

Using a consistency factor for detection and attribution of anthropogenic impacts on phenological phases in Germany

Sebastian Lehner^{a,b,*}, Christoph Matulla^b, Helfried Scheifinger^c

^a*Department of Meteorology and Geophysics, University of Vienna, Vienna, Austria*

^b*Climate Impact Team (CIT), Zentralanstalt für Meteorologie und Geodynamik (ZAMG), Vienna, Austria*

^c*Customer service Section Climate, Zentralanstalt für Meteorologie und Geodynamik (ZAMG), Vienna, Austria*

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*Corresponding author

Email address: `sebastian.lehner@zamg.ac.at` (Sebastian Lehner)

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1 **Abstract**

2 An important consequence of climate change is the impact on the seasonal
3 cycle of vegetation flora and fauna. Although it is generally understood that
4 anthropogenic mechanisms play a major role in the warming trend of the
5 climate and that the timing of such phases, especially spring timing events,
6 depends largely on the temperature, the link has yet to be quantitatively
7 shown for different kind of areas on a regional scale, due to high intrinsic
8 noise.

9 In this study, an end-to-end analysis to external forcings was carried out,
10 linking the earlier timing of phenological spring timing events to changed
11 climate conditions (increasing temperature) and this change in the environ-
12 ment to anthropogenic forcing, for the region of interest: Germany.

13 Besides a large ensemble originating from six different General Circulation
14 Models (GCMs), driven with various kinds of forcings, the E-OBS data set
15 was used as observational reference for near-surface air temperature and the
16 PEP725 for phenological observations. The latter contains over 100 differ-
17 ent phenological phases, from which - after quality checking - 12 phases are
18 evaluated.

19 To overcome the scale differences, a quantile mapping bias correction ap-
20 proach was used to downscale the GCM data. The generation of simulated
21 phenological time series was done with a temperature-day-sum model, which
22 had to be calibrated and optimised beforehand.

23 The signal-to-noise ratio was increased by generating samples of 50-year run-
24 ning trends, which make up the basis for the statistical evaluation. U-values
25 from the Mann-Whitney U-Test represent the foundation, on which the null

26 hypothesis for detection, that the observed changes can be explained with
27 naturally forced climate conditions only, was tested. Based thereupon, a
28 newly defined consistency factor was constructed, which allowed the assess-
29 ment of anthropogenic impact on phenological phases. Observed changes in
30 phenological phases were successfully attributed to anthropogenic impacts.

31 **1. Introduction**

32 Detection is the process of showing that an observed change in some vari-
33 able is significantly different from what is expected, if only internal climate
34 variability or naturally forced climate states are considered. Formulated in a
35 statistical sense, this boils down to test if the null hypotheses, that observed
36 changes can be explained by internal variability or naturally forced condi-
37 tions alone, has to be rejected. In the attribution part, it has to be shown
38 that this discrepancy - if found - is consistent with a combination of other,
39 differing kind of forcings and that it is inconsistent with remaining physi-
40 cally plausible explanations, which exclude the forcings investigated before
41 (see e.g. Hegerl et al. (2010); IPCC-AR5 (2014)).

42 There has already been quite some work done in assessing the fingerprint
43 of human activity on different elements of the biosphere and on more gen-
44 eral detection and attribution tasks covering all aspects of the climate system.
45 Related to meteorological variables, such as temperature, precipitation or cir-
46 culation systems, especially the focus on extreme event attribution, assessing
47 the change in likelihood and/or magnitude due to anthropogenic impacts, has
48 gained a lot of a traction (see e.g. Walther et al. (2002); Ahas et al. (2002);
49 Root et al. (2003), Menzel et al. (2006); Rosenzweig et al. (2008) for the for-

50 mer, or Hegerl et al. (1997); Karoly et al. (2003); Stone et al. (2009), Dean &
51 Stott (2009) Rosenzweig & Neofotis (2013); Stott et al. (2016) for the latter).
52 We considered here the task of investigating long-term shifts in phenological
53 timing events, hence extreme detection and attribution techniques are not
54 useful for our goal.

55 The number of detection and attribution studies has been increasing during
56 the last 20 years. This is largely due to improvements of General Circula-
57 tion Models (GCMs), as well as the fact, that with time, a potential human
58 influence on the climate is more likely to be observed and finally, that espe-
59 cially in recent years, public interest in attribution questions have increased
60 significantly. In general, the smaller the region, the more difficult the de-
61 tection as well as the attribution. The reason therefor being, that random
62 noise components represent a relatively larger part of an observed signal, or
63 in other words, variability of climate variables is inversely proportional to
64 the size of their respective region they represent. To overcome this issue,
65 the signal-to-noise ratio has to be increased (Hegerl et al. (2010); IPCC-AR5
66 (2014)). In this study, the goal was to circumvent this issue with the use of
67 long-term trends (see e.g. Scheifinger et al. (2003)).

68 Combining detection and attribution is a natural step in analysing chang-
69 ing patterns of observed plant species developments. Phenological station
70 records were investigated and tested, if the observed change in entry dates
71 can be explained by internal climate variability and/or naturally forced cli-
72 mate conditions alone. Twelve different phenological phases were inspected,
73 which range from early spring to late summer timing, thus covering a large
74 part of the vegetation cycle.

75 The analysis is considered an end-to-end analysis based on Stone et al. (2009).
76 This implies differently forced climate model output variables are used and
77 fed in an ecological model, from which the output is evaluated. To capture
78 all needed information, an ensemble consisting of multi-model 'pi-Control',
79 'historical' and 'historicalNat' GCM experiments was needed. On the other
80 end of the spectrum, a phenological temperature-day-sum model was used
81 to generate simulated entry dates from temperature series (see Hunter &
82 Lechowicz (1992), Chuine et al. (1998, 1999, 2000) or for a more general
83 overview in plant development models Chuine et al. (2003)). In general,
84 before temperature data from the GCMs can be used on a regional scale,
85 the data has to be downscaled. Variables in the GCM domain represent
86 the large-scale state, but to be able to compare them to E-OBS data and
87 the phenological observations, they must be transferred to the local-scale.
88 This was done via a quantile mapping bias correction approach, applied on
89 a daily basis, where the E-OBS observational data was used as reference,
90 or '*true state*' (see Panofsky et al. (1958), Maurer (2010), Abatzoglou &
91 Brown (2012), Thrasher et al. (2012), Maurer et al. (2013)). Important
92 aspects regarding the use of models and their associated uncertainties are
93 discussed in Hegerl & Zwiers (2011). The resulting entry dates time series
94 from the phenological model were then subject to the calculation of run-
95 ning 50-year trends. Furthermore, the Mann-Whitney U-Test was used as
96 statistic measurement tool to assess the null hypothesis (Mann & Whitney
97 (1947); Wilcoxon (1947, 1992)). It is a non-parametric statistical test about
98 homogeneity, which checks the significance whether two distributions origi-
99 nate from the same basic population. Here, it was adapted for the detection

100 of a discrepancy between observations and internal or naturally forced cli-
101 mate conditions, which can be assessed using the significance of the resulting
102 U -values from two tested samples. Additionally, the U -values were then used
103 to define a, so called, *consistency factor*, which takes into account two sig-
104 nals and compares the overlap/distinctness of those two to a third signal
105 (e.g. observations). The constructed *consistency factor* represents how con-
106 sistent the third signal is with the distinctness of the former two. Using
107 naturally forced data as one sample and the combined anthropogenic & nat-
108 urally forced as second, the distinctness between those two represents the
109 anthropogenic impact (neglecting physically possible interactions). Hence,
110 the resulting factor for consistency validates if the observations are consis-
111 tent when anthropogenic forcing is included (consistency hypothesis). The
112 same procedure was applied to naturally forced and 'piControl' experiments,
113 to evaluate the impact of natural forcing.

114 Used data is presented in section 2 and the adapted methods in section 3.
115 The quantile mapping bias correction approach is explained in section 4 and
116 section 5 is devoted to the optimisation, calibration and validation process
117 of the phenological model. The detection analysis is shown and discussed in
118 section 6 and the attribution issue in section 7. Finally, the paper ends with
119 concluding remarks containing an outlook.

120 **2. Data**

121 A range of different data was needed to fulfill the set out tasks. For phe-
122 nological data, the PEP725 data set was used (Templ et al., 2018). As ob-
123 servational reference, the gridded E-OBS data was employed (Haylock et al.,

124 2008; Hofstra et al., 2008; Van den Besselaar et al., 2011). Large-scale infor-
125 mation was utilised from six different GCM models, each providing a small
126 ensemble on naturally, internally and anthropogenically & naturally (com-
127 bined) forced conditions (Taylor et al., 2012).

128

129 *2.1. Phenological Station Observations*

130 The PEP725 data set (Templ et al., 2018) is a large, to some extent
131 quality-controlled, collection of phenological station data for Europe. It con-
132 sists of more than 100 different phenological phases, more than 20000 reg-
133 istered stations (in the form of latitude, longitude, altitude) and dates back
134 into the 19th century. For this study, because of availability and quality
135 reasons, only data from 1951 onward is exploited.

136 An example for the general spatial distribution can be seen in figure 1. For
137 the most part, this (stationary image due to averaging) mirrors the over-
138 all distribution in space and time quite accurately. Although not explicitly
139 shown, the latter is true, due to a large number of observations being present
140 each year (the United Kingdom being the only exception, where data was
141 observed only in the last couple of decades). The recorded quantity has been
142 decreasing over the last decades, however, this decline is not of significance,
143 relative to the overall amount of information available and much more im-
144 portantly, this reduction has no spatial component and happens everywhere
145 to approximately the same extent.

146 First, all of the available phenological data was sieved by a few characteris-
147 tics, namely:

148 (i) spatial homogeneity over time,

149 (ii) enough observations per year to guarantee statistical robustness,
150 (iii) phenological observations which are mainly responsive to temperature.
151 While (i) & (ii) act as general restrictions on the availability of the data and
152 are quite straightforward, the last point has to be explicitly checked for. The
153 reason for (iii) as criterion is simply a consequence of the temperature-day-
154 sum model. Phases with complex interactions between other meteorological
155 or non-meteorological factors (often autumn phases) cannot be modeled as
156 well with such a model, as those which are mainly responsive to temperature
157 (for responsiveness of ecological systems see e.g. Walther et al. (2002); Menzel
158 et al. (2006)). Running 30-year trends of entry dates in compliance with
159 temperature trends for the same region serve as measure. If the third quartile
160 of those trends is negative, the phase is determined to be responsive enough
161 (not shown explicitly here). The twelve phases leftover are listed in table 1.
162 To guarantee statistical robustness, only Germany provided a large enough
163 record in time and space for these phenological phenomena. The earliest
164 long term mean entry date is 110.53 for *Taraxacum officinale* - beginning of
165 flowering and the latest 244.58 for *Sambucus* - first ripe fruits, hence, a major
166 part of the vegetation period from early spring to late summer is covered.
167 However, note that they are not equally distributed. Most of the phases
168 occur before the summer solstice. The observed change in distribution from
169 1951-1970 to 1996-2015 is shown in figure 2.

170 *2.2. E-OBS - Observational data*

171 Near-surface air temperature from the E-OBS data set (v17.0) provides
172 gridded, observational, 'local-scale' information on a daily basis. It is avail-
173 able on a 0.25 degree regular lat-lon grid and covers 25N-75N x 50W-75E,

174 extending from 1950 onward. Average temperature as well as altitude infor-
175 mation for each grid-point was used. The data set contains only valid values
176 over land. For more information on the data itself, see e.g. Haylock et al.
177 (2008); Hofstra et al. (2008); Van den Besselaar et al. (2011). The spatial
178 range was dependent on the GCMs and is listed below.

179 The temperature data serves as a reference for bias correcting the GCMs, as
180 well as for the optimisation process, which is needed to derive the phenolog-
181 ical model parameters. Furthermore, the modeled phenological entry dates
182 - driven with E-OBS data - represent the observational state onto which
183 the GCM data is evaluated against in the statistical analysis. The altitude
184 information is used for a multiple linear regression model relating latitude,
185 longitude and altitude to phenological entry dates and is explained in more
186 detail in section 3.

187 *2.3. General Circulation Models - CMIP5*

188 A range of different models and experiments from the CMIP5 (Coupled
189 Model Intercomparison Project Phase 5, see Taylor et al. (2012)) was used,
190 delivering the large-scale information for near-surface air temperature. To
191 be able to assess different impacts on phenological entry dates, data sets
192 with distinct underlying forcings were needed. The 'piControl' (pre-industrial
193 Control) experiment is the foundation of every GCM and was used to de-
194 termine internal climate variability. To be able to evaluate the impact from
195 natural forcing, (e.g. volcanic activity, solar variability) 'historicalNat' ex-
196 periment runs were used and compared with 'historical' ones, which are ad-
197 ditionally driven by anthropogenic factors (e.g. greenhouse gases).

198 A short overview of all available GCMs is shown in table 2. The differing

199 spatial resolution between the models has to be taken into account. Further-
200 more, according to e.g. Von Storch et al. (1993), Tett et al. (1999), Stott
201 et al. (2000), a certain minimum threshold of grid-points per GCM should
202 be considered. Approximately 8 x 8 grid boxes are the minimum quantity, in
203 order to capture the necessary state of a system condition adequately by a
204 GCM in general. A bounding box with extents [0,20]°E & [42,58]°N, is used
205 to spatially average the data, which is deduced from the compromise that
206 enough GCM grid-points are covered, while being as close as possible to the
207 spatial extent posed by the phenological station observations.
208 More general information on GCMs and their characteristics can be found
209 in the Taylor et al. (2012) & IPCC-AR5 (2014) and for specific models in
210 Bentsen et al. (2013) & Voltaire et al. (2013) - NorESM1-M & CNRM-CM5
211 respectively.

212 **3. Methods**

213 *3.1. Quantile mapping bias correction*

214 For the consistency analysis, all of the data was spatially averaged, to gen-
215 erate representative time series for Germany. Therefore, the different data
216 sets had to be made comparable to each other, so that they conform to a
217 matching statistic (GCM - large-scale, E-OBS - local-scale). This downscal-
218 ing process was done through a quantile mapping bias correction. For this
219 application on temperature data, this method retains sufficient skill, hence
220 there is no need in heading for more sophisticated downscaling techniques
221 (which would probably be required when working with e.g. precipitation
222 data (see e.g. Thrasher et al. (2012))).

223 The GCM and E-OBS data sets were detrended in a two-way fashion, with
224 the first period being 1950-1985 and the second 1986 onward until the end of
225 the respective available time range (shifting means were accounted for), to
226 remove instationarities (the observed, non-linear trend characteristic). The
227 bias correction follows the general approach in e.g. Thrasher et al. (2012) and
228 was done on a daily basis. For every yearday, the distribution of mean daily
229 temperature from a model was modified such that it matches that of the ob-
230 servations. Therefore, the model as well as the observational data were sorted
231 and the corresponding empirical cumulative distribution functions (ecdf) cal-
232 culated. The resulting ecdf for the GCM data, was then interpolated in a
233 piecewise linear fashion to the GCM model. In the next step the observed
234 ecdf (from the E-OBS data) was inverted. This was done via reversing x and
235 y in the linear interpolation, hence determining the interpolants for the bins
236 located at the observational ecdf and evaluated at the GCM model ecdf val-
237 ues. The resulting ecdf is then the corrected distribution for the GCM model
238 values, which have to be sorted back to the original time of each point.

239 *3.2. Phenological station data to E-OBS grid*

240 First, the phenological station data had to be brought to the E-OBS grid.
241 Therefor, a multiple linear regression model (depending on latitude, longi-
242 tude and altitude) was derived. For every E-OBS grid-point in Germany, all
243 observations within a 100 km radius were either averaged - if the altitude dif-
244 ference of the phenological stations was less than 100 m to the corresponding
245 grid-point, or, if the altitude difference was more than 100 m, corrected with
246 the altitude coefficient derived from the MLR model. Latitude and longitude
247 do not need to be corrected in the same fashion, because they exhibit no sig-

248 nificant dependency to the entry date, for the region of interest. Quantiled
 249 entry dates in relation to binned latitude, longitude and altitude ranges are
 250 shown in figure 3. The variability of the entry dates along latitude and lon-
 251 gitude can be explained when taking into account the average topography
 252 in each respective bin (not shown). Hence, for the regional extent discussed
 253 here, only the effect of altitude was of significance when aggregating data
 254 from different heights. Altitude regression coefficients from the MLR model
 255 are shown in table 3.

256 3.3. Phenological Model

257 Phenological (especially spring time) phases correlate highly to the tem-
 258 perature development for a given year on a daily basis. A simple temperature-
 259 day-sum model according to Chuine et al. (1999) consists of the following
 260 parts. The entry date y is determined such that

$$f_c(y) = F^* \tag{1}$$

261 with

$$f_c(t) = \sum_{t_0}^t R_f(x_t) \tag{2}$$

262 where f_c is the state of forcing, F^* is a critical forcing state value describing
 263 the transition to the phase occurrence, $R_f(x_t)$ is the forcing rate function
 264 for the average daily temperature x_t on day t and t_0 is the starting date of
 265 summation. The forcing rate function (or development rate) is a simple step
 266 function of the form

$$R_f(x_t) = \begin{cases} 0 & \text{if } x_t \leq T_b \\ x_t - T_b & \text{if } x_t > T_b \end{cases} \tag{3}$$

267 with T_b the base temperature. Three parameters need to be determined
268 for the model to work properly: the starting day t_0 , the base temperature
269 T_b and the critical forcing state value or summation threshold F^* . Using
270 phenological and temperature observations, the optimal set of parameters
271 can be attained with an optimisation process. A brute force (due to a feasible
272 amount of calculation needed) and a probabilistic algorithm were applied for
273 this task (see Metropolis et al. (1953) for the latter). Due to temperature
274 being the only driving factor, the model is very sensitive to shifts in the
275 input series. Therefore, if using an optimised model for a different range
276 (climatology) of temperature series, the goodness of the results can not be
277 guaranteed. Consequently, it is important that temperature series using the
278 same set of parameters should exhibit statistics comparable to the reference
279 series from which the optimal parameters were derived. Note that, although
280 the model itself might be quite simple, it nevertheless works very well for
281 temperature-responsive phases, which are – by design – investigated here.

282 *3.4. Detection and attribution technique*

283 The Mann–Whitney U test is a non parametric statistical test, which ex-
284 amines homogeneity between two samples (Mann & Whitney (1947); Wilcoxon
285 (1947, 1992)). A few assumptions are implied: (i) the two samples are in-
286 dependent of each other, (ii) the data corresponds to some ordinal scale i.e.
287 a rank can be associated to each sample, to determine which is greater in a
288 statistical sense, (iii) the null hypothesis H_0 for which the test is done, sug-
289 gests that both signals originate from the same basic population and (iv) the
290 alternative hypothesis H_1 leads to the original distributions being not from
291 the same basic population. All of these assumption were readily fulfilled.

292 Technical details can be found in e.g. Schönwiese (2013).

293 After ranking the trend values of two data sets ('historical': H and 'historical-
294 Nat': N), which were compared, the corresponding U values were calculated
295 as follows:

$$U_X = R_X - \frac{(n_X(n_X + 1))}{2}, \quad (4)$$

296 where U_X is the U value for the trends of the data set X (i.e. either H or
297 N), R_X is the rank sum of X and n_X is the corresponding sample size.

298

$$U_{HN} = \min(U_H, U_N) \quad (5)$$

299 represents the minimum of both calculated U values and is an indication
300 about the overlap of two distributions. U_{HN} can then be normalised with
301 the total number of samples multiplied with each other:

$$U_{HN}^* = \frac{U_{HN}}{n_H n_N} \quad (6)$$

302 This spans the U^* value in a range between 0 and 0.5. A value of 0 suggest
303 no, 0.5 maximum overlap of the sample distributions. Based thereupon, a
304 'consistency factor' can be defined:

$$c = (0.5 - U_{HN}^*) + 2 U_{HO}^* (0.5 - U_{HN}^*), \quad (7)$$

305 where U_{HO}^* corresponds to the U^* value derived between the two samples
306 H 'historical' and O observations. The first term on the right-hand side
307 represents the difference between the distributions of the two signals - one
308 being the 'historical', the other the 'historicalNat' trends - in the form of U_{HN}^* ,
309 subtracted from 0.5. Thus, the whole term is large for no overlap between
310 the two samples and small the other way around. In the second term, the

311 difference between observations and historically forced runs, U_{HO}^* , is weighted
312 with the former term, which represents - in this case - the anthropogenic effect
313 (distinctness between 'historical' and 'historicalNat'). Therefore, c represents
314 how consistent the observations are with anthropogenic forcing.

315 The value range for the consistency factor is $[0, 1]$ and following, three cases
316 are outlined here:

317 (i) If the trend distributions of the 'historical' and 'historicalNat' forced
318 runs are different, U_{HN}^* will be close 0, hence the first term close to 0.5.
319 Depending on the similarity of observations and 'historical' distribu-
320 tions, in the optimal case - for matching pdfs - U_{HO}^* will be close to 0.5
321 resulting in the consistency factor being close to 1 (1 being the perfect
322 score).

323 (ii) If U_{HN}^* is close to 0.5, natural forcing prevails and the first as well as the
324 second term will both be close to zero, regardless of the value of U_{HO}^* .
325 The interpretation in this case is, that the two signals do not allow a
326 distinction between each other, thereby disallowing possible attribution.

327 (iii) For U_{HN}^* and U_{HO}^* both being close to 0, the resulting consistency fac-
328 tor will be around 0.5. Although detection can be successfully reached
329 (if the observations are distinct from the 'historicalNat' and 'piControl'
330 distributions), attribution might not be completely clear. A look at the
331 trend distributions themselves can help deduce a concluding statement.
332 E.g. there could be a case, where the anthropogenic forcing is visible
333 and causes a shift in the direction of the observations, but the ampli-
334 tude may be too small to be statistically consistent. Furthermore, it is
335 important to not only look at the value of c in a nutshell, but to plot

336 it, using the U^* values on the x and y axis, which will be discussed in
 337 section 7.

338 Furthermore, adding a naming convention for c in the above case for clarity
 339 (equation 7): $c = c_{HNO}$, then c_{NPO} and c_{HPO} (see equation 8 and 9 respec-
 340 tively) can be computed as well, which were used to test the consistency
 341 for physically plausible alternatives. This convention reads as follows: c_{xyz}
 342 represents the consistency factor for which the distinctness between x and y
 343 acts as weighting on the distinctness between x and z , thereby assessing the
 344 consistency between x and z .

345 To summarise, first of all, a successful detection is achieved, if the U^* values
 346 between the observations and 'historicalNat' as well as between observations
 347 and 'piControl' are not significant based on the Mann-Whitney U Test, in-
 348 dicating they originate from different underlying distributions. Second, the
 349 consistency factor allows the assessment which forcing - if any - is consis-
 350 tent with observations, thereby attributing the observed change to a cause.
 351 Although as mentioned above, to grasp the full picture, the c values should
 352 always be plotted using their U^* values, a threshold of $c = 0.5$ was derived
 353 using synthetic data (not shown), which can be used for a quick evaluation.
 354 If $c > 0.5$, attribution is suggested.

$$c_{NPO} = (0.5 - U_{NP}^*) + 2 U_{NO}^* (0.5 - U_{NP}^*), \quad (8)$$

$$c_{HPO} = (0.5 - U_{HP}^*) + 2 U_{HO}^* (0.5 - U_{HP}^*), \quad (9)$$

355 4. Preparing the GCM data

356 4.1. Characteristics of GCMs

357 Although GCMs simulate atmospheric and oceanic circulation on the ba-
358 sis of dynamical equations, the coarse resolution prevents the explicit treat-
359 ment of sub-scale processes, which hence have to be parameterised. This in-
360 turn, can lead to errors in modeling processes happening on smaller - not
361 resolved - scales. First of all, the characteristics of the different GCM tem-
362 perature series are investigated. Reasonable modeling results can only be
363 guaranteed, if the GCM temperature data exhibits no systematic biases to
364 the reference data, from which the phenological model was calibrated (E-
365 OBS data).

366 Inter-year distribution of temperature and especially the development up to
367 the entry-date of a phenological phase has a big impact on the phenological
368 model results. If the temperature in the weeks before an entry-date features
369 a positive Bias, the model prediction will always tend to generate earlier
370 entry-dates, resulting in a negative Bias for simulated phases. Because of
371 this sensitive interaction, the day-to-day distribution of near-surface temper-
372 ature is of high importance and therefor the bias correction has to be made
373 on a daily basis.

374

375 4.2. Bias corrected GCM data

376 10 year averaged mean year E-OBS data with a rolling 45 day filter uncov-
377 ers the non-linear trend over the period of interest (not shown). Furthermore,
378 before the correction was applied, the time series were made to be stationary.

379 To incorporate the former issue into the bias correction, the detrending was
380 split up into two unique periods, the first being 1950-1985 and the second
381 1986 onward until the end. Note that 'until the end' loosely refers to the
382 end of the congruent period between a single GCM run and the E-OBS data.
383 So e.g., if said run features data until 2005, E-OBS data afterwards was not
384 considered, in order to exclude possible errors arising from detrending based
385 on data which is not included in the Bias correction itself.

386 Figure 4 shows the Root Mean Square Error (RMSE) for mean near-surface
387 temperature per year/day (over the full time span) for the 'historical' GCM
388 ensemble (blue) and the 'historicalNat' GCM Ensemble (green) with respect
389 to E-OBS data. Dashed lines correspond to raw, solid lines to bias cor-
390 rected data. The corrected GCM data was then forwarded and fed into the
391 calibrated phenological model.

392 **5. Generating the simulated phenological entry dates**

393 *5.1. Optimising the phenological model*

394 As already mentioned before, three parameters - namely the start day of
395 summation (hereafter t_0), the base temperature (hereafter T_b) and the critical
396 temperature sum (hereafter F^*) - need to be optimised. Due to the nature
397 of optimisation processes, there are many iterative options available to solve
398 this problem. The two realised ways are discussed and one shown (due to
399 both methods generating comparable results). An application of the one not
400 shown - simulated annealing - can also be found in Chuine et al. (1998).

401 A quantity needs to be defined, in order to assess the quality of an optimisa-
402 tion iteration. The summed squared residual (SSR) day was used therefor,

403 which behaves similarly to the root mean square error (RMSE).
404 A very straightforward optimisation way is a, so called, brute force algo-
405 rithm, in which the domain spanned by the three parameters is sampled and
406 every possible combination is tested. The potential downside is missing op-
407 timal values since only a discrete spectrum is computed. To overcome this
408 issue, the domain for the parameters can be determined iteratively, with e.g.
409 starting from a very coarse grid resolution, but spanning a broad range of
410 min/max value for each parameter and subsequently lowering the step size
411 as well as the min/max range to increase the tested variable pairs. Luckily,
412 because of the characteristics of the phenological model, this simple brute
413 force approach worked quite well. The domains for each respective variable
414 were chosen to be: (i) t_0 : Lower bound: 1. Upper bound: long-term mean of
415 the respective phenological phase. (ii) T_b : Lower bound: $0^\circ C$. Upper bound:
416 long-term average daily temperature of the long-term mean entry date in de-
417 gree Celsius. (iii) F^* : Lower bound: $10^{2^\circ C}$. Upper bound: $10^{4^\circ C}$ to $10^{5^\circ C}$,
418 depending on the phenological phase. F^* has a more abstract characteris-
419 tic. For this parameter, simply starting very low (plant development time
420 spanning a couple of days) and iteratively working towards the optimum –
421 as described above – worked best. The parameter phase space for *Aesculus*
422 *hippocastanum* - leaf unfolding can be seen in figure 5. The valley like range
423 of comparable *SSR* values is apparent and hence, guarantees the robustness
424 of the optimisation.

425

426 For the simulated annealing approach, temperature values ranging from
427 0.2 to 20 and iterations from 50 to 200 were tested. The step range for the

428 algorithm was randomly drawn from an uniform distribution with bounds
429 $[-5,5]$ for t_0 , $[-3,3]$ for T_b and $[-2000,2000]$ for F^* . The optimal parameter
430 values derived from the brute force approach were chosen as initial condi-
431 tions. The results did not improve the optimised set of parameters derived
432 from the brute force approach, which may be again due to the phase space
433 characteristic and hence, the former result is used for further the application.

434 *5.2. Model validation*

435 The optimal set of parameters for each phase are shown in table 4. Note
436 that all except 2 phases exhibit a F^* value of 18500. With a step size of 500,
437 this suggests an optimal value between 18250 and 18750. Interestingly, the
438 other parameters vary much more, which corresponds to F^* boasting a quite
439 distinct structure where the optimum is found. This can largely attributed
440 to the time of year, where the respective phase occurs. The later the entry
441 date, the larger F^* . Although it has to be noted, that t_0 can interact in a
442 comparable way, compensating a lower F^* , with increasing values.

443 The phenological model was optimised for every E-OBS grid-point in Ger-
444 many and validated against some sampled time series. Those were chosen
445 from random grid-points and showed matching evolution in time. The three
446 parameter values did not exhibit strong dependency on space. However, this
447 might simply be due to the relatively small and topographically not too com-
448 plex spatial extent (regional scale).

449 In figure 6, simulated entry-dates using the optimised parameters and the
450 averaged E-OBS temperature data, representative for Germany, is shown.
451 SSR and the Pearson correlation coefficient are listed in each respective sub-
452 plot. This pictures an in-sample test, because of course, the same data from

453 which the parameters have been derived is used here to drive the model.
454 But nevertheless, it serves as an example how well the entry date of different
455 phenological phases can be modeled with only three degrees of freedom and
456 furthermore, no extrapolation using a completely differing input statistic is
457 sought after (were robust results would not be guaranteed). The only phase
458 for which the model performed noticeable weaker than the rest, is Sambucus
459 - first ripe fruits. This is due to the phase happening very late in the vegeta-
460 tion period - as can be seen on the ordinate - and thus incorporating many
461 complex interactions in the development process (even though temperature
462 is still the main driver). Additionally, the two phases Sambucus - beginning
463 of flowering, id=27 and Tilia - beginning of flowering, id=55, exhibit a dis-
464 tinct worse SSR and lower ρ , than all the other remaining phases, which can
465 again be associated to the longer vegetation period. Note that, however, the
466 starting date for the temperature summation in the model (t_0), is larger for
467 those later phenological phases, but this does not circumvent the intrinsic
468 uncertainty in complex evolutionary plant processes, arising from the longer
469 vegetation period.

470

471 5.3. Application to GCM data

472 Resulting phenological entry-date time series generating by feeding the
473 phenological model with the GCM data are shown in figure 7. Note that
474 especially in the first few decades, little difference between the two shown
475 experiments can be deduced. This changes in recent times, where the an-
476 thropogenic impact is much more apparent. There are some extreme outlier
477 years, were the phenological observations (modeled with E-OBS data) reside

478 outside the range of the GCM experiments. But this is simply due to the
479 shadings only accounting for one standard deviation, hence roughly 68% of
480 the full distribution. The associated simulated variance is shown in figure 8,
481 where error-bars indicate - again - one standard deviation. Contrary to the
482 time series, it can be seen that the modeled variance from the GCMs is higher
483 than that of the E-OBS realisation, picturing realistic ensemble behaviour,
484 as what would be expected. The 'piControl' GCM experiments were fed into
485 the phenological model as well. All of the generated entry-dates simulations
486 were then handed into the consistency analysis, beginning with the test for
487 the null hypothesis in the following section.

488 **6. Detection of a significant discrepancy between naturally and** 489 **internally forced climate conditions and observations**

490 Modeled phenological data is – as the observed one - very noisy, due to
491 high temperature year-to-year variations during the physiological develop-
492 ment process. To assess the underlying low frequency influence of different
493 forcings, the high frequency components have to be suppressed as much as
494 possible. Therefore, the signal-to-noise ratio was increased by calculating 50-
495 year running trends. This reduces the time series data to sets of trends, each
496 corresponding to one kind of forcing ('historical', 'historicalNat', 'piControl')
497 or to observations. Those four different categories were then subject to the
498 Mann-Whitney U-Test against each other (as outlined above).

499 Figure 9 shows the trend distributions as histogram plots with an overlying
500 Gaussian kernel density estimator. The corresponding U -values with their re-
501 spective p -values are shown in table 5. Significant values are marked therein

502 with a shaded background. For these cases, the null hypotheses cannot be
503 rejected, but has to be rejected for all other cases (no shading). For the used
504 two-tailed test, the resulting significance level is 0.05. The test itself is quite
505 sensitive to the median, therefore large distances between them propagate
506 into low p and U values (hence why the median is plotted for each sample as
507 well). It is quite apparent, that trends resulting from naturally forced condi-
508 tions or internal variability only, do not differ, in terms of the test statistic,
509 for all phases. At the same time, they exhibit a significant deviation with
510 respect to observations as well as 'historical' runs, which contain anthro-
511 pogenic forcing. The former part suggest the rejection of the null hypothesis,
512 that the observations can be explained with internal climate variability or
513 naturally forced conditions alone, hence successfully detecting the sought-
514 after discrepancy. The p and corresponding U values between observations
515 and 'historical' data show the significance of both originating from the same
516 distribution. This is true for every phenological phase but one: Sambucus
517 - beginning of flowering, which might be due to this phase happening very
518 late in the vegetation period and thereby already discussed associated un-
519 certainties. Phenological model parameters for this phase were the worst
520 overall (in terms of the optimisation metric), indicating higher modeling er-
521 ror, which could potentially cascade down into the statistical evaluation as
522 well. Furthermore, the distribution for the 'historical' experiments for this
523 phase almost shows a bimodal behaviour, which might suggest modeling is-
524 sues originating from the underlying GCMs. Lastly on this subject, this does
525 not influence forthcoming analysis in any way, as the statistical test here only
526 shows, that there is a discrepancy. Note that the median of 'historical' runs

527 is outside the 1σ range of internal climate variability, standalone indicating a
528 distinct difference between those experiments. Using 30-year running trends
529 instead of the 50-year window included much more noise, which was propa-
530 gated into the evaluation, but detection based on the same criteria was still
531 achieved for every phase (not shown).

532

533 **7. Attributing the observed change to anthropogenic causes**

534 The vital part in assessing the attribution issue is not if 'historical' GCM
535 runs are consistent with observations, which can be readily assessed e.g.
536 by the U statistics, but to show the consistency between anthropogenically
537 forced conditions and observations, while showing that other physically plau-
538 sible causes are inconsistent. Therefore, the above defined consistency factor
539 (equation 7) incorporates two experiments, from which the difference was
540 assessed (e.g.'historical' and 'historicalNat' hence, anthropogenic impact is
541 evaluated). This acts as a weighting factor which is applied to the U value
542 of the desired experiment (in the above case 'historical') together with the
543 observations. Furthermore, the alternative physically plausible consistency
544 between naturally forced conditions and observations has to be checked as
545 well, hence why the c value was calculated for all three variants mentioned
546 above: c_{HNO} , c_{NPO} and c_{HPO} . From these results, it can be deduced if (a)
547 anthropogenic forcing is consistent with observations, (b) natural forcing is
548 consistent with observations and (c) a combination of anthropogenic and
549 natural forcing is consistent with observations. These consistency factors are
550 shown in figure 10 for all phenological phases. The aforementioned threshold

551 of $c = 0.5$ is pictured as a thick, black, dashed line. From the full experiment
552 sets, 100 realisations per category were randomly drawn and thereupon c cal-
553 culated. This was repeated 10^4 times (bootstrap) from which associated con-
554 fidence ellipses were determined (two standard deviations, which is roughly
555 equivalent to the 95% confidence level). For the scatter plot itself, only a ran-
556 dom subset of all the 10^4 points is plotted, in order to not overload the figure.
557 The plots can be interpreted as follows: For c_{HNO} (blue), the scatter plot
558 corresponds to the U_{HN}^* values on the abscissa and to U_{HO}^* for the ordinate.
559 Thus, for c_{HNO} , the consistency between anthropogenic impact (distinctness
560 between 'historical' and 'historicalNat') and observations can be deduced.
561 The further the plotted values reside on the left, the greater the distinction
562 between 'historical' and 'historicalNat' categories. Furthermore, high y val-
563 ues correspond to a small distinction between 'historical' and observations.
564 What can be concluded, is that anthropogenic factors deviate significantly
565 from naturally ones and that 'historical' experiments are consistent with ob-
566 servations. The difference between the former and c_{HPO} (grey) is, that U_{HP}^*
567 is used for the abscissa location (as can be readily seen from the index con-
568 vention for c). If the resulting values reside further to the right-hand side
569 (10 out of 12 phases), the distinction between 'historical' and 'historicalNat'
570 is greater than between 'historical' and 'piControl' driven data. Thereupon
571 we can infer, that adding natural forcing onto internally forced climate con-
572 ditions, the discrepancy with regards to 'historical' increases, even though,
573 conversely, natural forcing is included in 'historical' experiment runs as well.
574 In the other case (2 out of 12 phases), the exact opposite can be reasoned.
575 When analysing the plots though, it has to be noted that both cases exhibit a

576 significant overlap, thus the reasoned statements might be disregarded as not
577 significant with respect to the overlapping area. On a more interesting note,
578 c_{NPO} (green) corresponds to U_{NP}^* on the abscissa and U_{NO}^* on the ordinate.
579 The far-right located scatter plots indicate that data driven by 'historicalNat'
580 shows no significant distinction to the one driven by 'piControl' experiment
581 runs. Additionally, the ordinate position close to the bottom signifies signif-
582 icant difference between 'historicalNat' and observations (which was already
583 assessed in the detection part, but can be seen here visually as well). Thus,
584 it is apparent from c_{NPO} (green), that natural forcing is not consistent with
585 observations, thereby failing to reveal the cause. Both c_{HNO} and c_{HPO} show
586 consistent results between associated forcings and observations. While for
587 the latter - being a combination of anthropogenic and natural forcing - there
588 would be no attribution to a single cause inferable, but when including the
589 information of c_{NPO} , it is apparent that the anthropogenic forcing is the only
590 underlying cause that is consistent with observed behaviour.

591

592 8. Concluding remarks

593 First of all, the resulting 12 phenological phases for Germany and the re-
594 spective parameter optimisation were found to be quite homogeneous across
595 the region of interest, suggesting a representative time series can be es-
596 tablished without concern for this area. The simple brute-force approach
597 showed comparable results to the probabilistic simulated annealing optimi-
598 sation technique. Due to the nature of the phenological model parameter
599 phase space, optimal values lying inside a broad valley, robustness in the

600 optimisation performance is signified.

601 Averaged and bias corrected GCM data was found to adequately represent
602 distinctly forced climate conditions. The resulting modeled phenological time
603 series showed realistic realisations of possible climate evolutions, indicating
604 that the calibrated phenological model did not inhibit possible extremes and
605 outliers.

606 The definition of the consistency factor based on the Mann-Whitney-U-Test
607 allowed the assessment which of the underlying forcing is a cause, consistent
608 with observations. In this form, c can be especially useful if data forced by a
609 specific cause is not available in sufficient quantities, or not available at all.
610 For the presented study, this was the case for experiments with only anthro-
611 pogenic forcings. It is - together with natural forcings - however, included
612 in 'historical' experiments, which were available at a much higher quantity.
613 Together with 'historicalNat' experiments and the inclusion of their distinct-
614 ness in the consistency factor, it was possible to extract the sole impact of
615 anthropogenic forcing.

616 As shown, the calculated consistency factors and U -statistics indicate: (i)
617 A correct rejection of the null hypotheses H_0 , that the observations can be
618 explained by internal climate variability or naturally forced climate condi-
619 tions only, for all 12 evaluated phenological phases. (ii) The attribution of
620 observed phenological evolution to anthropogenic forcing. The strength of
621 the attribution statements can readily be seen from the scatter plots of the
622 different consistency factors. The presented technique allows for a fast quan-
623 titative assessment about which underlying cause of a signal is responsible
624 for an observed development. It can easily be scaled up to include more

625 distinguishable forcings, which can then be tested against each other. For
626 example, one could derive the weighting from the distinctness of more than
627 one U^* values, thereby testing multiple physically plausible forcings at once
628 (although to negate the effect of causes cancelling each other, each forcing
629 should also always be investigated alone).

630 Additionally, since thereby employed procedures directly rely on tempera-
631 tures on a sub-continental scale, the successful detection and attribution
632 carried out for phenological phases implicitly implies the same for tempera-
633 ture. Although, possible distortions from the phenological model cannot be
634 fully excluded.

635 Future work could be based on several findings contained in this study. The
636 assessment of future phenological evolution, driven with climate change sce-
637 narios (downscaled climate projections), is perhaps the most obvious appli-
638 cation. However, it has to be noted that the phenological model should be
639 validated within a broader input range, as statistic of climate projections
640 can be significantly different from current conditions. Findings regarding the
641 phenological model might be of substantial importance for an application
642 within the realm of ecology or food security. The used downscaling approach
643 as well as the established optimisation procedure required in setting up the
644 phenological model may be directly used for that purpose. Another interest-
645 ing question is whether achieved results still hold in other as well as topo-
646 graphically more complex regions, too. Apart from that, it is of course worth
647 investigating the possibility of carrying out the process of detection and at-
648 tribution further, to an even higher degree of detail. This requires analyses
649 of a wider scope of forcing factors and can possibly be done on the basis of

650 the new generation of CMIP6 GCM models. Furthermore, extreme event
651 attribution techniques can be applied to years, in which the corresponding
652 entry date exhibited extreme outlier characteristic. Lastly, the consistency
653 factor can be applied in other fields as well, as long as the requirements for
654 the Mann-Whitney U Test hold.

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662

663 **Conflict of interest**

664 The authors declare no conflict of interest.

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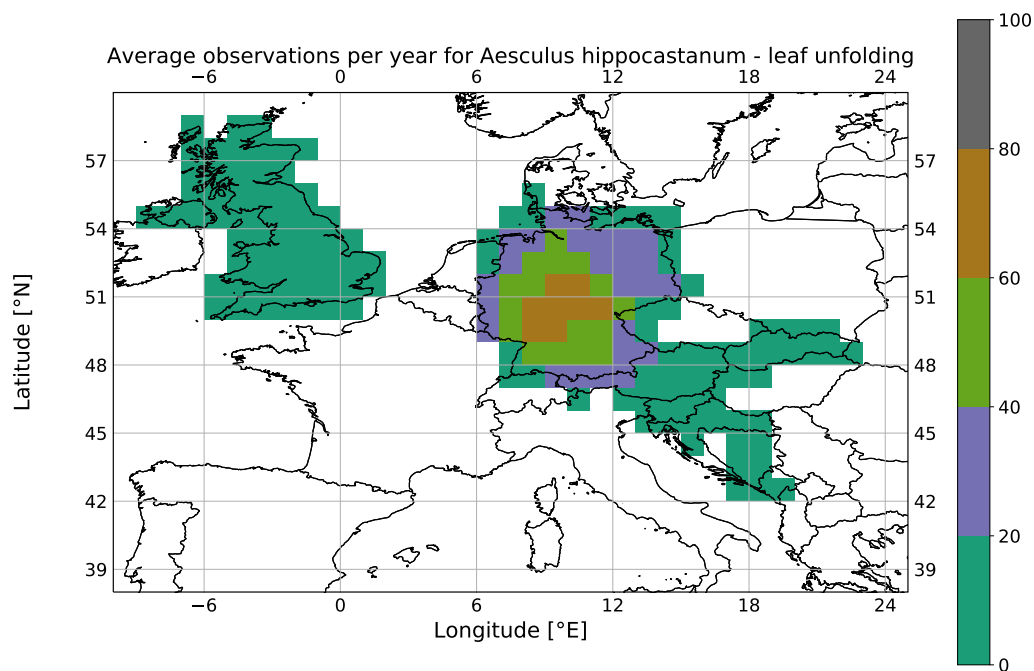


Figure 1: Average station observations per year for the phenological phase *Aesculus hippocastanum* - leaf unfolding. Note the density differences between countries. In central Europe, Germany stands out with the most dense observational record.

Pheno index	Pheno ID	Scientific name	Species name	Phase
1	101011	Aesculus hippocastanum	Horse chestnut	leaf unfolding
2	101060	Aesculus hippocastanum	Horse chestnut	beginning of flowering
11	106011	Betula	Birch	leaf unfolding
15	108011	Fagus	Beech	leaf unfolding
21	110010	Picea abies (P.excelsa)	Spruce	first leaves separated
23	111011	Quercus robur (Q.pedunculata)	Pedunculate oak	leaf unfolding
27	112060	Sambucus	Elder	beginning of flowering
29	112086	Sambucus	Elder	first ripe fruits
52	127060	Syringa vulgaris	Lilac	beginning of flowering
53	128060	Taraxacum officinale	Common dandelion	beginning of flowering
55	129060	Tilia	Linden	beginning of flowering
82	223060	Prunus cerasus	Sour cherry	beginning of flowering

Table 1: The twelve phenological phases considered for further investigation. The first column consists of a running index inside the PEP725 data set, the second one is an identification number, for which the first three digits correspond to the plant species and the last three to the phenological phase (see Meier (2001)).

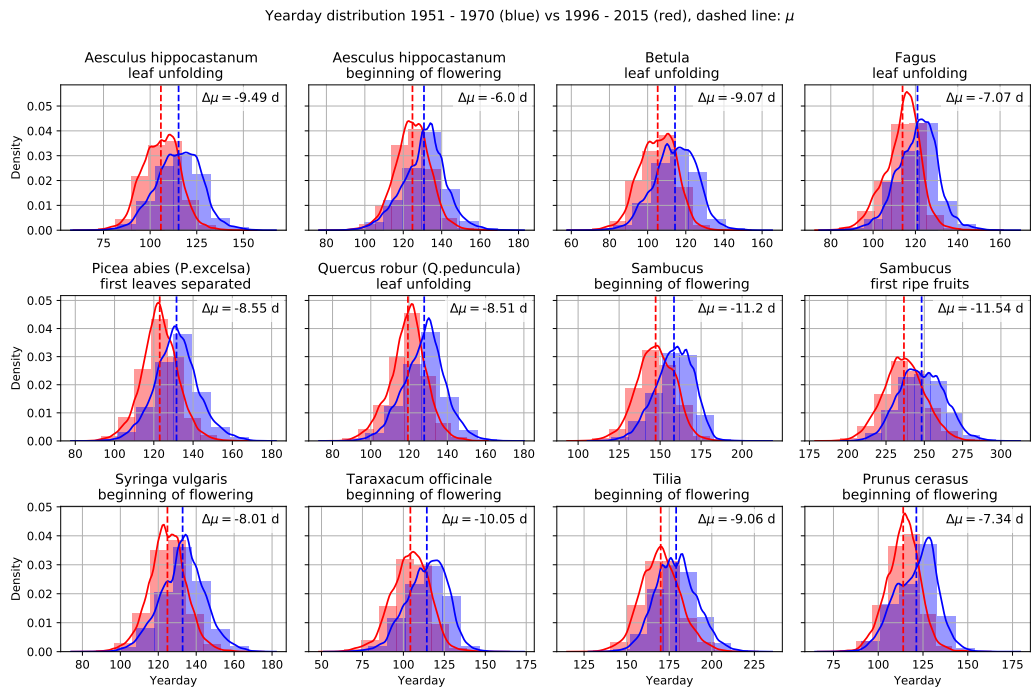


Figure 2: Change in the distribution of phenological observations between the periods 1951-1970 and 1996-2015 (spatially averaged in Germany per year).

Model	piControl	historical	historicalExt	historicalNat	spatial resolution in [°] lat x lon
CanESM2 ¹	1095	4	4	5	2.8 x 2.8
CCSM4 ²	155	-	-	4	0.9 x 1.25
CNRM-CM5 ¹	850	7	7	6	1.4 x 1.4
GFDL-CM3 ³	800	1	-	3	2.0 x 2.5
IPSL-CM5A-LR ²	1000	4	-	3	1.9 x 3.75
NorESM1-M ¹	500	3	3	1	1.9 x 2.5
Total	4400	19	14	22	

¹18500101 - 20121231, ²18500101 - 20051231, ³18600101 - 20051231

Table 2: Overview of included GCMs. The numbers in the second column 'piControl' correspond to the amount of years available, the others (columns three to five) to the quantity of ensemble members.

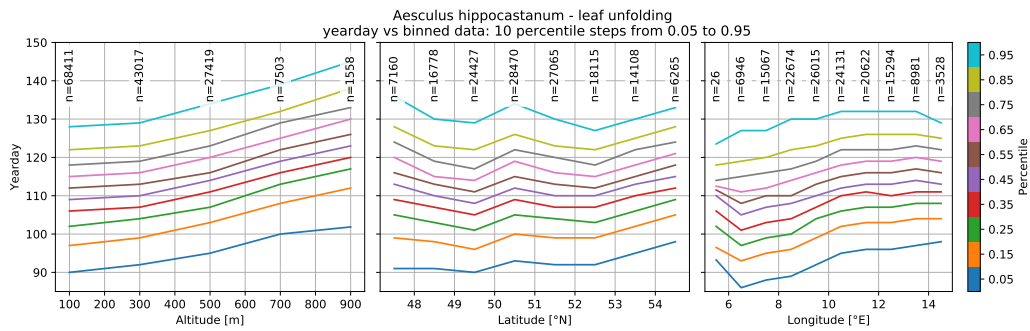


Figure 3: Quantiles of entry dates against altitude (left), latitude (middle) and longitude (right), calculated in bins of 200m, 1° and 1° steps respectively, for *Aesculus hippocastanum* - leaf unfolding. The shown numbers correspond to the quantity of observations in each bin. Lines go from the 5th percentile (bottom), in 5% steps up to the 95th percentile.

Pheno index	1	2	11	15	21	23	27	29	52	53	55	82
Coeff.	0.0131	0.0126	0.0105	0.0075	0.012	0.0117	0.0135	0.0121	0.0122	0.013	0.0172	0.0101

Table 3: Altitude regression coefficients for phenological entry dates from the MLR model. Only data under 1000m was used, as there were too few observations at higher altitudes to guarantee statistical robustness.

RMSE mean near-surface temperature (1951-2005) for GCM Ensembles, reference: E-OBS
Uncorrected (dashed), & corrected (solid)

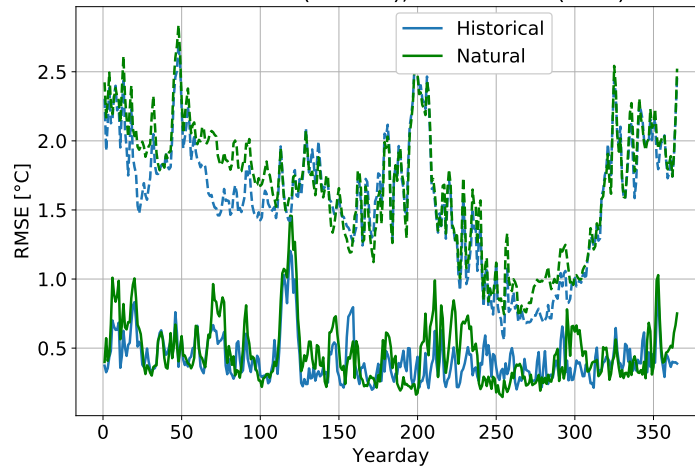


Figure 4: Root Mean Square Error (RMSE) for mean near-surface temperature per yearday (over the full time period) for 'historical' experiments (blue) and 'historicalNat' experiments (green) with respect to E-OBS data. Raw GCMs as dashed, corrected ones as solid lines.

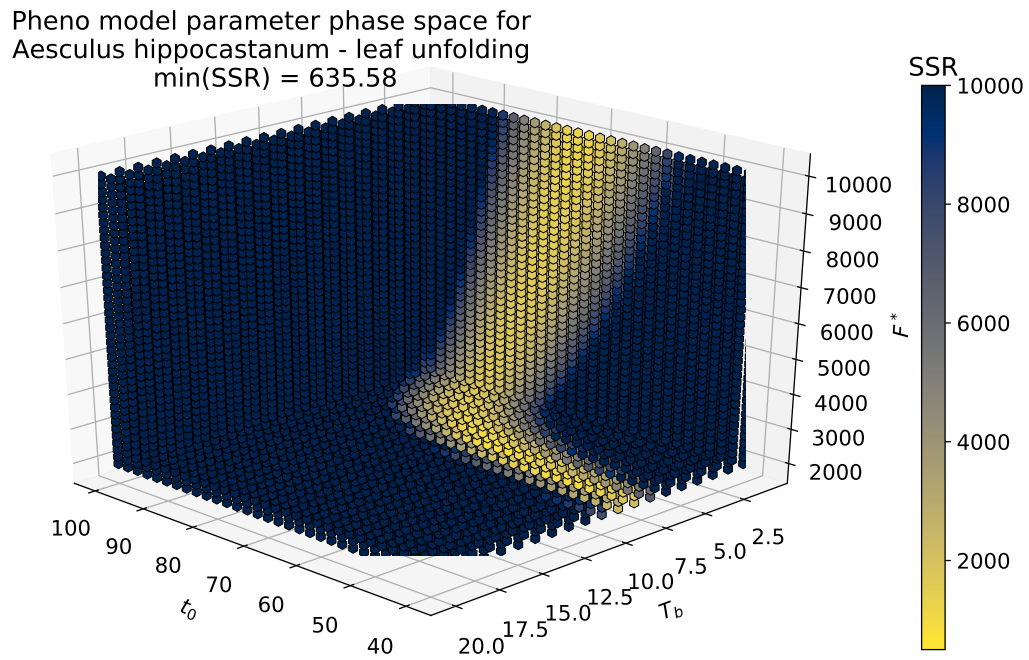


Figure 5: Phenology model parameter phase space for the three parameters to be optimized for *Aesculus hippocastanum* - leaf unfolding. The coloring corresponds to SSR (summed squared residuals) values, hence lower values represent higher agreement between the model and observations.

Pheno index	t_0 [d]	T_b [$^{\circ}C$]	F^* [$^{\circ}C$]	SSR
1	26	1	16000	525
2	11	5	18500	377
11	16	1	18500	307
15	36	1	18500	371
21	26	4	18500	464
23	31	3	18500	342
27	61	7	18500	1299
29	117	6	86000	2275
52	16	5	18500	572
53	1	2	18500	696
55	91	9	18500	906
82	26	2	18500	558

Table 4: Optimal set of phenological model parameters for the twelve phenological phases.

Observed pheno time series (red) vs modelled (E-OBS data, dashed black)

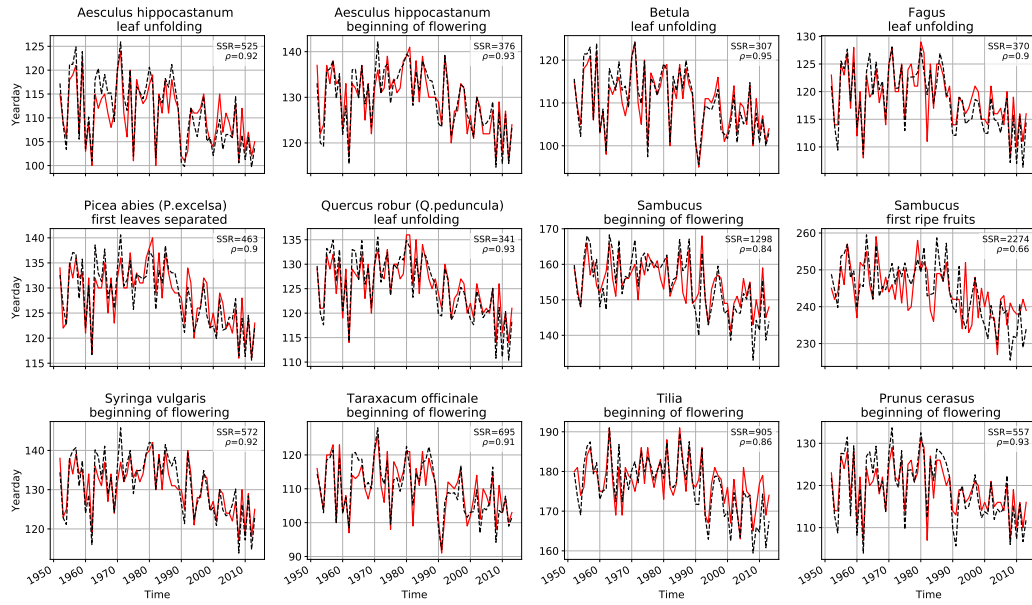


Figure 6: Phenological time series model validation: Observations (red) and modelled E-OBS data (dashed black) averaged over Germany. *SSR*: summed squared residuals between observations and model; ρ : pearson correlation coefficient.

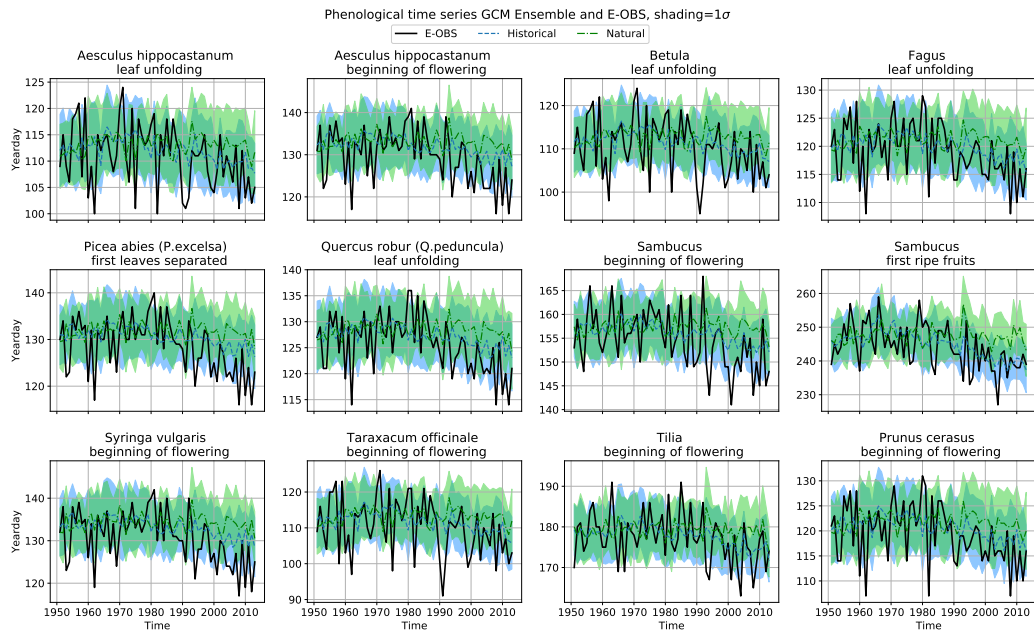


Figure 7: Modelled phenological entry-date time series for 'historical' GCMs (blue), 'historicalNat' (green) - both bias corrected - and E-OBS (black) data. Shading indicates one standard deviation.

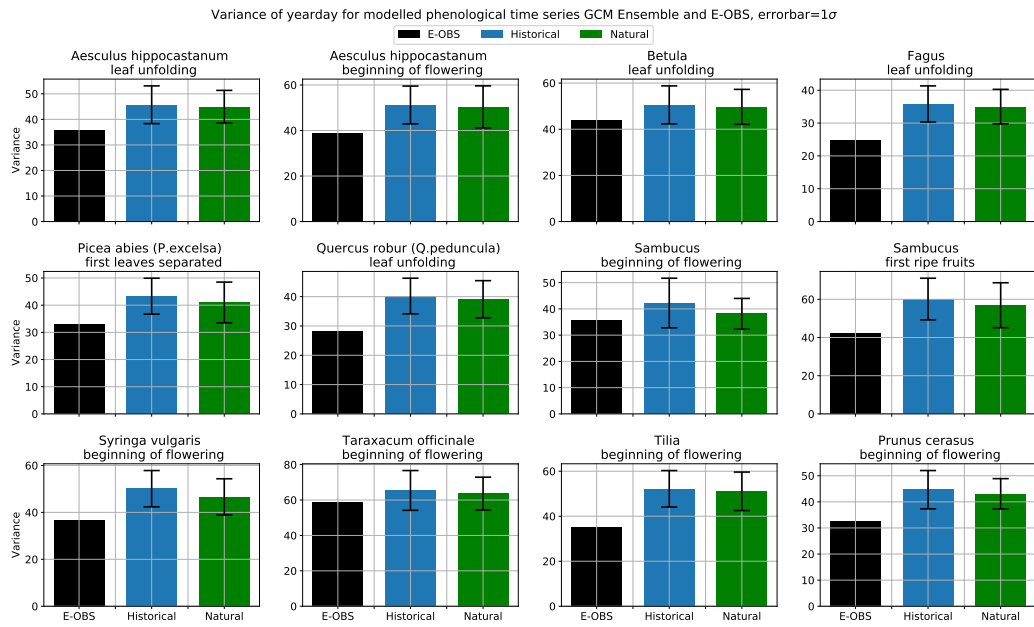


Figure 8: Variance of modelled entry dates for data as in figure 7. Errorbars indicate one standard deviation.

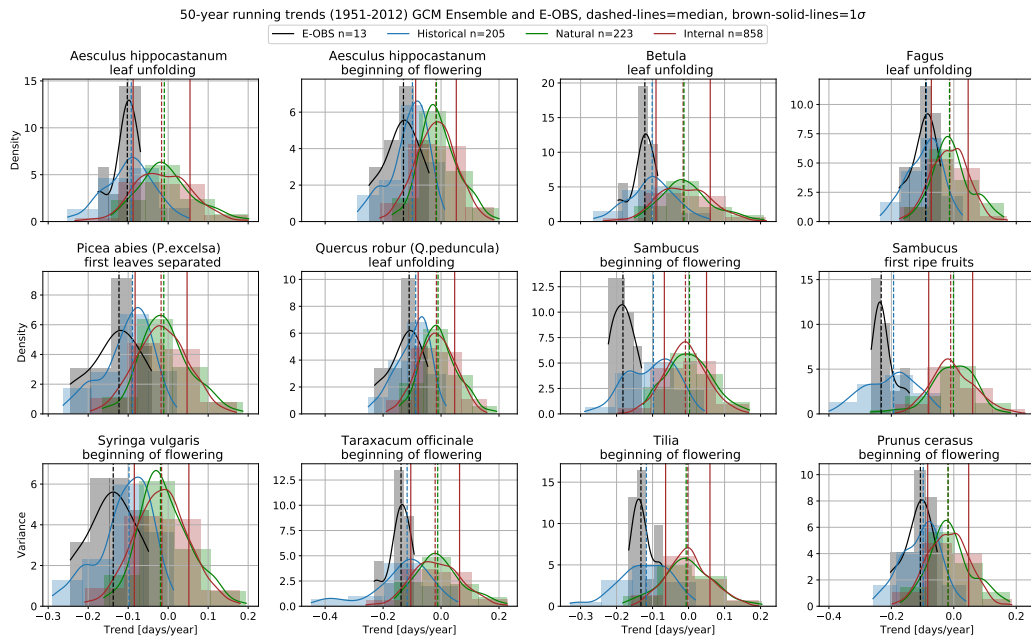


Figure 9: 50-year running trend distributions for E-OBS (black), 'historical' (blue), 'historicalNat' (green) and 'piControl' experiments (brown). Associated statistical analysis of the Mann-Whitney U-Test is shown in table 5. Dashed lines indicate median values of their respective distribution, solid brown vertical lines one standard deviation for internal climate variability ('piControl' experiments).

Mann-Whitney U-Test results for detection, grey background: Null hypothesis cannot be rejected (two-tailed Test)

Aesculus hippocastanum leaf unfolding			Aesculus hippocastanum beginning of flowering			Betula leaf unfolding			Fagus leaf unfolding		
M-W U-Test	p	U^*	M-W U-Test	p	U^*	M-W U-Test	p	U^*	M-W U-Test	p	U^*
hist & nat	1.95e-36	0.15	hist & nat	8.10e-43	0.12	hist & nat	1.07e-36	0.15	hist & nat	1.41e-38	0.14
hist & pic	3.29e-45	0.18	hist & pic	1.96e-50	0.16	hist & pic	3.76e-46	0.18	hist & pic	4.97e-52	0.16
hist & eobs	3.41e-01	0.42	hist & eobs	1.42e-01	0.38	hist & eobs	7.04e-02	0.35	hist & eobs	6.80e-01	0.47
nat & pic	1.50e-01	0.47	nat & pic	7.71e-02	0.46	nat & pic	2.64e-01	0.48	nat & pic	3.77e-01	0.48
nat & eobs	1.79e-07	0.07	nat & eobs	1.49e-07	0.07	nat & eobs	1.81e-08	0.04	nat & eobs	6.31e-07	0.09
pic & eobs	7.44e-07	0.10	pic & eobs	9.91e-07	0.10	pic & eobs	8.56e-08	0.07	pic & eobs	1.73e-06	0.11
Picea abies (P. excelsa) first leaves separated			Quercus robur (Q. pedunculata) leaf unfolding			Sambucus beginning of flowering			Sambucus first ripe fruits		
M-W U-Test	p	U^*	M-W U-Test	p	U^*	M-W U-Test	p	U^*	M-W U-Test	p	U^*
hist & nat	4.80e-41	0.12	hist & nat	4.55e-40	0.13	hist & nat	6.15e-41	0.13	hist & nat	1.59e-61	0.04
hist & pic	1.16e-49	0.17	hist & pic	5.90e-50	0.17	hist & pic	1.60e-57	0.14	hist & pic	1.06e-101	0.02
hist & eobs	9.25e-02	0.36	hist & eobs	1.29e-01	0.37	hist & eobs	4.57e-05	0.16	hist & eobs	2.93e-01	0.41
nat & pic	1.09e-01	0.47	nat & pic	1.12e-01	0.47	nat & pic	6.72e-02	0.46	nat & pic	6.99e-01	0.49
nat & eobs	1.46e-07	0.07	nat & eobs	1.49e-07	0.07	nat & eobs	1.40e-09	0.00	nat & eobs	5.83e-09	0.02
pic & eobs	5.97e-07	0.10	pic & eobs	5.87e-07	0.10	pic & eobs	7.71e-10	0.00	pic & eobs	6.47e-10	0.00
Syringa vulgaris beginning of flowering			Taraxacum officinale beginning of flowering			Tilia beginning of flowering			Prunus cerasus beginning of flowering		
M-W U-Test	p	U^*	M-W U-Test	p	U^*	M-W U-Test	p	U^*	M-W U-Test	p	U^*
hist & nat	5.28e-41	0.12	hist & nat	1.22e-37	0.14	hist & nat	1.01e-42	0.12	hist & nat	6.54e-38	0.14
hist & pic	9.19e-51	0.16	hist & pic	2.74e-47	0.18	hist & pic	7.84e-75	0.09	hist & pic	1.14e-50	0.16
hist & eobs	5.01e-02	0.34	hist & eobs	1.77e-01	0.39	hist & eobs	6.90e-01	0.47	hist & eobs	4.57e-01	0.44
nat & pic	1.86e-01	0.47	nat & pic	1.39e-01	0.47	nat & pic	4.43e-01	0.48	nat & pic	3.08e-01	0.48
nat & eobs	6.38e-08	0.05	nat & eobs	2.30e-08	0.04	nat & eobs	1.11e-07	0.06	nat & eobs	3.82e-07	0.08
pic & eobs	2.13e-07	0.08	pic & eobs	1.08e-07	0.07	pic & eobs	5.19e-09	0.03	pic & eobs	8.34e-07	0.10

Table 5: Statistical analysis for testing the null hypothesis, that two samples originate from the same basic population. Shading indicates significant outcome, where the null hypothesis cannot be rejected. No shading suggests the contrary, leading to the rejection of the null hypothesis and thereby detection of a significant discrepancy.

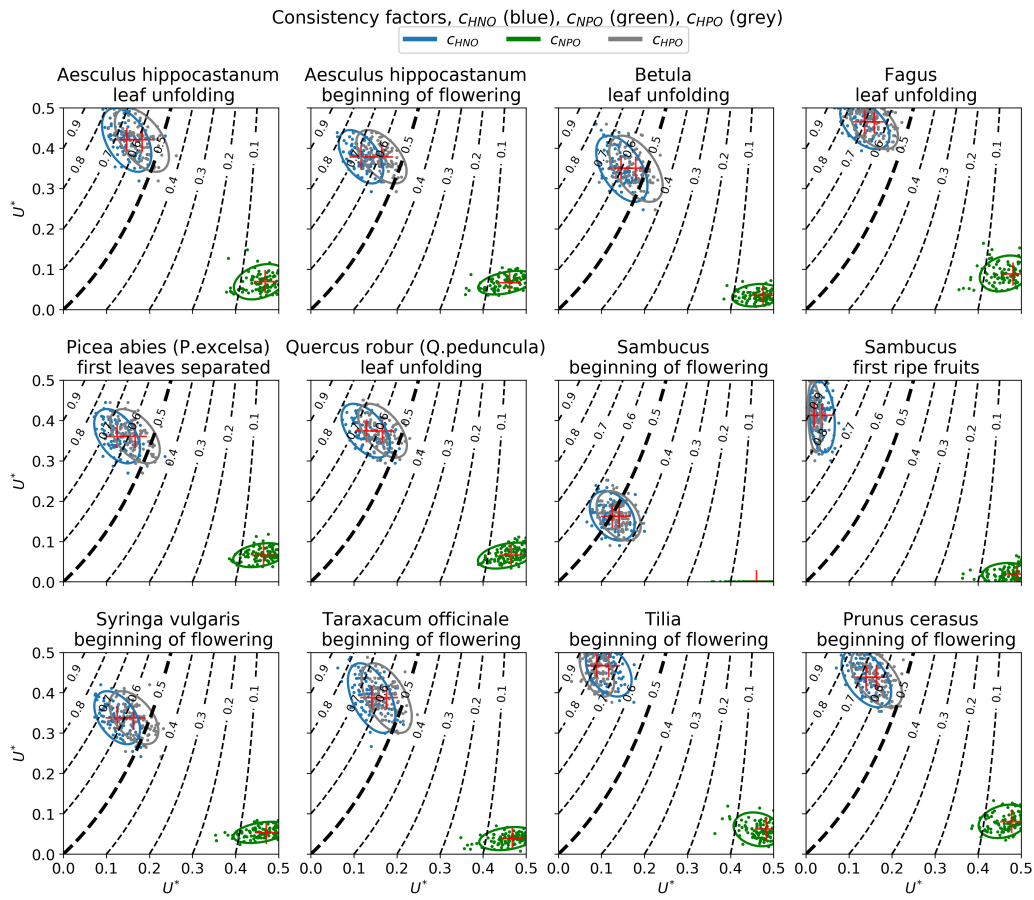


Figure 10: Consistency factors c_{HNO} , c_{NPO} and c_{HPO} . U^* on the abscissa corresponds to the respective x, y samples indicated by the index convention c_{xyz} and on the ordinate to x, z . Ellipses feature two standard deviations (roughly 95% confidence level).