

Seasonal climate signals driving flowering of *Robinia pseudoacacia* in Piedmont (Italy): implications for apiculture under climate change

Fausto Carbonari

Chiara Epifani

chiara.epifani@crea.gov.it

CREA-AA-RM: CREA Centro di Ricerca Agricoltura e Ambiente <https://orcid.org/0000-0002-1636-2116>

Research Article

Keywords: *Robinia pseudoacacia*, Flowering phenology, Seasonal climate signals, Thermal indices, Apiculture

Posted Date: November 17th, 2025

DOI: <https://doi.org/10.21203/rs.3.rs-7957891/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License. [Read Full License](#)

Version of Record: A version of this preprint was published at International Journal of Biometeorology on April 14th, 2026. See the published version at <https://doi.org/10.1007/s00484-026-03184-7>.

Manuscript title:

Seasonal climate signals driving flowering of *Robinia pseudoacacia* in Piedmont (Italy): implications for apiculture under climate change

Authors and affiliations

Fausto Carbonari

Council for Agricultural Research and Economics, Research Centre for Agriculture and Environment,
Via della Navicella 2/4, 00184 Rome, Italy

Email: fausto.carbonari@crea.gov.it

ORCID: 0009-0001-2121-365X

Chiara Epifani * (corresponding author)

Council for Agricultural Research and Economics, Research Centre for Agriculture and Environment,
Via della Navicella 2/4, 00184 Rome, Italy

Email: chiara.epifani@crea.gov.it

ORCID: 0000-0002-1636-2116

Abstract

Flowering dynamics of *Robinia pseudoacacia* L. (black locust), a key honey plant in southern Europe, are highly sensitive to climate variability and thus serve as a reliable indicator of environmental change. Despite the ecological and economic importance of this species, long-term studies on its flowering behaviour remain limited in Italy. This study analyses a multi-decadal time series of flowering onset dates collected in Piedmont (1981–2025) and validated at the regional scale using data from the IPHEN – Italian Phenological Network (2011–2025). Seasonal thermal indices, derived from the AgERA5 dataset, were evaluated through linear regressions and Monte Carlo cross-validation. During 1981–2025, flowering onset advanced by about 0.5 days per year (p -value < 0.01), consistent with the local warming trend observed over the same period. Among the thermal indices tested, spring temperatures were the main drivers: a 1 °C increase in the spring maximum temperature index (mTmax_spring) advanced flowering onset by more than 4 days on average. The winter index (mTmax_winter) also showed a significant, though weaker, negative association, suggesting that milder winters may contribute to earlier flowering, likely by modulating dormancy processes. In contrast, autumn correlations appeared to result from spurious trends linked to global warming. Validation with the IPHEN dataset confirmed the robustness of the spring signal and the predictive role of the winter index, which allows estimates as early as late February, with an average error of about 5 days. The results help clarify the climatic mechanisms driving flowering onset in black locust and provide practical insights for apicultural planning in a changing climate.

Key words: *Robinia pseudoacacia*, Flowering phenology, Seasonal climate signals, Thermal indices, Apiculture

Statements and declarations

Acknowledgments

The authors express their gratitude to the beekeepers from the Piedmont region and to all participants in the IPHEN project for their valuable collaboration in data collection. The authors used ChatGPT

(OpenAI, San Francisco, CA, USA) to assist in English translation and language polishing. The authors reviewed and edited the output as necessary and take full responsibility for the final content.

Author contributions

Chiara Epifani supervised the study, contributed to data curation and methodological development, designed the statistical framework, and wrote the first draft of the manuscript. Fausto Carbonari managed the data, developed and implemented the Python scripts for the statistical analyses, and contributed to data visualization. Both authors contributed to the study conception and design, commented on previous versions of the manuscript, and approved the final version.

Funding

This study was supported by the Italian Ministry of Agriculture and Food Sovereignty (MASAF) through the National Rural Network Programme (Rete PAC), within the executive project Rete Fenologica Nazionale, which includes the IPHEN project coordinated by CREA – Research Centre for Agriculture and Environment (CREA-AA).

Data availability

The meteorological data used in this study are publicly available through the AgERA5 dataset (Copernicus Climate Change Service, C3S Climate Data Store; DOI: 10.24381/cds.6c68c9bb, accessed on 17 June 2025). The phenological data from Montaldo Scarampi and IPHEN are available upon reasonable request to the corresponding author. Example data structures are available upon reasonable request.

Code availability

All codes developed with Python are not publicly available in a repository but can be obtained upon reasonable request to the corresponding author.

Conflict of interest

The authors declare that they have no relevant financial or non-financial interests to disclose.

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Seasonal climate signals driving flowering of *Robinia pseudoacacia* in Piedmont (Italy): implications for apiculture under climate change

Fausto Carbonari¹, Chiara Epifani^{1*}

¹Council for Agricultural Research and Economics, Research Centre for Agriculture and Environment, 00184 Rome, Italy

*chiara.epifani@crea.gov.it

Abstract

Flowering dynamics of *Robinia pseudoacacia* L. (black locust), a key honey plant in southern Europe, are highly sensitive to climate variability and thus serve as a reliable indicator of environmental change. Despite the ecological and economic importance of this species, long-term studies on its flowering behaviour remain limited in Italy. This study analyses a multi-decadal time series of flowering onset dates collected in Piedmont (1981–2025) and validated at the regional scale using data from the IPHEN – Italian Phenological Network (2011–2025). Seasonal thermal indices, derived from the AgERA5 dataset, were evaluated through linear regressions and Monte Carlo cross-validation. During 1981–2025, flowering onset advanced by about 0.5 days per year ($p\text{-value} < 0.01$), consistent with the local warming trend observed over the same period. Among the thermal indices tested, spring temperatures were the main drivers: a 1 °C increase in the spring maximum temperature index (mTmax_spring) advanced flowering onset by more than 4 days on average. The winter index (mTmax_winter) also showed a significant, though weaker, negative association, suggesting that milder winters may contribute to earlier flowering, likely by modulating dormancy processes. In contrast, autumn correlations appeared to result from spurious trends linked to global warming. Validation with the IPHEN dataset confirmed the robustness of the spring signal and the predictive role of the winter index, which allows estimates as early as late February, with an average error of about 5 days. The results help clarify the climatic mechanisms driving flowering onset in black locust and provide practical insights for apicultural planning in a changing climate.

Key words: *Robinia pseudoacacia*, Flowering phenology, Seasonal climate signals, Thermal indices, Apiculture

Introduction

Plant phenology represents a sensitive indicator of climate change, with important ecological and applied implications (Rosenzweig et al. 2008). Among the various stages of the life cycle, flowering is particularly responsive to rising temperatures (Fitter et al. 1995; Fitter and Fitter 2002), with potential effects on plant–pollinator interactions and associated ecosystem services (Walther et al. 2002; Parmesan 2006; Cleland et al. 2007; Memmott et al. 2007; Le Conte and Navajas 2008; Kudo and Ida 2013), including apiculture (Reddy et al. 2013; Van Espen et al. 2023). Numerous studies conducted at European and global scales have documented an advancement of phenological phases linked to spring warming, confirming the high sensitivity of temperate tree species to current climatic conditions (Menzel 2000; Menzel et al. 2006; Piao et al. 2019). These findings have guided the development of most phenological models, which are mainly based on spring thermal indices and reflect the dominant role of thermal forcing during this phase (Schwartz 2013; Chuine and Régnière 2017).

In this context, *R. pseudoacacia* L. represents a case of particular interest, both for its ecological characteristics and for its socio-economic relevance. It is a species native to North America, widely naturalised in Europe and the main source of nectar for acacia honey, a high-value product that, in Italy, represents the most appreciated and profitable spring honey.

Studies conducted in Hungary and Poland have shown a significant advance in flowering in relation to spring temperatures (Walkovszky 1998; Jatzak and Walawender 2009; Jabłońska et al. 2015). Most long-term records for *R. pseudoacacia* originate from Central and Eastern Europe (e.g. Walkovszky 1998; Jabłońska et al. 2015), while data from Western Europe remain scarce. In Italy, the available evidence is still limited and based on relatively short time series, often referring to vegetative phases rather than flowering (Orlandi et al. 2014). On the other hand, the marked interannual variability in acacia honey yields, linked to nectar production and mediated by flowering dynamics, is well documented (Osservatorio Nazionale Miele and ISMEA 2023; Osservatorio Nazionale Miele 2024). In addition, there is the problem of late frosts, which can interact with phenological advancement: although some studies in Central Europe have shown a reduction in the risk of damage from late frosts (Scheifinger et al. 2003), in general phenological advancement can increase vulnerability to such events, which may act as selective forces with ecological and evolutionary implications (Inouye 2000; Augspurger 2013).

Although spring forcing is recognized as the main driver of flowering, the role of thermal conditions preceding spring remains poorly explored. In temperate tree species, the transition from dormancy to flowering is regulated by the interaction between winter chilling signals and spring forcing, which determine dormancy release and promote growth resumption (Amasino 2010; Vitasse and Basler 2013; Luedeling et al. 2013). Winter cold, in addition to modulating hormonal balances, also appears crucial for ensuring the efficient mobilization of carbon reserves: in temperate fruit species, insufficient chilling can impair the use of stored reserves during vegetative recovery (Marafon et al. 2011; Pagter et al. 2015; Kaufmann and Blanke 2017). Although black locust appears to have a reduced or uncertain chilling requirement (Cook et al. 2012; Kim et al. 2022), yet further long-term analyses are needed to quantify the contribution of different seasons, particularly winter, to the species' phenological variability. Clarifying these aspects is essential for understanding the climatic mechanisms that regulate flowering in this species.

This study addresses this gap by using two sets of flowering start dates collected in Piedmont: a historical series spanning over thirty years (1981–2025) relating to a single site near Montaldo Scarampi (province of Asti) and a complementary dataset from the IPHEN phenological network (2011–2025), encompassing multiple sites distributed across six provinces. Through trend analysis, detrending and linear regressions with seasonal thermal indices, the study aims to (i) quantify the contribution of autumn, winter and spring temperatures to the interannual variability of flowering onset, with particular attention to the role of winter conditions, and (ii) verify the robustness of the results on a regional scale. In this way, the study contributes to clarifying the climatic mechanisms that regulate the phenology of *R. pseudoacacia* and provides useful elements for assessing the resilience of beekeeping production in a context of climate change.

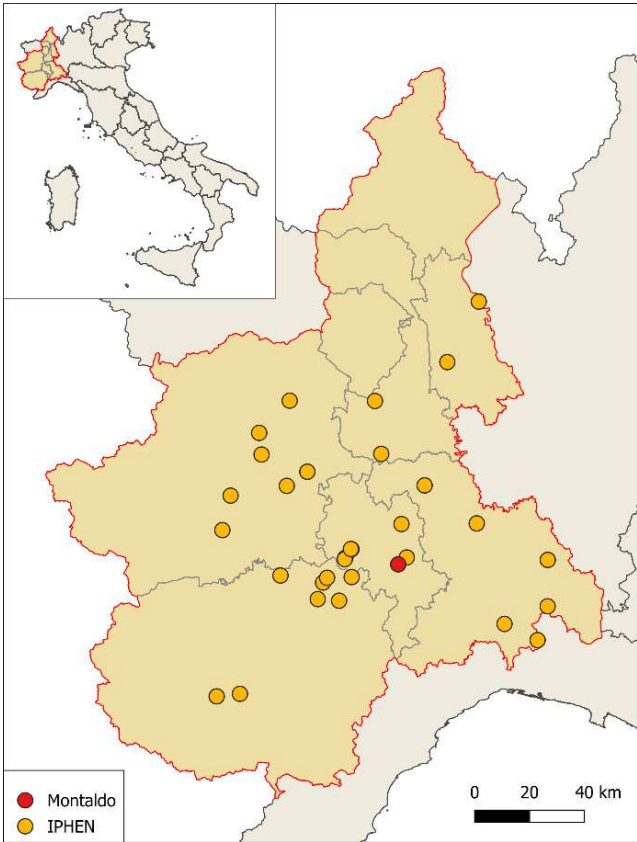
Materials and methods

Phenological and climatic data

The first phenological dataset comprises a historical series of *R. pseudoacacia* flowering start dates collected annually between 1981 and 2025 for a total of 40 observations, with data missing only in 1988, 1993, 1994, 1997 and 2000. The data were collected in a black locust forest located at a beekeeping farm in Montaldo Scarampi (province of Asti, Piedmont, Italy; 44°50'00.9"N, 8°15'55.6"E; 260 m a.s.l.) and were provided by the Beekeepers' Association of Piedmont (Associazione Produttori Miele Piemonte – Aspromiele). The observations, recorded directly by the beekeeper who owns the farm, report the start and end dates of flowering for the entire black locust forest rather than for individual trees. Although collected using less formalised methods than standardised protocols (e.g. IPHEN), this multi-decadal series is

76 exceptional in scope and continuity, providing a rare opportunity to access the long-term climate influence on *R.*
77 *pseudoacacia*.

78 The second dataset, extracted from the national IPHEN project (Mariani et al. 2013), includes 38 observations of
79 flowering onset (BBCH61) collected between 2011 and 2025 from 31 sites across six Piedmont provinces (Fig. 1). The
80 network applies a standardised BBCH protocol (Meier 2001) to monitor the full phenological cycle of *R. pseudoacacia*,
81 from winter dormancy release to the end of flowering. All phenological phases are recorded weekly on ten trees per site,
82 using the median of observations to minimise individual variability. Data are collected by trained volunteer observers,
83 mainly beekeepers, in collaboration with their regional associations, and undergo quality control before archiving.
84 Although site continuity varies over time, as the project relies on volunteer observers, the presence of several stations
85 near Montaldo Scarampi ensures adequate spatial coverage for regional validation. Missing years are 2012, 2014, 2015,
86 2020, and 2021.



87 **Fig. 1** Map of phenological sites: Montaldo Scarampi (historical series 1981–2025) and 31 IPHEN stations (data series from 2011 to
88 2025) distributed across six provinces of Piedmont

89 To ensure consistency between the two datasets, only the first annual observation of the BBCH61 phase was retained for
90 each IPHEN site, making the data directly comparable with those from Montaldo Scarampi. Dates were converted from
91 calendar format to Day of the Year (DOY, where January 1 = 1) to allow uniform temporal comparison.

92 Finally, daily minimum, maximum and mean temperature data for 1980–2025 were obtained from the AgERA5 dataset
93 (Copernicus Climate Change Service, C3S; Boogaard et al. 2020) for the grid cells corresponding to the phenological
94 sites.

95 **Seasonal thermal indices**

96 To evaluate the influence of climatic conditions on the onset of flowering in *R. pseudoacacia*, a set of seasonal thermal
97 indices was calculated. These indices summarise temperature trends in the months preceding flowering, focusing on
98 autumn, winter and early spring, to quantify the thermal accumulation that regulates flowering timing. Seasons were
99 defined according to meteorological convention: autumn (September–November) and winter (December–February),
100 while the spring window was restricted to March 1 – April 15, to ensure a realistic temporal link and avoid overlap with
101 flowering onset, which in the Montaldo Scarampi series never occurred before April 20 and in the IPHEN dataset not
102 before April 16.

103 The preceding summer was excluded because it is too distant from the following year's flowering onset. During this
104 period, physiological processes such as bud formation and carbohydrate storage occur and are generally completed by
105 late summer or extend into autumn (Barbaroux and Breda 2002; Cooke et al. 2012; Delpierre et al. 2016; Silvestro et al.
106 2019). Consequently, any summer influence is assumed to be already incorporated into autumn temperature dynamics.

107 Temperature data for 1980–2025 were aggregated by the previously defined seasons. For each season, three indices were
108 computed: the mean of daily minimum, mean, and maximum temperatures. Each index name explicitly combines the
109 acronym mT (mean temperature) with the temperature type and season (e.g., mTmin_winter indicates the seasonal mean
110 of daily minimum temperatures from December to February).

111 **Preliminary checks and detrending**

112 A preliminary analysis was conducted on the phenological datasets (Montaldo Scarampi and IPHEN) to check data
113 quality, normality and potential outliers. The interquartile range (IQR) method and visual inspection of boxplots were
114 first used, followed by the Shapiro-Wilk test (Shapiro and Wilk 1965) and D'Agostino-Pearson test (D'agostino et al.
115 1990). Normality was accepted when both returned *p-value* > 0.05. In such cases, the Grubbs test (Grubbs 1950) was
116 applied to confirm the significance of visually identified outlier.

117 For the Montaldo Scarampi time series, whose length exceeds 30 years, linear trends and autocorrelation were assessed.
118 When a significant trend was detected (*p-value* < 0.05), the series was detrended by subtracting the linear component,
119 and subsequent analyses were conducted on the residuals (Iler et al., 2017) to avoid spurious correlations arising from
120 long-term climatic trends (Wu et al., 2007). Residual autocorrelation was tested with the Ljung–Box test (Ljung & Box,
121 1978) with lag = 1 year, and when significant, an AR(1) correction was applied and rechecked for effectiveness (Iler et
122 al., 2017).

123 **Identification of thermal predictors and model development**

124 To identify the most effective thermal predictors, Pearson's correlation coefficient (*r*; Pearson 1895) was calculated to
125 quantify the linear relationship between flowering onset date and each thermal index. Correlations were computed on
126 both the original and detrended series to distinguish long-term trends from interannual variability, the latter reflecting the
127 response of flowering onset to year-to-year climatic fluctuation.

128 All thermal indices showing statistically significant correlations (*p-value* < 0.05) in both the original and detrended series
129 were retained for further analysis. Among these, the thermal index with the highest absolute correlation value was selected
130 as the most representative predictor. This procedure ensured that only indices consistently related to flowering onset,
131 independent of long-term trends, were included in subsequent analyses. These indices were considered the most reliable
132 descriptors of the link between seasonal temperatures and flowering onset in *R. pseudoacacia*.

133 The selected predictors were then used in linear regression analyses. Simple regressions quantified the effect of each
134 index individually, while a multiple regression including all selected indices assessed their combined influence on the
135 interannual variability of flowering onset. This approach provided an integrated model of both individual and joint thermal
136 effects.

137 Finally the residuals normality was tested with the Shapiro–Wilk test and their independence with the Durbin–Watson
138 test (Durbin and Watson 1950), suitable for detecting first-order autocorrelation.

139 **Spatial and temporal validation**

140 The potential to extend the analysis to a broader spatial scale was explored using the IPHEN dataset. The aim was to
141 verify whether the relationships identified in the long-term Montaldo Scarampi series, representative of long-term
142 dynamics, were also observable at other locations within the region. Although the IPHEN dataset covers a shorter and
143 more recent period, it provides valuable support for testing the spatial robustness of the results. This procedure enabled
144 validation of the model on an independent dataset with wider spatial coverage.

145 As a first step, the historical Montaldo Scarampi series (phenological and thermal data) was reduced to a 30-year period
146 (1991–2025). This time frame, consistent with climate analysis standard ensured homogeneity and partial temporal
147 overlap with the IPHEN dataset. All methodological steps described earlier, detrending, autocorrelation testing and
148 Pearson correlation analysis, were reapplied to this reduced series to confirm the stability and consistency of the most
149 significant thermal indices and to validate the results obtained for 1981–2025.

150 Subsequently, the Montaldo Scarampi data (1991–2025) were combined with the IPHEN dataset (2011–2025) to create a
151 larger, spatially representative dataset. On this combined series, a linear regression model was developed using a single
152 thermal index, selected from those previously identified, giving preference to the one corresponding to the season farthest
153 from flowering to allow earlier forecasting.

154 For model validation, a Monte Carlo cross-validation procedure (Shao 1993) was adopted, repeated over 1000 iterations.
155 In each iteration, the dataset was randomly divided into training and test sets (70/30 and 60/40 splits). Predictive
156 performance was evaluated on the test set by calculating R^2 , MAE, and RMSE, reported as averages over the 1000
157 iterations. This approach allowed assessment of the model’s robustness on an independent dataset and provided a reliable
158 estimate of its predictive capability.

159 The entire statistical processing and analysis workflow was implemented in a reproducible and automated way to ensure
160 consistency and traceability of results. To this end, the Python environment (v3.11.2; Van Rossum and Drake 2009) was
161 used with the following packages: “pandas” (v2.3.2; McKinney 2010), “NumPy” (v2.3.3; Harris et al. 2020), “xarray”
162 (v2025.9.0; Hoyer and Hamman 2017), “SciPy” (v1.16.2; Virtanen et al. 2020), “statsmodels” (v0.14.5; Seabold and
163 Perktold 2010), “scikit-learn” (v1.7.2; Pedregosa et al. 2011), “matplotlib” (v3.10.6; Hunter 2007) and “seaborn”
164 (v0.13.2; Waskom 2021). The “Real Statistics Resource Pack” add-in for Excel (v9.6.1; Zaiontz 2025) was also used for
165 normality testing and outlier detection.

166 **Results**

167 **Descriptive analysis of flowering onset dates**

168 The two phenological datasets, Montaldo Scarampi (1981–2025) and IPHEN (2011–2025), showed similar means and
169 comparable interannual variability. Further details are provided in the Supplementary Materials (Table S1). Distributions

were consistent with normality, except for the IPHEN series, from which one outlier was removed to ensure homogeneity (Figs. S1, S2; Tables S2, S3, S4). Overall, both datasets provided a solid and statistically consistent basis for subsequent analyses. The analysis first focused on the longer Montaldo Scarampi series, with IPHEN data subsequently used for regional-scale validation.

The historical series from Montaldo Scarampi revealed a progressive advancement of flowering onset during 1981–2025 particularly pronounced after 2000. The z-scores indeed showed an increase in negative values in more recent years, confirming the progressive advancement of the BBCH61 phase (Fig. 2).

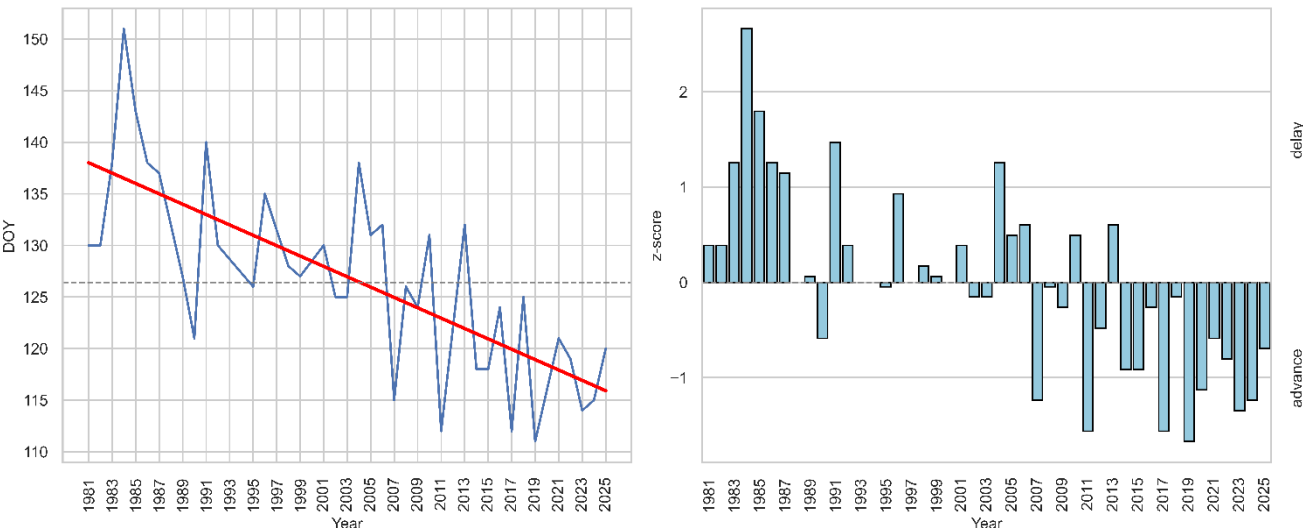


Fig. 2 Flowering onset dates (BBCH61, DOY) in the period 1981–2025. Left: temporal trend with average (grey dotted line) and regression line (in red). Right: z-scores for the same dates, where positive values indicate a delayed flowering start and negative values indicate an early start

Because altitude can affect phenology, its influence on the comparability between the Montaldo Scarampi and IPHEN series was assessed. The IPHEN sites were grouped into three classes, defined according to the 25th and 75th percentiles of the distribution of elevation (h): low ($h \leq 238.5$ m), intermediate ($238.5 < h \leq 317.0$ m), and high ($h > 317.0$ m). A qualitative gradient emerged, with earlier flowering (BBCH61) at lower elevations and later at higher ones, though differences among classes were not statistically significant (Kruskal–Wallis $H = 1.30$, $p\text{-value} > 0.05$) (Fig. S3, Table S5).

The site-level analysis, based on the Spearman correlation between elevation and flowering onset date, showed a non-significant positive and weak coefficient ($\rho = 0.23$, $n = 31$, $p\text{-value} > 0.05$). Overall, in our sample, altitude influenced phenology only qualitatively and was not a determining factor. The altitude of Montaldo Scarampi (260 m a.s.l.), within the intermediate range, the most represented class in the IPHEN series (15 sites), therefore poses no limitation for comparison.

Seasonal and phenological temperature trends

Seasonal thermal indices showed a progressive warming trend from 1981 to 2025. Anomalies were most pronounced in autumn and winter, with recurrent positive values over the last decade, while spring displayed a less linear pattern with alternating warm and cool years (Fig. S4). This framework outlines the climatic context underlying the observed phenological variability and forms the basis for subsequent analyses of the links between seasonal temperatures and flowering onset.

196 Trend analysis revealed a significant advancement of flowering onset, at a rate of approximately 0.5 days per year, and
 197 confirmed a marked warming in the seasonal thermal indices (Table 1). Mean autumn and winter indices increased
 198 significantly, while spring indices showed moderate rises in mean and maximum temperatures and no significant change
 199 in minimum values.

200 **Table 1** Results of trend analysis and application of the autocorrelation test (Ljung–Box) on the phenological and thermal time series
 201 from Montaldo Scarampi (1981–2025)

Variable	β (d/year or °C/year)	R ²	Detrended	Ljung–Box <i>Q</i>
BBCH61 (DOY)	-0.5**	0.54	Yes/No	0.16
mTmax_autumn	0.04**	0.35	Yes	3.83
mTmax_winter	0.05**	0.21	Yes	0.31
mTmax_spring	0.04*	0.12	Yes	1.27
mTmed_autumn	0.05**	0.50	Yes	3.99†
mTmed_winter	0.06**	0.36	Yes	0.41
mTmed_spring	0.03*	0.14	Yes	0.07
mTmin_autumn	0.04**	0.43	Yes	2.11
mTmin_winter	0.05**	0.30	Yes	0.22
mTmin_spring	0.02	0.07	No	0.06

Notes: * *p*-value <0.05; ** *p*-value <0.01 for linear trend tests (β)

† *p*-value <0.05 for the Ljung–Box autocorrelation test (*Q* statistic).

202 The presence of significant trends required detrending to separate long-term climate change effects from interannual
 203 fluctuations linked to phenological plasticity (Table 1). Thermal indices showing significant trends were detrended and
 204 analysed only in residual form. The phenological series was treated with a dual approach: retained in its original form to
 205 quantify the direct climate change effect and detrended to explore physiological relationships with thermal indices,
 206 independent of the influence of shared trends. Autocorrelation tests (Ljung–Box) confirmed no serial dependence in the
 207 detrended data, except for mTmax_autumn, which was corrected using an autoregressive model.

208 Relationships between thermal indices and flowering onset

209 Pearson correlations between flowering onset dates and thermal indices, before and after detrending, revealed distinct
 210 seasonal patterns (Table 2). In autumn, initially significant negative correlations disappeared after detrending, indicating
 211 that they reflected shared trends rather than physiological links. In winter, however, the signal persisted: indices
 212 maintained significant negative correlations even after detrending (up to $r = -0.51$), suggesting a possible physiological
 213 role in dormancy control. The strongest relationships occurred in spring, where thermal indices based on mean and
 214 maximum temperatures showed stable negative correlations with the phenological phase (up to $r = -0.72$), regardless of
 215 detrending, while the thermal indices based on minimum temperature showed no trend (see also Table 1).

216 **Table 2** Pearson correlation coefficients between flowering onset date and seasonal thermal indices before and after detrending (D) at
 217 the Montaldo Scarampi site (1981–2025)

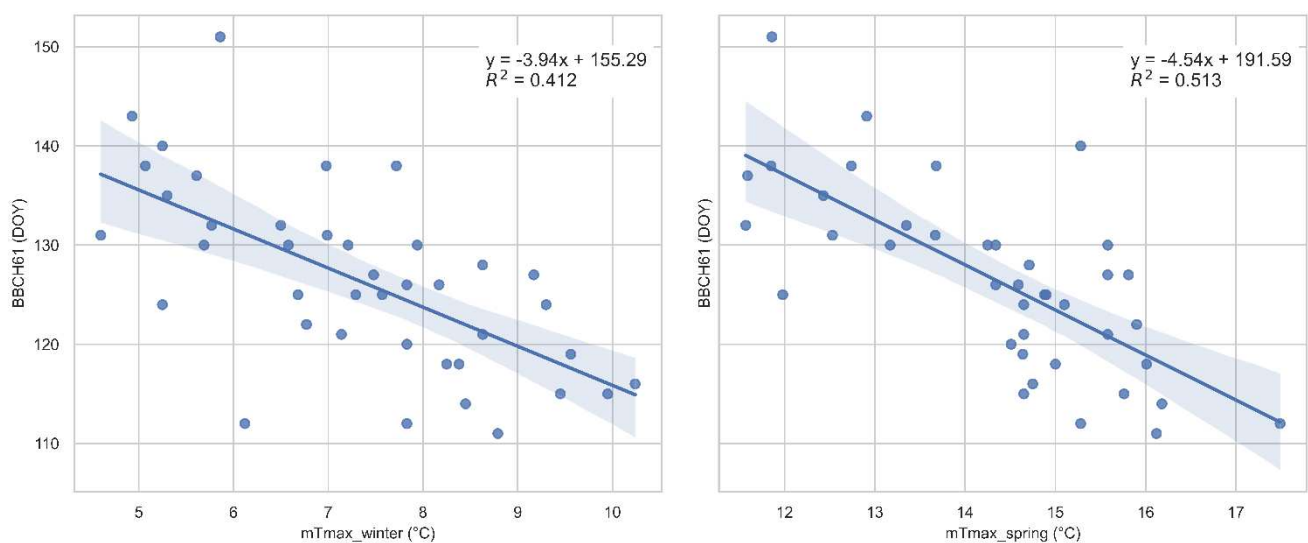
Season	mTmin	mTmin D	mTmean	mTmean D	mTmax	mTmax D
Autumn	-0.59**	-0.21	-0.60**	-0.17	-0.50**	-0.12
Winter	-0.62**	-0.38*	-0.68**	-0.44**	-0.64**	-0.51**

Season	mTmin	mTmin D	mTmean	mTmean D	mTmax	mTmax D
Spring	-0.58**	n.t.	-0.70**	-0.67**	-0.72**	-0.72**

Notes: * p -value<0.05; ** p -value<0.01; n.t.=no trend

218 Ultimately, mTmax_winter and mTmax_spring showed the highest absolute correlation coefficients and remained
219 significant even after detrending. These two indices were therefore selected to build both simple and multiple linear
220 regression models.

221 Linear regression analysis confirmed that these indices significantly explain the interannual variability of flowering onset
222 (Fig. 3, Table S6). The relationship between the BBCH61 phase and mTmax_winter was negative and highly significant
223 ($\beta = -3.94 \pm 0.76$ days / °C, p -value < 0.001), indicating that a 1 °C increase of the index is associated with an advancement
224 of about 4 days in flowering onset.



225 **Fig. 3** Relationship between the BBCH61 phase expressed in DOY and the mTmax_winter index (left) and mTmax_spring (right) at
226 Montaldo Scarampi (1981–2025). The blue line represents the linear regression fit with a 95% confidence interval (blue area)

227 A similar but stronger signal emerged for the spring thermal index based on maximum temperatures (mTmax_spring,
228 period March 1–April 15). The linear regression yielded a coefficient of $\beta = -4.54 \pm 0.72$ days / °C (p -value < 0.001) and
229 $R^2 = 0.51$ ($n = 40$), indicating that flowering onset is associated with an advancement of about 4.5 days per 1 °C increase
230 in this index. It is important to note that such advances, although seemingly large, should be interpreted in light of the
231 nature of the index itself: being a seasonal mean, a 1 °C variation represents an average warming across the entire period.

232 The multiple regression model combining both thermal indices explained a larger proportion of phenological variability
233 ($R^2 = 0.61$, $n = 40$). Both predictors were significant: $\beta = -2.22 \pm 0.75$ days / °C (p -value < 0.01 for mTmax_winter and
234 $\beta = -3.31 \pm 0.78$ days / °C (p -value < 0.001) for mTmax_spring. Holding other factors constant, a 1 °C increase in the
235 winter index is associated with an advancement of about 2 days in flowering onset, while a similar increase in the spring
236 index corresponds to an advance of over 3 days. The combination of the two indices offers a more complete representation
237 of phenological dynamics: the spring component exerts the primary influence, whereas the winter component modulates
238 the plant's initial physiological state, likely linked to dormancy processes.

239 Residuals met the assumptions of normality (Shapiro–Wilk $W = 0.99$ for winter, 0.98 for spring, and 0.98 for the multiple
240 model; p -values > 0.05) and independence (Durbin–Watson $d = 1.29$, 1.18, and 1.15, respectively), confirming the
241 robustness of the results.

242 Spatial and temporal validation of the models

243 The analysis was extended to a spatial scale using the IPHEN dataset to verify whether the relationships identified in the
244 long-term Montaldo Scarampi series were consistent across other regional sites.

245 As a first step, the Montaldo Scarampi series was restricted to 1991–2025 to ensure homogeneity and direct comparability
246 with the IPHEN series. For this interval, all thermal indices were recalculated and subjected to preliminary checks,
247 normality tests, detrending, autocorrelation, and Pearson correlations (Tables S7, S8, S9). Based on these results, the
248 winter and spring mTmax indices again proved to be the best candidates for subsequent validation.

249 Comparison of the trend analyses for the two-time intervals (1981–2025 and 1991–2025) revealed significant differences,
250 offering complementary insights into the evolution of seasonal thermal patterns. Over the longer period, both indices
251 showed significant upward trends, whereas in the more recent interval only mTmax_winter retained this feature ($\beta = 0.06$
252 $^{\circ}\text{C}/\text{year}$, $p\text{-value} < 0.05$) (Table S8). This divergence suggests that warming during 1991–2025 was more pronounced and
253 persistent in winter than in spring, where the trend was no longer significant ($\beta = 0.03$ $^{\circ}\text{C}/\text{year}$, $p\text{-value} > 0.05$), likely due
254 to higher interannual variability. Consequently, detrending was applied only to the winter index, in order to remove the
255 component linked to the climatic trend and better isolate the potential physiological relationship with flowering onset.

256 Pearson correlation coefficients between flowering onset dates and seasonal thermal indices for 1991–2025 (Table S9)
257 showed patterns consistent with those observed over the full 1981–2025 period. Even during 1991–2025, the spring
258 indices confirmed a strong negative association with the BBCH61 phase, in particular mTmax_spring showed $r = -0.66$
259 ($p\text{-value} < 0.01$). The absence of a significant trend made detrending unnecessary, confirming the stability and reliability
260 of this index as a physiologically meaningful predictor, even over the shorter period comparable to the IPHEN series.

261 Winter thermal indices also showed a moderate negative relationship, particularly mTmax_winter ($r = -0.60$ before
262 detrending and -0.47 after), with a slight weakening compared to the 1981–2025 period (from -0.64 before detrending to
263 -0.51 after). This confirms a stable winter signal, although weaker than the spring one. In this interval as well, correlations
264 between autumn indices and flowering onset disappeared after detrending, indicating spurious relationships.

265 In summary, the winter and spring mTmax indices proved to be robust climatic indicators, explaining phenological
266 variability even over the more recent and shorter 1991–2025 period. The consistency between analyses before and after
267 detrending supports their use as predictors in the subsequent external validation on a broader spatial scale.

268 At this stage, the analysis focused exclusively on winter thermal index (mTmax_winter), based on two complementary
269 considerations: (i) many existing models (e.g., IPHEN, Alilla et al. 2022) rely on spring thermal accumulations. Although
270 mTmax_spring showed the strongest association with the BBCH61 phase, it can only be calculated near the phenological
271 event, limiting operational applicability; (ii) the analysed data showed that climate change has had a more pronounced
272 and persistent impact on winter than on spring temperatures. In increasingly mild winters, using a winter index becomes
273 particularly relevant for tracking phenological evolution and testing model robustness under future climate conditions.
274 Validating the winter index thus represents a key step in assessing its effectiveness as a component of an integrated
275 operational forecasting system.

276 For the spatial validation phase, the Montaldo Scarampi (1991–2025) and IPHEN (2011–2025) datasets were merged into
277 a single combined dataset. Normality tests (Shapiro–Wilk and D’Agostino–Pearson) performed on the merged data
278 confirmed that the distribution of flowering onset dates did not deviate from normality ($p\text{-value} = 0.18$ and 0.17 ,
279 respectively; Fig. S6, Table S10), meeting the assumptions for linear regression and Monte Carlo validation. These results

280 indicate no systematic differences between Montaldo Scarampi and IPHEN data that would prevent their aggregation.
281 The removal of one outlier from the IPHEN series further improved the statistical homogeneity of the merged dataset.

282 A linear regression model was developed to evaluate the ability of winter index to explain phenological variability and
283 support operational forecasting (Table S11, Fig. S7). The simple linear regression revealed a significant relationship
284 between mTmax_winter and flowering onset date ($\beta = -2.91 \pm 0.58$ days / °C, $p\text{-value} < 0.001$; $R^2 = 0.27$), with normally
285 distributed residuals (Shapiro–Wilk $W = 0.97$, $p\text{-value} > 0.05$) and a Durbin–Watson d value of 0.55. Although d value
286 indicates moderate positive autocorrelation, typical of annual climatic data, it does not substantially affect the coefficient
287 estimation β , as confirmed by its strong significance ($p\text{-value} < 0.001$). This behaviour reflects the climatic persistence of
288 meteorological time series rather than model misspecification, consistent with the thermal memory of the atmospheric
289 system (D. S. Wilks, 2006).

290 To evaluate model stability and predictive reliability, a Monte Carlo cross-validation (repeated random sub-sampling,
291 1000 iterations) was applied to the combined Montaldo Scarampi (1991–2025) + IPHEN dataset ($n = 68$). Two
292 training/test split ratios were tested (70/30 and 60/40). Results indicate good stability, with similar performance across
293 both configurations (Table 3). The MAE and RMSE distributions were nearly symmetrical, whereas the R^2 distributions
294 showed the typical asymmetry inherent to this metric (Figs. S8, S9).

295 **Table 3** Performance metrics from Monte Carlo cross-validation (1000 iterations) for the model based on mTmax_winter. MAE and
296 RMSE values are expressed in days, while R^2 is dimensionless. All metrics are reported as mean $\pm$ standard deviation (σ)

Training/Test	Dataset	MAE	RMSE	R^2
70-30	Train	4.97 $\pm$ 0.42	6.41 $\pm$ 0.54	0.28 $\pm$ 0.08
	Test	5.29 $\pm$ 0.88	6.71 $\pm$ 1.15	0.14 $\pm$ 0.26
60-40	Train	4.95 $\pm$ 0.52	6.37 $\pm$ 0.67	0.28 $\pm$ 0.10
	Test	5.31 $\pm$ 0.75	6.78 $\pm$ 0.99	0.14 $\pm$ 0.22

297 Overall, the two split schemes yielded consistent results. MAE and RMSE values were comparable in both training and
298 testing phases, with absolute errors around 5 days and RMSE between 6.4 and 6.8 days. The coefficient of determination
299 ranged from 0.14 to 0.28, reflecting variability due to sample size and spatial heterogeneity (Table 3). Although the model
300 based on mTmax_winter explains only a modest share of total variability, it provides early phenological forecasts with
301 limited mean error (≈ 5 days) and good reproducibility, making it valuable for operational use.

302 The 60/40 split is considered more rigorous, as it tests model performance on a larger validation set, providing a more
303 stable and representative estimate of real-world conditions. Conversely, the 70/30 split allocates more data to training,
304 advantageous when the total sample size is small, though at the expense of a less robust test evaluation. The R^2 values
305 from the 70/30 split, while modest, align with Basler (2016), who noted that the predictive performance of phenological
306 models declines when site-aggregated rather than individual-plant data are used.

307 Despite moderate R^2 values, the model based on mTmax_winter provides timely forecasts: the MAE is within ± 5 days of
308 observed flowering, matching the 7-day temporal resolution of the IPHEN observations used for validation. This accuracy
309 enables reliable identification of the week when the BBCH61 phase occurs, offering a temporal resolution suited to
310 beekeeping operations and making the model a practical tool even in spatially heterogeneous contexts. Moreover, the
311 MAE was lower than the temporal resolution of the phenological observations, indicating that model deviations fall within
312 the observational uncertainty and are not statistically distinguishable from measurement noise.

313 Discussion

314 The results confirm that the advancement of flowering onset at Montaldo Scarampi reflects the high sensitivity of *R.*
315 *pseudoacacia* to climate warming. Although based on a single site, this finding aligns with trends observed in other
316 temperate trees (Menzel et al. 2006; Piao et al. 2019) and it is supported by regional IPHEN data. For black locust, this
317 sensitivity is particularly relevant, as it highlights the species' marked phenotypic plasticity (Granata et al. 2020), a trait
318 that may enhance its ability to adjust phenology to a rapidly changing climate. Similar plasticity occurs in other naturalized
319 species, supporting their success across heterogeneous European environments (Davidson et al. 2011; Bouteiller et al.
320 2021). However, such phenological shifts, though adaptive for the species, may lead to a mismatch with honeybee colony
321 development, potentially limiting nectar exploitation during early springs (Le Conte and Navajas 2008).

322 The thermal indices calculated for Montaldo Scarampi show a steady increase in seasonal temperatures during both 1981–
323 2025 and 1991–2025, consistent with warming trends reported for Italy and the Euro-Mediterranean region (Brunetti et
324 al. 2006; Lionello and Scarascia 2018; Bilbao et al. 2019).

325 Among the thermal indices, mTmax_spring retains strong correlations even after detrending over the 1981–2025 period,
326 indicating a direct link with the thermal forcing that drives vegetative recovery (Delpierre et al. 2016; Kim et al. 2022).
327 In the shorter period, 1991–2025, this index shows slightly higher r coefficient but no significant trend. In both periods,
328 mTmax_winter remains significantly correlated, though with weaker coefficients, whereas the disappearance of
329 correlations with autumn indices after detrending, indicates spurious effects associated with the common warming trend,
330 consistent with Fitter et al. (1995).

331 Overall, the phenology of black locust is mainly driven by spring thermal signals but is also influenced by winter
332 conditions. In temperate trees, such signals usually reflect the chilling requirement. In our case, the observed thermal
333 relationships provide indirect evidence, as direct quantification would require additional budburst data (BBCH03),
334 currently limited in the IPHEN dataset. This indirect signal nonetheless supports the hypothesis that winter temperatures
335 can modulate the timing of reproductive activation, according to Fornaciari et al. (2023), who reported a significant
336 correlation between maximum temperatures of February and early flowering in deciduous tree species in Italy. The
337 interpretation is physiologically plausible, as in *R. pseudoacacia* the floral buds open when leaves are already developed
338 or still developing, indicating an early spring flowering (Farkas and Zajácz 2007), a pattern also frequently observed
339 during IPHEN field surveys.

340 Our results are consistent with the phenological mechanisms in temperate broadleaf species, where dormancy–growth
341 transition is regulated by thermal and photoperiodic cues (Chuine et al. 2013; Silvestro et al. 2025), confirming the
342 dominant role of spring temperatures in advancing phenological phases (Menzel et al. 2006; Piao et al. 2019).

343 The phenological series from Montaldo Scarampi, consistent with the IPHEN data, provides a unique reference for black
344 locust in Italy and a basis for model validation. The R^2 values obtained during spatial validation, although relatively low,
345 are consistent with those reported in phenological studies based on multi-individual observations, which naturally show
346 higher variability than analyses on single plants under controlled conditions (Basler 2016). The mean absolute error, of
347 about 5 days, falls within the standard range of IPHEN observations (Alilla et al. 2022).

348 Some limitations, however, remain. Phenological data were not collected under fully uniform protocols, an intrinsic
349 limitation, although harmonization criteria were applied to reduce heterogeneity. The AgERA5 climatic data provide

continuous spatial and temporal coverage throughout the study period, but the grid resolution (≈ 9 km) may be limiting in areas with complex topography.

Finally, the analysis focused solely on thermal variables, excluding other potentially relevant factors such as water availability and photoperiod. This choice reflects the dominant role of temperature in temperate species phenology but narrows the model's applicability and points to future research integrating multiple climatic drivers.

Conclusions

Some methodological choices were crucial for ensuring robust results. Detrending allowed genuine climatic signals to be distinguished from spurious relationships due to shared trends, while focusing on a few thermal indices minimized collinearity and ensured model stability even with relatively short time series.

Although the spring thermal index was the strongest predictor, the winter index was retained to assess the influence of early cold-season conditions on phenological dynamics. Despite its weaker signal, this index offers valuable insights into phenological mechanisms and, because the necessary meteorological data are available by late February, enables timely forecasts to support beekeeping management.

From a scientific standpoint, the results indicate that *R. pseudoacacia* phenology is mainly driven by spring temperatures but also influenced by winter conditions. This dual sensitivity supports the hypothesis of a possible chilling requirement in the species (Murray et al. 1989; Cesaraccio et al. 2004), whose direct quantification still requires specific observations of dormancy-breaking phases.

Integrating winter thermal signals into spring forcing models offers a promising path toward more robust forecasting systems. Future work should extend the analysis to more sites and climatic contexts to test generalizability and explore other environmental drivers such as photoperiod and water availability. Beyond spatial expansion, analysing IPHEN data, distinguishing years with direct flowering from those with prior leaf emergence, could yield new insights into the link between winter dynamics and the dormancy–flowering sequence, an aspect not assessable in the historical Montaldo Scarampi series.

This study complements existing operational models based on cumulative temperatures, offering insights valuable for both scientific understanding and practical use. Although incorporating the spring index is necessary to enhance the predictive performance of the winter index, the latter retains operational value, as it can be computed as early as late February. These early estimates represent an important step toward forecasting tools capable of supporting beekeeping management under growing climatic uncertainty. In a context where acacia honey production is increasingly affected by climate change, such tools can serve as tangible resources for beekeepers, bridging local observation, climate modelling, and apiary management.

Acknowledgments The authors express their gratitude to the beekeepers from the Piedmont region and to all participants in the IPHEN project for their valuable collaboration in data collection. The authors used ChatGPT (OpenAI, San Francisco, CA, USA) to assist in English translation and language polishing. The authors reviewed and edited the output as necessary and take full responsibility for the final content.

Supplementary Information The online version contains supplementary material available at [...].

Author's Contributions Chiara Epifani supervised the study, contributed to data curation and methodological development, designed the statistical framework, and wrote the first draft of the manuscript. Fausto Carbonari managed

387 the data, developed and implemented the Python scripts for the statistical analyses, and contributed to data visualization.
388 Both authors contributed to the study conception and design, commented on previous versions, and approved the final
389 manuscript.

390 **Funding** This study was supported by the Italian Ministry of Agriculture and Food Sovereignty (MASAF) through the
391 National Rural Network Programme (Rete PAC), within the executive project Rete Fenologica Nazionale, which includes
392 the IPHEN project coordinated by CREA – Research Centre for Agriculture and Environment (CREA-AA).

393 **Data Availability** The meteorological data used in this study are publicly available through the AgERA5 dataset,
394 Copernicus Climate Change Service (C3S) Climate Data Store (CDS), DOI: 10.24381/cds.6c68c9bb (Accessed on 17-
395 Jun-2025). The phenological data from Montaldo Scarampi and IPHEN are available upon reasonable request to the
396 corresponding author. Example data structures are available upon reasonable request.

397 **Code Availability** All codes developed with Python are not publicly available in a repository but can be obtained upon
398 reasonable request to the corresponding author.

399 **Declarations**

400 **Conflict of interest** The authors have no relevant financial or non-financial interests to disclose.

401 **Ethics approval** Not applicable.

402 **Consent to participate** Not applicable.

403 **Consent for publication** Not applicable.

404 **References**

405 Alilla R, De Natale F, Epifani C, et al (2022) The Flowering of Black Locust (*Robinia pseudoacacia* L.) in Italy: A
406 Phenology Modeling Approach. *Agronomy* 12:1623. <https://doi.org/10.3390/agronomy12071623>

407 Amasino R (2010) Seasonal and developmental timing of flowering. *Plant J* 61:1001–1013.
408 <https://doi.org/10.1111/j.1365-313X.2010.04148.x>

409 Augspurger CK (2013) Reconstructing patterns of temperature, phenology, and frost damage over 124 years: Spring
410 damage risk is increasing. *Ecology* 94:41–50. <https://doi.org/10.1890/12-0200.1>

411 Barbaroux C, Breda N (2002) Contrasting distribution and seasonal dynamics of carbohydrate reserves in stem wood of
412 adult ring-porous sessile oak and diffuse-porous beech trees. *Tree Physiol* 22:1201–1210.
413 <https://doi.org/10.1093/treephys/22.17.1201>

414 Basler D (2016) Evaluating phenological models for the prediction of leaf-out dates in six temperate tree species across
415 central Europe. *Agric For Meteorol* 217:10–21. <https://doi.org/10.1016/j.agrformet.2015.11.007>

416 Bilbao J, Román R, De Miguel A (2019) Temporal and spatial variability in surface air temperature and diurnal
417 temperature range in Spain over the period 1950–2011. *Climate* 7:. <https://doi.org/10.3390/cli7010016>

418 Boogaard H, Schubert J, De Wit A, et al (2020) Agrometeorological indicators from 1979 to present derived from
419 reanalysis. In: Copernicus Clim. Chang. Serv. Clim. Data Store. [https://cds.climate.copernicus.eu/datasets/sis-](https://cds.climate.copernicus.eu/datasets/sis-agrometeorological-indicators?tab=overview)
420 [agrometeorological-indicators?tab=overview](https://cds.climate.copernicus.eu/datasets/sis-agrometeorological-indicators?tab=overview). Accessed 17 Jun 2025

421 Bouteiller XP, Moret F, Ségura R, et al (2021) The seeds of invasion: enhanced germination in invasive European
 422 populations of black locust (*Robinia pseudoacacia* L.) compared to native American populations. *Plant Biol*
 423 (Stuttgart) 23:1006–1017. <https://doi.org/10.1111/plb.13332>

424 Brunetti M, Maugeri M, Monti F, Nanni T (2006) Temperature and precipitation variability in Italy in the last two
 425 centuries from homogenised instrumental time series. *Int J Climatol* 26:345–381. <https://doi.org/10.1002/joc.1251>

426 Cesaraccio C, Spano D, Snyder RL, Duce P (2004) Chilling and forcing model to predict bud-burst of crop and forest
 427 species. *Agric For Meteorol* 126:1–13. <https://doi.org/10.1016/j.agrformet.2004.03.002>

428 Chuine I, de Cortazar-Atauri IG, Kramer K, Hänninen H (2013) Plant Development Models. In: Schwartz MD (ed)
 429 Phenology: An Integrative Environmental Science. Springer Netherlands, Dordrecht, pp 275–293

430 Chuine I, Régnière J (2017) Process-Based Models of Phenology for Plants and Animals. *Annu Rev Ecol Evol Syst*
 431 48:159–182. <https://doi.org/10.1146/annurev-ecolsys-110316-022706>

432 Cleland EE, Chuine I, Menzel A, et al (2007) Shifting plant phenology in response to global change. *Trends Ecol Evol*
 433 22:357–365. <https://doi.org/10.1016/j.tree.2007.04.003>

434 Cook BI, Wolkovich EM, Parmesan C (2012) Divergent responses to spring and winter warming drive community level
 435 flowering trends. *Proc Natl Acad Sci* 109:9000–9005. <https://doi.org/10.1073/pnas.1118364109>

436 Cooke JEK, Eriksson ME, Junttila O (2012) The dynamic nature of bud dormancy in trees: environmental control and
 437 molecular mechanisms. *Plant Cell Environ* 35:1707–1728. <https://doi.org/10.1111/j.1365-3040.2012.02552.x>

438 D. S. Wilks. (2006) Statistical methods in the atmospheric sciences, second edition

439 D’agostino RB, Belanger A, D’agostino RB (1990) A Suggestion for Using Powerful and Informative Tests of
 440 Normality. *Am Stat* 44:316–321. <https://doi.org/10.1080/00031305.1990.10475751>

441 Davidson AM, Jennions M, Nicotra AB (2011) Do invasive species show higher phenotypic plasticity than native
 442 species and, if so, is it adaptive? A meta-analysis. *Ecol Lett* 14:419–431. <https://doi.org/10.1111/j.1461-0248.2011.01596.x>

444 Delpierre N, Vitasse Y, Chuine I, et al (2016) Temperate and boreal forest tree phenology: from organ-scale processes
 445 to terrestrial ecosystem models. *Ann For Sci* 73:5–25. <https://doi.org/10.1007/s13595-015-0477-6>

446 Durbin J, Watson GS (1950) Testing for serial correlation in least squares regression. I. *Biometrika* 37:409–428.
 447 <https://doi.org/10.1093/biomet/37.3-4.409>

448 Farkas Á, Zajác E (2007) Nectar production for the Hungarian honey industry. *Eur J Plant Sci Biotechnol* 1:125–151

449 Fitter AH, Fitter RSR (2002) Rapid Changes in Flowering Time in British Plants. *Science* (80-) 296:1689–1691.
 450 <https://doi.org/10.1126/science.1071617>

451 Fitter AH, Fitter RSR, Harris ITB, Williamson MH (1995) Relationships Between First Flowering Date and
 452 Temperature in the Flora of a Locality in Central England. *Funct Ecol* 9:55. <https://doi.org/10.2307/2390090>

453 Fornaciari M, Marrapodi S, Ruga L, et al (2023) Tree responses and temperature requirements in two central Italy
 454 phenological gardens. *Int J Biometeorol* 67:1607–1617. <https://doi.org/10.1007/s00484-023-02522-3>

455 Granata MU, Bracco F, Catoni R (2020) Phenotypic plasticity of two invasive alien plant species inside a deciduous
 456 forest in a strict nature reserve in Italy. *J Sustain For* 39:346–364.
 457 <https://doi.org/10.1080/10549811.2019.1670678>

458 Grubbs FE (1950) Sample Criteria for Testing Outlying Observations. *Ann Math Stat* 21:27–58.
 459 <https://doi.org/10.1214/aoms/1177729885>

460 Harris CR, Millman KJ, van der Walt SJ, et al (2020) Array programming with NumPy. *Nature* 585:357–362.
 461 <https://doi.org/10.1038/s41586-020-2649-2>

462 Hoyer S, Hamman J (2017) xarray: N-D labeled Arrays and Datasets in Python. *J Open Res Softw* 5:10.
 463 <https://doi.org/10.5334/jors.148>

464 Hunter JD (2007) Matplotlib: A 2D Graphics Environment. *Comput Sci Eng* 9:90–95.
 465 <https://doi.org/10.1109/MCSE.2007.55>

466 Inouye DW (2000) The ecological and evolutionary significance of frost in the context of climate change. *Ecol Lett*
 467 3:457–463. <https://doi.org/10.1046/j.1461-0248.2000.00165.x>

468 Jabłońska K, Kwiatkowska-Falińska A, Czernecki B, Walawender JP (2015) Changes in Spring and Summer
 469 Phenology in Poland — Responses of Selected Plant Species to Air Temperature Variations. *Polish J Ecol*
 470 63:311–319. <https://doi.org/10.3161/15052249PJE2015.63.3.002>

471 Jateczak K, Walawender J (2009) Average rate of phenological changes in Poland according to climatic changes –
 472 evaluation and mapping. *Adv Sci Res* 3:127–131. <https://doi.org/10.5194/asr-3-127-2009>

473 Kaufmann H, Blanke M (2017) Changes in carbohydrate levels and relative water content (RWC) to distinguish
 474 dormancy phases in sweet cherry. *J Plant Physiol* 218:1–5. <https://doi.org/10.1016/j.jplph.2017.07.004>

475 Kim S, Kim TK, Yoon S, et al (2022) Quantifying the importance of day length in process-based models for the
 476 prediction of temperate spring flowering phenology. *Sci Total Environ* 843:156780.
 477 <https://doi.org/10.1016/j.scitotenv.2022.156780>

478 Kudo G, Ida TY (2013) Early onset of spring increases the phenological mismatch between plants and pollinators.
 479 *Ecology* 94:2311–2320. <https://doi.org/10.1890/12-2003.1>

480 Le Conte Y, Navajas M (2008) Climate change: impact on honey bee populations and diseases. *Rev Sci Tech l'OIE*
 481 27:485–510. <https://doi.org/10.20506/rst.27.2.1819>

482 Lionello P, Scarascia L (2018) The relation between climate change in the Mediterranean region and global warming.
 483 *Reg Environ Chang* 18:1481–1493. <https://doi.org/10.1007/s10113-018-1290-1>

484 Luedeling E, Kunz A, Blanke MM (2013) Identification of chilling and heat requirements of cherry trees—a statistical
 485 approach. *Int J Biometeorol* 57:679–689. <https://doi.org/10.1007/s00484-012-0594-y>

486 Marafon AC, Citadin I, Amarante L do, et al (2011) Chilling privation during dormancy period and carbohydrate
 487 mobilization in Japanese pear trees. *Sci Agric* 68:462–468. <https://doi.org/10.1590/S0103-90162011000400011>

488 Mariani L, Alilla R, Cola G, et al (2013) IPHEN—a real-time network for phenological monitoring and modelling in

Italy. *Int J Biometeorol* 57:881–893. <https://doi.org/10.1007/s00484-012-0615-x>

McKinney W (2010) Data Structures for Statistical Computing in Python. In: *Proceedings of the 9th Python in Science Conference*. pp 56–61

Meier U (2001) Growth stages of mono-and dicotyledonous plants. *BBCH Monograph*. Berlin

Memmott J, Craze PG, Waser NM, Price M V. (2007) Global warming and the disruption of plant–pollinator interactions. *Ecol Lett* 10:710–717. <https://doi.org/10.1111/j.1461-0248.2007.01061.x>

Menzel A (2000) Trends in phenological phases in Europe between 1951 and 1996. *Int J Biometeorol* 44:76–81. <https://doi.org/10.1007/s004840000054>

Menzel A, Sparks TH, Estrella N, et al (2006) European phenological response to climate change matches the warming pattern. *Glob Chang Biol* 12:1969–1976. <https://doi.org/10.1111/j.1365-2486.2006.01193.x>

Murray MB, Cannell MGR, Smith RI (1989) Date of Budburst of Fifteen Tree Species in Britain Following Climatic Warming. *J Appl Ecol* 26:693. <https://doi.org/10.2307/2404093>

Orlandi F, Ruga L, Bonofiglio T, et al (2014) Fifteen-year phenological plant species and meteorological trends in central Italy. *Int J Biometeorol* 58:661–667. <https://doi.org/10.1007/s00484-013-0646-y>

Osservatorio Nazionale Miele (2024) MIELE. Andamento produttivo e di mercato per la stagione 2023. Valore della Terra Agric. e nuova Rural. Econ. e sostenibilità, Qual. e Consum. consapevole. Riv. multimediale n. 1/2024

Osservatorio Nazionale Miele, ISMEA (2023) REPORT MANCATE PRODUZIONI PRIMAVERILI 2023 E STIMA DEL DANNO

Pagter M, Andersen UB, Andersen L (2015) Winter warming delays dormancy release, advances budburst, alters carbohydrate metabolism and reduces yield in a temperate shrub. *AoB Plants* 7:1–15. <https://doi.org/10.1093/aobpla/plv024>

Parmesan C (2006) Ecological and Evolutionary Responses to Recent Climate Change. *Annu Rev Ecol Evol Syst* 37:637–669. <https://doi.org/10.1146/annurev.ecolsys.37.091305.110100>

Pearson K (1895) Contributions to the Mathematical Theory of Evolution. - II. Skew Variation in Homogeneous Material. *Philos Trans R Soc London* 186:343–414

Pedregosa F, Varoquaux G, Gramfort A, et al (2011) Scikit-learn: Machine Learning in Python. *J Mach Learn Res* 12:2825–2830

Piao S, Liu Q, Chen A, et al (2019) Plant phenology and global climate change: Current progresses and challenges. *Glob Chang Biol* 25:1922–1940. <https://doi.org/10.1111/gcb.14619>

Reddy PVR, Verghese A, Rajan VV (2013) Potential impact of climate change on honeybees (*Apis* spp.) and their pollination services. *Pest Manag Hortic Ecosyst* 18:121–127

Rosenzweig C, Karoly D, Vicarelli M, et al (2008) Attributing physical and biological impacts to anthropogenic climate change. *Nature* 453:353–357. <https://doi.org/10.1038/nature06937>

522 Scheifinger H, Menzel A, Koch E, Peter C (2003) Trends of spring time frost events and phenological dates in Central
523 Europe. *Theor Appl Climatol* 74:41–51. <https://doi.org/10.1007/s00704-002-0704-6>

524 Schwartz MD (2013) *Phenology: An Integrative Environmental Science, II*. Springer Dordrecht Heidelberg New York
525 London

526 Seabold S, Perktold J (2010) statsmodels: Econometric and statistical modeling with python. In: 9th Python in Science
527 Conference. 9th Python in Science Conference

528 Shao J (1993) Linear Model Selection by Cross-validation. *J Am Stat Assoc* 88:486–494.
529 <https://doi.org/10.1080/01621459.1993.10476299>

530 Shapiro SS, Wilk MB (1965) An analysis of variance test for normality (complete samples). *Biometrika* 52:591–611.
531 <https://doi.org/10.1093/biomet/52.3-4.591>

532 Silvestro R, Deslauriers A, Prislan P, et al (2025) From Roots to Leaves: Tree Growth Phenology in Forest Ecosystems.
533 *Curr For Reports* 11:12. <https://doi.org/10.1007/s40725-025-00245-9>

534 Silvestro R, Rossi S, Zhang S, et al (2019) From phenology to forest management: Ecotypes selection can avoid early
535 or late frosts, but not both. *For Ecol Manage* 436:21–26. <https://doi.org/10.1016/j.foreco.2019.01.005>

536 Van Espen M, Williams JH, Alves F, et al (2023) Beekeeping in Europe facing climate change: A mixed methods study
537 on perceived impacts and the need to adapt according to stakeholders and beekeepers. *Sci Total Environ*
538 888:164255. <https://doi.org/10.1016/j.scitotenv.2023.164255>

539 Van Rossum G, Drake FL (2009) *Python 3 Reference Manual*. CreateSpace, Scotts Valley, CA

540 Virtanen P, Gommers R, Oliphant TE, et al (2020) SciPy 1.0: fundamental algorithms for scientific computing in
541 Python. *Nat Methods* 17:261–272. <https://doi.org/10.1038/s41592-019-0686-2>

542 Vitasse Y, Basler D (2013) What role for photoperiod in the bud burst phenology of European beech. *Eur J For Res*
543 132:1–8. <https://doi.org/10.1007/s10342-012-0661-2>

544 Walkovszky A (1998) Changes in phenology of the locust tree (*Robinia pseudoacacia* L.) in Hungary. *Int J*
545 *Biometeorol* 41:155–160. <https://doi.org/10.1007/s004840050069>

546 Walther G, Post E, Convey P, et al (2002) Ecological responses to recent climate change. *Nature* 416:389–395.
547 <https://doi.org/10.1038/416389a>

548 Waskom M (2021) seaborn: statistical data visualization. *J Open Source Softw* 6:3021.
549 <https://doi.org/10.21105/joss.03021>

550 Zaiontz C (2025) *Real Statistics Resource Pack*

551

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupplementaryMaterial.pdf](#)