ECOG-03591

Supplementary material
Appendix 1

Material and methods

Input data
All the data used in the present work have been already published. A detailed presentation and discussion of these data are provided in Bertrand et al. 2011 and 2016.

Floristic data
Plant community observations (from which the climatic debt is assessed) come from 67289 georeferenced and dated floristic surveys recorded during the period 1987–2008 and stored in the French National Forest Inventory (NFI; Robert et al. 2010), Sophy (Brisse et al. 1995) and EcoPlant (Gégout et al. 2005) databases.

Environmental and biological determinants of the climatic debt
The effects of a set of 23 factors have been tested as in Bertrand et al. (2016). These abiotic, biotic and anthropogenic factors can be ordered considering their impact on the plant community response in the face of climate change (Dickinson et al. 2014, Essl et al. 2015, Bertrand et al. 2016). At the exception of climate data (representative of climate conditions at 1km²), all the variables described below have been directly informed or computed from forest inventory observations.

First, eight factors have been selected to depict species’ persistence facing climate change in plant communities (Table A1; Bertrand et al. 2016). Species’ persistence is expected to increase the temporal inertia of species assemblages in the face of climate change which contributes to amplify the climatic debt. The factors involved in species’ persistence prevent reshuffling of species communities
towards warm-adapted species assemblages as fast as expected from climate warming alone, but they promote tolerance and/or resistance of species in existing communities which allow them to absorb part of the climate warming leading to an increase in the climatic debt. Species’ intrinsic ability to tolerate climate change has been inferred as the temperature and precipitation niche breadths (i.e. the difference between the minimum and maximum annual mean temperature and annual precipitation where the species occurred). Both measures were then averaged across all species co-occurring within a given plant assemblage to get two community mean values characterizing the focal plant assemblage’s tolerance to thermal ($TO_T$) and water ($TO_W$) stresses. Species may also persist through evolutionary adaptation, acclimation, and/or phenotypic plasticity by shifting their ecological requirements (that is, niche shifts), to survive to the new climate conditions. Such biological factors were summarized in an index measuring the thermal niche shifts over the time considering any temporal changes in sampling effort (Bertrand et al. 2016), and then averaged among all species co-occurring in observed plant communities ($DC$). Species longevity (which increases the species resistance/tolerance to climate change and promotes community stability; Davis 1986) were collected from the LEDA database (Kleyer et al. 2008) and averaged among all plants co-occurring in observed communities ($LG$). The best soil conditions in forests (that is, low acidity and high nitrogen content) amplify the climatic debt (Bertrand et al. 2016), most probably by alleviating part of the climatic constraints on plant development. Plants have a higher resistance or tolerance to climate change in high quality soil conditions (e.g. Bertrand et al. 2012), which improves their persistence in existing communities. In the absence of direct soil observations over all the floristic surveys, soil conditions were inferred from bioindication models using the floristic assemblage to predict soil pH ($pH$; Riofrío-Dillon et al. 2012) and C:N ratio (i.e. a measure of N-nutrient availability, $N$; Riofrío-Dillon 2013) (RMSD = 0.9 and 3.1 for 254 independent pH and C:N ratio observations, respectively). Microclimate buffering due to local topography changes ($THET$; e.g. Scherrer and Körner 2011) and canopy cover ($TBUF$; e.g. Lenoir et al.
provide short-distance climate escapes and cooler conditions at the forest floor respectively, which contribute to local species’ persistence facing climate change. Microclimate buffering is related to extrinsic adaptive capacities of a species in the face of climate change, i.e. external processes that human can manage for species conservation by acting on habitat for instance (e.g. Beever et al. 2016). Its effect on species depends to the magnitude of decrease in species exposure to climate change induced by microclimate buffering, and if this decrease is sufficient for the species to tolerate the climate change (species sensitivity) (De Frenne et al. 2013; Dickinson et al. 2014; Lenoir et al. 2017).

THET was inferred as temperature heterogeneity within each 1 km$^2$ unit (that is, the spatial resolution of all climatic grids I used due to the 500 m uncertainty in the geographic location of the floristic surveys) by using a finer-resolution temperature grid (2,500 m$^2$; Bertrand et al. 2016). TBUF was computed from the microclim model (Kearney et al. 2014) at the scale of each forest survey observation as the difference between the temperatures perceived on the forest floor considering and not considering the observed canopy cover. The microclim model was fed by the forest canopy cover estimated for each forest inventory observation, topography information (horizon, slope, aspect and elevation) and mean monthly climate conditions (a detailed description of the computation are provided in Bertrand et al. 2016).

Second, five factors have been used to depict species’ migration facing climate change (Table A1; Bertrand et al. 2016). Species’ migration is expected to promote reshuffling of species assemblages in the face of climate change which contributes to mitigate the climatic debt. The factors involved in species’ migration are expected to promote the immigration of warm-adapted species in communities disturbed by climate warming driving a process termed communities’ thermophilization (e.g. De Frenne et al. 2013). Climatic niche tracking (which underlies poleward and upward range shifts in response to climate warming) was inferred for each species as the similarity observed between the current thermal niche and the one expected if climatic niche tracking was maximal in data (Bertrand et
al. 2016). Values of species co-occurring in plant communities were then averaged (NC). Both proximity to past species’ habitat (HP) and temporal changes in species’ habitat aggregation (dHA) have been computed for each species to define habitat connectivity. Both variables have been computed from temporal changes in thermal (defined as the projection across the geographical space of the realized thermal niche computed from data) and forest (derived from spatio-temporal Corine Land Cover layers) habitats, and then averaged considering the plant composition in communities.

Competition for water resources, which contributes to select warm-adapted species in plant communities and hence favors their migration (Bertrand et al. 2016), was included in the analysis. An increase in competition for water resources induces a decrease in water availability for low competitive plant species. Under such a condition, the mortality of these species is expected to increase promoting the installation of warm-adapted plant species in response to the current climate warming. Competition for water resources was computed for each species as the mean value of the hydric niche differentiation (i.e. $I-D$ with $D$ is the Schoener’s $D$ index assessing niche overlap; Schoener 1968) among plants co-occurring in observed communities ($C_W$). A high niche differentiation among co-occurring species depicts a high resource partitioning likely driven by a strong resource competition in a plant community (Bertrand et al. 2016). Species longevity is inversely correlated to species' migration under the assumption that short-lived species have an earlier access to reproduction, and hence to migration, than the long-lived one. As a consequence, such a effect was also accounting for to depict species’ migration in the analysis.

Third, 11 factors have been used to describe several dimensions of the environment from baseline environmental conditions and environmental changes. Climate conditions were extracted from spatio-temporal layers (Bertrand et al. 2011, 2016, Bertrand 2012; 1 km² of spatial resolution). Baseline climate conditions were computed as the annual mean temperature ($T$) and the annual precipitation ($P$) over the 1965–1986 baseline period. Plant community exposure to climate change were computed as
changes in annual mean temperatures ($TC$) and annual precipitations ($PC$) between the year of the floristic observations and the 1965–1986 baseline period. The direct impact of light availability ($L$) on the composition of understory plant communities (through disturbing resident communities as light increases sharply; e.g. Wagner et al. 2011) was inferred as the average value of the L-Ellenberg index of each species co-occurring in communities (Ellenberg et al. 1992). Competition for soil nutrients ($C_N$), competing with climate change effects (Bertrand et al. 2016), was inferred as the mean value of N-nutrient niche differentiation (using the same method as the one used to compute $C_W$; see above) among plants co-occurring in observed communities. Anthropogenic and natural disturbances were inferred by five more variables: the presence/absence of recent silvicultural practices ($SILVP$), the presence/absence of human-mediated and natural disturbances ($DISTURB$) and the presence/absence of exotic trees ($EXOT$) extracted from the NFI database, as well as the proximity to road ($RP$; ranging from forest path to highway, computed from the GEOFABRIK spatial layers) and the human population density ($HPD$; extracted from the Insee database). The effects of all these variables are not investigated in the present study, but are used to fix the effects of species exposure to global changes in the model. Such factors are known to interact in or impact directly the biodiversity response to climate change without reflecting any species’ persistence or migration mechanisms. They depict environmental pressures that inflate the climatic debt through community reshuffling towards another environmental equilibrium (compared to the climate one) or mortality (Bertrand et al. 2016).

Although several variables were computed from bioindication methods ($L$, $pH$, $N$ and the floristically reconstructed temperature used to infer the climatic debt), they were largely uncorrelated ($R^2<0.1$), demonstrating no circularity issues among these indexes.

**Inference of the climatic debt**
The climatic debt was not computed in the present study but existing values were analyzed from Bertrand et al. (2016). The climatic debt \((dT)\) was computed as the difference between the annual mean temperature at a given location and year, and the annual mean temperature of the same location and year but inferred from plant assemblages \((FrT\) as floristically reconstructed temperature) (Bertrand et al. 2011, 2016). A positive difference means that the observed reshuffling in a plant community is lagging behind climate warming (Bertrand et al. 2011), and thus depicts a climatic debt for that species assemblage (Devictor et al. 2012). \(FrT\) values were modeled in a previous studies (Bertrand et al. 2011) using a transfer function that combines a weighted averaging \(PLS\) regression (accounting for linear effect; ter Braak and van Dame 1989) and a Breiman’s random forest model (accounting for nonlinear and interaction effects among species occurrences in residuals of the weighted averaging \(PLS\) model; Breiman 2001) to infer temperatures from plant community composition (presence/absence of a set of 760 herbaceous species). This approach was validated on an independent data set of 5136 floristic surveys \((R^2=0.83, \text{RMSD}=0.97 \, ^\circ \text{C};\text{ Bertrand et al. 2011})\). Floristic surveys used to adjust and valid the model came from the NFI, Sophy and EcoPlant databases.

**Analytical approach**

I have employed the same approach that it has been conducted in Bertrand et al. (2016), but I used a different and appropriate statistical method to test for spatial nonstationarity in the climatic debt determinism. The analysis was conducted by fitting Geographically Weighted Regression \((GWR;\text{ Fotheringham et al. 2002})\). The hypothesis behind this particular regression was that the fitted coefficients of a global model (i.e. fitted to all the data as in Bertrand et al. 2016) may not represent local variations in the data (Bivand et al. 2008). \(GWR\) explores spatial nonstationarity by moving a weighted window over the spatial distribution of data, estimating one set of coefficient values at every observation from the adjustment of a local linear model (Bivand et al. 2008). The weighted window was
determined by cross-validation searching for the proportion of observations to include in the weighted scheme that minimized the root mean square error of predictions (Bivand et al. 2008), and fixed to the 100 closest observations of each floristic survey present in the sample. This set of observations is weighted using a Gaussian spatial weighting function in order to give more weight to the data closed to the focal floristic observation in the local model adjustment.

The GWR model that was fitted is:

\[ dT = a_1T + a_2TC + a_3P + a_4PC + a_5L + a_6pH + a_7N + a_8TO_T + a_9TO_W + a_{10}C_W + a_{11}C_N + a_{12}DC + a_{13}NC + a_{14}LG + a_{15}HP + a_{16}dHA + a_{17}THET + a_{18}RP + a_{19}HPD + a_{20}TIME + a_{21}TBUF + a_{22}SILVP + a_{23}DISTURB + a_{24}EXOT + \varepsilon \]

where \( a_{1,...,24} \) are the local estimated coefficients that I used to quantify the magnitude of the effect of each variable (see the text above for a definition and description of each variable as well as Bertrand et al. 2016 for more details), and \( \varepsilon \) denotes the residuals. All the variables were centered and reduced to allow parameter comparison.

The GWR model was adjusted using a sub-sampling approach \((n = 1000)\) in order to compute robust and accurate parameter estimation and uncertainty. Each subsample was composed of a set of 4830 floristic observations selected among 45806 floristic surveys (all coming from the NFI database since 1993). Observation selection was conducted considering a grid of 10 by 10 km covering France. Random selection was performed to select one floristic observation per grid cell. It means that each subsample had the same number of floristic observations and was composed of observations homogeneously distributed throughout the French forest territory. Such a spatial sampling aims to limit the effects of both spatial autocorrelation and any other sampling bias in the model. Floristic observations in each of the 1000 subsamples were weighted in the GWR model by the inverse of the total number of observations per year in order to correct for an unbalanced temporal distribution of samples. The local coefficients of factors involved in species’ persistence and migration mechanisms
were summed in order to assess their respective effects on the climatic debt in each of the 1000 subsamples. I tested the significance of these cumulative effects locally by comparing the distribution of their 1000 local coefficient values to 0. I considered that significant negative and positive coefficient values had at least 95% of the 1000 coefficients values less and more than 0 (i.e. a bootstrap test with a threshold $\alpha = 0.05$), respectively. Finally, I mapped the effects of species’ persistence (i.e. the sum of $a_6, a_7, a_8, a_9, a_{12}, a_{14}, a_{17}$ and $a_{21}$ coefficients in the formula presented above) and migration (i.e. the sum of $a_{10}, a_{13}, a_{14}, a_{15}$ and $a_{16}$ coefficients), and compared their magnitude between biogeographical regions. I also summed the effects of species’ persistence and migration in order to identify the main mechanisms that drive the climatic debt throughout French forests. More negative and positive values mean higher mitigating and amplifying effects on the climatic debt, respectively. The effect of species longevity was null in this computation as its contribution to species’ persistence and migration cannot be disentangled.

Analyses were conducted using the $R$ freeware (R Core Team 2017) and the $spgwr$ (Bivand and Yu 2015) R-package to fit the $GWR$ model.
Table A1: Definition, source and numerical description of the factors involved in species’ persistence and migration.

<table>
<thead>
<tr>
<th>Mechanism</th>
<th>Code</th>
<th>Name</th>
<th>Definition</th>
<th>Average [min, max]</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>pH</td>
<td>C</td>
<td>Soil pH</td>
<td>Proxy of soil acidity which can impact flora through both ecosystem degradation and nutrition. Depict a decreasing gradient of acidity which can be associated to both an increasing gradient of soil richness and a decreasing gradient of soil toxicity.</td>
<td>6 [3; 8.5]</td>
<td>Radío-Dillon et al. 2012</td>
</tr>
<tr>
<td>N</td>
<td>NC</td>
<td>Soil nitrogen content</td>
<td>Use of the soil C:N ratio which is a proxy of soil fertility in term of N-availability which can impact flora through both ecosystem degradation and nutrition. The soil C:N ratio was inversed to depict an increasing gradient of soil nitrogen content.</td>
<td>14.9 [10; 33.2]</td>
<td>Radío-Dillon 2013</td>
</tr>
<tr>
<td>TO_t</td>
<td>TO</td>
<td>Thermal-stress tolerance</td>
<td>Proxy of plant thermal tolerance to climate change. Computed as the mean of thermal niche amplitude among co-occurring species in the community.</td>
<td>11.1°C [6; 14.4]</td>
<td>Bertrand et al. 2016</td>
</tr>
<tr>
<td>TO_h</td>
<td>TO</td>
<td>Water-stress tolerance</td>
<td>Proxy of plant hydric tolerance to climate change. Computed as the mean of hydric niche amplitude among co-occurring species in the community.</td>
<td>1941 mm [1145; 2549]</td>
<td>Bertrand et al. 2016</td>
</tr>
<tr>
<td>DC</td>
<td>DC</td>
<td>Thermal niche shift</td>
<td>Proxy of contemporary evolutionary adaptation, acclimatisation and/or phenotypic plasticity occurring in the community. Computed as the mean of temporal thermal niche shift among co-occurring species in the Community under the species distribution conservation assumption. Values range from 0 to 1 for low to high species distribution conservatism between 1965-1986 and 1987-2008, and as a consequence from low to high evolutionary adaptation, acclimatisation and/or phenotypic plasticity.</td>
<td>0.996 [0.82; 1]</td>
<td>Bertrand et al. 2016</td>
</tr>
<tr>
<td>THET</td>
<td>THET</td>
<td>Temperature heterogeneity</td>
<td>Computed as the standard deviation of a 2,500 m² temperature grid within a 1 km radius. An increasing value of local temperature heterogeneity means an increase in microclimate refugia for plants.</td>
<td>0.5°C [0; 2.7]</td>
<td>Bertrand et al. 2016</td>
</tr>
<tr>
<td>TBUF</td>
<td>TBUF</td>
<td>Temperature buffering effect due to canopy cover</td>
<td>Estimation of the temperature buffered by forest canopy (based on the microclim model). Computed as the difference between the temperature perceived near the ground considering and not considering the presence of canopy cover.</td>
<td>2.1°C [0.1; 4.2]</td>
<td>Kearney et al. 2014</td>
</tr>
<tr>
<td>LG</td>
<td>LG</td>
<td>Species longevity</td>
<td>Species longevity amplifies the resistance of the resident communities facing climate change when it increases. In contrast, this index is also inversely correlated to species’ migration under the assumption that short-lived species have an earlier access to reproduction and hence to migration than the long-lived one.</td>
<td>8.1 years [1.6; 30]</td>
<td>LEDA database</td>
</tr>
<tr>
<td>NC</td>
<td>NC</td>
<td>Thermal niche tracking</td>
<td>Proxy of species’ migration in order to escape climate change. Computed as the mean of temporal thermal niche overlap among co-occurring species in community under the niche conservation assumption. Values range from 0 to 1 for low and high niche tracking leading to niche conservatism between 1965-1986 and 1987-2008.</td>
<td>0.988 [0.829; 1]</td>
<td>Bertrand et al. 2016</td>
</tr>
<tr>
<td>HP</td>
<td>HP</td>
<td>Past species habitat patches’ proximity</td>
<td>Proxy of human pressure on forests through habitat fragmentation affecting plant migration efficiency. Computed as the minimal distance to the closest past suitable habitat where short and long distances mean high and low proximity to a new forest patch.</td>
<td>145 m [0; 9988]</td>
<td>Bertrand et al. 2016</td>
</tr>
<tr>
<td>dHA</td>
<td>dHA</td>
<td>Temporal changes in species habitat aggregation</td>
<td>Proxy of forest habitat change through land-use conversion. Computed as the difference between aggregation indices of forest in 1990 and 2006 within a 10 km radius. Negative and positive values depict forest disaggregation and aggregation over time, respectively.</td>
<td>-1.97% [-97; 27.7]</td>
<td>Bertrand et al. 2016</td>
</tr>
<tr>
<td>Cw</td>
<td>Cw</td>
<td>Species competition for water</td>
<td>Computed as the average of hydric niche differentiation among co-occurring species in the community. It ranges from 0 to 1 for low to high niche differentiation interpreted as a gradient from low to high water resource competition in community.</td>
<td>0.815 [0.52; 0.932]</td>
<td>Bertrand et al. 2016</td>
</tr>
</tbody>
</table>
References


Appendix 2

Analysis and discussion of the GWR results

Model quality

GWR explains between 34.7 and 77.9% of the total variation of the climatic debt (i.e. adjusted R² value expressed in %) throughout the French forests (Fig. A1). At the French scale, the mean adjusted R² value (0.607; Fig. A1B) is higher than the one reported previously using PLS regression which is a more global statistical approach (R² = 0.413 from Bertrand et al. 2016). It is noteworthy that part of this difference in the explanation of the climatic debt between the two approaches is due to different statistical objectives. In fact, the PLS regression used by Bertrand et al. 2016 had a lower R² value than a simple linear model (for instance) due to the component selection which allows to fit the model on a limited but clean part of the climatic debt variation that the set of explanatory variables can explain considering potential noises or biases presents in the data (such as multicollinearity for instance). However, these results demonstrate the high quality of the GWR adjustment and the high confidence that we can have in the species’ persistence and migration effects reported in the present study. GWR improves the explanation of the determinism of the climatic debt and shows the importance to account for spatial variability when the process is modeled from a database covering a large area (notably due to changes in ecological context and/or species pool that occur at local or regional scales).

Areas with the lowest R² values (as in northwestern France) are areas where the set of explanatory factors failed to explain the climatic debt. It means that other ecological, biological or anthropogenic factors drive the climatic debt in these areas or that proxies that I computed and used as explanatory variables failed to mirror ecological, biological or anthropogenic drivers (see Bertrand et al. 2016 for a discussion on the limitation of variables used to depict forest disturbances and management for instance). To get a more accurate understanding of the determinism of the climatic
debt in these cases, it will need to conduct local or regional studies with relevant measures of the environment and the ecological context at this scale.

**Variable contribution**

Despite it is not the aim of the present study, I provide additional results about the contribution of each factor involved in species’ persistence and migration mechanisms that I have tested in the GWR model. The contribution has been computed as the coefficient values of each variable divided by the sum of coefficient values of the set of factors involved in species’ migration or persistence (mapped in Figs. 1A and B), and expressed in percent. It assesses the weight of each variable in the definition of the species’ persistence and migration effects on the climatic debt. I show that the contributions highly vary among the factors and throughout forests (Figs. A2 and A3).

Species’ tolerance to hydric stresses highly contributes to determine the species’ persistence effect on the climatic debt in the northern part of France (reaching 60% in some areas), while species’ tolerance to thermal stresses and climatic niche shifts (depicting adaptation, acclimation, and/or phenotypic plasticity effects) highly drive this determinism in the southwestern and southeastern part of France, respectively (Fig. A2). Such a spatial pattern is likely to demonstrate local or regional variations in hydric and thermal stresses on the forest flora. It also demonstrates that rapid climatic niche shifts occurred since 1993 in Mediterranean forests. However, it is difficult to state whether some traits of the Mediterranean vegetation and/or the increasing climatic stress observed in this region explain the high contribution of climatic niche shifts. Other factors contribute less than 20% to the species’ persistence effect on the climatic debt.

Species’ competition to water resources highly contributes to determine the species’ migration effect on the climatic debt in the northern part of France (reaching 60% in some areas; Fig. A3). This result as well as the high contribution of species’ tolerance to water stress reported above highlight that
the water resource is an important dimension of the climate change effect on forest plants in this area. It does not mean that water is a more limiting resource than in Mediterranean region, but that the species pool is likely less adapted to the recent changes in water regime in northern France than in the South (where the exposure to drought has selected highly adapted species to limited water availability; e.g. Thuiller et al. 2005). Climatic niche tracking (depicting species’ migration towards suitable climate conditions) mainly drives the species’ migration effect in Mediterranean and alpine biogeographical regions (except in the western part of the Pyrenees; Fig. A3). The rugged topography encountered in these areas (promoting short-distance climate escapes) as well as the proximity between the Alps and the Mediterranean area (favoring exchange of species adapted to a large range of thermal conditions) are favorable conditions for climatic niche tracking. Temporal changes in species’ habitat aggregation also mainly contribute to determine the species’ migration effect on the climatic debt across smaller areas. Earliness of seed dispersal and proximity to past species’ habitat have low contributions (less than 20%) except in the southwestern part of France.

These results confirm the previous order of the most important factors involved in species’ persistence and migration established by Bertrand et al. (2016). However, they allow to move beyond the previous global findings (Bertrand et al. 2016) by highlighting some areas where transitions among the effects of all the drivers occur. These results could serve of starting point of future detailed analysis aiming to verify the different plant response pathways to climate change reported here, and to understand what are the causes of this spatial structure.

**Multicollinearity issue**

GWR is often considered highly sensitive to multicollinearity (e.g. Wheeler and Tiefelsdorf 2005) while some recent results showed it is robust to its effects (Fotheringham and Oshan 2016). Multicollinearity among explanatory variables inflates the variance of regression parameters which
potentially leads to both unstable model fit (due to high variance) and error in identification of relevant predictors as well as in their relative importance assessment (e.g. Dormann et al. 2013). It is still a big issue in statistics especially when real data varying in space and time are studied. No statistical models or methods are able to fully tackle this issue, but it is possible to assess whether multicollinearity is a matter of concern.

I computed correlation among explanatory variables, condition number computed from the eigenvalues of the model matrix ($CN$; e.g. Belsley et al. 2004), and variance inflation factor ($VIF$; e.g. Belsley et al. 2004) in order to assess whether multicollinearity can alter my results and conclusions. First, explanatory variables are weakly correlated among them (Bertrand et al. 2016). The upper correlation value reaches a $R^2$ of 0.381 which is lower than the accepted threshold of 0.49 (that Dormann et al. 2013 have shown to be an appropriate indicator for when collinearity begins to severely distort model estimation). Second, $CN$ values (which assess the multicollinearity effect on the model fit) vary between 7.1 and 56.7 throughout the French forest territory (Fig. A4). $CN$ exceed the accepted threshold of 30 (which identifies a potential severe multicollinearity concern; Belsley et al. 2004) in only rare areas such as small parts of the center (close to Paris) and the southwestern of France (covering a total of 10800 km$^2$; Fig. A4B). Third, $VIF$ values (which assess the sensitivity of each explanatory variable to multicollinearity) vary between 1.1 and 15.4 among the set of explanatory variables involved in species’ persistence and migration mechanisms throughout French forests (Figs. A5 and A6). $VIF$ values exceed the accepted threshold of 10 (which identifies a potential severe multicollinearity concern for a variable; Belsley et al. 2004) for local temperature heterogeneity in a restricted part of the northern France (Fig. A5). All other factors have relatively low $VIF$ values. These results demonstrate that multicollinearity is low in the present data, and as a consequence its impact on the $GWR$ model is unlikely altering my estimation of the species’ persistence and migration effects on the climatic debt as well as the conclusions of the study.
**Figure A1**: Map of adjusted $R^2$ inferred from GWR (10 x 10 km² spatial resolution). Lower (A) and upper (C) boundaries of the 95% confidence interval, and mean estimate (B) are mapped and computed from 1000 bootstrapped models.
Figure A2: Map of the contribution of each ecological and biological factors involved in species’ persistence (10 x 10 km² spatial resolution): species’ tolerances to hydric (A) and thermal stresses (B), climatic niche shift (C), pH (D), species longevity (E), N-nutrient availability (F), local temperature heterogeneity (G) and climate canopy buffering (H). Mean contribution estimates are mapped and computed from 1000 bootstrapped GWR models. The contribution of each variable is computed as the coefficient value of each of them divided by the sum of coefficient values of the set of factors involved.
in species’ persistence (i.e. the effect of species’ persistence on the climatic debt reported in Fig. 1B),
and expressed in percent.
**Figure A3:** Map of the contribution of each ecological and biological factors involved in species’ migration (10 x 10 km² spatial resolution): competition for water resources (A), climatic niche conservatism (B), temporal changes in species’ habitat aggregation (C), seed dispersal earliness (D) and proximity from past species’ habitat (E). Mean contribution estimates are mapped and computed from 1000 bootstrapped GWR models. The contribution of each variable is computed as the coefficient value of each of them divided by the sum of coefficient values of the set of factors involved in species’ migration (i.e. the effect of species’ migration on the climatic debt reported in Fig. 1A), and expressed in percent.
Figure A4: Map of the condition number (CN) of the GWR model (10 x 10 km² spatial resolution). Lower (A) and upper (C) boundaries of the 95% confidence interval, and mean estimate (B) are computed from 1000 bootstrapped GWR models. A CN value more than 30 means that serious multicollinearity concerns can alter the model fit (Besley et al. 2004).
Figure A5: Map of the variance inflation factor (VIF) computed from GWR for variables involved in species’ persistence mechanisms (10 x 10 km² spatial resolution): species’ tolerances to hydric (A) and thermal stresses (B), climatic niche shift (C), pH (D), species longevity (E), N-nutrient availability (F), local temperature heterogeneity (G) and climate canopy buffering (H). Mean VIF estimates are mapped and computed from 1000 bootstrapped models. A VIF value more than 10 means that the variable is potentially affected by serious multicollinearity concerns (Belsley et al. 2004).
**Figure A6:** Map of the variance inflation factor (VIF) computed from GWR for factors involved in species’ migration mechanisms (10 x 10 km² spatial resolution): competition for water resources (A), climatic niche conservatism (B), temporal changes in species’ habitat aggregation (C), seed dispersal earliness (D) and proximity from past species’ habitat (E). Mean VIF estimates are mapped and computed from 1000 bootstrapped model. A VIF value more than 10 means that the variable is potentially affected by serious multicollinearity concerns (Belsley et al. 2004).
References


