Supplemental materials:
Climate change increases the risk of false springs in European trees

OR

False spring risk increases across European trees in the face of climate change

OR

Heightened risk of false springs with climate change across six European tree species

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Methods: Spatial predictor

Spatial autocorrelation (SA) is a common issue in spatial ecology given that nearby spatial units tend to be more similar than units far apart, and thus, cannot be considered as independent units, which is a frequent assumption in statistical tests (Diniz-Filho *et al.*, 2003). If model residuals are spatially autocorrelated, and thus, non-independent then model coefficients and errors may be biased in a hard-to-predict way (Mauricio Bini *et al.*, 2009). On the contrary, if model residuals are not autocorrelated, then SA should not be of concern (Hawkins, 2012).

To control for spatial autocorrelation and to account for spatially structured processes independent from our environmental predictors of false springs, we generated an additional spatial predictor for the model. To avoid collinearity, we computed our spatial predictor from the residuals of a linear model of false springs as a function (Equation S1) of all other factors that are also spatially structured (e.g. spring temperature, altitude, distance to the coast), following the logic of spatial filter modelling (Diniz-Filho & Bini, 2005). The calculation of the spatial predictor followed the next steps: (a) we fit a linear model of false spring versus environmental factors, (b) we extracted the residuals of the regression Equation S1, which represent the portion of the variation in the number of false springs that is independent from the predictors in the model and (c) we utilized the residuals as our y_i values in a selection of spatial eigenvectors to retain only the minimal subset of spatial eigenvectors that are able to remove SA from model residuals. Specifically, we selected eigenvectors following the the minimization of Moran's I of the residuals (MIR) approach (Griffith & Peres-Neto, 2006; Diniz-Filho *et al.*, 2012; Bauman *et al.*, 2017). (d) Next, we fit a linear model between the residuals of Equation S1 and the subset of selected eigenvectors. And, finally, (e) we took the fitted values from this regression as our spatial predictor in our final model (see equation from main text, Equation 1), which can be interpreted as a latent variable summarizing the spatial structure in false springs that is unaccounted for by the rest of the environmental factors in our model (Morales-Castilla *et al.*, 2012). A spatial predictor generated in this way has three major advantages. First, it ensures that no SA is left in model residuals. Second, it avoids introducing collinearity issues with other predictors in the model. And third, it can be interpreted as a latent variable summarizing spatial processes (e.g. local adaptation, plasticity, etc.) occurring at multiple scales.

$$
\begin{aligned}
y_i = \alpha_{[i]} &+ \beta_{NAO_{[i]}} + \beta_{MST_{[i]}} + \beta_{Elevation_{[i]}} + \beta_{DistanceCoast_{[i]}} \\
&+ \beta_{ClimateChange_{[i]}} + \beta_{NAO \times Species_{[i]}} + \beta_{MST \times Species_{[i]}} + \beta_{Elevation \times Species_{[i]}} \\
&+ \beta_{DistanceCoast \times Species_{[i]}} + \beta_{ClimateChange \times Species_{[i]}} \\
&+ \beta_{NAO \times ClimateChange_{[i]}} + \beta_{MST \times ClimateChange_{[i]}} + \beta_{Elevation \times ClimateChange_{[i]}} \\
&+ \beta_{DistanceCoast \times ClimateChange_{[i]}} + \sigma_{[i]} \qquad \text{(S1)}
\end{aligned}
$$

Species rate of budburst calculations

Due to the paucity of data for BBCH 7 in the PEP725 dataset, we were unable to use observations for both budburst and leafout to determine the durations of vegetative risk. Instead, we used data from a growth chamber experiment (Flynn & Wolkovich, 2018) to determine the average number of days between budburst and leafout for our study species. We took the mean number of days between budburst and leafout for the entire experiment, which was 12 days. We compared this number to a field observation study (Donnelly *et al.*,

2017) that looked at the time between budburst and leafout across 10 species over 5 years. Finally, we assessed data that were provided by the USA National Phenology Network and the many participants who contribute to its Nature's Notebook program (USA-NPN,2019; www.usanpn.org/data/observational) for *Aesculus flava* (Sol.), *Aesculus glabra* (Willd.), *Alnus incana* (Moench.), *Betula nigra* (L.), *Betula papyrifera* (Marshall), *Fagus grandifolia* (Ehrh.), *Fraxinus americana* (L.), *Fraxinus nigra* (Marshall) and *Quercus velutina* (Lam.) and took the mean number of days between budburst and leafout. Across all three approaches, the average number of days between budburst and leafout was approximately 12 days.

Again, due to a lack of BBCH 7 data, we were unable to determine species-specific averages of number of days between budburst and leafout. We used a similar approach as above by using data from the growth chamber experiment (Flynn & Wolkovich, 2018) but instead of finding whole experiment means we determined species-specific averages. We used the rate of budburst of *Acer saccharum* (Marshall) for *Aesculus hippocastanum* (Buerki *et al.*, 2010), *Alnus incana* for *Alnus glutinosa*, *Betula papyrifera* for *Betula pendula* (Wang *et al.*, 2016), *Fagus grandifolia* for *Fagus sylvatica*, *Fraxinus nigra* for *Fraxinus excelsior* and *Quercus alba* (L.) for *Quercus robur* (Hipp *et al.*, 2017).

Results: The effects of climatic and spatial variation on false spring incidence

Most species had mean spring temperatures that ranged from -5°C to 12°C, but for *Alnus glutinosa* and *Fraxinus excelsior* temperatures rarely dropped below 0°C, whereas *Quercus robur* experienced some of the lowest spring temperatures (see Figure S1).

The overall model output estimates are for *Aesculus hippocastanum* as species were used as two-way interactions to simulate modeled groups on the main effects. The model estimates on the logit scale were converted to probability percentages for easier interpretation by using the 'divide by 4' rule (Gelman & Hill, 2006) and then back converted to the original scale.

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Supplement: Tables and Figures

Table 1: Data collected from PEP725 for each species and the calculated number of false spring years

Species	Num. of Observations	Num. of False Springs	Num. of Sites	Num. of Years
Aesculus hippocastanum	156468	44746	10157	66
Alnus glutinosa	91094	27296	6775	65
Betula pendula	154897	46685	10139	66
Fagus sylvatica	129133	29237	9099	66
Fraxinus excelsior	92665	8256	7327	65
Quercus robur	131635	16657	8811	66

Table 2: Mean day of budburst and standard deviation for each species for before (1951-1983) and after climate change (1984-2016).

	1951-1983		1984-2016	
	mean	sd	mean	sd
Aesculus hippocastanum	102.2	12.44	95.35	12.09
Alnus glutinosa	102.8	14.81	94.90	14.71
Betula pendula	101.3	11.76	95.44	11.25
Fagus sylvatica	109.1	9.978	103.7	9.623
Fraxinus excelsior	119.4	11.79	113.5	11.53
Quercus robur	115.9	11.31	109.6	10.95

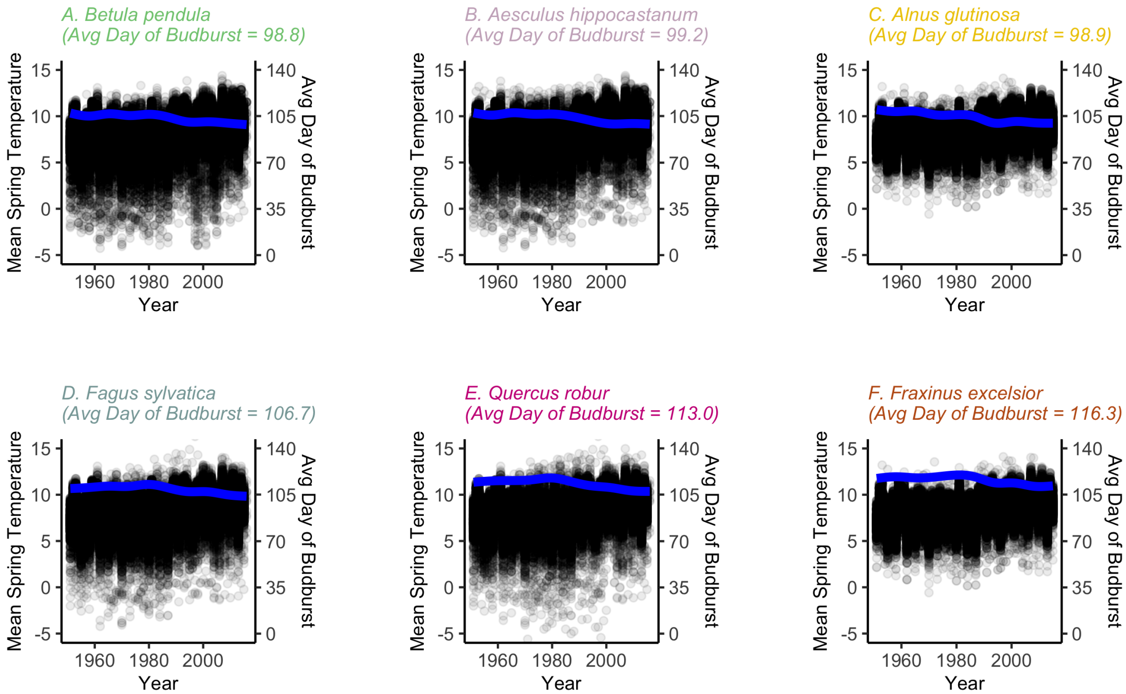

Figure 1: Mean spring temperatures are plotted for each site and year (from 1951-2016) for each species. The blue line is a smoothing spline, indicating the trend of average day of budburst for each year for each species. Species are ordered by average day of budburst, with the earliest being *Betula pendula* and the latest being *Fraxinus excelsior* and species names are color-coded to match the other figures.

Table 3: Summary of simple linear regression model of day of budburst before and after climate change.

	Estimate	10%	90%
Intercept	104.88	104.85	104.90
Climate Change	-5.88	-5.93	-5.83

Table 4: Summary of simple linear regression model of day of year of last freeze (-2.2ÂřC) before and after climate change.

	Estimate	10%	90%
Intercept	128.87	128.84	128.89
Climate Change	-5.86	-5.92	-5.81

Table 5: Summary of simple linear regression model of average minimum temperature between budburst and leafout before and after climate change.

	Estimate	10%	90%
Intercept	7.17	7.16	7.17
Climate Change	0.81	0.80	0.82

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Table 6: Summary of main Bernouilli model of false spring risk without the species interactions (estimates presented on logit scale for *Aesculus hippocastanum*).

	Estimate	10%	90%	Species	NA
Aesculus hippocastanum	0.12	0.16	0.14	7.80	NAO Index
Aesculus hippocastanum	-0.50	-0.45	-0.48	10.80	Mean Spring Temperature
Aesculus hippocastanum	0.38	0.43	0.40	9.80	Distance from Coast
Aesculus hippocastanum	0.16	0.22	0.19	8.80	Elevation
Aesculus hippocastanum	-0.08	-0.05	-0.06	6.80	Space Parameter
Aesculus hippocastanum	0.33	0.37	0.35	5.80	Climate Change
Alnus glutinosa	0.01	0.13	0.07	7.75	NAO Index
Betula pendula	0.01	0.11	0.06	7.70	NAO Index
Fagus sylvatica	0.21	0.32	0.26	7.65	NAO Index
Fraxinus excelsior	0.10	0.24	0.17	7.60	NAO Index
Quercus robur	0.16	0.28	0.22	7.55	NAO Index
Alnus glutinosa	-0.40	-0.27	-0.33	10.75	Mean Spring Temperature
Betula pendula	-0.55	-0.44	-0.50	10.70	Mean Spring Temperature
Fagus sylvatica	-0.60	-0.48	-0.54	10.65	Mean Spring Temperature
Fraxinus excelsior	-0.24	-0.07	-0.16	10.60	Mean Spring Temperature
Quercus robur	-0.44	-0.31	-0.37	10.55	Mean Spring Temperature
Alnus glutinosa	0.27	0.40	0.33	9.75	Distance from Coast
Betula pendula	0.35	0.47	0.41	9.70	Distance from Coast
Fagus sylvatica	0.34	0.46	0.40	9.65	Distance from Coast
Fraxinus excelsior	0.58	0.74	0.66	9.60	Distance from Coast
Quercus robur	0.23	0.37	0.30	9.55	Distance from Coast
Alnus glutinosa	0.14	0.29	0.21	8.75	Elevation
Betula pendula	0.16	0.29	0.22	8.70	Elevation
Fagus sylvatica	0.12	0.26	0.19	8.65	Elevation
Fraxinus excelsior	-0.27	-0.09	-0.18	8.60	Elevation
Quercus robur	0.03	0.19	0.11	8.55	Elevation
Alnus glutinosa	-0.10	0.00	-0.05	6.75	Space Parameter
Betula pendula	-0.12	-0.03	-0.07	6.70	Space Parameter
Fagus sylvatica	-0.16	-0.06	-0.11	6.65	Space Parameter
Fraxinus excelsior	-0.08	0.05	-0.01	6.60	Space Parameter
Quercus robur	-0.10	0.01	-0.05	6.55	Space Parameter
Alnus glutinosa	0.36	0.47	0.41	5.75	Climate Change
Betula pendula	0.36	0.46	0.41	5.70	Climate Change
Fagus sylvatica	-0.02	0.08	0.03	5.65	Climate Change
Fraxinus excelsior	-0.23	-0.10	-0.17	5.60	Climate Change
Quercus robur	-0.11	0.00	-0.05	5.55	Climate Change
Overall Estimate	0.10	0.21	0.15	8.00	NAO Index

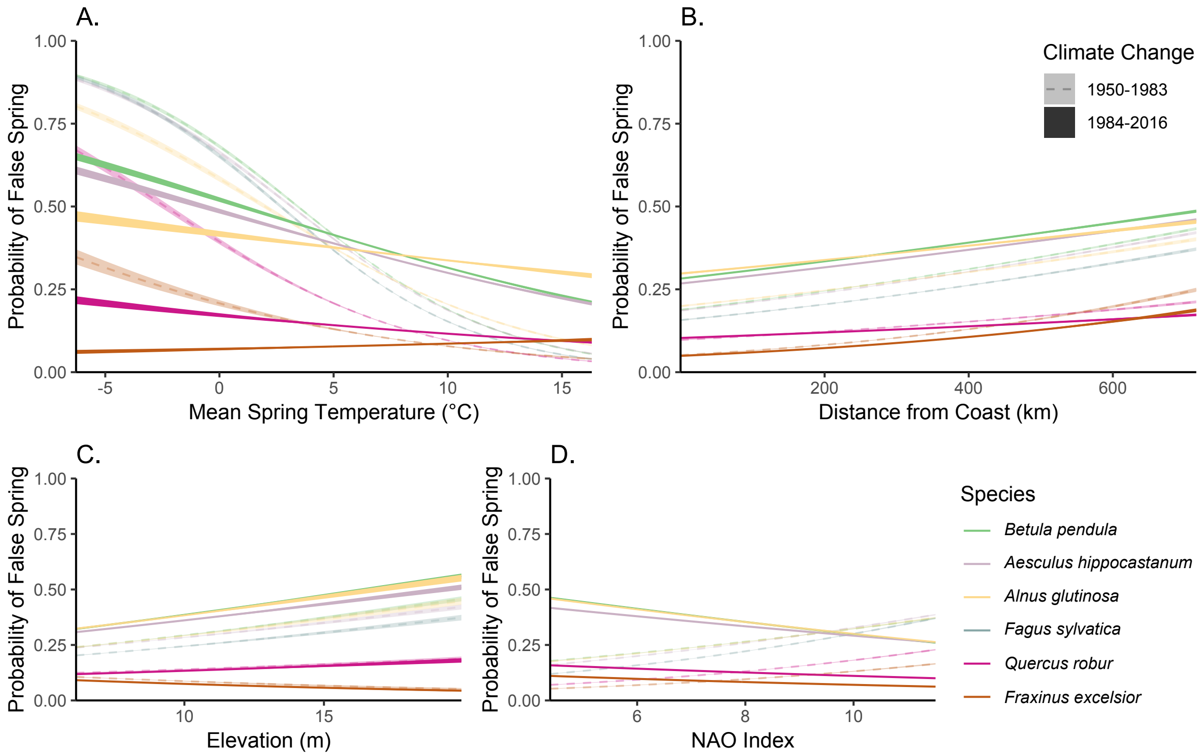

Figure 2: Average predictive comparisons for all climate change interactions with each of the main effects (i.e., mean spring temperature, distance from the coast, elevation, and NAO index) for all species.

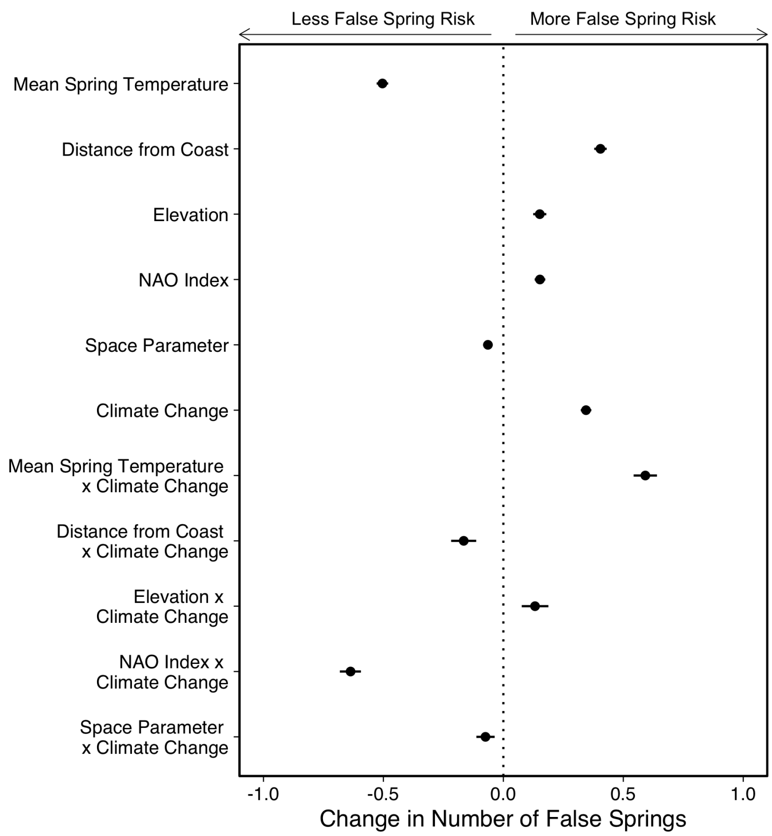

Figure 3: Model output with different durations of vegetative risk for each species. More positive values indicate an increased probability of a false spring whereas more negative values suggest a lower probability of a false spring. Dots and lines show means and 10% uncertainty intervals. Values closer to zero have less of an effect on false springs. There were 622,565 zeros and 132,463 ones for false springs in the data.

Table 7: Summary of Bernouilli model of false spring risk with varying durations of vegetative risk for each species without the species interactions (estimates presented on logit scale for *Aesculus hippocastanum*).

	Estimate	10%	25%	75%	90%
NAO Index	0.15	0.13	0.14	0.16	0.17
Mean Spring Temperature	-0.50	-0.53	-0.51	-0.49	-0.48
Distance from Coast	0.40	0.38	0.39	0.42	0.43
Elevation	0.15	0.12	0.14	0.16	0.18
Space Parameter	-0.06	-0.08	-0.07	-0.06	-0.04
Climate Change	0.34	0.32	0.34	0.35	0.37
NAO Index by Climate Change	-0.64	-0.68	-0.65	-0.62	-0.59
Mean Spring Temperature by Climate Change	0.59	0.54	0.57	0.61	0.64
Distance from Coast by Climate Change	-0.17	-0.22	-0.19	-0.14	-0.11
Elevation by Climate Change	0.13	0.08	0.11	0.15	0.19
Space Parameter by Climate Change	-0.07	-0.11	-0.09	-0.06	-0.04

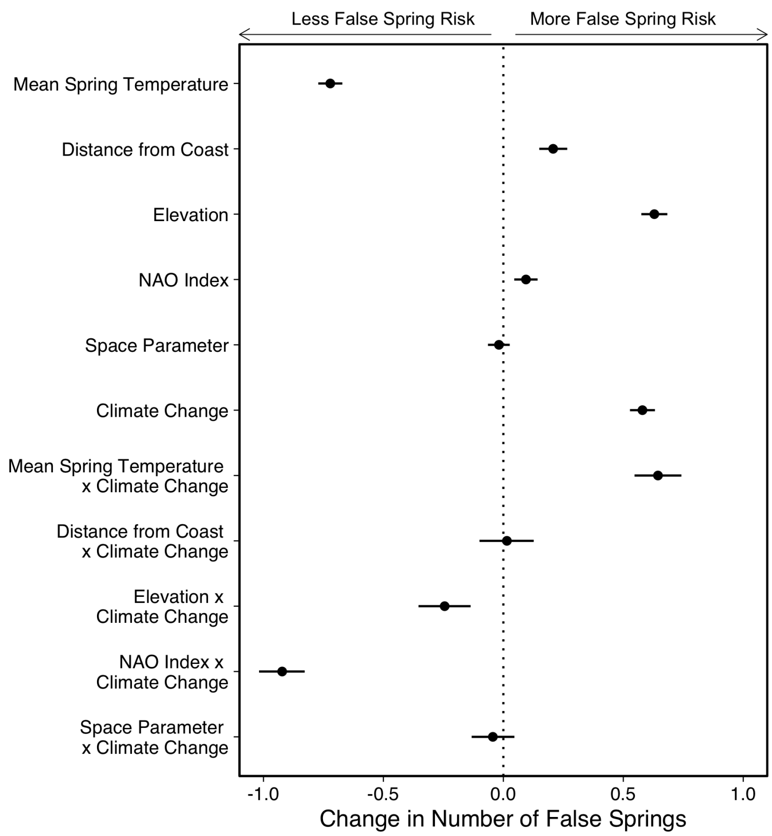

Figure 4: Model output with a lower temperature threshold (-5°C) for defining a false spring. More positive values indicate an increased probability of a false spring whereas more negative values suggest a lower probability of a false spring. Dots and lines show means and 10% uncertainty intervals. Values closer to zero have less of an effect on false springs. There were 730,996 zeros and 23,855 ones for false springs in the data.

Table 8: Summary of Bernouilli model of false spring risk with a lower temperature threshold (-5°C) for defining a false spring without the species interactions (estimates presented on logit scale for *Aesculus hippocastanum*).

	Estimate	10%	25%	75%	90%
NAO Index	0.09	0.05	0.07	0.11	0.14
Mean Spring Temperature	-0.72	-0.77	-0.74	-0.70	-0.67
Distance from Coast	0.21	0.15	0.18	0.23	0.27
Elevation	0.63	0.58	0.61	0.65	0.68
Space Parameter	-0.02	-0.06	-0.04	0.00	0.03
Climate Change	0.58	0.53	0.56	0.60	0.63
NAO Index by Climate Change	-0.92	-1.02	-0.96	-0.88	-0.83
Mean Spring Temperature by Climate Change	0.64	0.55	0.60	0.69	0.74
Distance from Coast by Climate Change	0.01	-0.10	-0.03	0.06	0.13
Elevation by Climate Change	-0.24	-0.35	-0.29	-0.20	-0.14
Space Parameter by Climate Change	-0.04	-0.13	-0.08	-0.01	0.05