain amount of chilling in winter for rapid leaf
9 out in spring. If this chilling requirement is not fulfilled, an increasing amount of warming is
10 required for leaf out. Implications of these chilling requirements at the biome level are not clear.
11 One approach to estimate their importance is to generalize the exponential relationships between
12 chilling and warming established for single species. Previous work using NDVI data suggests that
13 this is indeed feasible but much has been limited to specific biomes or a very few years of data for
14 the modelling.

15 We find chilling requirements for northern temperate and boreal biomes by fitting various
16 phenology models to green-up dates determined from NDVI using various methods and 12 years of
17 data. The models predict that in northern middle and high latitudes the advance of green-up will be
18 limited to a total of four to five days on average (but up to 15 days regionally) over the time period
19 2000-2060 as estimated using two contrasting climate simulations. This results from the
20 exponentially increasing warming requirements for leaf out when winter chilling falls below a
21 threshold as shown by a comparison with models that consider only spring warming. The model
22 evaluation suggests an element of regional adaptation of the warming required for leaf out in large
23 biomes.

24

1. Introduction

Leaf phenology is linked with the carbon, water and energy exchange between the land surface and the atmosphere on hourly to interannual time scales. One of the most important aspects of leaf phenology is leaf emergence as it modifies the atmospheric boundary layer and thus introduces feedbacks with the local and regional climate (Fitzjarrald et al., 2001; Freedman et al., 2001; Taylor et al., 1997). Incorporation of leaf phenology from remote sensing (RS) data in general circulation models (GCMs) has lead to an improved representation of carbon fluxes and of latent heat and sensible heat fluxes (Lawrence and Slingo, 2004; Randall et al., 1996; Van den Hurk et al., 2003). Land-surface parameterizations in GCMs, however, do not entail robust models for the prediction of leaf phenology.

The atmospheric CO₂ record (Keeling et al., 1996), observations in phenological gardens (Menzel, 2000) and NOAA Advanced Very High Resolution Radiometers (AVHRR) Normalized Difference Vegetation Index (NDVI) show an earlier start and later end of the growing season in the northern hemisphere as well as a larger annual amplitude in the 1990s compared to earlier decades (Myneni et al., 1997; Shabanov et al., 2002). While the earlier increase of the NDVI could at least partly reflect earlier snow melt, the earlier start of the growing season found in ground observations of phenology and the changes in the seasonal cycle of the atmospheric CO₂ concentration ([CO₂]_a) imply a large scale earlier green up of vegetation (Keeling et al., 1996; Menzel and Fabian, 1999; Randerson et al., 1999; Sparks et al., 1997).

Thus the observed NDVI increase in spring can be interpreted as a plant physiological response to increasing temperatures in the northern latitudes in a consistent and compelling way, although some part of the NDVI increase is likely caused by earlier snow melt and the resulting feedbacks to regional climate (Dye and Tucker, 2003; Shabanov et al., 2002).

1 The relationship between leaf budburst and temperature is, however, more intricate than a direct
2 response of growth to spring warming. Controlled experiments show that many temperate and
3 boreal tree species require a period of cool temperatures (below 10°C) in winter for rapid budburst
4 in response to warming in spring (Chuine and Cour, 1999; Murray et al., 1989; Myneni et al.,
5 1997). If the amount of chilling falls below a certain threshold more warming is required to initiate
6 budburst. In these experiments the amount of chilling is measured in the number of days with an
7 average temperature below some threshold (“Number of Chill Days”, NCD) counted from a start
8 date. The warm period is measured as a heat sum, typically the number of hours or days with an
9 average temperature above another threshold since another start date and is referred to as “Growing
10 Degree Days” (GDD) or “thermal time”. The experiments show that when for a single a certain
11 threshold NCD, the “chilling requirement”, is exceeded, plants will leaf out with minimal GDD.
12 When, however, the chilling requirement cannot be fulfilled (e.g. due to warm winters) then the
13 GDD requirement for leaf out increases in an exponential fashion with decreasing chilling received
14 (Cannell and Smith, 1986; Chuine and Cour, 1999; Murray et al., 1989; Myneni et al., 1997).
15 The observed earlier green-up in the northern hemisphere reflects warmer springs (any given GDD
16 is reached earlier) and a still satisfied chilling requirement; or at least the lost NCD are compensated
17 for by a sufficiently large increase in GDD.
18 A significant drop in the NCD, however, could lead to delayed budburst due to the exponentially
19 increasing GDD requirements with decreasing NCD (Cannell and Smith, 1986; Murray et al.,
20 1989), or at least a significant slowing of the advancement of leaf appearance to earlier times.
21 Thus, paradoxically, there is a distinct possibility that global warming and associated warmer
22 springs, which are predicted to be most pronounced in the high northern latitudes, will lead to a
23 delayed budburst and this could provide a negative feedback to earlier greening of vegetation in
24 spring. This effect is at present not incorporated in land-surface models and this leads to

1 uncertainties in projections of climate change, associated greening of land-surface vegetation and
2 the magnitude of the land-surface carbon sink.

3
4 To improve the representation of the timing of green-up in land surface models (coupled to GCMs),
5 we translate the exponential relationships between chilling and heat accumulation established for
6 single species to relationships for whole biomes. Previous work (Botta et al., 2000; Kaduk and
7 Heimann, 1996) suggests that similar relationships hold for both.

8 For some biomes, however, the analysis of RS data indicates that simpler models using only
9 chilling or warming give equally good or even better results (Botta et al., 2000; Picard et al., 2005).
10 We show in this paper, that this might be a consequence of a sampling design that is either too
11 limited in space, only fairly small regions are used, or in time, only one year of data is used. In our
12 current analysis we exploit the information available in data sets that cover a time span of 12 years
13 and cross validate our models on data not used for their calibration.

14
15 We use various methods to determine the time of green-up from the FASIR NDVI data 1984-1995
16 (Los et al., 2000), e.g. (Kaduk and Heimann, 1996; Moulin et al., 1997; White et al., 1997) and then
17 explore commonly used phenology model as well as derive new models that predict the time of the
18 green-up in temperate and boreal biomes from GDD and NCD. Moreover, since it is widely
19 assumed that tree phenology adapts to the local climate, i.e. that provenance plays a role in leaf
20 dynamics, we explore in particular the question of whether phenology models can be improved by
21 taking local temperature averages into account. We show that it is crucial to use multiple years of
22 data to obtain stable models and reliable estimates for the prediction error. Finally we apply our
23 models to estimate the sensitivity of green-up to chilling requirement for two projected warming
24 scenarios in the middle of the 21st century.

1 Our aims are to: a) estimate the effect of chilling requirements on earlier green up at the biome
2 level; b) derive climate driven phenology models that determine green-up for northern temperate
3 and boreal biomes as these are predicted to be most affected by global warming, which are
4 appropriate for landscape scale land surface models, c) evaluate whether there are local adaptations
5 of green-up apparent within the biomes and d) explore the possible future change in green-up.
6 As we consider large spatial scales we do not refer to “leaf budburst”, which suggests local scale or
7 individual plants, and instead use the term “green-up” by which we mean the time of the beginning
8 of landscape scale leaf display.

9 **2. Data and Methods**

10 **2.1. Input data sets**

11 **2.1.1. Land cover**

12 We use the University of Maryland (UMd) $0.5 \times 0.5^\circ$ global land cover from the International
13 Satellite Land Surface Climatology Project (ISLSCP) initiative II (Hall et al., 2005; Hansen et al.,
14 2000) as vegetation distribution. It distinguishes 14 classes and details the percentage cover of each
15 class for each $0.5 \times 0.5^\circ$ pixel. We consider the following classes (1) Evergreen Needleleaf Forest
16 (ENF), (3) Deciduous Needleleaf Forest (DNF), (4) Deciduous Broadleaf Forest (DBF), (5) Mixed
17 Forests (MixF), (6) Woodlands (Wldd), and (9) Open Shrublands (OpSh) (Table 1). The UMd land-
18 cover data set also details the percentage cover of each class for each $0.5 \times 0.5^\circ$ pixel. The
19 classification does not distinguish between tropical and temperate broadleaf forests; thus DBF
20 comprises temperate deciduous and tropical dry deciduous broadleaf forest. The phenological
21 processes of temperate (and boreal) and tropical vegetation are, however, determined by different
22 climate variables; we limit ourselves here to the temperate and boreal areas and we identify these
23 areas based on latitude (section 2.3).

2.1.2. NDVI

We use the 10-day, $0.5 \times 0.5^\circ$ NDVI data from ISLSCP II (FASIR NDVI version 4.131) for the years 1984-1995, that are derived from the Pathfinder AVHRR Land project (PAL) data. PAL data are corrected for sensor degradation, atmospheric ozone absorption, Rayleigh scattering and sensor differences of successive NOAA platforms (James and Kalluri, 1994). The FASIR (Fourier adjusted, sensor and solar zenith angle corrected, interpolated and reconstructed) NDVI is additionally corrected for: (1) residual sensor degradation and differences in sensor calibration (Los, 1998), (2) volcanic aerosol effects resulting from the eruption of El Chichon (1982) and Mt Pinatubo (1991) (Los et al., 2000), (3) BRDF effects (Los et al., 2005), (4) dense cloud cover over tropical forests (Behrenfeld et al., 2001), (5) short-term atmospheric and cloud effects (Los et al., 2000; Sellers et al., 1996), and (6) missing winter data over the boreal forest (Los et al., 2000; Sellers et al., 1996).

Using 10-day instead of monthly NDVI partially remedies the fact that the NDVI tends to be biased towards later dates in the early growing season due to the maximum value compositing during processing of the NDVI (Holben, 1986; James and Kalluri, 1994).

To evaluate the effect of the interpolation and adjustment of the FASIR data on derived green-up dates we also use the data set without the Fourier Adjustment and Interpolation corrections and refer to these data as viASR.

We selected the FASIR NDVI data in order to have a long consistent time series of RS data concurrent with a consistent, observation based consistent global temperature data set (the GSWP-2 data of Zhao and Dirmeyer (2003) (see 2.1.4). A larger number of years allows for a better calibration and evaluation of the green-up models than would be possible with fewer years. We resolve the problem of erroneously identifying snow-melt as green-up by considering snow cover data (Armstrong and Brodzik, 2002).

2.1.3. Snow cover

The NDVI is sensitive to the presence of snow; snowmelt and green-up have similar radiative signatures in the AVHRR NDVI, as do snowfall and leaf-fall (Shabanov et al., 2002). We therefore use the weekly 25 km snow cover data from the National Snow and Ice Data Center (NSIDC) (Armstrong and Brodzik, 2002) to determine periods of snow cover for each pixel. We consider a pixel to be snow covered if the central point is snow covered according to these data in the week that has the largest temporal overlap with the 10-day period of the NDVI data under consideration.

2.1.4. Temperature

For the determination of GDDs and NCDs for the phenology models we use daily averages of the global 3 hourly, $1 \times 1^\circ$ near surface temperature reanalysis data from the NCEP-DOE Reanalysis 2 which were hybridized with the University of East Anglia CRU data set 1983-1996 from the GSWP-2 (Zhao and Dirmeyer, 2003).

To evaluate the potential future changes in the time of green-up we use climate predictions for 2051-2060 from the MPI ECHAM5 GCM for the IPCC Forth Assessment Report (FAR) (obtainable from PCMDI: http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php). We use two contrasting climate change scenarios, SRES A2 and B1, to span a range of temperature predictions: the A2 storyline describes a very heterogeneous world with high population growth and a significant increase in global temperatures; and the B1 storyline describes a convergent world with low population growth and a more moderate increase in global temperatures (IPCC, 2000). We use the data for 1981-2000 from the 20th century climate simulation for comparison and data adjustment as follows: we reduce the biases due to an incorrect mean state of the GCM by calculating daily anomalies for all simulations and adding them to the 1983-1995 mean of the GSWP-2 daily means. The anomalies are calculated for each day of the 10 years of the projections 2051-2060 and for 1986-1995 with respect to the 2046-2065 and the 1981-2000 means respectively. For comparing with the 20th century climate simulation we add the simulated 1986-1995 daily anomalies to the 1983-1995 means of the GSWP-2 temperatures. For comparing with climate change projections we

add the difference between the simulated 2046-2065 and the 1981-2000 daily means to the daily means of the GSWP-2 temperatures, to account for the mean change in climate, and then add the daily 2051-2060 anomalies.

2.2.Determination of green-up from NDVI

Our derivation of green-up models (Figure 1) starts with the determination of green-up from NDVI separately for each 0.5° pixel. Several methods to determine a “leaf-out date” from remotely sensed data exist. For example, White et al., (1997) calculate green up from the midpoint between the annual minimum and maximum NDVI. Moulin et al., (1997) determine green-up as the largest increase in NDVI above a threshold. Kaduk and Heimann, (1996) use the largest increase in the NDVI after the mean monthly temperature reached 5°C as an indication of green-up. More recently, Kang et al. (2003) explored a threshold approach similar to the one of White et al. (1997) using MODIS leaf area index (LAI) data. Zhang et al. (2003) propose the time of the largest curvature of exponential functions fitted to the EVI as the time of green-up.

For detecting green-up in northern latitudes it is crucial to distinguish between the NDVI increases related to snow melt and to greening of vegetation. This problem is dealt with in different ways: White et al., (1997) use a large NDVI threshold, Kaduk and Heimann (1996) use a temperature threshold above which snow occurrence is unlikely, Zhang et al. (2003) use quality assurance (QA) flags to select snow free NDVI data. Delbart et al. (2005) used the Normalized Difference Water Index (NDWI), which is sensitive to water on the land surface and therefore potentially allows for determination of the time period between snow-melt and budburst. However, the NDWI is only available for a limited number of years and does not overlap with the GSWP-II data. Moreover, the NDWI can not detect vegetation greenness changes if the soil surface is already very wet (saturated or standing water), which is common after snow melt, and there are issues with the calibration that

1 impact the trend in the data (Hüttich et al., 2006). We therefore prefer to use snow cover data to
2 explicitly indicate the end of snow melt and potential begin of large scale green-up.

3
4 We use the following methods to infer green-up from the NDVI data:

- 5 a) the relative threshold based method of White et al. (1997),
- 6 b) a curvature method similar to the approach of Zhang et al. (2003), though, instead of determining
7 the maximum curvature of fitted exponentials, we simply fit cubic splines (natural) to the NDVI
8 (using the spline function from (Press et al., 2002)) and record the date of the largest second
9 derivative of the spline before the maximal NDVI in a year as the time of green-up,
- 10 c) a method incorporating a climate condition (Kaduk and Heimann, 1996), which we modify by
11 taking the largest increase in NDVI after the 30 day running mean temperature reached 5°C, instead
12 of the mean monthly temperature, and
- 13 d) the curvature method of Moulin et al. (1997) for which we exclude “evergreen” and “desert”
14 pixels. Note, however, that we are using a different NDVI and vegetation classification than Moulin
15 et al. (1997). We record the time of the first minimum of the index as defined by Moulin et al.
16 (1997) before the maximal NDVI of the year as the time of green-up.

17 All these four methods detect green-up for a pixel based on the information relating to that pixel.
18 They are therefore insensitive to changes of the optical properties of the surface across the fairly
19 large land cover classes.

20 For all methods we set green-up to occur on day five of the 10 day period for which it is indicated
21 by the NDVI data. We record whether the pixel is still snow covered according to the snow cover
22 data and determine the first snow free detection.

23 **2.3.Definition of biome areas**

1 The UMD land cover classes reflect only plant growth form and do not represent meaningful biomes
 2 in the sense of an assemblage of climate adapted plant functional types. Our aim here is to define
 3 large scale bioclimatic regions by being as inclusive as possible but still arrive at meaningful
 4 delineations of temperate and boreal biomes. We therefore divide the UMD land cover classes
 5 mainly on the basis of latitude. This implicitly uses climate, since temperature and latitude are
 6 correlated, however, it stills result in more varied biomes. We accept more variation in the
 7 occurrence of plant functional types in our biomes and thus potentially larger errors in the derived
 8 green-up models to gain wider applicability of the models. To support the selection of the latitudes
 9 delineating the biomes we also examined the growing degree days (GDD, $S_f(t)$, for the definitions of
 10 symbols see Table 2), and the number of chilling days (NCD, $S_c(t)$) at green-up. We used the
 11 following set of rules:

- 12 - For Evergreen Needleleaf Forest (ENF) pixels located south of 45°N predominantly in the
 13 southern US and southern Japan (Figure 2, Figure 4) show high GDD at green-up. We do not
 14 consider these areas to be temperate or boreal coniferous forest and limit our analysis to areas north
 15 of 45°N.
- 16 - In Deciduous Needleleaf Forest (DNF) six pixels showed high GDD and NCD according to
 17 method c) compared to all other pixels. All of them were located west of 100°E, in the more western
 18 population of deciduous needleleaf forest dominated by Larch (Figure 2). We exclude the eight
 19 pixels of this biome west of 100°E from our analysis. While this might bias our analysis towards the
 20 more eastern Larch stands, we believe that potential misclassification (these 8 pixels have just about
 21 50% cover by class 3) justifies the exclusion.
- 22 - For Deciduous Broadleaf Forest (DBF) the areas south of 30°N which showed rather high GDD
 23 and low NCD are excluded. These pixels are located on Yukatan and in South-East Asia, which we
 24 do not consider temperate deciduous forest. For this biome we limit our analysis therefore to areas
 25 North of 30°N.

1 - In Mixed Forest (MixF) and Woodland (Wdld) we consider here only the areas north of 45°N. The
2 NCD and GDD requirements seem to be quite different north and south of 45°N (Figure 3). This
3 reasonable as in Mediterranean climate a limited number of cold days can serve as an indicator that
4 the winter is over, whereas in the more temperate and boreal areas a higher chilling requirement is
5 appropriate.

6 - From Open Shrublands (OpSh), which comprises tundra and deserts in the interior of the
7 continents south of 45°N, which tend to have rain driven phenology, we want to consider mainly the
8 tundra. We limit our analysis therefore to the area north of 50°N (we use 50 instead of 45°N solely
9 to exclude the Gobi completely). We also excluded one pixel at 70°N, which had a GDD of more
10 than 1200 in method c).

11

12 We also exclude all pixels that have a GDD larger than 1000 in order to remove the extreme tail of
13 the GDD distribution. This condition resulted in dropping only around 5% and 2% of the data in
14 biomes ENF and DBF respectively, and of less than 1% in the other biomes.

15

16 These restrictions allow us to focus on homogeneous bioclimatic areas, which are ecologically
17 meaningful in contrast to whole land cover classes and we will therefore refer to the areas described
18 above as “biomes” instead of land cover classes. Also, we retain a suitable number of pixels per
19 biome for the derivation of the phenological models (Table 1, column 6), although there are only
20 237 pixels in DNF and about 169 in DBF. There are, however, only 245 and 233 pixels in land
21 cover class DNF and DBF respectively in the northern Hemisphere; the reduced number of pixels in
22 DBF results from the exclusion of Yukatan.

23 **2.4.Phenological models for leaf budburst**

Four models describing the time of budburst, t_{bb} (see Table 2), of temperate plants in response to temperature have typically been used in the literature: the Spring Warming Model, the Sequential Model, the Parallel Model and the Alternating Model (Chuine et al., 1998; Hanninen et al., 1990; Kramer, 1996; Murray et al., 1989; Sarvas, 1974). In all models budburst occurs when GDD exceeds a threshold F^* , i.e. $t_{bb} = t_{F^*}$. These four models reflect different assumptions about the ecophysiology of the budburst process.

- In the Spring Warming Model (SWM) forcing units for budburst, $R_f(t)$, are accumulated from a fixed date (e.g. 1 January) and F^* is constant. It therefore assumes that there is no internal state of dormancy or rest of the buds, which needs to be broken by chilling; leaf buds react at any time in the same way to increasing temperatures. We compare our more complex models, which consider a chilling effect, with this model to evaluate the importance of including chilling in green-up models.
- The Sequential Model postulates that budburst is not possible at all until dormancy has been broken by a certain amount of chilling, the chilling requirement, C^* .
- The Parallel Model weakens the assumptions of the Sequential model; the effectiveness of the temperature forcing is only reduced if the chilling requirement is not fulfilled: chilling, $R_c(t)$, and $R_f(t)$ accumulate in parallel, but chilling states below C^* reduce the rate of forcing.
- The Alternating Model (AM) uses a variable F^* , to weaken the assumption of the Sequential model: F^* drops exponentially with increasing chilling state, $S_c(t)$. There is some confusion in the literature as to whether or not there is a fixed chilling requirement in the Alternating Model, which prevents accumulation of the warming until it is fulfilled. (Chuine et al., 1998) postulate such a requirement whereas other authors do not include it (Kramer, 1996; Murray et al., 1989). We follow (Murray et al., 1989) and do not include such a fixed chilling requirement in the Alternating Model.

In all models the temperature thresholds for the accumulation of chilling or forcing units (T_c , T_f), are assumed to be constant and species specific. However, models may reduce the effectiveness of chilling or forcing temperatures, i.e. reduce $R_c(t)$ or $R_f(t)$, above or below these thresholds, respectively (Chuine et al., 1998; Kramer, 1996; Murray et al., 1989).

Since many authors found an exponential relationship between F^* and $S_c(t)$ (Chuine et al., 1998, 1999; Heide, 1993; Murray et al., 1989; Myking, 1997; Zhang et al., 2004) we focus here on the AM, as the other models do not allow for the frequently observed relationship between the amount of warming and chilling required for budburst.

We modify the AM, F_I , and introduce an explicit dependence on the local mean annual or mean winter temperature (Table 2, functions F_i , $i=2, \dots, 5$), and explore them together with the SWM (F_θ) and AM (F_I) across our biomes for the northern hemisphere. The inclusion of a temperature mean allows in particular explicitly capturing changes in phenology within single biomes in the model. The SWM is a special case of all other models if the chilling requirement, or the effect of annual mean temperature on the bud burst threshold is set to zero.

Through this hierarchy of models we explore whether the inclusion of chilling improves the green-up prediction using the SWM as a reference model. We evaluate through the modifications (F_i , $i=2, \dots, 5$) of the standard AM, F_I , whether the inclusion of provenance, as reflected by local mean annual temperatures (previous January to January mean), T_a , or mean winter (November, December, January) temperature, T_w , improves the models. Note that, according to Taylor's Theorem model 3 (function F_3), is the first order approximation of any model that assumes a (reasonably) smooth dependence of the coefficients in F_1 on T . In other words F_3 is the first order approximation of any model of the form: $F(t) = a(T) + b(T) \cdot \exp(-c(T) \cdot S_c(t))$ with regular $a(T)$, $b(T)$, and $c(T)$. Thus, evaluating model 3 in fact evaluates to first order any model that uses temperature dependent coefficients in F_1 .

2.5. Model calibration

1 Models are parameterized by least squares. We first fit all six models F_0 – F_5 (Table 2) to all sets of
2 green-up dates obtained from the four methods a)-d). GDD and NCD at the time of green-up and T_x
3 ($x=a, w$) for each of the 12 years (1984 – 1995) and each biome. This results in 480 cases per biome.
4 To limit the number of parameters and ensure that (first and second) derivatives of the models exist,
5 we fix the starting dates (t_{C0} , and t_{F0}) for $S_c(t)$ or $S_f(t)$ to the first of November and the first of
6 January, respectively (Murray et al., 1989). We also set the threshold temperatures for chilling and
7 forcing to zero, $T_c = T_f = 0$ (Heide, 1993; Myking, 1997; Zhang et al., 2004). The functions F_i ,
8 $i=0, \dots, 5$, then depend only on the parameters a_j , b_k , and c_l , and can be differentiated with respect to
9 all their parameters. If we would allow start dates and thresholds to vary as well, then the
10 differentials are climate dependent and the recalculation of the derivatives requires larger
11 computational resources. We use a *varpro* algorithm for nonlinear least squares (netlib.org), with a
12 gradient method using derivatives, and for comparison with (Chuine et al., 1998) a simulated
13 annealing implementation (Press et al., 2002).

14
15 The models were calibrated on one year of data and on the entire record of 12 years. Calibrating the
16 models on a single year of data however leads to overfitting, i.e. the models are specific to that one
17 year. Consequently the models cannot portray well a more generalized relationship reflecting the
18 conditions in other years and have reduced predictive power (Smith, 1996). The “best” model
19 would be obtained by using all available data, but this would preclude evaluation of the model. A
20 method that avoids overfitting and allows assessment of predictive power of a model is the leave-
21 one-out (LOO) cross-validation (CV) (Allen, 1974) which we use here. We partition the data into
22 12 sets of 11 years to calibrate the model and 1 year for validation by leaving out each year once.
23 All four models are calibrated and validated on these 12 sets. The LOO CV method avoids
24 overfitting (Ng, 1997), reduces bias introduced by relying on any one particular division of the data
25 (Allen, 1974) and yields uncertainty estimates for the parameters.

2.6. Statistical methods

To evaluate differences between any two sets of modelled GDD data or green-up dates from NDVI or the different functions F_0 – F_5 we use the paired two sample Wilcoxon rank sum test, with the Null hypothesis, H_0 , of equal means, to test whether the modelled means are the same. To determine whether there is a difference in the distribution of the modelled data between any two of the F_1 – F_5 we use in addition the Kolmogorov-Smirnov test, with H_0 of equal distributions. Tests are conducted using the implementations in R (R Development Core Team, 2005).

3. Results

3.1. Green-up dates from remote sensing

The curvature methods b) and d) detect green-up when large fractions of pixels are actually still snow covered (Table 3, Table 4). This leaves too few pixels for deriving green-up models that are meaningful for whole biomes. Detection of green-up during the snow free period can be forced, e.g. by excluding snow covered times, or by using NDVI values from snow free times to fill the snow covered period for evergreen biomes. This will lead, however, to other artefacts; any function fitted to the NDVI data filled with a recent snow free value will still have its maximal curvature very close to the time of snow melt (Figure 4). We therefore focus our analysis methods a) and c) that are less sensitive to snow artefacts.

Method a) of (White et al., 1997) detects green-up 10-40 days later than the curvature methods (Table 5) and significant fractions of pixels are snow free according to the snow cover data (Table 4). Thus the significant increases in NDVI detected by method a) reflect increases in leaf area index, LAI, rather than changes in snow cover.

Compared to method a) method c) indicates 8-10 days later green-up except for DBF where the mean green-up times are only a day apart (Table 4).

To evaluate the impact of the smoothing by the Fourier adjustment and Interpolation of the FASIR corrections on the inferred time of green-up we determined green-up using the viASR data. Method a) detects green-up within five days of the FASIR data for DNF, DBF, MixF and Wdld. For ENF the average green-up based on the viASR data is 11 days earlier. This is due to the fact that for ENF the October values are used in the FASIR winter data. Thus the minimum (winter) NDVI value for the FASIR data is larger than for the viSAR data and therefore the half range is reached later in the year. The 11 days earlier green-up implies, however, that more pixels will be affected by snow cover at green-up (compare to the green-up dates from method b). We consider therefore the green-up derived from the FASIR data to be more realistic for ENF. For OpSh the viASR data lead to 15 days later estimates of green-up for the snow free pixels and 9 days later estimates of green-up for all pixels. This results from the fact that the viASR data comprise many points in the far north which have only data from the late spring until autumn. These points have either been excluded from the FASIR data or they have been filled with low values. The latter leads to detection of an earlier green-up with method a) on the FASIR data. Again we consider green-up dates obtained with the FASIR data to be more appropriate.

The mean green-up time of the region 35°N-75°N determined via method a) shows a trend of about four days to earlier times for the 12 years considered here (-0.36 d/a for 1986-1995), which is well in line with in situ observations (Menzel, 2000; Menzel and Fabian, 1999), e.g. 0.3-0.5 days per year in Europe from in situ observations in phenological gardens (Menzel, 2000), and other evaluations of remote sensing observations.

3.2. Calibration of the phenological models

1 Functions F_2 , F_4 and F_5 (see Table 2) turn out to be difficult to calibrate. The *varpro* algorithm
2 virtually always fails for function F_4 , for all biomes and all years, mostly due to ill-conditioning. F_5
3 can only be fitted in about half of the cases and F_2 in half to two thirds. F_0 can always be fitted
4 while the fitting of F_1 and F_3 fails only in about a sixth of the cases (Table 5).
5 The mean 1984-1995 residuals of the GDD fits are in general largest for F_0 and smallest for F_5 , as
6 expected from the number of parameters. The residuals for F_4 are typically the second largest,
7 because an optimal parameter set could not be found for a large number of cases; so the model is
8 not appropriate for describing the green-up dates despite its complexity. The fits of F_2 and F_3 have
9 very similar residuals, which are somewhat smaller than the ones of F_1 and in general only a little
10 larger than the ones of F_5 (Table 5). Kolmogorov-Smirnov and Wilcoxon rank sum tests suggest
11 that except for three cases there is no significant difference ($p < 0.05$) between the residuals of the
12 fits of F_2 and F_3 , and for these three cases F_3 allows the better fits. Where the tests suggests a
13 difference in the fits between functions F_3 and F_5 , the difference is small and there are only 2-5
14 years for which F_3 and F_5 could both be fitted making the tests uncertain and potential gains from
15 using F_5 small.

16

17 Using simulated annealing to determine the models gives only slightly different results. Again, the
18 residuals for F_0 are larger than those from F_1 , F_2 , and F_3 , but residuals for F_5 remain large which
19 probably reflects that no unique solution could be found for the large parameter space. Again, F_4
20 either results in large residuals or the algorithm fails. While with simulated annealing the residuals
21 for F_3 are consistently smaller than the ones for F_1 and F_2 , there is most likely again no significant
22 difference between F_2 , and F_3 .

23

24 Trading simplicity and appropriateness versus accuracy of the models suggests disregarding F_2 , F_4
25 and F_5 (Table 5). The NCD-GDD relationships were appropriately described with F_0 , F_1 and F_3 ;

1 controlled experiments also suggest that a single exponential relationship is appropriate for
2 modelling these relationships (Hunter and Lechowicz, 1992; Kramer, 1994; Murray et al., 1989)
3 We conclude that any dependence on the mean winter or annual temperature can be well described
4 by using temperature dependent parameters in F_1 , which leads to F_3 , and that additional terms, as in
5 F_2 , F_4 and F_5 , are redundant as they do not lead to improved models.

7 **3.3.Statistical analysis**

8 Calibrating the models on single years leads to overfitting of the models and to low predictive
9 power. For all methods, biomes and models the 12-year mean error of the green-up predictions
10 more than 50% higher than the error for the year on which the model was calibrated. The prediction
11 error increases if the calibration error decreases – the better the reproduction of the calibration data
12 the worse the generalization to other years.

13 The mean prediction errors from LOO CV *varpro* calibrations (see 2.5), i.e. the errors on the years
14 not used for calibration, are nearly as small as the mean errors of the models calibrated for one year
15 on the calibration data (Table 6). In other words the general models obtained from calibration on 11
16 years of data have a mean prediction error approaching the mean error of overfitted models on the
17 one calibration year. Also, the LOO CV approach results in acceptable models where these models
18 cannot be determined from single years of data (see DNF in Table 6).

19
20 The biome mean absolute calibration errors of the GDD at green-up for the 12 years 1984-1995
21 from LOO CV are significantly larger for F_0 than for F_1 for all biomes as indicated by a paired
22 Wilcoxon signed rank test (all p-values < 0.025). This shows that including a chilling requirement
23 leads to better model calibration.

1 The calibration errors of the GDD at green-up of F_3 , using T_a , is significantly smaller than the one
 2 for F_1 for biomes ENF, DBF, and Wldd (all p-values < 0.05). For OpSh the p value for 3 years is
 3 large leading to a 12 year mean of $p=0.11$. Using T_w with model F_3 is not significantly better than
 4 using T_a for biomes DBF, Wldd and OpSh. For biome ENF using T_w leads to smaller calibration
 5 errors and for MixF F_3 can be fitted, which was not possible with T_a , with smaller errors than for F_1 .
 6 Do for the biomes ENF, DBF, MixF, Wldd and OpSh considering temperature dependent
 7 parameters reduces the calibration error compared to constant parameters, even when a chilling
 8 requirement is included.
 9
 10 The prediction errors for the green-up date show that model F_1 gives significant lower errors than
 11 model F_0 for ENF, DNF, DBF, MixF with mean $p < 0.05$, for Wldd with $p < 0.1$, and OpSh with
 12 $p < 0.17$; the mean p for OpSh is dominated by one p value for one year close to 1.
 13 Model F_3 with T_a is significantly better ($p < 0.05$) than F_1 for OpSh and Wldd as well as ENF if one
 14 or two years with p close to one are excluded. For DBF the prediction error from F_3 is not
 15 consistently smaller than that from F_1 . For ENF model F_3 with T_w is significantly better than F_1
 16 ($p < 0.05$). For MixF for all but 3 years the prediction errors of model $F_3(T_w)$ are significantly smaller
 17 than the ones of F_1 .
 18
 19 The fits from method c) do not allow significantly more accurate predictions than the ones from
 20 method a) except in DNF and OpSh. These are the biomes where the green-up detected by the
 21 methods is most different (Table 4). Any higher accuracy of method c), however, might just simply
 22 result from the climate condition of the method as any regularity of year to year temperatures will
 23 increase its predictive accuracy. We therefore suggest that the method tends to predict when the
 24 running mean temperature reaches 5°C and not so much green-up.

3.4.Sensitivity of green-up models to current climate and 21st century warming projections

Mean observed green-up (1986-1995) according to method a) occurred at day 144 compared to a prediction of day 145.9 simulated using our best models (Table 8) and the GSWP2 temperatures. Simulating green-up with the temperatures from the 20th century climate model control run leads to a mean green-up day of 146.6. The simulated green-up times are consistently slightly later (~2 days), as indicated by the 10 year means, but interannual variability is very similar between observations and simulations (Figure 6). The latitudinal distribution of observations and simulations agrees well, with the exception of the green-up simulated using the climate model temperatures for the region 35°N-42°N where the green-up is estimated quite early (Figure 7). As expected from the previous sections our best models, which all include a chilling requirement, predict an earlier and therefore more appropriate time of green-up for the 20th century climate simulation than the spring warming models, F_0 , we also determined (Figure 8).

The simulated green-up under the B1 scenario of climate change in 2050-2060 is on average 4-5 days earlier than the green-up simulated with the 20th century control run 1985-1996 (Figure 8). The A2 climate leads to 1-2 days earlier green-up than the B1 climate. The spring warming models suggest an even larger advance of green-up of 7-9 days in the 2050s for the A2 scenario. This indicates that chilling requirements are no longer fulfilled in the A2 scenario and the warming cannot compensate for the loss of NCD required for green-up.

Regionally, larger changes in the green-up data (up to nearly two weeks earlier) are predicted in central Europe, Russia, Northern Siberia and the Rocky mountains (Figure 9).

4. Discussion

1 Our results indicate that method a) of (White et al., 1997) is preferable over the other methods
2 considered to obtain green-up estimates from coarse scale AVHRR – NDVI data. Functions F_1 for
3 DNF and DBF, $F_3(T_w)$ for ENF and MixF and $F_3(T_a)$ for the Wdld, and OpSh provide the best
4 models for prediction of the time of green-up. F_0 does, however, provide a nearly as good a model
5 for DNF as F_1 .

6 Zhang et al. (2003) determined a generic relationship between NCD and GDD for northern forests
7 using one year of data with a variation of method b). EVI affected by snow cover, as indicated by
8 the QA flags, are substituted with the most recent snow free value. Our results indicate that the
9 green-up dates determined by this methods are influenced by the snow melt time (as discussed in
10 3.1). Moreover, we expect that their model cannot be transferred to the analysis of other years
11 without further calibration. Moulin et al. (1997) also found that their curvature based method should
12 not be used when there is a significant amount of snow cover.

13 Method c) is strongly determined directly by climate variations and was less successful in
14 predicting variations in vegetation activity. It relies on a constant relationship of climate properties
15 and vegetation activity and is likely to break down when this relationship changes, e.g. due to
16 climate change. Moreover, method c) does not lead to significantly more reliable models than
17 method a) (see 3.3). We therefore will not consider it further.

18 Overall we prefer method a). It resulted in small residuals and reproduced the trend to earlier
19 observed green-up over the time period 1984-1995 in line with in situ observations. The method
20 provides reasonable estimates for the time of green-up; the green-up dates determined with this
21 method are only 10-20 days after snowmelt. This estimate more or less agrees with the time of
22 major leaf expansion (Marell et al., 2006; Pornon and Lamaze, 2007). (White et al., 2009)
23 compared of 10 methods to detect green-up from RS and also found that our method a)
24 ($\text{Midpoint}_{\text{pixel}}$ of (White et al., 2009)) was one of the only two that was well correlated to start of
25 spring (SOS) measures and resulted in a low bias. They also find that overall NDVI based SOS

1 estimates best match with observations of “first leaf appearance”. (Shutova et al., 2006) shows a
2 high correlation to in-situ phenology data across Fennoscandia with results from their method to
3 detect the start of the growing season, which is very similar to our method a).

4 Our model fitting indicates that a chilling requirement present in the all temperate and boreal
5 biomes we considered

6

7 The fact that the AM (F_1) model accurately predicts green up in biomes DNF and DBF suggests that
8 there is no significant adaptation of the phenology of green-up to the local mean temperatures. This
9 finding is supported by studies on European tree species: Kramer’s (1995) study of seven European
10 tree species found no significant difference of leaf unfolding times between local and transplanted
11 individuals of the same species from different latitudinal ranges. Chuine et al. (1998) also found
12 that only one out of eight European deciduous broadleaf species showed a limited local adaptation
13 of its flowering time. This implies that it is not justified to include local adaptations of phenology
14 into the model for these biomes.

15 For biomes ENF, MixF, Wdld, and OpSh, which cover larger and diverse areas, our model fitting
16 finds significant adaptation of phenology and/or species to the local climate, as the models improve
17 when mean annual or winter temperature are included.

18

19 The error spread in green-up date from our models compare well with results of other authors. For
20 example (Picard et al., 2005) find RMSE of 5-8 days for their budburst models for one limited
21 region in Siberia, which should be compared the RMSE of our model predictions of 3.8-8.4 days
22 for DNF and 8.5-14.3 days for OpSh. (Rötzer et al., 2004) find MAE of 4.7 and 4.9 days for their
23 models for the leafing in south-east Germany of *Quercus robur* and *Fagus sylvatica*, respectively,
24 which should be compared to our MAE of about 9.6 days for DBF; and MAE of 4.4 and 5 days for
25 the May shoot of *Picea abies* and *Pinus sylvestris* which should be compared to our MAE of about

1 10 and 8 days for ENF and MixF, respectively. Since our models apply for whole northern
2 hemisphere biomes, instead of single species or limited regions, for which much better models
3 should be expected, our results are very acceptable. They also compare favourably with the errors in
4 a RS based analysis by (Botta et al., 2000) who found RMSE in the range of 10-20 days, depending
5 on the biome).

6
7 Calibrating models with small data sets , e.g. just one year of data or a small region (e.g. (Chuine
8 and Cour, 1999; Kaduk and Heimann, 1996; Picard et al., 2005), leads to overfitted models which
9 have limited predictive power, underestimate the uncertainty for the calibration year, and
10 overestimate the prediction error (Smith, 1996). For example, when (Picard et al., 2005) fit their
11 model separately to four years, the overfitting is evident from the four very different parameter sets
12 they obtain (e.g. their F^* varies from 23 to 269), which might not even be physiologically
13 reasonable. F^* should reflect the warming requirement and one would not expect such a large
14 variation from year to year. If Picard et al. (2005) calibrate their model with all four years they
15 obtain ecologically reasonable values of 4.1°C for T_b , and 65 for F^* . Parameter uncertainty and
16 prediction error, however, remain unclear.

17 Contrary to this, with LOO CV we obtain well supported parameter values with an uncertainty
18 range (Table 7). Our parameter estimates are very consistent between calibrations, as each relies on
19 11 years, and should therefore reflect mainly the phenological processes and less so any interannual
20 variability. The parameter range from the LOO calibrations provides an estimate of the uncertainty
21 in the parameters obtained from the calibration using all 12 years of data.

22 Moreover we obtain a robust estimate of the prediction error. Due to the continuity of the error as a
23 function of the parameters of the models one may assume that the mean prediction error from the 12
24 LOO CV runs reflects the prediction error of the models using all 12 years for calibration.

The simulated interannual variability of the time of green-up 1986-1995 using the GSWP 2 as well as the 20th century simulated control temperatures as well as latitudinal variability are quite similar to the variability of the observations (Figure 6). This gives confidence that the modelled sensitivity is realistic and the models can indicate the sensitivity to future climate change.

The fact that our best models all include a chilling requirement and that spring-warming only models indicate a later, less accurate, green-up suggest that green-up is best described by accounting for chilling.

The dependencies of the model parameters on the mean temperatures of a previous period act in a way such that relatively responses become similar. For example the GDD threshold for OpSh decreases as the mean annual temperature decreases. This allows similar accumulation of GDD for relatively cold and warm regions within the same biome. This is somewhat analogue to Linsser's hypothesis (Linsser, 1867) that a growth stage would be reached at some constant fraction of the annual heat sum.

The change in green-up timing from the 1990s to the 2050s for the northern biomes is potentially only about five days on average (Figure 8), which is modest compared to the change over the last 2-3 decades. The spring warming models indicate a much earlier green-up in the future even though they simulated a later green-up for the past decades than the models including a chilling requirement.

This shows that the limited advance of green-up in the future is due to the opposing effects of climate warming on warming and chilling with warming increasing GDD experienced by the biota but also reducing the chilling, increasing the GDD required for green-up.

Regionally, however, still an up to 15 days earlier green-up is predicted (Figure 9).

5. Conclusions

1 White et al. (1997) proposed a method to detect green up from satellite NDVI data of (mostly) snow
2 free conditions. We found that this method leads to better results than several RS green-up detection
3 methods that cannot distinguish between green up and the end of snow melt.

4 We used the satellite based estimates of green up to derive phenological models to predict green up
5 from climate data for the northern hemisphere north of 45°N. Phenological models were derived
6 for ENF, DNF, MixF, and Wdld, north of 30°N for DBF and north of 50°N for OpSh, and these
7 models are suitable for inclusion into climate models

8 The best model estimates for predicting green-up from chilling and growing degree days have
9 acceptable prediction errors between 5 and 10 days (Table 8) as estimated from LOO CV which
10 compares very favourably with other studies.

11 To our knowledge this study is the first one using LOO CV for error estimation of large scale
12 phenology models; (Häkkinen, 1999) used it for *Betula Pendula* only. Moreover, we not only
13 estimate the prediction error, but also obtain a range indicating the uncertainty of the model
14 parameters from LOOCV. Using multiple years and LOO CV is critical to obtain stable models that
15 are not overfitted and generalize well.

16 Determining phenology models requires observations that cover a broad range of climatic
17 conditions as otherwise any relationship between warming and chilling requirement might not be
18 reflected in the data. For biomes covering large areas models taking into account a local mean
19 temperature allows a slightly, however significantly, smaller prediction error. This suggests that
20 phenology comprises an element of adaptation of vegetation to the local climate.

21

22 Our experiments with our best models, which all include a chilling requirement, and the spring-
23 warming models using temperature predictions climate model simulations show that the inclusion
24 of a chilling requirement in phenology models changes projections of green-up by several days.
25 Spring warming models without a chilling requirement predict too late green-up for the current

1 climate and overestimate the advance of green-up times in future climates. To assess the effect of a
2 changing climate on green up, the balance has to be considered between, increasing GDD resulting
3 in earlier green-up, and decreasing chilling, increasing the GDD requirement.

4 **6. Acknowledgements**

5 Parts of this work were carried out while Jörg Kaduk was on sabbatical leave from the University of
6 Leicester at the University of Wales, Swansea (now Swansea University). Jörg Kaduk received a
7 visiting scientist grant from the NERC centre of excellence CLASSIC. The manuscript benefited
8 from discussions with our colleagues Dr. Susanne Hoche, Dr. Sue Page and the suggestions of two
9 anonymous reviewers.

10 **7. References**

- 11 Allen DM (1974) The relationship between variable selection and data augmentation and a method
12 for prediction. *Technometrics* 16:125-127.
- 13 Armstrong L, Brodzik MJ (2002) Northern Hemisphere EASE-Grid Weekly Snow Cover and Sea
14 Ice Extent Version 2. National Snow and Ice Data Center, Boulder, CO, USA.
- 15 Botta A, Viovy N, Ciais P, Friedlingstein P, Monfray P (2000) A global prognostic scheme of leaf
16 onset using satellite data. *Global Change Biology* 6:709-725.
- 17 Cannell MGR, Smith RI (1986) Climatic Warming, Spring Budburst and Frost Damage to Trees.
18 *Journal of Applied Ecology* 23:177-191.
- 19 Chuine IP, Cour P (1999) Climatic determinants of budburst seasonality in four temperate zone tree
20 species. *New Phytologist* 143:339-349.
- 21 Chuine IP, Cour P, Rousseau DD (1998) Fitting models predicting dates of flowering of temperate-
22 zone trees using simulated annealing. *Plant, Cell & Environment* 21:455-466.
- 23 Chuine IP, Cour P, Rousseau DD (1999) Selecting models to predict the timing of flowering of
24 temperate trees: implication for tree phenology modelling. *Plant, Cell & Environment* 22:1-13.
- 25 Dye DG, Tucker CJ (2003) Seasonality and trends of snow-cover, vegetation index, and
26 temperature in northern Eurasia. *Geophysical Research Letters* 30:58-51-58-54.
- 27 Fitzjarrald DR, Acevedo OC, Moore KE (2001) Climatic Consequences of Leaf Presence in the
28 Eastern United States. *Journal of Climate* 14:598-614.
- 29 Freedman JM, Fitzjarrald DR, Moore KE, Sakai RK (2001) Boundary Layer Clouds and
30 Vegetation–Atmosphere Feedbacks. *Journal of Climate* 14:180-197.
- 31 Hall FG, Collatz G, Los S, Brown de Colstoun E, Landis DE (2005) ISLSCP Initiative II.
- 32 Hanninen H, Hakkinen R, Hari P, Koski V (1990) Timing of Growth Cessation in Relation to
33 Climatic Adaptation of Northern Woody-Plants. *Tree Physiol.* 6:29-39.
- 34 Hansen MC, DeFries RS, Townshend JRG, Sohlberg R (2000) Global land cover classification at
35 1km spatial resolution using a classification tree approach. *International Journal of Remote Sensing*
36 21:1331-1364.

1 Heide OM (1993) Dormancy release in beech buds (*Fagus sylvatica*) requires both chilling and long
2 days. *Physiologia Plantarum*:187-191.

3 Holben BN (1986) Characteristics of maximum-value composite images from temporal AVHRR
4 data. *International Journal of Remote Sensing* 7:1417-1434.

5 Hunter AF, Lechowicz MJ (1992) Predicting the Timing of Budburst in Temperate Trees. *Journal*
6 *of Applied Ecology* 29:597-604.

7 Häkkinen R (1999) Statistical evaluation of bud development theories: application to bud burst of
8 *betula pendula* leaves. *Tree Physiol.* 19:613-618.

9 Hüttich C, Herold M, Schmullius C, Egorov V, Bartalev SA SPOT-VGT NDVI and NDWI trends
10 1998-2005 as indicators of recent land cover change processes in northern Eurasia. in 2nd
11 Workshop of the EARSeL SIG on Land Use and Land Cover, Bonn, pp. 336-344.

12 IPCC (2000) Special Report on Emissions Scenarios. Cambridge University Press, Cambridge,
13 United Kingdom.

14 James ME, Kalluri SNV (1994) The Pathfinder AVHRR land data set - an improved coarse
15 resolution data set for terrestrial monitoring. *International Journal of Remote Sensing* 15:3347-
16 3363.

17 Kaduk J, Heimann M (1996) A prognostic phenology scheme for global terrestrial carbon cycle
18 models. *Climate Research* 6:1-19.

19 Keeling CD, Chin JFS, Whorf TP (1996) Increased activity of northern vegetation inferred from
20 atmospheric CO₂ measurements. *Nature* 382:146-149.

21 Kramer K (1994) Selecting a model to predict the onset of growth of *Fagus sylvatica*. *Journal of*
22 *Applied Ecology* 31:172-181.

23 Kramer K (1996) Phenology and growth of European trees in relation to climate change, Landbouw
24 Universiteit Wageningen.

25 Lawrence DM, Slingo JM (2004) An annual cycle of vegetation in a GCM. Part II: global impacts
26 on climate and hydrology. *Climate Dynamics* 22:107 - 122.

27 Linsser C (1867) Die periodischen Erscheinungen des Pflanzen-Lebens in ihrem Verhältniss zu den
28 Wärme-Erscheinungen. . *Mem. Acad. Imp. St. Petersburg* (7).

29 Los SO (1998) Estimation of the ratio of sensor degradation between NOAA-AVHRR channels 1
30 and 2 from monthly NDVI composites. *IEEE Transactions on Geoscience and Remote Sensing*
31 36:206-213.

32 Los SO, Collatz GJ, Sellers PJ, Malmström CM, Pollack NH, DeFries RF, Bounoua L, Parris MT,
33 Tucker CJ, Dazlich DA (2000) A global 9-year biophysical landsurface data set from NOAA
34 AVHRR data. *Journal of Hydrometeorology*:183-199.

35 Los SO, North PRJ, Grey WMF, Barnsley MJ (2005) A method to convert AVHRR normalized
36 difference vegetation index time series to a standard viewing and illumination geometry. *Remote*
37 *Sensing Environment* 99:400-411.

38 Marell A, Hofgaard A, Danell K (2006) Nutrient dynamics of reindeer forage species along
39 snowmelt gradients at different ecological scales. *Basic and Applied Ecology* 7:13-30.

40 Menzel A (2000) Trends in phenological phases in Europe between 1951 and 1996. *International*
41 *Journal of Biometeorology* 44:76-81.

42 Menzel A, Fabian P (1999) Growing season extended in Europe. *Nature* 397:659.

43 Moulin S, Kergoat L, Viovy N, Dedieu G (1997) Global-scale assessment of vegetation phenology
44 using NOAA/AVHRR satellite measurements. *Journal of Climate* 10:1154-1170.

45 Murray MB, Cannell MGR, Smith RI (1989) Date of Budburst of Fifteen Tree Species in Britain
46 Following Climate Warming. *Journal of Applied Ecology* 26:693-700.

47 Myking T (1997) Dormancy, Budburst and Impacts of Climatic Warming in Coastal-Inland and
48 Altitudinal *Betula Pendula* and *B. Pubescens* Ecotypes. *Progress in Biometeorology* 12:51-66.

49 Myneni RB, Keeling CD, Tucker CJ, Asrar G, Nemani RR (1997) Increased plant growth in the
50 northern high latitudes from 1981 to 1991. *Nature* 386:698-702.

1 netlib.org Nonlinear least squares by variable projection.

2 Ng AY Preventing "overfitting" of cross-validation data. in ICML, pp. 245-253.

3 Picard G, Quegan S, Delbart N, Lomas MR, Le Toan T, Woodward FI (2005) Bud-burst modelling

4 in Siberia and its impact on quantifying the carbon budget. *Global Change Biology* 11:2164-2176.

5 Pornon A, Lamaze T (2007) Nitrogen resorption and photosynthetic activity over leaf life span in

6 an evergreen shrub, *Rhododendron ferrugineum*, in a subalpine environment *New Phytologist*

7 175:301-310.

8 Press WH, Teukolsky SA, Vetterling WT, Flannery BP (2002) *Numerical Recipes Multi-Language*

9 *Code CD ROM*. 2.11 edn. Cambridge University Press, pp. 1 CD-ROM ; 4 3/4 in.

10 R Development Core Team (2005) *R: A Language and Environment for Statistical Computing*. R

11 Foundation for Statistical Computing, Vienna, Austria.

12 Randall DA, Dazlich DA, Zhang C, Denning AS, Sellers PJ, Tucker CJ, Bounoua L, Los SO,

13 Justice CO, Fung I (1996) A revised land surface parameterization (SiB2) for GCMs .3. The

14 greening of the Colorado State University general circulation model. *Journal of Climate* 9:738-763.

15 Randerson JT, Field CB, Fung IY, Tans PP (1999) Increases in early season ecosystem uptake

16 explain recent changes in the seasonal cycle of atmospheric CO₂ at high northern latitudes.

17 *Geophysical Research Letters* 26:2765–2769.

18 Rötzer T, Grote R, Pretzsch H (2004) The timing of bud burst and its effect on tree growth.

19 *International Journal of Biometeorology* 48:109-118.

20 Sarvas R (1974) Investigations on the annual cycle of development of forest trees. II. Autumn

21 dormancy and winter dormancy. *Communicationes Instituti Forestalis Fenniae*, p. 101p.

22 Sellers PJ, Los SO, Tucker CJ, Justice CO, Dazlich DA, Collatz GJ, Randall DA (1996) A revised

23 land surface parameterization (SiB2) for atmospheric GCMs, part 2. The generation of global fields

24 of terrestrial biophysical parameters from satellite data. *Journal of Climate* 9:706-737.

25 Shabanov NV, Zhou L, Knyazikhin Y, Myneni RB, Tucker CJ (2002) Analysis of interannual

26 changes in northern vegetation activity observed in AVHRR data from 1981 to 1994. *IEEE*

27 *Transactions on Geoscience and Remote Sensing* 40:115-130.

28 Shutova E, Wielgolaski FE, Karlsen SR, Makarova O, Berlina N, Filimonova T, Haraldsson E,

29 Aspholm PE, Flø L, Høgda KA (2006) Growing seasons of Nordic mountain birch in northernmost

30 Europe as indicated by long-term field studies and analyses of satellite images. *International Journal*

31 *Biometeorology* 51:155-166.

32 Smith M (1996) *Neural Networks for Statistical Modeling*. International Thomson Computer Press,

33 Boston.

34 Sparks TH, Carey PD, Combes J (1997) First Leafing dates of trees in Surrey between 1947 and

35 1996. *The London Naturalist* 76:15-20.

36 Taylor CM, Säid F, Lebel T (1997) Interactions between the land surface and mesoscale rainfall

37 variability during HAPEX-Sahel. *Monthly Weather Review* 125:2211-2227.

38 Van den Hurk BJM, Viterbo P, Los SO (2003) Impact of leaf area index seasonality on the annual

39 land surface evaporation in a global circulation model. *Journal of Geophysical Research* 108:ACL

40 5-1 - ALC 5-9.

41 White MA, de Beurs KM, Didan K, Inouye DW, Richardson AD, Jensen OP, O'Keefe J, Zhang G,

42 Nemani RR, van Leeuwen WJD, Brown JF, de Wit A, Schaepman M, Lin XM, Dettinger M, Bailey

43 AS, Kimball J, Schwartz MD, Baldocchi DD, Lee JT, Lauenroth WK (2009) Intercomparison,

44 interpretation, and assessment of spring phenology in North America estimated from remote

45 sensing for 1982-2006. *Global Change Biology* 15:2335-2359.

46 White MA, Thornton PE, Running SW (1997) A continental phenology model for monitoring

47 vegetation responses to interannual climatic variability. *Global Biogeochemical Cycles* 11:217-234.

48 Zhang X, Friedl MA, Schaaf CB, Strahler AH (2004) Climate controls on vegetation phenological

49 patterns in northern mid- and high latitudes inferred from MODIS data. *Global Change Biology*

50 10:1133–1145.

1 Zhao M, Dirmeyer PA (2003) Production and Analysis of GSWP-2 Near-Surface Meteorology Data
2 Sets. COLA Technical Report. Center for Ocean-Land-Atmosphere Studies.
3
4

Figure Captions

Figure 1 Schematic representation of the model development (NH: northern hemisphere).

Latitudinal restrictions are applied to a land cover map resulting in the delineation of biome areas.

The application of a method for detecting green-up on the NH 0.5x0.5o NDVI data gives NH green-up dates. Determining the climate indices NCD and GDD at green-up and mean temperatures results after restriction to the biome areas in sets of GDD, NCD green-up date and mean temperature data for the biome pixels for 12 years. Applying a calibration method to determine the parameters for the different model forms leads to the green-up models.

Figure 2 Distribution of land cover classes North of 30oN from the University of Maryland vegetation classification (Hansen et al., 2000) (see 2.3Error! Reference source not found.).

Figure 3 Growing degree days (GDD) and number of chilling days (NCD) at leaf out in 1984 according to method a) in biome 5. Small grey crosses are pixels north of 45oN and black plusses are pixels between the equator and 45oN.

Figure 4 NDVI , snow covered period and NDVI filled with nearest snow free NDVI value during periods with snow cover for the year 1983 for the pixel of biome ENF centred on 100.25oE and 59.75oN. Any fit of a function to the filled NDVI will have its maximal curvature very close to the time of snow melt.

Figure 6 Time of green-up for the years 1986-1995 in the areas common to observations and simulations according to the detection by method a) (solid black line) and the derived models using the GSWP2 temperature data (dashed line) and the temperature data from the 20th century control experiment (solid grey line)

1

2 Figure 7 Mean time of green-up for the years 1986-1995 averaged over 0.5 degree latitudinal bands
3 in the common areas according to the detection by method a) (solid black line) and the derived
4 models using the GSWP2 temperature data (dashed line) and the temperature data from the 20th
5 century control experiment (solid grey line)

6

7 Figure 8 Time of green-up according to the best models determined (solid black line) and from the
8 spring warming models (short dashed black line) using the temperature data from the 20th century
9 control experiment for the 10 years 1986-1995, from the B1 climate change simulation for 2051-
10 2060 (solid grey line) and according to the best models determined (dash-dot black line) and the
11 spring warming models (long dashed black line) for the A2 climate change simulation for 2051-
12 2060, respectively.

13

14 Figure 9 Change in the mean time of green-up (negative means to earlier times) from 1986-1995 to
15 2051-2060 as predicted from the simulated 20th century and the A2 scenario temperatures.

16

1 **Table Captions**

2 Table 1 Number of pixels in the landcover classes and regions in the UMd land cover data and the
3 number of pixels in the Biomes we consider after the screening detailed in Section 2.3 was applied.

4
5 Table 2 Notation and formulation of the major types of phenology models (Spring Warming,
6 Sequential, Parallel, and Alternating models) tested in this paper following notation from (Chuine et
7 al., 1998; Hanninen, 1990; Kramer, 1996; Murray et al., 1989). There are some slight variations in
8 the literature.

9
10 Table 3 Number of grid points in land cover classes 1, 3-6, and 9 for which methods a) – d) detect
11 green-up in 1984 as well as the number of points which are snow free and snow covered according
12 to the snow cover data (Armstrong and Brodzik, 2002) at the time of the detected green-up. Also
13 given the mean number of grid points per biome, i.e. the points remaining after the screening
14 detailed in section 2.3 for which green-up was detected, and the mean number of points 1984-1995,
15 which were snow free at the time green-up was detected.

16
17 Table 4 Mean day of year of green-up 1984–1995 for the methods a) – d) per biome for the cases
18 (A) when all pixels are considered, and (B) when only those cells are considered which were snow
19 free at the time of the detected green-up.

20
21 Table 5 Number of successful fits, average and standard deviation of the mean absolute GDD error
22 mean 1984-1995 of the fit to the NCD-GDD relationship with functions F0-F3 to the leaf out dates
23 from method a) considering snow free pixels at leaf out only.

24

1 Table 6 12 year mean average error in green up date for methods a) and c) and functions F0, F1 and
2 F3. The upper eight rows show the mean errors from fitting each function each year for the year
3 they were fitted on. The lower eight rows show the mean absolute prediction errors from Leave One
4 Out Cross Validation (LOO CV, i.e. fitting the functions on 11 years and predicting the 12th). The
5 large errors from some combinations are due to 1-3 outliers where the minimization algorithm
6 could not find a good fit.

7
8 Table 7 Parameters for the selected models from the 12 LOO CV runs for every other year 1984-
9 1995 and the parameters resulting when the data of all twelve years are used. Years indicate which
10 year was left out from the model calibration. Parameter values are quite similar for all model
11 calibrations. Typically the parameter values resulting from the calibration using all twelve years of
12 data are very close to the values from the LOO CV calibrations.

13
14 Table 8: Definition and error characteristics of the selected models for green-up for the biomes
15 considered here. The models are calibrated using the *varpro* algorithm and GDD and NCD data
16 from the years 1984 – 1995 with t_{C0} and t_{F0} set to the first of November and the first of January,
17 respectively, and the threshold temperatures for chilling and forcing set to zero, $T_c = T_f = 0$. Error
18 data are based on 12 LOO CV runs for the years 1984-1995.

19

Figures

Figure 1 Schematic representation of the model development (NH: northern hemisphere). Latitudinal restrictions are applied to a land cover map resulting in the delineation of biome areas. The application of a method for detecting green-up on the NH 0.5x0.5° NDVI data gives NH green-up dates. Determining the climate indices NCD and GDD at green-up and mean temperatures results after restriction to the biome areas in sets of GDD, NCD green-up date and mean temperature data for the biome pixels for 12 years. Applying a calibration method to determine the parameters for the different model forms leads to the green-up models.

Figure 2 Distribution of land cover classes North of 30°N from the University of Maryland vegetation classification (Hansen et al., 2000) (see 2.3Error! Reference source not found.).

Figure 3 Growing degree days (GDD) and number of chilling days (NCD) at leaf out in 1984 according to method a) in biome 5. Small grey crosses are pixels north of 45°N and black plusses are pixels between the equator and 45°N.

Figure 4 NDVI , snow covered period and NDVI filled with nearest snow free NDVI value during periods with snow cover for the year 1983 for the pixel of biome ENF centred on 100.25°E and 59.75°N. Any fit of a function to the filled NDVI will have its maximal curvature very close to the time of snow melt.

1

Figure 5 Annual change in the time of green up (days/year) estimated from method a).
Negative values indicated an advancement of the time of green up to earlier dates in the year.

Detected from NDVI
 Simulated, GSWP2
 Simulated, climate model

Figure 6 Time of green-up for the years 1986-1995 in the areas common to observations and simulations according to the detection by method a) (solid black line) and the derived models using the GSWP2 temperature data (dashed line) and the temperature data from the 20th century control experiment (solid grey line)

Figure 7 Mean time of green-up for the years 1986-1995 averaged over 0.5 degree latitudinal bands in the common areas according to the detection by method a) (solid black line) and the derived models using the GSWP2 temperature data (dashed line) and the temperature data from the 20th century control experiment (solid grey line)

Figure 8 Time of green-up according to the best models determined (solid black line) and from the spring warming models (short dashed black line) using the temperature data from the 20th century control experiment for the 10 years 1986-1995, from the B1 climate change simulation for 2051-2060 (solid grey line) and according to the best models determined (dash-dot black line) and the spring warming models (long dashed black line) for the A2 climate change simulation for 2051-2060, respectively. For the 20th century control simulation the spring warming models imply a later green-up than the models including chilling demonstrating the effectiveness of chilling reducing the warming required for green-up. For the A2 scenario, however, the spring warming models simulate earlier green-up suggesting that chilling requirements are not fulfilled any more leading to significantly larger warming requirements in the models requiring chilling.

Figure 9 Change in the mean time of green-up (negative means to earlier times) from 1986-1995 to 2051-2060 as predicted from the simulated 20th century and the A2 scenario temperatures.

1 **Tables**

2
3 **Table 1** Number of pixels in the landcover classes and
4 regions in the UMd land cover data and the number of pixels in
5 the Biomes we consider after the screening detailed in Section
6 2.3 was applied.

Class	Number of pixels in landcover class and area				Number of pixels in Biome
	NH	>30°N	>45°N	>50°N	
1 ENF	1730	1714	1646	1396	1646
3 DNF	245	245	245	245	237
4 DBF	233	169	17	0	169
5 MixF	2268	2206	1904	1500	1904
6 Wdld	5353	4202	3491	3132	3491
9 OpSh	7684	6838	4490	3994	3994

7

1 **Table 2** Notation and formulation of the major types of phenology models (Spring Warming,
2 Sequential, Parallel, and Alternating models) tested in this paper following notation from
3 (Chuine et al., 1998; Hanninen, 1990; Kramer, 1996; Murray et al., 1989). There are some slight
4 variations in the literature.

Symb.	Units Notes and Definitions		
Parameters			
t _{C0}	Start date for counting chilling rate		
t _{F0}	Start date for counting forcing rate		
C*	Critical value of the state of chilling		If S _c (t) > C*, then the chilling requirement is fulfilled. Transition from rest to quiescence.
F*	critical value of the state of forcing	°C	If S _f (t) > F*, then budburst occurs
T _c	temperature threshold for chilling	°C	
T _f	temperature threshold for forcing	°C	
Variables			
t	Time	day	
T	Mean daily temperature	°C	
T _x	Mean annual temperature (x=a) or mean Oct.-Dec. temperature (x=w)	°K	
t _{bb}	Day of year of bud-burst		
t _{C*}	Day of year when the chilling requirement is first fulfilled.		
t _{F*}	Day of year when the forcing requirement is first fulfilled.		
R _c (t)	Chilling rate function	$R_c(t)=\begin{cases} 0 & T>T_c \\ 1 & T\leq T_c \end{cases} \quad t\geq t_{C0}$	
R _f (t)	Forcing rate function	$R_f(t)=\begin{cases} T-T_f & T\geq T_f \\ 0 & T<T_f \end{cases} \quad t\geq t_{F0}$ °C day ⁻¹	

$$S_c(t) \quad \text{State of chilling, number of chilling days (NCD)} \quad \text{day} \quad \sum_{s=t_{C0}}^t R_c(s)$$

$$S_f(t) \quad \text{State of forcing, growing degree days (GDD)} \quad ^\circ\text{C} \quad \sum_{s=t_{F0}}^t R_f(s)$$

Models

Spring Warming Model

$$F_0(t) = a$$

Alternating Model

Original form (Murray et al., 1989)

$$F_1(t) = a + b \cdot S_c(t) + c \cdot S_f(t)$$

Variations of the Alternating Model including mean temperature (x=a,w)

Two exponentials

$$F_2(t) = a + b_1 \cdot \exp(-c_1 \cdot S_c(t)) + b_2 \cdot \exp(-c_2 \cdot S_f(t))$$

Parameters linearly temperature dependent

$$F_3(t) = a + (b_1 + b_2 \cdot T_x) \cdot \exp(-(c_1 + c_2 \cdot T_x) \cdot S_c(t)) + (d_1 + d_2 \cdot T_x) \cdot \exp(-(e_1 + e_2 \cdot T_x) \cdot S_f(t))$$

$$F_4(t) = (a_1 + a_2 \cdot T_x) + (b_1 + b_2 \cdot T_x) \cdot \exp(-(c_1 + c_2 \cdot T_x) \cdot S_c(t)) - d_1 \cdot T_x$$

$$F_5(t) = a + (b_1 + b_2 \cdot T_x) \cdot \exp(-(c_1 + c_2 \cdot T_x) \cdot S_c(t)) + (d_1 + d_2 \cdot T_x) \cdot \exp(-(e_1 + e_2 \cdot T_x) \cdot S_f(t))$$

1

2 **Table 3** Number of grid points in land cover classes 1, 3-6, and 9 for
 3 which methods a) – d) detect green-up in 1984 as well as the number of
 4 points which are snow free and snow covered according to the snow cover
 5 data (Armstrong and Brodzik, 2002) at the time of the detected green-up.
 6 Also given the mean number of grid points per biome, i.e. the points
 7 remaining after the screening detailed in section 2.3 for which green-up was
 8 detected, and the mean number of points 1984-1995, which were snow free
 9 at the time green-up was detected.

Land cover class/Biome	Mean number of points in land cover class 1984-1995		Mean number of points in biome 1984-1995	
	leaf out detected	Snow free at leaf out	leaf out detected	Snow free at leaf out
Method a				
ENF	1682	1301	1598	1219
DNF	245	143	237	141
DBF	229	228	169	168
MixF	2247	1851	1865	1472
Wdld	5241	4161	3416	2362
OpSh	5498	3610	2447	847
Method b				
ENF	1689	324	1601	253
DNF	245	9	237	9
DBF	215	182	169	139
MixF	2241	631	1865	331

Wdld	5150	2013	3417	451
OpSh	6024	2560	2547	119
Method c				
ENF	1697	1490	1604	1402
DNF	245	206	237	200
DBF	230	225	169	166
MixF	2251	2002	1865	1626
Wdld	5285	4553	3418	2756
OpSh	6169	4907	2509	1556
Method d				
ENF	1690	187	1602	121
DNF	245	0	237	0
DBF	216	133	169	88
MixF	2242	273	1865	61
Wdld	5170	1610	3417	131
OpSh	6149	2317	2547	60

1

2

1
2
3
4

5
6
7

Table 4 Mean day of year of green-up 1984–1995 for the methods a) – d) per biome for the cases (A) when all pixels are considered, and (B) when only those cells are considered which were snow free at the time of the detected green-up.

Mean day of leaf out 1983–1995 mean												
A All pixels							B Only Snow free pixels at leaf out					
Method	Biome						Biome					
	ENF	DNF	DBF	MixF	Wdld	OpSh	ENF	DNF	DBF	MixF	Wdld	OpSh
a)	145.6	147.7	112.7	137.6	144.7	174.7	145.7	143.1	112.7	136.2	141.0	168.0
b)	126.4	136.5	89.6	122.2	129.8	167.7	108.5	112.7	93.1	106.5	105.9	161.9
c)	154.0	153.3	113.3	144.4	150.9	180.5	153.6	152.9	113.8	144.1	149.6	180.4
d)	126.3	142.4	75.0	122.3	132.5	170.4	121.0	131.5	71.2	114.1	122.2	178.6

1 **Table 5** Number of successful fits, average and
2 standard deviation of the mean absolute GDD error mean
3 1984-1995 of the fit to the NCD-GDD relationship with
4 functions F_0 - F_3 to the leaf out dates from method a)
5 considering snow free pixels at leaf out only. For F_2 & F_3
6 the mean annual temperature, T_a , was used in the fits.

Function	GDD mean absolute error 1984-1995 mean					
	Biome					
	ENF	DNF	DBF	MixF	Wdld	OpSh
F_0						
No. fits	12	12	12	12	12	12
Ave	126.22	33.52	192.29	78.23	96.15	71.86
Std	15.71	11.48	34.09	7.45	8.98	8.34
F_1						
No. fits	12	9	12	12	12	12
Ave	94.02	28.47	76.08	67.95	77.26	56.44
Std	15.84	10.62	10.28	7.90	8.80	7.09
$F_2(T_a)$						
No. fits	8	5	6	9	6	9
Ave	90.93	27.93	67.76	65.34	73.45	50.97
Std	16.37	8.13	8.73	8.77	7.60	4.61
$F_2(T_w)$						
No. fits	7	6	6	9	9	9
Ave	94.95	29.01	70.42	64.59	74.42	54.18
Std	14.62	6.55	7.75	8.47	6.91	8.62
$F_3(T_a)$						

No. fits	12	3	11	7	7	12
Ave	90.75	30.59	67.52	65.48	72.81	52.35
Std	14.58	7.29	7.68	8.33	10.94	6.59
<hr/>						
$F_3(T_w)$						
No. fits	11	7	12	9	11	11
Ave	85.59	25.49	68.53	65.64	75.03	52.91
Std	10.15	9.74	6.74	8.22	8.97	7.81
<hr/>						
$F_5(T_a)$						
No. fits	10	6	4	6	4	4
Ave	91.85	27.13	59.44	60.71	75.14	52.64
Std	13.20	10.38	6.31	6.39	2.46	4.10
<hr/>						
$F_5(T_w)$						
No. fits	5	6	7	8	4	6
Ave	84.26	22.67	61.69	60.21	72.27	49.99
Std	12.34	9.12	5.87	4.17	2.73	4.37
<hr/>						

Table 6 12 year mean average error in green up date for methods a) and c) and functions F_0 , F_1 and F_3 . The upper eight rows show the mean errors from fitting each function each year for the year they were fitted on. The lower eight rows show the mean absolute prediction errors from Leave One Out Cross Validation (LOO CV, i.e. fitting the functions on 11 years and predicting the 12th). The large errors from some combinations are due to 1-3 outliers where the minimization algorithm could not find a good fit.

12 year mean average absolute error in green up

		Biome					
	Model	ENF	DNF	DBF	MixF	Wdld	OpSh
Mean error in the year used for fitting							
Method a)							
	F_0	13.37	4.75	16.96	8.90	10.97	10.18
	F_1	9.84	33.74	6.82	7.62	8.71	7.77
	F_3, T_a	18.20	50.00	6.13	11.74	8.31	36.04
	F_3, T_w	13.83	54.39	6.58	12.06	8.53	8.28
Method c)							
	F_0	11.60	3.01	16.80	8.60	9.08	4.33
	F_1	9.64	2.66	7.11	7.91	7.72	3.80
	F_3, T_a	9.36	28.54	6.02	7.88	7.47	5.50
	F_3, T_w	27.15	23.17	6.34	12.29	6.93	4.55
Mean prediction error from LOO CV							
Method a)							
	F_0	13.50	5.47	19.00	8.99	11.00	10.51
	F_1	10.09	5.36	10.01	7.77	8.88	8.06

F_3, T_a	9.94	21.88	9.61	N/A	8.39	7.84
F_3, T_w	9.82	118.74	10.14	7.74	9.17	44.33

Method c)

F_0	12.25	3.38	18.37	8.71	9.12	4.30
F_1	10.53	3.38	10.20	8.14	7.99	3.82
F_3, T_a	10.55	6.62	10.22	N/A	7.67	3.71
F_3, T_w	10.31	44.15	21.22	8.10	7.83	3.74

1

2

Table 7 Parameters for the selected models from the 12 LOO CV runs for every other year 1984-1995 and the parameters resulting when the data of all twelve years are used. Years indicate which year was left out from the model calibration. Parameter values are quite similar for all model calibrations. Typically the parameter values resulting from the calibration using all twelve years of data are very close to the values from the LOO CV calibrations.

	Biome	DNF			DBF			ENF					
	Model for F*												
	10-elfor, 10-elfor, 10-elfor			10-elfor, 10-elfor, 10-elfor			10-elfor, 10-elfor, 10-elfor, 10-elfor, 10-elfor, 10-elfor, 10-elfor, 10-elfor, 10-elfor, 10-elfor, 10-elfor, 10-elfor						
	Parameters												
	a	b	c	a	b	c	a ₁	a ₂	b ₁	b ₂	c ₁	c ₂	
1984	128.80	-3.15E-09	-0.12	-301.50	1.25E+03	7.47E-03	-5860.0	24.16	618.1	-2.48	-4.41E-02	1.22E-04	
1985	137.20	-3.71E-07	-0.10	-434.00	1.37E+03	6.24E-03	-6166.0	25.43	898.7	-3.61	-4.90E-02	1.49E-04	
1986	127.50	-5.20E-10	-0.13	-273.60	1.22E+03	7.66E-03	-5721.0	23.62	523.4	-2.10	-5.08E-02	1.45E-04	
1987	127.80	-2.60E-10	-0.14	-345.00	1.33E+03	7.29E-03	2914.0	-11.43	1774.0	-3.18	1.34E-01	-4.86E-04	
1988	127.00	-1.15E-09	-0.13	-279.80	1.24E+03	7.66E-03	1293.0	-2.25	-4033.0	14.64	5.85E-02	-2.43E-04	
1989	130.20	-3.78E-08	-0.11	-302.60	1.25E+03	7.44E-03	-5643.0	23.29	503.1	-2.02	-5.35E-02	1.56E-04	
1990	130.50	-1.91E-08	-0.11	-417.90	1.35E+03	6.44E-03	-6128.0	25.22	777.1	-3.11	-4.70E-02	1.38E-04	
1991	128.60	-6.46E-09	-0.12	-314.30	1.28E+03	7.40E-03	-5488.0	22.93	889.2	-3.60	-5.42E-02	1.70E-04	

1992	128.00	-1.71E-08	-0.11	-396.20	1.34E+03	6.60E-03	-6005.0	24.92	1042.0	-4.20	-5.11E-02	1.59E-04
1993	123.90	-3.70E-09	-0.12	-479.60	1.42E+03	6.04E-03	2771.0	-10.82	2610.0	-6.22	1.42E-01	-5.14E-04
1994	126.00	-3.38E-09	-0.12	-677.10	1.63E+03	5.02E-03	-1871.0	9.25	-1921.0	7.00	1.05E-01	-4.30E-04
1995	124.60	-4.59E-12	-0.15	-465.10	1.41E+03	6.09E-03	-6159.0	25.12	332.4	-1.32	-4.22E-02	1.02E-04
Mean	128.30	-3.86E-08	-0.12	-390.60	1.34E+03	6.78E-03	-3505.0	14.95	334.5	-0.85	3.93E-03	-4.43E-05
Stddev	3.42	1.05E-07	0.01	115.90	1.14E+02	8.35E-04	3723.0	14.77	1729.0	5.82	8.07E-02	2.84E-04

Parameters from fit using all 12 years

-6089.0	25.27	1150.0	-4.64	-4.95E-02	1.55E-04	-6089.0	25.27	1150.0	-4.64	-4.95E-02	1.55E-04
---------	-------	--------	-------	-----------	----------	---------	-------	--------	-------	-----------	----------

Table 8 continued

	Biome		MixF				Wdld						OpSH					
Model for F*																		
	Model for F*						Model for F*						Model for F*					
	a ₁	a ₂	b ₁	b ₂	c ₁	c ₂	a ₁	a ₂	b ₁	b ₂	c ₁	c ₂	a ₁	a ₂	b ₁	b ₂	c ₁	c ₂
1984	-774.6	3.31	3.47e+03	-10.15	2.10e-02	-3.36e-05	-2528.0	9.58	1.50e+04	-51.91	7.24e-02	-2.22e-04	-5648.0	23.14	1510.00	-6.09	-1.56e-02	3.57e-05
1985	-434.5	2.16	9.60e+03	-32.40	8.18e-02	-2.49e-04	-2739.0	10.35	1.64e+04	-56.59	6.64e-02	-1.99e-04	-8408.0	34.25	3833.00	-15.45	-1.27e-02	3.42e-05
1986	-843.7	3.54	3.76e+03	-11.20	2.08e-02	-3.39e-05	-2742.0	10.33	1.61e+04	-55.80	6.82e-02	-2.07e-04	-2712.0	11.52	-706.70	2.52	1.15e-01	-4.68e-04
1987	-929.2	3.81	4.33e+03	-13.21	1.71e-02	-2.06e-05	-2665.0	10.07	1.51e+04	-52.02	6.46e-02	-1.93e-04	-2921.0	12.28	-577.80	2.05	1.20e-01	-4.86e-04
1988	-900.5	3.91	6.74e+03	-22.11	4.09e-02	-9.90e-05	-2444.0	9.27	1.77e+04	-61.43	9.73e-02	-3.12e-04	-6504.0	26.27	1781.00	-7.11	-1.72e-02	4.27e-05
1989	-1229.0	5.10	9.30e+03	-31.33	1.76e-02	-1.08e-05	-2695.0	10.20	1.59e+04	-55.19	7.41e-02	-2.28e-04	-2560.0	10.99	-794.90	2.83	1.06e-01	-4.30e-04
1990	-292.2	1.43	2.02e+03	-4.87	3.70e-02	-9.81e-05	-3022.0	11.41	1.74e+04	-60.43	6.08e-02	-1.78e-04	-6699.0	26.83	1594.00	-6.32	-1.69e-02	3.95e-05
1991	-1571.0	6.42	9.47e+03	-31.97	1.00e-04	5.73e-05	-2690.0	10.14	1.87e+04	-65.10	7.30e-02	-2.23e-04	-2815.0	11.85	-624.50	2.23	1.28e-01	-5.18e-04
1992	-806.8	3.36	3.32e+03	-9.57	1.92e-02	-3.05e-05	-1330.0	5.17	1.83e+04	-63.51	2.94e-02	-5.53e-05	-2914.0	12.30	-817.50	2.91	1.18e-01	-4.73e-04
1993	-1162.0	4.81	8.42e+03	-28.10	1.75e-02	-1.23e-05	-2323.0	8.80	1.64e+04	-56.53	1.59e-02	-1.12e-05	-2508.0	10.74	-686.00	2.45	1.13e-01	-4.61e-04
1994	-892.4	3.88	6.57e+03	-21.35	3.20e-02	-6.39e-05	-428.4	1.87	1.29e+04	-44.34	4.03e-02	-1.04e-04	-11210.0	45.99	7140.00	-29.00	-1.13e-02	3.43e-05
1995	-1052.0	4.46	2.20e+03	-5.28	1.00e-04	5.13e-05	-3564.0	13.31	1.44e+04	-49.72	1.59e-01	-5.44e-04	-7973.0	32.49	3498.00	-14.12	-1.27e-02	3.38e-05
Mean	-907.3	3.85	5.77e+03	-18.46	2.54e-02	-4.52e-05	-2431.0	9.21	1.62e+04	-56.05	6.84e-02	-2.06e-04	-5239.0	21.55	1262.00	-5.26	5.11e-02	-2.18e-04

Stddev	339.0	1.31	2.92e+03	10.63	2.16e-02	8.01e-05	812.4	2.97	1.70e+03	6.01	3.60e-02	1.34e-04	2935.0	11.78	2518.00	10.06	6.86e-02	2.67e-04
--------	-------	------	----------	-------	----------	----------	-------	------	----------	------	----------	----------	--------	-------	---------	-------	----------	----------

Parameters from fit using all 12 years

-777.2	3.34	4.93e+03	-15.42	2.96e-02	-6.28e-05	-2709.0	10.24	1.69e+04	-58.41	7.05e-02	-2.14e-04	-2825.0	11.90	-616.80	2.20	1.23e-01	-4.97e-04
--------	------	----------	--------	----------	-----------	---------	-------	----------	--------	----------	-----------	---------	-------	---------	------	----------	-----------

Table 8 Definition and error characteristics of the selected models for green-up for the biomes considered here. The models are calibrated using the *varpro* algorithm and GDD and NCD data from the years 1984 – 1995 with t_{C0} and t_{F0} set to the first of November and the first of January, respectively, and the threshold temperatures for chilling and forcing set to zero, $T_c = T_f = 0$. Error data are based on 12 LOO CV runs for the years 1984-1995.

Biome	Model for F*	Green-up prediction error (days)		
		Mean	Std. dev.	Range
ENF	$F_3(t) = (-6089 + 26.3 \cdot T_w) + (1150 - 4.64 \cdot T_w) \cdot \exp(-(0.049 - 0.000155 \cdot T_w) \cdot S_c(t))$	9.82	1.41	7.3 – 13.1
DNF	$F_1(t) = 127.8 - 2.6 \cdot 10^{-9} \exp((-0.123 S_c(t)))$	5.36	1.46	2.7 – 7.2
	$F_0(t) = 115.2$	5.47	1.40	2.7 – 7.6
DBF	$F_1(t) = -381.7 + 1333 \exp((-0.00674 S_c(t)))$	9.61	3.81	6.0 – 20.4
MixF	$F_3(t) = (-777.2 + 3.344 \cdot T_w) + (492.8 - 15.42 \cdot T_w) \cdot \exp(-(0.02956 + 0.000063 \cdot T_w) \cdot S_c(t))$	7.74	1.13	6.8 – 9.5
Wdld	$F_3(t) = (-2709 + 10.24 \cdot T_a) + (1686 - 58041 \cdot T_a) \cdot \exp((0.0705 - 0.000214 \cdot T_a) \cdot S_c(t))$	8.39	0.64	7.3 – 9.4
OpSh	$F_3(t) = (-2825 + 11.9 \cdot T_a) + (-616.8 + 2.2 \cdot T_a) \cdot \exp((0.1226 - 0.000497 \cdot T_a) \cdot S_c(t))$	7.84	1.19	6.9 – 8.6