Special issue:

*“The role of plasticity in phenotypic adaptation to rapid environmental change”*

# Phenotypic plasticity in response to climate change: the importance of cue variation

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## Supplementary materials

### *Box S1: Empirical evaluation of cues for plasticity*

Plasticity cues can be very difficult to identify in empirical systems. By directly manipulating the environment, experimental work can determine which specific cue triggers phenotypic expression (e.g. defenses induced by predator “smell”, or kairomone [1]). A particular advantage of such laboratory experiments is that they allow cues to be identified by decoupling them from (i) other environmental variables that may covary with them *in natura*, and (ii) other environmental variables that drive selection on the plastic trait. For example, experimental work on shade responses in plants allowed disentangling the effects of spectral quality (red/far red ratio, an indicator of the presence of competitors) and the amount of light (photosynthetically active radiation, signaling neutral shade e.g. from a rock [2]). However, adequate manipulation of the cue may be more complex than anticipated, because the timing and pattern of variation in the environment is also important in eliciting phenotypic responses. For example, laying date in a Dutch great tit population is more sensitive to patterns of temperature than to average temperature per se [3,4] and so are thermal reaction norms of parasitic wasps [5]. Failing to integrate environmental variability in experiments may lead to poorly evaluate responses to an environmental factor [6].

In nature, in contrast, the difficulty is to assess which environmental variable is actually used by the organisms. This requires long term ($\geq$ 20 years [7]) correlative studies. Many studies of phenotypic plasticity in the wild use a priori knowledge [7], others evaluate which environmental variable explains the highest proportion of phenotypic variance. For climatic predictors (e.g. in studies of phenology), the most common method to achieve this is to use sliding window analyses. But until recently and the development of statistical packages such as `climwin` [7,8], there was no formal statistical framework to assess the validity of detected cues. The recent methodological developments will allow assessing cues in the wild with more confidence, and will facilitate comparisons across studies. However, combining both experimental and *in situ* correlative approaches is required for a better understanding of each system. For example, an effect of mean temperature on laying date in great tits in the wild is known, but experimental work in the lab revealed later laying date in captivity than in the wild, suggesting the existence of other cues [9].

While organisms respond to complex environments that combine several environmental variables, a majority of studies only investigate one variable as a potential cue [7]. The use of simultaneous cues is extremely difficult to evaluate for wild populations, as this requires not only to define a set of potentially relevant variables that can be used as cues, but also to have access to long term data for a larger panel of environmental variables. These approaches are also very demanding in terms of power for data analysis, and are still rarely done in the wild (but see [10]).

*Table S1*

Data summary, detailing for each population: forest type, time span over which data are available for blue tits and caterpillar phenology, and samples sizes for individual laying dates. The phenology of caterpillars is approximated by caterpillar frass mass collected regularly in coprometers, such that the day with the highest quantity of frass in each year corresponds to the date of the peak of caterpillar abundance of the year [11].

| | *D-Rouvière* | *D-Muro* | *E-Muro* | *E-Pirio* |
|---|---|---|---|---|
| *Forest type* | Deciduous | Deciduous | Evergreen | Evergreen |
| *Nb. mean laying date obs. (year span)* | 27<br>(1991 – 2017) | 25<br>(1993 – 2017) | 20<br>(1998 – 2017) | 42<br>(1976 – 2017) |
| *Nb. females / nb. obs. of laying date* | 905 / 2040 | 752 / 1433 | 322 / 796 | 884 / 2120 |
| *Nb. caterpillar date obs. (year span)* | 10<br>(1991 – 2002) | 25<br>(1993 – 2017) | 17<br>(2001 – 2017) | 31<br>(1987 – 2017) |
| *Caterpillar abundance (mean ± se, in mg/m²/day)* | 60.23 ± 8.33 | 2069.08 ± 447.70 | 517.86 ± 94.30 | 183.04 ± 23.63 |

*Table S2*

Temporal trends in the four study sites for a) blue tits (laying date); b) caterpillars (date of peak abundance) and c) temperature (daily mean, daily maximum and daily minimum) during the reproductive period (from April to end of June) estimated over the period 1991-2017. Significant trends (p-value < 0.05) are in bold. Sample sizes are given in Table S1.

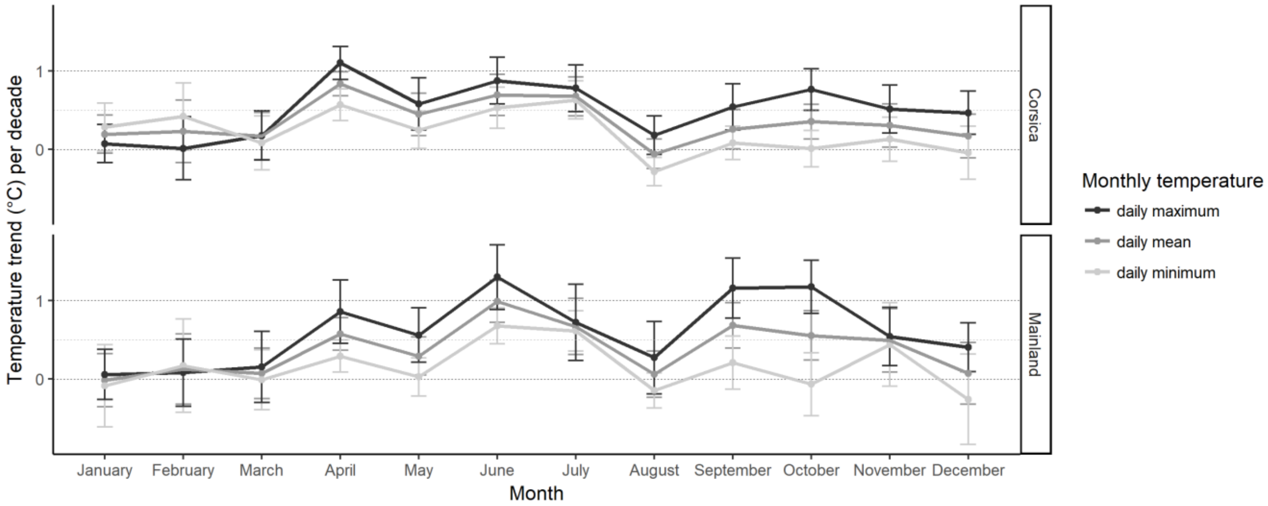
| *a)* | *Laying date change (days per decade, ± se)* | *t-value* | *p-value* | *$r^2$* |
|---|---|---|---|---|
| *D-Rouvière* | 0.10 (± 0.13) | 0.08 | 0.94 | -0.04 |
| *D-Muro* | -0.61 (± 0.14) | -0.43 | 0.67 | -0.04 |
| *E-Muro* | **-3.57 (± 0.16)** | **-2.23** | **0.04** | **0.17** |
| *E-Pirio* | **-3.15 (± 0.05)** | **-5.91** | **<0.0001** | **0.45** |

| *b)* | *Food peak change (days per decade, ± se)* | *t-value* | *p-value* | *$r^2$* |
|---|---|---|---|---|
| *D-Rouvière* | -20.03 (± 11.51) | -1.76 | 0.12 | 0.19 |
| *D-Muro* | -2.99 (± 1.80) | -1.66 | 0.11 | 0.07 |
| *E-Muro* | -8.33 (± 3.93) | -2.12 | 0.05 | 0.18 |
| *E-Pirio* | **-3.57 (± 1.35)** | **-2.65** | **0.01** | **0.17** |

| *c)* | *Statistic* | *Temperature change (°C per decade, ± se)* | *t-value* | *p-value* | *$r^2$* |
|---|---|---|---|---|---|
| *Corsica* | Mean | **0.66 (± 0.2)** | **3.93** | **0.0005** | **0.36** |
| | Min | **1.03 (± 0.3)** | **2.96** | **0.0067** | **0.23** |
| | Max | **1.25 (± 0.3)** | **3.80** | **0.0008** | **0.34** |
| *Mainland* | Mean | **0.61 (± 0.2)** | **3.92** | **0.0006** | **0.36** |
| | Min | **0.91 (± 0.4)** | **2.55** | **0.0172** | **0.17** |
| | Max | **1.10 (± 0.4)** | **2.68** | **0.0128** | **0.19** |

*Figure S1*

Time trends of the daily mean (in dark grey), daily minimum (in light grey) and daily maximum (in black) temperature per month across years for Corsican sites (D-Muro, E-Muro and E-Pirio) and the mainland site (D-Rouvière) for the 1991-2017 period. Values are slopes of a regression of temperature against year as a linear trend, estimated for each statistic (mean, max and min) for each month (± se).



## *Box S2: Methods: Details of sliding windows analyses*

### General procedure

In order to estimate the period during which climate most strongly influences the phenology of blue tits and caterpillars, we implemented sliding window analyses using the package `climwin` [7,8]. Correlation between mean laying date or caterpillar date with temperature and rainfall was tested across years for every period of more than 1 day in all years. For mean laying date of blue tits, data on known second clutches were removed, and individuals with laying dates later than 30 day after the first laying date of the year in each population were eliminated from the data sets. We tested several summary statistics for both temperature and rainfall: daily mean, maximum, minimum temperature during each period for all populations. We defined Extreme Climatic Events (or ECE) as the highest 5% of the distribution of a climatic variable over a period of reference [12]. We chose this reference to be the period of sensitivity to mean temperature (population specific best model, see below) for the years 1991-2017. For each climatic parameter, we tested for both linear and quadratic reaction norms. We allowed the window to overlap with the period of reproduction and development (respectively for birds and caterpillars), as a way to assess whether plasticity is predictive, i.e. if the best cues are found before and not during the breeding season.

Among all tested combinations of climate parameters, summary statistics, and relationship functions, we retained the models that best predicted the among-year variation in the mean phenotype for each population and species. Model choice was based on three indicators of the ability of the models to explain the among-year variation of the phenotype:

i) The $\Delta AIC$ is the difference between the Akaike Information Criterion (AIC) of a given model and that of a basic model including an intercept only, hereafter the base model. This difference estimates the ability of the focal model to explain the temporal variance in the mean phenotype, as compared to the base model. The lower the $\Delta AIC$, the higher the explicative power of the detected cue windows.

ii) The critical probability $P_c$ represents the probability to detect the best windows as a signal just by chance (akin to a p-value). We ran randomization procedure to test for the probability of false positives. We ran five simulation models using different randomizations of the mean phenotype across years (five randomisations are sufficient when using $P_c$ according to robustness analyses of van de Pol et al. 2016) for each type of climate variable and summary statistics. The best model in these simulations with randomized datasets was chosen based on $\Delta AIC$, and the probability of false positive in cue detection was then quantified as $P_c$. The smaller the $P_c$, the lower the probability that the cue window is detected just by chance.

iii) The confidence set (%CI), quantifies the extent to which there are several models with very similar explanatory power, and thus provides a confidence interval on window limits. It is the percentage of all tested window models (for a given combination of climatic variable and summary statistics) that are required to reach 95% of the sum of all Akaike weights ($wAIC = \exp(\Delta AIC)$). The models within this set compose the 95% confidence set of windows for the particular climatic variables tested. A small %CI suggests that only a few window models contribute to the cumulative predictive power of all tested windows, such that the best window is a reliable signal. The smaller the %CI, the higher the reliability of the detected cues windows (opening and closing day of the windows are detected precisely).

The best model is the one that combines the smallest ΔAIC, the smallest %CI and the smallest $\mathrm{P_c}$. In small datasets with lack of statistical power, %CI will increase. A window could have the best $\Delta AIC$ but a high $P_c$, meaning that the signal, despite strong statistical explicative power, is likely to be detected just by chance. In such a case, we evaluated the second best $\Delta AIC$; if the latter was associated with high $P_c$, we moved on to the third best $\Delta AIC$, etc.and selected the first model in the list with low $P_c$. In small data sets, windows length will be sub-estimated [7]. For the summary statistic that best explains among-year variation of the phenotype, we estimated the median windows of models in the confidence set at 95%.

Note that mean temperature and the number of ECE are significantly positively correlated for blue tits windows in D-Rouvière ($r^2 = 0.68$), D-Muro ($r^2 = 0.48$) and E-Pirio ($r^2= 0.26$), but not in E-Muro (p-value = 0.09, $r^2 = 0.12$).

**Comparison of windows between populations**

We wanted to test if the differences in best cue windows of blue tits from D-Rouvière and E-Pirio were significant. We focused only on these two populations because statistical power was high and equivalent in these populations, but much lower in the two other D-Muro and E-Muro populations. We computed the $\Delta AIC_{same\ windows}$ of a model where a single window was estimated for both populations. This was done by running the analysis on a pooled dataset including both the D-Rouvière and E-Pirio populations, with a fixed effect for population, in interaction with climate (i.e. mean temperature in window). Interactions between population and climate effects in the base line model allowed estimating different reaction norms of plasticity of laying date with respect to temperature for each population, but still using the same cue window for both populations. We then compared this model to the sum of $\Delta AIC$ of the best models (models 1) of D-Rouvière and E-Pirio estimated separately ($\Delta AIC_{different\ windows}$). Note that when the two populations are analyzed separately, compared to a model with no population effect, two additional parameters are estimated (open and close days for the second population). We thus added 2 points of $\Delta AIC$ in $\Delta AIC_{different\ windows}$ compared with the model ($\Delta AIC_{same\ windows}$). If the sum of $\Delta AIC_{different\ windows}$ is lower than the $\Delta AIC_{same\ windows}$, then estimating two different windows for the two populations provides a better fit to the data than a single common window, providing evidence that populations differ in their climate windows.

For comparison, the three sliding windows analyses are implemented with the same reference day (starting day of the sliding windows) equal to 1st July (however, results are consistent regardless of what reference day is used).Results from the sliding windows analyses show that,

$$\begin{aligned}\Delta AIC_{different\ windows} &= \sum \Delta AIC = \Delta AIC_{D-\text{Rouvière}} + \Delta AIC_{E-Pirio} + 2 \\ &= -35.44 - 39.08 + 2 \\ &= -72.52\end{aligned}$$

and

$$\Delta AIC_{same\ windows} = -19.98$$

This clearly indicates that D-Rouvière and E-Pirio have different opening and closing days of temperature windows.

*Table S3*

Consistency of information from local records of temperature (iButtons with temperature log every hour) and data from meteorological stations. Data from iButtons are available from 2009 to 2016 in D-Rouvière, and from 2013 to 2016 in E-Pirio, E-Muro and D-Muro. The congruence was estimated by regressions of the local average daily temperature (minimum daily temperature + maximum daily temperature / 2) from i-buttons placed near nest-boxes over corresponding mean daily temperatures from national meteorological stations (meteorological stations of Calvi for Corsican sites and Saint Martin de Londres for the D-Rouvière site). $r^2$ is the coefficient of determination. Significant slopes (p-value < 0.05) are in bold. Sample sizes are given in Table S1.

| | *Intercept* | | | *Slope* | | | *$r^2$* |
|---|---|---|---|---|---|---|---|
| | Estimates (± se) | t-value | p-value | Estimates (± se) | t-value | p-value | |
| *D-Rouvière* | 4.66 (± 0.40) | 11.68 | <0.0001 | **0.84 (± 0.02)** | **37.68** | **<0.0001** | 0.65 |
| *D-Muro* | 1.85 (± 0.39) | 4.73 | <0.0001 | **0.91 (± 0.02)** | **40.92** | **<0.0001** | 0.73 |
| *E-Muro* | 0.80 (± 0.46) | 1.76 | 0.08 | **0.98 (± 0.02)** | **40.24** | **<0.0001** | 0.78 |
| *E-Pirio* | -0.26 (± 0.25) | -1.02 | 0.31 | **0.96 (± 0.01)** | **68.19** | **<0.0001** | 0.84 |

*Table S4*

Results from sliding windows analyses for blue tits and caterpillars. The best models are highlighted in red for each population. $\Delta AIC$: Difference between the Akaike information criteria of the focal model and that of the base model (a model including the intercept only, see electronic supplementary material Box S2 for details about $\Delta AIC$ , $P_c$ and %CI). Each line presents the best model from a sliding window analysis with the corresponding climate factors, statistics and function. Open and close day of time windows are counted backwards, starting from the reference day (= earliest date of phenotype + 30 day), consistent with the output format of the sliding windows implemented in climwin [7,8]. Note that in the main text, results are transformed to be expressed forward, with a reference Day 1= 1st January (see also table S5).

Sliding windows analyses 1 to 12 and ECE were implemented with the described combination of climate variable, summary statistics and reaction norm function. In the specific case of models "Cue1 + ECE", sliding windows analyses were implemented including in the base model the best temperature window estimated in model 1, in order to take into account the effects of annual mean temperature. However, in the table, we report for these "Cue1 + ECE" models the global $\Delta AIC$ i.e. the sum of the $\Delta AIC$ of the model 1 and of the model "Cue1 + ECE". The $\Delta AIC$ of all models in the table are thus directly comparable (with reference to a base model with intercept only).

| **Blue tits** | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Parameters** | | | **D-Rouvière** | | | | | | **D-Muro** | | | | | |
| **Model** | Cue | Statistic | Function | Threshold | Open | Close | $\Delta AIC$ | $P_c$ | %CI | Threshold | Open | Close | $\Delta AIC$ | $P_c$ | %CI |
| **1** | Temperature | Mean | Lin | **-** | **98** | **24** | **-35.44** | **0.0007** | **2** | **-** | **78** | **16** | **-16.84** | **0.002** | **6** |
| **2** | Temperature | Max | Lin | - | 46 | 46 | -11.37 | 0.52 | 77 | - | 49 | 48 | -14.13 | 0.45 | 69 |
| **3** | Temperature | Min | Lin | - | 46 | 34 | -22.54 | 0.0007 | 3 | - | 49 | 49 | -12.60 | 0.47 | 75 |
| **4** | Temperature | Mean | Quad | - | 99 | 23 | -35.12 | 0.002 | 2 | - | 4 | 1 | -17.22 | 0.05 | 8 |
| **5** | Temperature | Max | Quad | - | 77 | 69 | -11.25 | 0.90 | 71 | - | 289 | 276 | -15.88 | 0.996 | 47 |
| **6** | Temperature | Min | Quad | - | 45 | 34 | -21.26 | 0.002 | 3 | - | 4 | 2 | -20.48 | 0.05 | 20 |
| **7** | Rain | Mean | Lin | - | 350 | 350 | -8.60 | 0.90 | 93 | - | 199 | 195 | -15.07 | 0.73 | 83 |
| **8** | Rain | Max | Lin | - | 350 | 350 | -8.60 | 0.89 | 91 | - | 155 | 155 | -13.91 | 0.55 | 81 |
| **9** | Rain | Min | Lin | - | 161 | 159 | -9.66 | 0.82 | 94 | - | 155 | 155 | -13.91 | 0.94 | 94 |
| **10** | Rain | Mean | Quad | - | 292 | 292 | -12.20 | 0.83 | 82 | - | 348 | 348 | -22.75 | 0.009 | 9 |
| **11** | Rain | Max | Quad | - | 351 | 350 | -12.86 | 0.95 | 85 | - | 348 | 348 | -22.75 | 0.002 | 14 |
| **12** | Rain | Min | Quad | - | 350 | 350 | -12.13 | 0.82 | 94 | - | 348 | 348 | -22.75 | 0.93 | 87 |
| **ECE** | Temperature | Sum | Lin | 13.36 | 96 | 40 | -7.91 | 0.37 | 67 | 15.82 | 53 | 24 | -5.72 | 0.58 | 77 |
| **Cue 1 + ECE** | Temperature | Sum | Lin | - | - | - | - | - | - | - | - | - | - | - | - |
| | **Parameters** | | | **E-Muro** | | | | | | **E-Pirio** | | | | | |
| **Model** | Cue | Statistic | Function | Threshold | Open | Close | $\Delta AIC$ | $P_c$ | %CI | Threshold | Open | Close | $\Delta AIC$ | $P_c$ | %CI |
| **1** | Temperature | Mean | Lin | - | 55 | 12 | -14.92 | 0.04 | 41 | **-** | **54** | **17** | **-39.08** | **7.5 e-05** | **1** |
| **2** | Temperature | Max | Lin | - | 52 | 14 | -14.29 | 0.13 | 49 | - | 28 | 28 | -22.46 | 7.6 e-05 | 10 |
| **3** | Temperature | Min | Lin | - | 310 | 310 | -8.99 | 0.75 | 90 | - | 28 | 28 | -22.46 | 0.1 | 56 |
| **4** | Temperature | Mean | Quad | - | 236 | 234 | -12.77 | 0.84 | 52 | - | 17 | 54 | -37.72 | 0.001 | 1 |
| **5** | Temperature | Max | Quad | - | 32 | 14 | -15.01 | 0.32 | 52 | - | 28 | 28 | -20.10 | 0.05 | 20 |
| **6** | Temperature | Min | Quad | - | 308 | 299 | -11.37 | 0.84 | 73 | - | 28 | 28 | -20.10 | 0.12 | 37 |
| **7** | Rain | Mean | Lin | - | 27 | 22 | -11.35 | 0.73 | 92 | - | 74 | 8 | -18.05 | 6.2 e-05 | 6 |
| **8** | Rain | Max | Lin | - | 24 | 22 | -14.54 | 0.78 | 91 | - | 64 | 6 | -8.66 | 0.88 | 84 |
| **9** | Rain | Min | Lin | - | 175 | 174 | -5.92 | 0.74 | 94 | - | 111 | 107 | -10.18 | 0.94 | 94 |
| **10** | Rain | Mean | Quad | - | 24 | 17 | -15.46 | 0.87 | 62 | - | 24 | 38 | -19.21 | 0.001 | 7 |
| **11** | Rain | Max | Quad | - | 24 | 19 | -17.33 | 0.24 | 42 | - | 250 | 250 | -8.32 | 0.99 | 67 |
| **12** | Rain | Min | Quad | - | 330 | 330 | -5.07 | 0.74 | 94 | - | 64 | 6 | -11.20 | 0.94 | 94 |
| **ECE** | Temperature | Sum | Lin | **17.15** | **47** | **24** | **-18.24** | **0.002** | **5** | 18.15 | 50 | 17 | -17.78 | 0.002 | 32 |
| **Cue 1 + ECE** | Temperature | Sum | Lin | 17.15 | 47 | 24 | -25.84 | 0.21 | 62 | 18.15 | 50 | 33 | -49.10 | 0.03 | 50 |
| **Caterpillars** | | | | | | | | | | | | | | | |
| | **Parameters** | | | **D-Muro** | | | | | | **E-Pirio** | | | | | |
| **Model** | Cue | Statistic | Function | Threshold | Open | Close | $\Delta AIC$ | $P_c$ | %CI | Threshold | Open | Close | $\Delta AIC$ | $P_c$ | %CI |
| **1** | Temperature | Mean | Lin | **-** | **88** | **33** | **-21.17** | **0.001** | **7** | **-** | **94** | **8** | **-24.8** | **0.0002** | **2** |
| **ECE** | Temperature | Mean | Lin | 15.92 | 88 | 57 | -15.91 | 0.005 | 21 | 21.7 | 41 | 40 | -9.26 | 0.25 | 64 |
| **Cue 1 + ECE** | Temperature | Mean | Lin | 15.92 | 78 | 76 | -10.73 | 0.14 | 60 | 21.7 | 18 | 18 | -6.45 | 0.74 | 82 |

*Table S5*

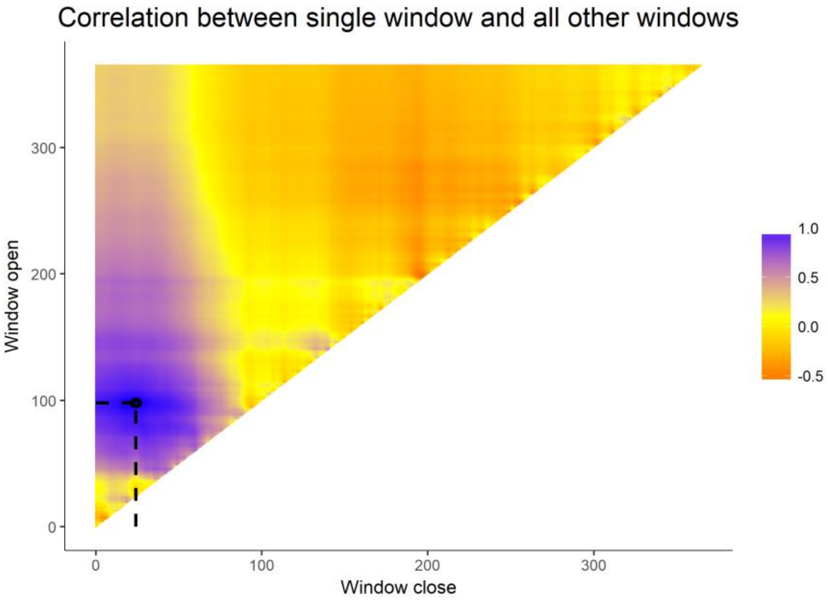
Estimated best and median mean temperature cue windows (see electronic supplementary material Box S2 for details about choice of best windows and estimation of median windows). 1 = 1st January. Negative value of ordinal means day in the previous year (before 1st January).

| | Blue tits | | | | Caterpillars | | | |
|---|---|---|---|---|---|---|---|---|
| ***Ordinal day (1= 1st January)*** | Best Window | | Median window | | Best Window | | Median window | |
| | Open day | Close day | Open day | Close day | Open day | Close day | Open day | Close day |
| *D-Rouvière* | 17 | 91 | 22 | 91 | - | - | - | - |
| *D-Muro* | 35 | 97 | 19 | 88 | 42 | 97 | 10 | 107 |
| *E-Muro* | 74 | 117 | -75 | 89 | - | - | - | - |
| *E-Pirio* | 90 | 127 | 87 | 130 | 72 | 158 | 80 | 156 |

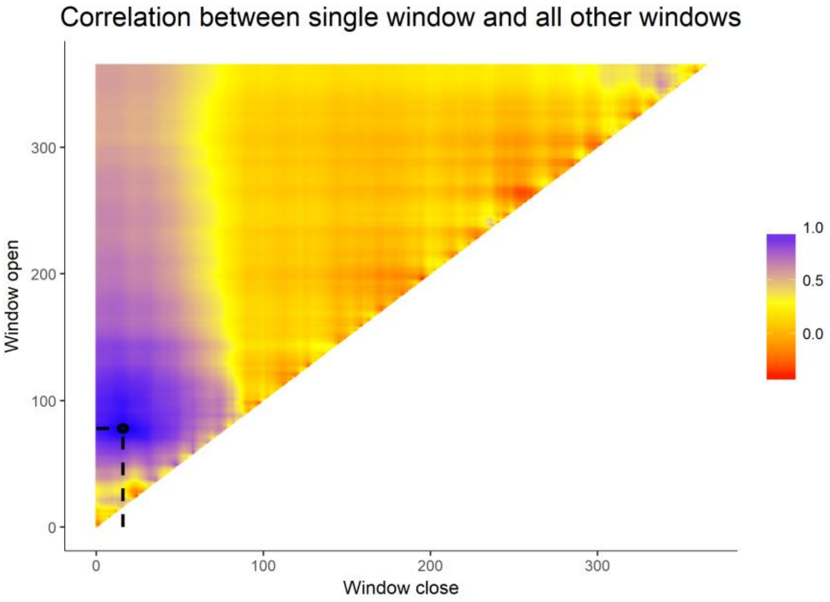
*Figure S2*

Correlation between the window estimated from the best model (represented by the black dot) and all other possible windows of mean temperature for a) D-Rouvière, b) D-Muro, c) E-Muro and d) E-Pirio population (positive autocorrelation in purple; negative autocorrelation in red). Graphics from the function `autowin` in `climwin` R package. Some differences in patterns of correlation are visible among populations: in deciduous populations, the peak of correlation is less steep than in the evergreen populations. This is in line with the interpretation that the environment is less predictable in evergreen populations.

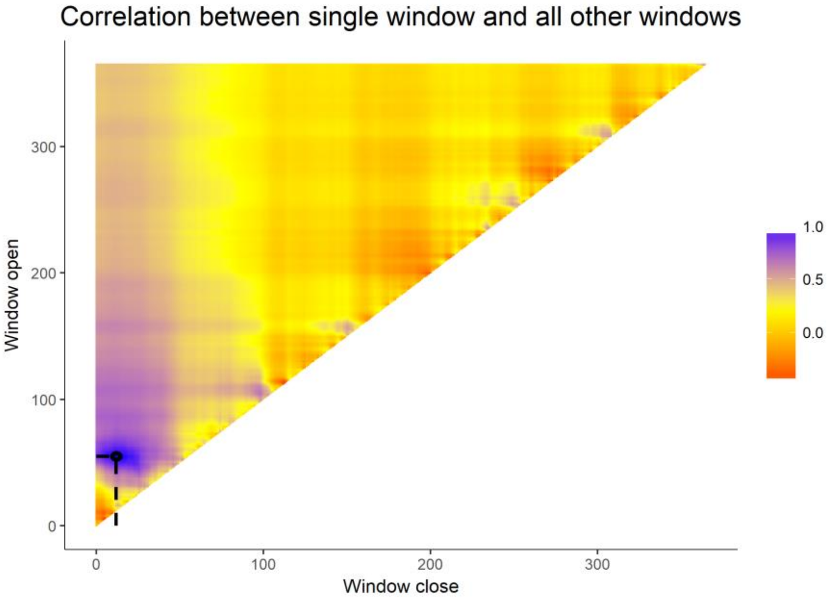
a)



b)



c)


Correlation between single window and all other windows
Window open
300
200
100
0
0
100
200
300
Window close
1.0
0.5
0.0

d)

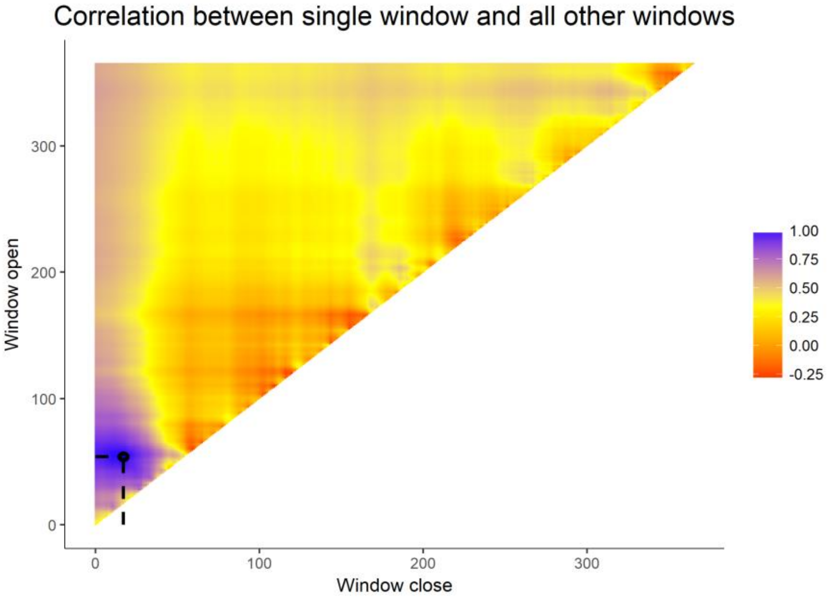

Correlation between single window and all other windows
Window open
300
200
100
0
0
100
200
300
Window close
1.00
0.75
0.50
0.25
0.00
-0.25

*Table S6*

Temporal trend in the number of positive ECE at 5% during the cue window. $r^2$ is the coefficient of determination. Significant slopes (p-value < 0.05) are in bold. Sample sizes are given in Table S1.

| | *Number of ECE (per decade, ± se)* | *t-value* | *p-value* | *$r^2$* |
|---|---|---|---|---|
| *D-Rouvière* | 0.73 (± 0.71) | 1.03 | 0.31 | 0.002 |
| *D-Muro* | **0.71 (± 0.29)** | **2.45** | **0.02** | **0.11** |
| *E-Muro* | **0.49 (± 0.16)** | **2.98** | **0.005** | **0.16** |
| *E-Pirio* | **1.8 (± 0.5)** | **3.48** | **0.001** | **0.21** |

### *Table S7*

Blue tit reaction norm favoured by selection estimated by the regression of the date of caterpillar peak abundance on the detected cues for blue tits. For evergreen populations, we present results for cues taken both as mean temperature (MeanT) and the number of positive ECEs. Models with both MeanT and ECE are not better than models with MeanT (or ECE) alone (not shown). $r^2$ is the coefficient of determination. Significant slopes (p-value < 0.05) are in bold. Sample sizes are given in Table S1.

| *Climate* | | *Intercept* | | | *Slope* | | | *$r^2$* |
|---|---|---|---|---|---|---|---|---|
| | | Estimates (± se) | t-value | p-value | Estimates (± se) | t-value | p-value | |
| *D-Rouvière* | MeanT | 192.72 (± 29.17) | 6.61 | 0.0002 | **-8.39 (± 3.62)** | **-2.32** | **0.049** | 0.33 |
| *D-Muro* | MeanT | 169.02 (± 9.02) | 18.75 | <0.0001 | **-4.88 (± 0.83)** | **-5.90** | **<0.0001** | 0.59 |
| *E-Muro* | MeanT | 228.36 (± 39.36) | 5.80 | <0.0001 | **-7.99 (± 2.93)** | **-2.73** | **0.02** | 0.29 |
| | ECE | 125.42 (± 3.94) | 31.81 | <0.0001 | -1.87 (± 1.50) | -1.25 | 0.23 | 0.03 |
| *E-Pirio* | MeanT | 216.74 (± 20.87) | 10.39 | <0.0001 | **-4.43 (± 1.47)** | **-3.01** | **0.005** | 0.21 |
| | ECE | 162.07 (± 2.38) | 68.09 | <0.0001 | **-0.97 (± 0.25)** | **-3.84** | **0.0006** | 0.31 |

*Table S8*

Synchrony between blue tits and their preys, assessed by the regression between mean laying date of blue tits and caterpillar date of peak abundance. $r^2$ is the coefficient of determination. Significant slopes (p-value < 0.05) are in bold. Sample sizes are given in Table S1.

| | *Intercept* | | | *Slope* | | | *$r^2$* |
|---|---|---|---|---|---|---|---|
| | Estimates (± se) | t-value | p-value | Estimates (± se) | t-value | p-value | |
| *D-Rouvière* | 8.33 (± 76.56) | 0.11 | 0.92 | 1.21 (± 0.79) | 1.53 | 0.16 | 0.13 |
| *D-Muro* | 7.50 (± 14.85) | 0.51 | 0.62 | **1.11 (± 0.15)** | **7.32** | **<0.0001** | 0.69 |
| *E-Muro* | 8.40 (± 46.03) | 0.18 | 0.86 | **1.06 (± 0.43)** | **2.45** | **0.03** | 0.24 |
| *E-Pirio* | 44.74 (± 24.38) | 1.83 | 0.08 | **0.85 (± 0.19)** | **4.49** | **0.0001** | 0.39 |

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