

The climatic debt is growing in the understorey of temperate forests: Stand characteristics matter

Benoit Richard, Jean-luc Dupouey, Emmanuel Corcket, Didier Alard, Frédéric Archaux, Michaël Aubert, Vincent Boulanger, François Gillet, Estelle Langlois, Sébastien Macé, et al.

To cite this version:

Benoit Richard, Jean-luc Dupouey, Emmanuel Corcket, Didier Alard, Frédéric Archaux, et al.. The climatic debt is growing in the understorey of temperate forests: Stand characteristics matter. Global Ecology and Biogeography, 2021, 30 (7), pp.1474-1487. $10.1111/\text{geb.}13312$. hal-03293479

HAL Id: hal-03293479 <https://hal.science/hal-03293479v1>

Submitted on 21 Jul 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

The climatic debt is growing in the understory of

temperate forests: stand characteristics matter

Running title:

• Explaining the climatic debt of temperate forests

Authors

- 6 Benoit Richard^{1,2} | Jean-Luc Dupouey³ | Emmanuel Corcket⁴ | Didier Alard⁴ |
- 7 Frédéric Archaux⁵ | Michaël Aubert² | Vincent Boulanger⁶ | François Gillet⁷ |
- 8 Estelle Langlois² | Sébastien Macé⁶ | Pierre Montpied³ | Thérèse Beaufils⁷ | Carole
- 9 Begeot⁷ | Patrick Behr³ | Jean-Michel Boissier⁸ | Sylvaine Camaret⁹ | Richard
- 10 Chevalier⁵ | Guillaume Decocq¹ | Yann Dumas⁵ | Richard Eynard-Machet¹⁰ | Jean-
- 11 Claude Gégout³ | Sandrine Huet¹¹ | Valéry Malécot¹¹ | Pierre Margerie² | Arnaud
- 12 Mouly⁷ | Thierry Paul³ | Benoît Renaux¹² | Pascale Ruffaldi⁷ | Fabien Spicher¹ |
- 13 Erwin Thirion³ | Erwin Ulrich⁶ | Manuel Nicolas⁶ | Jonathan Lenoir^{1*}

Authors' affiliations

- ¹UMR CNRS 7058 « Ecologie et Dynamique des Systèmes Anthropisés » (EDYSAN),
- Université de Picardie Jules Verne, Amiens, France
- ²Normandie Université, UNIROUEN, INRAE, ECODIV, Rouen, France
- ³Université de Lorraine, AgroParisTech, INRAE, SILVA, Nancy, France
- ⁴Université de Bordeaux, INRAE, BIOGECO, Pessac, France
- ⁵ INRAE, UR EFNO, Domaine des Barres, Nogent-sur-Vernisson, France
- ⁶Office National des Forêts, Département RDI, Fontainebleau, France
- ⁷UMR CNRS 6249 Chrono-Environnement, Université Bourgogne Franche-Comté,
- Besançon, France
- ⁸Ecosylve, Les Déserts, France
- ⁹UFR LLSH, Université Savoie Mont Blanc, Domaine Universitaire de Jacob-
- Bellecombette, Chambéry, France
- ¹⁰e-Sciences, Cognin, France
- ¹¹Agrocampus-Ouest, INRAE, Université d'Angers, IRHS, Beaucouzé, France
- ¹²Conservatoire botanique national du Massif central, Chavaniac-Lafayette, France

The climatic debt is growing in the understory of temperate forests: stand characteristics matter

Running title:

• Explaining the climatic debt of temperate forests

- **Abstract**
- **Aim**

uffles biological assemblages towards left the pecies, a process coined thermophilization
pecies, a process coined thermophilization
per Review and the period of the period of the series of vegent
per performance of the pe Climate warming reshuffles biological assemblages towards less cold-adapted but more warm-adapted species, a process coined thermophilization. However, the velocity at which this process happens is generally lagging behind the velocity of climate change, generating a climatic debt which temporal dynamic remains misunderstood. Relying on high-resolution time series of vegetation data from a long-term monitoring network of permanent forest plots, we aim at quantifying the temporal dynamic – up to a yearly resolution – of the climatic debt in the understory of temperate forests before identifying the key determinants allowing to modulate it.

- **Location**
	- France
- **Time period**
- 1995-2017

Taxa studied

Vascular plants

disturbances decreased the climatic debt, while natural disturbances and herbivory

had no impact.

Conclusions

 Although often overlooked in understanding the climatic debt of forest biodiversity, changes in forest stand characteristics may modulate the climatic debt by locally modifying microclimatic conditions. Notably, the buffering effect of the upper canopy 40 layer implies microclimate dynamics that may provide more time for understory plant communities to locally adapt.

Keywords

Biodiversity, climate change, climatic debt, anthropogenic disturbances, long-term

monitoring, plant community, thermophilization

For Per Review

-
-
-

Introduction

mization and local extinction processes
2012). Locally, changes in species' abup
becies range shifts, are leading to impo
n (Hillebrand *et al.*, 2010; Walther, 201
ocal species assemblages are increasing
(i.e. species fro Climate change induces a global redistribution of biodiversity at various spatial scales, with profound consequences on ecosystem functioning and the provision of ecosystem services (Hooper *et al.*, 2012; Pecl *et al.*, 2017). Typical biodiversity redistribution consists of species shifting their geographical range poleward in latitude and/or upslope in elevation (Lenoir & Svenning, 2015), tracking shifting isotherms through colonization and local extinction processes (Jump & Peñuelas, 2005; Dullinger *et al.*, 2012). Locally, changes in species' abundance and population dynamics, preceding species range shifts, are leading to important re-assemblages in community composition (Hillebrand *et al.*, 2010; Walther, 2010). For example, some studies reported that local species assemblages are increasingly dominated by warm-adapted species (i.e. species from lower elevations and/or latitudes) at the expense of cold-adapted species (i.e. species from higher elevations and/or latitudes), a process referred to as "thermophilization" of communities (Gottfried *et al.*, 2012; De Frenne *et al.*, 2013; Zellweger *et al.*, 2020). However, species and communities may respond asynchronously and most likely with time lags relative to the forcing environmental changes, so that plant species assemblages shifting from one equilibrium state to another may not reflect environmental conditions prevailing at the time of the survey but may rather reflect former environmental conditions (Davis, 1984, 1989; Blonder *et al.*, 2017). Such discrepancies between the observed velocity of climate change and the slower velocities at which species and communities are actually responding have been termed "climatic debt" (i.e. the fact

 that biotic responses are lagging behind climate change) (Menéndez *et al.*, 2006; Bertrand *et al.*, 2011, 2016; Devictor *et al.*, 2012; Zellweger *et al.*, 2020).

re index (CTI) (Devictor *et al.*, 2008; Ze

evalue of either individual species' then

mperature across all species co-occurrir

changes over time (i.e. the proportion of

ring or disappearing from the focal com

respondi To assess the magnitude of the climatic debt or lag between the velocity of mean annual temperature (MAT) changes and the velocity of thermophilization of communities, one needs first to quantify the degree of thermophilization of local species assemblages. The most straightforward approach is to compute the community temperature index (CTI) (Devictor *et al.*, 2008; Zellweger *et al.*, 2020). The CTI is the average value of either individual species' thermal optima or species- indicator values for temperature across all species co-occurring in a focal community. How CTI changes over time (i.e. the proportion of cold- and warm- adapted species appearing or disappearing from the focal community) likely reflects how communities are responding to climate changes (Devictor *et al.*, 2008; Bertrand *et al.*, 2011). This index thus provides an intuitive proxy to estimate the velocity of thermophilization of communities, and can be subsequently compared to the velocity of observed temperature changes (e.g. both expressed in units of degrees Celsius per decade; Devictor *et al.*, 2008). Changes in CTI (or analogous index) over time have already been used to document thermophilization and delayed biotic responses of a wide range of taxonomic groups (e.g. plants, butterflies, fishes and birds; Devictor *et al.*, 2012; Bertrand *et al.*, 2011; Cheung *et al.*, 2013; Gaüzère *et al.*, 2017). However, most of these studies relied on a relatively restricted number of observations over time, usually a baseline survey and one or two resurveys at best, to compute changes in CTI values over time (Savage & Vellend, 2015; Ash *et al.*, 2017; Fadrique

Page 21 of 115 **Figure 21 of 115** Global Ecology and Biogeography

mposition changes from long-term mor
mposition changes from long-term mor
nitoring programs relying on frequent
tervals) during a sufficiently long time
ed to capture a temporal dynamic in the
confirm linearity over time. *et al.*, 2018). Some previous studies even relied on non-permanent or quasi- permanent plots to assess changes in CTI values over time (Bertrand *et al.*, 2011; De Frenne *et al.*, 2013; Becker-Scarpitta *et al.*, 2019; Zellweger *et al.*, 2020). Unfortunately, such studies relying on non-permanent plots tend to infer temporal changes blurred by space-for-time substitutions, which are known to overestimate the magnitude of thermophilization of communities in response to contemporary climate warming (Elmendorf *et al.*, 2015). Even when studies rely on strictly permanent plots, it requires more than one or two resurveys to build a detailed time series of community composition changes from long-term monitoring programs. Strictly permanent monitoring programs relying on frequent resurveys (e.g. from one-year to five-year intervals) during a sufficiently long time period (e.g. at least two decades) are needed to capture a temporal dynamic in the velocity of community thermophilization and confirm linearity over time. Although such long-term time series of biodiversity monitoring already exist (Dornelas *et al.*, 2018), we still lack a good knowledge and understanding of the temporal dynamic of the climatic debt. Whether the climatic debt of plant communities is steadily growing over time and what are the main underlying determinants of this dynamic remain open questions in global change ecology (Essl *et al.*, 2015; Bertrand *et al.*, 2016; Zellweger *et al.*, 2020). For instance, a previous study focusing on temperate forests has suggested an increasing climatic debt in the response of understory plant communities from the lowlands (Bertrand *et al.*, 2011). A follow-up study has revealed that this growing climatic debt involved a complex combination of abiotic

(2008) have shown that plant community composition (e.g. dwarf birch, willow,

graminoids, forbs and mosses) on warmed plots (open-top chambers) did not differ

 $\mathbf{1}$

Page 23 of 115 **Figure 23** of 115

 from that on ambient plots where herbivores grazed, suggesting no effect of herbivory on the climatic debt. Altogether, these findings show contrasting impacts of herbivory on the climatic debt.

eys (every year to every five years) to g
edented time series of CTI values for ur
d outside the fenced area. Using this ir
compare the rates of CTI changes to th
riod 1995-2017; (ii) test whether the cli
nunities increase Here, we rely on a long-term (1995-2017) national (France) monitoring network of permanent forest plots organized in a paired design of exclosure (fenced area excluding ungulates) *vs.* control plots – the RENECOFOR monitoring program – with multiple resurveys (every year to every five years) to generate a high- resolution and unprecedented time series of CTI values for understory plant communities inside and outside the fenced area. Using this information-rich time series, we aimed to: (i) compare the rates of CTI changes to the velocity of MAT changes during the period 1995-2017; (ii) test whether the climatic debt of understory plant communities increased steadily over time; and (iii) assess the relative contribution of several abiotic and biotic factors known to be influential from the scientific literature, including baseline environmental conditions, stand characteristics that are influenced by anthropogenic and natural disturbances, and biotic disturbances from large herbivores.

Materials and Methods

A long-term national monitoring network of forest ecosystems

 To assess changes in understory plant communities, we used vegetation data collected every five years, and even every year for some sites, throughout a long-term French monitoring network of forest ecosystems (RENECOFOR,

 http://www1.onf.fr/renecofor). The RENECOFOR network belongs to the European ICP Forests Level II monitoring program (ICP Forests, http://www.icp-forests.org) and aims at monitoring the health and functioning of forest ecosystems. This monitoring network was established in 1992 by the French National Forest Service (ONF, Office National des Forêts). It includes 102 permanents plots distributed in state and communal forests throughout the whole metropolitan French territory (www1.onf.fr/renecofor/sommaire/sites) (Ulrich, 1995 ; Nicolas *et al.*, 2014). All plots are located in mature and even-aged pure stands, and cover an area of 2 ha with a central fenced zone of 0.5 ha to exclude large herbivores (**Fig. 1**) (for more details, see Boulanger *et al.*, 2018).

For Prices, (Chen, 1000) Nicolary

1.5 ha to exclude large herbivores (**Fig.**

118).

118).

Etation surveys have been conducted ev

urveys in 2000, 2005, 2010 and 2015).

Ne discarded 58 plots which suffered free discarde Since 1995, vegetation surveys have been conducted every five years (baseline survey in 1995 and resurveys in 2000, 2005, 2010 and 2015). From the total pool of 102 permanent plots, we discarded 58 plots which suffered from major data gaps throughout the studied time period (e.g. the resurvey of 2010 was systematically missing for 53 plots due to a shortage in funding). This yielded a total of 44 plots for which a full time series, at a 5-yr interval, was available between 1995 and 2015, hereafter referred to as the five-year dataset (**Fig. 1**). Among these 44 plots, 8 plots were monitored annually without discontinuity between 1995 and 2017, hereafter referred to as the yearly dataset (**Fig. 1**). The whole workflow of analyses was carried out separately for both the five-year and yearly datasets, as these two datasets are very complementary (*Supporting Information App. Fig. 1*). Although the five-year dataset covers a large spatial extent representative of all temperate

Page 25 of 115 **Figure 25** of 115

 forests in France, its temporal resolution is rather coarse. *Per contra*, the yearly dataset covers a restricted spatial extent but provides a very detailed time series at high temporal resolution. More information on the spatial location and dominant tree species for each of 44 study plots are provided in *Supporting Information App. Table 1*.

standardized protocols under a quality
quality assurance and quality control
ses organized the year before each mon
rveying the same plots in the same fore
x *et al.*, 2009). During each monitoring
spring and in summer/au During each monitoring campaign, the vegetation was surveyed by expert botanists according to standardized protocols under a quality assurance and quality control procedure. The quality assurance and quality control procedure involved intercalibration exercises organized the year before each monitoring campaign with all expert botanists surveying the same plots in the same forest (Camaret & Brêthes, 2004; Archaux *et al.*, 2009). During each monitoring campaign, all plots were surveyed both at spring and in summer/autumn, to cover the entire growing 189 season. All vascular plants were recorded in eight $2 \text{ m} \times 50 \text{ m}$ subplots: four inside and four outside the fenced area of 0.5 ha (**Fig. 1**). The cover-abundance of all taxa occurring in four vegetation layers (tree: > 7 m; high shrub: 2–7 m; low shrub: 0.3–2 m; herb: < 0.3 m) was recorded. Species names were standardized following the nomenclature of *Flora Europaea* (Tutin *et al.*, 2001). A total of 877 taxa were recorded in all vegetation layers, including 751 occurring in the herb layer (hereafter understory plants). Here, we restricted our analyses to understory plants, including tree seedlings, because they represent a relevant component of forest biodiversity which is not directly (but indirectly via the upper canopy layers) impacted by forest management practices, and are expected to be the most

 responsive to climate warming. Only taxa identified at the species or subspecies levels were kept for analyses. Identifications at the genus level were considered as incomplete and excluded from our analyses (i.e. 80 taxa excluded; see the list of species provided in *Supporting Information App. Table 2*). Our dataset encompassed a total of 782 vegetation records, including 347 records from the yearly dataset (492 species) and 435 records from the five-year dataset (593 species). Seasonal surveys (spring and summer/autumn) were aggregated by year with the maximum cover- abundance coefficient retained whenever a species was recorded at both dates. This yielded to a total of 186 and 220 vegetation records for the yearly and five-year dataset, respectively.

Time series of temperature data

For a species was record

Sand 220 vegetation records for the year

Sand 220 vegetation records for the year

Perature data

Sand Sand Sand Sand Sandy

Section 1998

Perature data

Perature data

Section 1998

Perature (MA To compare the velocity of mean annual temperature (MAT) changes with the velocity of temperature changes inferred from understory plant communities, we first extracted time series of MAT changes. We obtained macroclimate temperature time series from the global dataset TerraClimate (Abatzoglou *et al.*, 2018), which provides monthly climate data for every year from 1958 up to 2018 at a spatial 215 resolution of 2.5 arc-minute $\approx 3.3 \text{ km} \times 4.64 \text{ km}$ at 45° of latitude). We also extracted climatic time series from the CHELSA database (Karger *et al.*, 2017) but found very similar trends between TerraClimate and CHELSA (*Supporting Information App. Fig. 2*). Thus, we decided to use only TerraClimate in our subsequent analyses as it better covers the end of our study period (i.e. 2017). As TerraClimate provides only maximum and minimum monthly temperatures, we first calculated the monthly

the period 1992-2017), except for three
alies were negative.
ature conditions from local species asse
re index (CTI) (Devictor *et al.*, 2008, 20
l based on occurrence data by averagin
across all species $i(Sp_i)$ occurring mean for each of the 44 studied plots (by averaging maximum and minimum temperature values for each month), and then computed mean annual temperature (hereafter MAT) for each year between 1958 and 2017. Between 1958 and 2017, MAT increased across all 44 studied plots, leading to a shift from negative to only positive anomalies towards the end of the reference period (1958–2017) (*Supporting Information App. Fig. 3*). From the very beginning (1992) of the RENECOFOR monitoring program until 2017, anomalies were mostly positive (values ranging from -0.56 to 1.54 over the period 1992-2017), except for three years (1993, 1996 and 2010), for which anomalies were negative. To infer temperature conditions from local species assemblages, we used the community temperature index (CTI) (Devictor *et al.*, 2008, 2012) (see Equation 1). The CTI was computed based on occurrence data by averaging the indicator values 233 (IVs) for temperature across all species $i(Sp_i)$ occurring in a given relevé j 234 (containing S species, with $S \ge 2$). Here, we used presence/absence data instead of weighting IVs by each species' abundance/dominance in the relevés. We did that to give the same weight to common and rare species. As each RENECOFOR plot includes 8 subplots, we calculated the CTI values at the subplot level and kept this information at the subplot level without aggregating it at the plot level. 239 (1) $CTI_j =$ $\sum_{i \,=\, 1}^{S}$ IV Temperature S p_i $\mathcal{S}_{\mathcal{C}}% ^{X}(\mathcal{C}_{\mathcal{C}}% ^{X})$ Species' IVs for temperature were extracted from both the CATMINAT (Julve, 1998)

 and EcoPlant (Gégout *et al.*, 2005) databases, and we used them in combination to take advantage of their respective strengths (*Supporting Information App. Fig. 4*).

 Based on the time series of MAT values and the time series of CTI values, both expressed in degrees Celsius, we computed the lag as the difference between 258 the two (MAT $-$ CTI), thus getting a new time series of the difference: the climatic debt (Bertrand *et al.*, 2016).

The main determinants of the climatic debt

 Although we were primarily interested in assessing the temporal dynamic of the difference between MAT and CTI values, thereby testing the effect of time itself on the direction and magnitude of this difference – as we assumed the climatic debt to

 increase over time – we also assessed the relative contributions of several abiotic and biotic determinants known to potentially modulate the climatic debt. For instance, it has already been demonstrated that MAT during or prior to the baseline survey was a strong and positive determinant of the climatic debt in understory plant communities, suggesting greater lags in initially warmer areas (Bertrand *et al.*, 2016). Hence, to account for that potential confounding effect, we computed baseline temperature conditions from TerraClimate as the average of MAT values during the 1961-1990 reference period (i.e. 30-yr average typically used to capture long-term climatic conditions) and added it as a covariate to explain the climatic debt.

reference period (i.e. 30-yr average typicalitions) and added it as a covariate to expression and added it as a covariate to expression and added it as a covariate to expression and added it as a covariate to expandent ura In addition to baseline temperature conditions, we gathered information on anthropogenic and natural disturbances, and stand characteristics, all available from the RENECOFOR monitoring program. Because local disturbances may have significant effects on understory plant communities and are known to accelerate their thermophilization rates and reduce the climatic debt (Bengtsson *et al.*, 2000; Stevens *et al.*, 2015; Brice *et al.*, 2019), we built several variables capturing these local disturbances (*Supporting Information App. Fig. 6 & 7*). First, we distinguished between natural (e.g. windstorm) and anthropogenic disturbances (i.e. local disturbances associated to forest management practices such as thinning, cleaning and tree extraction). For each of these two types of disturbances, we computed the cumulative sum of disturbance events occurring within a given forest plot prior to each survey year. Here, we assumed that repeated disturbance events are likely to

In may lag and happen during the next
varm-adapted species germinating from
thus paying off part of the climatic del
d characteristics at the plot level, inclu
year; stand age in 1995; and the type c
ferous). We hypothesi accelerate the thermophilization rate and thus reduce the climatic debt of understory plant communities. Then, irrespective of the type of disturbance, we also computed the anteriority, i.e. the number of years, between the last disturbance event and the year of the survey, assuming that a very short anteriority (less than a year) will impact less the difference between MAT and CTI values. Indeed, plant community composition is unlikely to change during the vegetation season that is just following a stand thinning event. However, significant changes in plant community composition may lag and happen during the next couple of years with light demanding and warm-adapted species germinating from the soil seed bank and increasing CTI values, thus paying off part of the climatic debt. We also retrieved information about stand characteristics at the plot level, including: stand basal area during the monitoring year; stand age in 1995; and the type of dominant tree species (i.e. deciduous *vs.* coniferous). We hypothesized that plots with higher stand basal area and located in older forest stands are likely to be more buffered against the adverse effect of macroclimate warming (Zellweger *et al.*, 2019), thus further inflating the climatic debt of understory plant communities (De Frenne *et al.*, 2013). The exclosure effect (i.e. fenced area excluding ungulates and large herbivores vs. control plots outside the fenced area) was added as a covariate in all our analyses on the temporal trends in CTI values and the climatic debt. According to the scientific literature, climate change impacts on vegetation dynamics tend to be inhibited by large herbivores (Post & Pedersen, 2008; Kaarlejärvi *et al.*, 2013), hence we hypothesized a greater climatic debt outside than inside the fenced area.

$\mathbf{1}$ $\overline{2}$ $\overline{7}$

Statistical analyses

(44 or 8 levels depending on the datase

(8 levels), nested within the plot ID, we

hierarchical structure of the sampling

time. For MAT values, we only used th

ffect and the RENECOFOR plot ID as

ubplot level was not us We used linear mixed-effects models (LMMs) to assess the velocity of MAT changes and thermophilization of understory plant communities. For CTI values, we used the continuous variable "year" of the monitoring as the main fixed effect while accounting for potentially diverging temporal dynamics between the outside and 313 inside of the fenced area, by adding the interaction effect: year \times exclosure. The RENECOFOR plot ID (44 or 8 levels depending on the dataset used) and the vegetation subplot ID (8 levels), nested within the plot ID, were used as a random term to account for the hierarchical structure of the sampling design and the repeated surveys over time. For MAT values, we only used the "year" of the monitoring as a fixed effect and the RENECOFOR plot ID as a random term. Indeed, for MAT, the subplot level was not used in the random component of LMMs since all 8 subplots within a given plot have similar MAT values. To allow between- site variation in the temporal dynamics of MAT and CTI values, we set the random term (e.g. plot ID) of our LMMs so that it modifies the slope coefficient (i.e. random slope term) of the variable "year" for each level of the random term variable. The coefficient estimate of the "year" variable in our LMMs was used as a proxy for estimating the velocities of temperature changes, both for MAT and CTI values. Assumptions of normality and homoscedasticity of the residuals of our models were visually checked and no departure from normality and homoscedasticity were 328 detected. Significance of the predictors in LMMs were assessed using Wald χ^2 tests, after fitting models with the restricted maximum likelihood estimation.

 vegetation subplot ID (8 levels), nested within the plot ID, as a random slope term modifying the effect of "year" of monitoring. The explained variance of LMMs was 355 determined by calculating the marginal (R^2m) , associated with fixed effects only) and 356 conditional (R^2c , associated with both fixed and random effects) R^2 values (Nakagawa & Schielzeth, 2013) using the r.squared.GLMM function from the MuMIn package.

headyses were performed with the R soft
dels were performed with the nlme pack
nodel selection procedure was assessed
, using the dredge function. Other pack
on and graphical visualization: dplyr v
(Hijmans, 2019); ggplot2 All statistical analyses were performed with the R software version 3.6.0 (R 360 Core Team, 2019). Models were performed with the nlme package $v.3.1$ -140 (Pinheiro *et al.*, 2019), and the model selection procedure was assessed with the MuMIn package v.1.43.6 (Bartoń, 2019), using the dredge function. Other packages were used for data handling extraction and graphical visualization: dplyr v.0.8.3 (Wickham *et al*., 2019); raster v.2.9-23 (Hijmans, 2019); ggplot2 v.3.2.0 (Wickham, 2016); cowplot v.1.0.0 (Wilke, 2019); and sf v.0.7-7 (Pebesma, 2018) .

Results

Temporal trends in macroclimate and community temperatures

 Using the 5-yr interval dataset, mean annual temperature (MAT) during 1995–2015 369 increased by 0.23 ± 0.02 °C/decade (95 % Confidence Intervals (CI): 0.18 - 0.28 , $t =$ 370 9.05, $P < 0.001$; **Fig. 2a**). In the yearly dataset, MAT increased by 0.31 ± 0.05 °C/decade (95 % CI: 0.20-0.42, *^t* = 5.51, *P* < 0.001; **Fig. 2b**) during 1995–2017. Over the same time periods, the velocities of CTI changes were weaker, but similar trends 373 and magnitudes were observed in both the five-year $(0.10 \pm 0.03 \degree \text{C/decade}, 95 \%$

374 CI: 0.04-0.15, $t = 3.62$, $P < 0.001$; **Fig. 2a**) and yearly $(0.08 \pm 0.03 \degree \text{C/decade}, 95 \%$ 375 CI: 0.01-0.14, $t = 2.15$, $P = 0.031$; **Fig. 2b**) datasets. No significant differences were observed in CTI trends between inside and outside of the fenced area. Further, the difference between MAT and CTI values showed a tendency to increase steadily over time (**Fig. 2**): the lag in the response of herbaceous plant communities to climate warming increased linearly over time. Although we found a significant effect of time, 380 it contributed weakly to the overall variation in MAT and CTI values: $R^2m \le 0.01$ 381 while R^2c ranged between 0.92 to 0.96.

Factors contributing to the climatic debt

b she over
an variation in MYT and CT
een 0.92 to 0.96.
 g to the climatic debt
d five year datasets, the model averaging
 $C - CTT$) selected 4 and 3 candidate me
candidate models explained 55% and 7
nce between MAT and CTI For both the yearly and five-year datasets, the model averaging procedure to explain 384 the climatic debt (MAT – CTI) selected 4 and 3 candidate models $(AAICc < 2)$, respectively. The best candidate models explained 55% and 70% of the total 386 variation in the difference between MAT and CTI values for the five-year $(R^2m =$ 387 0.33; $R^2 c = 0.55$) and yearly $(R^2 m = 0.46; R^2 c = 0.70)$ datasets, respectively. The best candidate model for the five-year dataset contained 6 variables including the year of sampling, stand age, the anteriority of the last disturbance, the cumulative number of anthropogenic disturbances, stand basal area, and baseline temperature conditions. For the yearly dataset, the best candidate model included the same 6 variables together with the type of dominant tree species (*Supporting Information App. Tables 3 & 4 and App. Fig. 9 & 10*).

 $\mathbf{1}$

Page 35 of 115 **Figure 20 All 20 and Struck 20 and Struck** Global Ecology and Biogeography

 Irrespective of the dataset considered in our analyses, we found very consistent and similar trends in the factors contributing to the climatic debt (**Fig. 3**). For instance, the year of sampling had a positive effect on the magnitude of the difference, confirming an increasing climatic debt of understory plant communities 398 over time (five-year dataset = 0.06 ± 0.03 SE, *Fig. 3a*; yearly dataset = 0.31 ± 0.04 SE, *Fig. 3b* and *Fig. 4a*).

rature conditions had the strongest pos

r dataset = 0.77 \pm 0.04 SE, *Fig. 3a*; yes

ating greater lags in plots with warme

beriod 1961–1990. We also found a posi

h the variables stand age in 1995 and l

the magnitud Baseline temperature conditions had the strongest positive influence on the 401 climatic debt (five-year dataset = 0.77 ± 0.04 SE, *Fig. 3a*; yearly dataset = 0.72 ± 0.04 0.10 SE, *Fig. 3b*), indicating greater lags in plots with warmer baseline temperature conditions during the period 1961–1990. We also found a positive effect of stand characteristics, through the variables stand age in 1995 and basal area during the year of monitoring, on the magnitude of the lag. More specifically, the lag was larger 406 in denser (five-year dataset = 0.22 ± 0.04 SE, *Fig. 3a*; yearly dataset = 0.35 ± 0.05 407 SE, *Fig. 3b* and *Fig. 4b*) and older (five-year dataset = 0.15 ± 0.04 SE, *Fig. 3a*; 408 yearly dataset = 0.46 ± 0.07 SE, Fig. 3b and Fig. 4c) forests. We found no clear differences in the climatic debt between coniferous and deciduous forests as well as between inside and outside of the fenced area.

 In contrast, forest disturbance had a negative effect on the climatic debt (*Fig.*). Notably, the magnitude of the lag was negatively correlated with the anteriority 413 of the last disturbance event (five-year dataset = -0.12 ± 0.02 SE, Fig. 3a, yearly 414 dataset = -0.10 ± 0.03 SE, *Fig. 3b*), revealing that lags decrease in plots recently disturbed. Moreover, the cumulative number of anthropogenic disturbances were

416 negatively correlated to the climatic debt (five-year dataset = -0.17 ± 0.04 SE, *Fig. 3a*; yearly dataset = -0.19 ± 0.07 SE, *Fig. 3b*), indicating that lags decrease in the most frequently disturbed plots, following logging events. The cumulative number of natural disturbances was only retained in the models based on the five-year dataset, 420 albeit its tendency towards a negative effect did not differ from zero (-0.04 ± 0.04) SE, *Fig. 3a*).

Discussion

Velocities of thermophilization

Source 19 Alternation
poral resolution in the data (i.e. the yearly similar increase in temperature condumities over the period 1995–2017, concess. This finding adds to a growing boding value of plant communities across Irrespective of the temporal resolution in the data (i.e. the yearly vs. five-year dataset), we show a very similar increase in temperature conditions inferred from understory plant communities over the period 1995–2017, consistent with a thermophilization process. This finding adds to a growing body of evidence describing thermophilization of plant communities across many forest ecosystems around the globe (e.g. in temperate, boreal and tropical ecosystems; Lenoir *et al.*, 2010; Bertrand *et al.*, 2011; De Frenne *et al.*, 2013; Savage & Vellend, 2015; Fadrique *et al.*, 2018; Zellweger *et al.*, 2020), as well as across other ecosystems and taxonomic groups (e.g. in mountain plant communities, Gottfried *et al.*, 2012; marine fishes and invertebrates, Cheung *et al.*, 2013; birds and butterflies, Devictor *et al.*, 2012; bumblebee communities, Fourcade *et al.*, 2018). The velocities of 435 thermophilization we report here (ranging from 0.08 to 0.10 \textdegree C/decade) are broadly in the range of those reported in the scientific literature (from 0.03 to 0.38

Formerical constraints may weakly interesting temperatures (Lenoir *et al.*, 2020

assist in the most recent updates support

are community thermophilization which

ce) (Bertrand *et al.*, 2011; Martin *et al.*

at datase °C/decade; *Supporting Information App. Table. 5*), but also are among the highest rates recorded for plant communities (maximum value of 0.27 °C/decade; Duque *et al.*, 2015). Specifically, we show velocities that are twice as fast as the average thermophilization rate estimated for understory plant communities across temperate deciduous forests in Europe (i.e. 0.041 °C/decade; De Frenne *et al.*, 2013). Nevertheless, these rates are still much lower than those found in marine ecosystems, where environmental constraints may weakly limit the dispersal of species in response to rising temperatures (Lenoir *et al*., 2020). Our findings consist in the most recent updates supporting and consolidating previous reports of plant community thermophilization which happened across the same study area (France) (Bertrand *et al.*, 2011; Martin *et al.*, 2019). Focusing on a completely independent dataset from the period 1965–2008, Bertrand *et al.* (2011) were the first to highlight a thermophilization of understory plant communities in the French forests. More recently, Martin *et al.* (2019) have described a similar thermophilization trend extending to other plant communities at national and regional scales in France over the period 2009–2017. Unlike these previous studies relying either on massive collection of opportunistic surveys over time (Bertrand *et al.*, 2011) or citizen science data (Martin *et al.*, 2019), our study is the first that used a long-term monitoring program based on strictly permanent plots intensively monitored over time (up to every year), providing a very detailed time series of changes in understory plant community composition. Hence, we argue that the velocities we report here do not suffer from biases due to space-for-time

Explain the variation in temperature condities. This suggests that other abiot
the macroclimatic context as well as lo
ced by anthropogenic disturbances may
perature conditions.
and its potential determinants
are results i substitutions and are thus likely to be more accurate than those previously reported (Elmendorf *et al.*, 2015), which matters for informing our society on future scenarios of biodiversity changes (IPBES, 2019). Furthermore, our yearly resurveys over a period of 25 years confirm that the thermophilization rate of understory plant communities in temperate forests is following a linear trajectory over time. This is an important and novel finding that helps us to understand the temporal dynamic of the biotic responses to anthropogenic climate change. Yet, time alone had a very minor contribution to explain the variation in temperature conditions inferred from understory plant communities. This suggests that other abiotic and biotic determinants, such as the macroclimatic context as well as local stand characteristics influenced by anthropogenic disturbances may potentially explain local variations in temperature conditions.

The climatic debt and its potential determinants

 One of our most striking results is that the velocity at which atmospheric air temperatures are rising is twice faster, on average, than the velocity at which understory plant communities are responding, generating a climatic debt that is steadily growing over time, even after accounting for the relative contribution of several abiotic and biotic determinants modulating it. Although the idea of an increasing climatic debt over time has already been suggested (Bertrand *et al.*, 2011), we provide the first evidence that the climatic debt of understory plant communities in response to the ongoing climate change is steadily increasing over time. This contrasts with a previous report showing no clear temporal signal in the

For that the climatic debt was better separated in the climatic debt was better separated in the five-year of a bigger role in blurring the long-term en the frequency between resurveys is demonstrate that forest stand char climatic debt of herbaceous plant communities in French forests (Bertrand *et al.*, 2016). Considering the velocity of the predicted future climate change (Loarie *et al.*, 2009), this is an important result because it raises the question whether the lag will continue to steadily accumulate and approach a potential critical breakpoint for understory biodiversity and forest ecosystem functioning. Interestingly, the linear increase of the climatic debt over time is clearer and more pronounced (higher effect size) in the yearly dataset than in the five-year dataset. This is probably because the long-term increasing trend in the climatic debt was better separated from inter- annual variations in the yearly dataset than in the five-year dataset. Inter-annual variations tend to play a bigger role in blurring the long-term response of understory plant communities when the frequency between resurveys is lower. Importantly, we demonstrate that forest stand characteristics and anthropogenic disturbances significantly matter in modulating the climatic debt, by either increasing (positive effect) or mitigating (negative effect) the lag. For instance, both the anteriority of the last disturbance event and the cumulative number of anthropogenic disturbances have a negative effect on the climatic debt. Such findings are in accordance with recent works indicating that local disturbances

speed up the process of thermophilization in plant communities (Stevens *et al.*,

2015; Brice *et al.*, 2019; Zellweger *et al.*, 2020). However, it remains to be

investigated in more details whether the thermophilization of understory plant

communities following anthropogenic disturbances is due to warm-adapted species

- that are: (i) replacing more mesophilous species (pure turnover); (ii) increasing the
	-

and 2015 are also replacing relatively

(i.e. species loss) (*Supporting Informat*.
 \ddot{F} turnover. Not only the richness of war

se of cold-adapted species, but this effect

the richness of light- and nitrogen-dema
 local species pool (nestedness); or both simultaneously. For instance, Closset-Kopp *et al.* (2018) have shown that understory plant communities in heavily managed forest stands had the tendency to be richer in warm-adapted species in 2015 than in 1970, mostly due to an increase in local species richness but no species turnover. In our study, both processes seem to occur. Indeed, while the total number of species per plot increases over time, suggesting a process of nestedness, the set of warm- adapted species that are colonizing (i.e. species gain) the plots of our monitoring network between 1995 and 2015 are also replacing relatively more mesic species that are disappearing (i.e. species loss) (*Supporting Information, App. Fig. 11*), suggesting a process of turnover. Not only the richness of warm-adapted species increases at the expense of cold-adapted species, but this effect is concomitant with a relative increase in the richness of light- and nitrogen-demanding species at the expense of species tolerating shade conditions and nitrogen-poor soils (*Supporting Information, App. Fig. 12*). These trends further confirm the importance of local disturbances as key factors modulating the lag between macroclimatic conditions and plant community thermophilization. Noteworthy, our results contrast with those from Bertrand *et al.* (2016), who reported non-significant effects of anthropogenic disturbances on the climatic debt of understory plant communities. Looking at the effects of stand characteristics, our results underline the key role of stand age and basal area to modulate the climatic debt. Older and denser (high basal area) forest stands provide particular microclimatic conditions (e.g. cooler ground-level temperatures due to increased shading and humidity conditions) that are likely to buffer the adverse effects of macroclimatic warming on understory

apted species through either species tu
s) that will reduce the climatic debt. P:
t communities in temperate forests im
which can consequently reduce the mi
survival of forest-dwelling species unde
ret al., 2017). Acceptin plant communities thus providing thermal microrefugia for species persistence (Lenoir *et al.*, 2017; De Frenne *et al.*, 2019; Zellweger *et al.*, 2020). In contrast, repeated disturbances are likely to create canopy openings in forest stands, modifying the microhabitat and associated microclimate that strongly exacerbate the impact of macroclimate temperature warming for understory vegetation (Vanderwel & Purves, 2014; Zellweger *et al.*, 2020). This can in turn lead to drastic changes in the overall composition of the plant community (i.e. by increasing the proportion of warm-adapted species through either species turnover or an increase in local species richness) that will reduce the climatic debt. Paying off the climatic debt of understory plant communities in temperate forests implies to break off this microclimate stability, which can consequently reduce the microrefugia capacity of forest habitats for the survival of forest-dwelling species under anthropogenic climate change (Lenoir *et al.*, 2017). Accepting the idea that the climatic debt of understory plant communities might be a positive sign of local adaptation has significant implications on the concept of climatic debt itself, which might be interpreted as a macroclimatic debt but not a microclimatic debt .

 Contrary to our initial expectation that large herbivores should contribute to the climatic debt by further increasing the lag in the response of understory plant communities to macroclimate warming, we found no difference in the observed climatic debt between outside and inside the fenced area. This suggests that the climatic debt generated by the buffering effect of microclimate in the understory may mostly stem from the canopy layer and independently from the shrub layer, as

nditions were warmer during the period
rand *et al.*, 2016), such as in the lowlar
ct that warmer baseline conditions incom
munities could also stem from a bias
I values in communities where immigr
per regions likely outsi large herbivores are mostly impacting woody species from the understory shrub layer (Olofsson *et al.*, 2009; Boulanger *et al.*, 2018). The indirect effects of herbivores on vegetation responses to climate warming can be highly dependent on the ecological context, as pointed out by Vuorinen *et al*., (2020). Together with previous studies, our results show that the climatic debt in understory plant communities seem to be much more pronounced in situations where temperature conditions were warmer during the period preceding the baseline surveys (Bertrand *et al.*, 2016), such as in the lowlands (Bertrand *et al.*, 2011). However, the fact that warmer baseline conditions increase the climatic debt of understory plant communities could also stem from a bias towards an underestimation of CTI values in communities where immigrating species can only come from even warmer regions likely outside the calibration range used to compute the CTI values. This could therefore lead to a systematic overestimation of the observed climatic debt in the warmest part of the study area. This hypothesis is supported by the extreme values observed in the distribution of indicator values (IVs) from the EcoPlant database (*Supporting Information App. Fig. 5*), which may indicate that the model calibration range is too limited and should be extended to other environmental conditions (i.e. here, the Mediterranean regions to capture the pool of immigrating species coming from for warmer conditions). This potential bias supports general recommendations to take into account existing differences in sensitivity between species pools when assessing temporal changes in CTI values (Burrows *et al.*, 2019; Williams *et al.*, 2020). More data on species IVs, either expert-

 $\mathbf{1}$

References

herb layer changes (1970-2015) in a temperate forest with contrasting habitat

es (1970-2015) in a temperate forest wi
itions? *Journal of Ecology*.
ma*tic Instability, Time, Lags, and Com*
u*nity ecology* Community ecology. (ed.
4. Harper; Row.
gs in vegetation response to greenhouse
nez-Sánchez, F. Case), pp. 269–284. Harper; Row. 6445. M.B. (1989) Lags in vegetation response to greenhouse warming. *Climatic Change*, **15**, 75–82. De Frenne, P., Rodríguez-Sánchez, F., Coomes, D.A., Baeten, L., Verstraeten, G., nd, M., … Verheyen, K. (2013) Microclimate moderates plant responses to macroclimate warming. *Proceedings of the National Academy of Sciences of the*

-
- *United States of America*, **110**, 18561–5.
- De Frenne, P., Zellweger, F., Rodríguez-Sánchez, F., Scheffers, B.R., Hylander, K.,
	- b, M., ... Lenoir, J. (2019) Global buffering of temperatures under forest
	- canopies. *Nature Ecology and Evolution*, **3**, 744–749.
		-

F., Moyes, F., Bates, A.E., Magurran,

for IME: A database of biodiversity time
 Ecology and Biogeography, 27, 760–786

er, A., Thuiller, W., Moser, D., Zimmer

() Extinction debt of high-mountain pla

(). *Nature Climat* Devictor, V., Julliard, R., Couvet, D. & Jiguet, F. (2008) Birds are tracking climate warming, but not fast enough. *Proceedings of the Royal Society B: Biological Sciences*, **275**, 2743–2748. Devictor, V., Swaay, C. van, Brereton, T., Brotons, L., Chamberlain, D., Heliölä, J., ... Jiguet, F. (2012) Differences in the climatic debts of birds and butterflies at a continental scale. *Nature Climate Change*, **2**, 121–124. Dornelas, M., Antão, L.H., Moyes, F., Bates, A.E., Magurran, A.E., Adam, D., … Zettler, M.L. (2018) BioTIME: A database of biodiversity time series for the Anthropocene. *Global Ecology and Biogeography*, **27**, 760–786. Dullinger, S., Gattringer, A., Thuiller, W., Moser, D., Zimmermann, N.E., Guisan, A., ... Hülber, K. (2012) Extinction debt of high-mountain plants under twenty-first- century climate change. *Nature Climate Change*, **2**, 619–622. Duque, A., Stevenson, P.R. & Feeley, K.J. (2015) Thermophilization of adult and juvenile tree communities in the northern tropical Andes. *Proceedings of the National Academy of Sciences of the United States of America*, **112**, 10744–10749. Ellenberg, H., Weber, H.E., Düll, R., Wirth, V., Werner, W. & Paulißen, D. (1992) Zeigerwerte von Pflanzen in Mitteleuropa. *Scripta Geobotanica*. Elmendorf, S.C., Henry, G.H.R., Hollister, R.D., Fosaa, A.M., Gould, W.A., Hermanutz, L., ... Walker, M. (2015) Experiment, monitoring, and gradient methods used to infer climate change effects on plant communities yield consistent patterns.

 Proceedings of the National Academy of Sciences of the United States of America, **112**, 448–52.

Essl, F., Dullinger, S., Rabitsch, W., Hulme, P.E., Pyšek, P., Wilson, J.R.U. &

Richardson, D.M. (2015) Delayed biodiversity change: no time to waste. *Trends in*

Ecology & Evolution, **30**, 375–378.

heterogeneous responses of Andean fo

S. & Öckinger, E. (2018) Climate and la

iness and community composition in su

ervation.

& Devictor, V. (2017) Where do they g

t diversity on reducing climatic debt in

. Fadrique, B., Báez, S., Duque, Á., Malizia, A., Blundo, C., Carilla, J., … Feeley, K.J. (2018) Widespread but heterogeneous responses of Andean forests to climate change. *Nature*.

 Fourcade, Y., Åström, S. & Öckinger, E. (2018) Climate and land-cover change alter bumblebee species richness and community composition in subalpine areas.

Biodiversity and Conservation.

Gaüzère, P., Princé, K. & Devictor, V. (2017) Where do they go? The effects of

topography and habitat diversity on reducing climatic debt in birds. *Global Change*

Biology, **23**, 2218–2229.

 Gégout, J.C., Coudun, C., Bailly, G. & Jabiol, B. (2005) EcoPlant: A forest site database linking floristic data with soil and climate variables. *Journal of Vegetation Science*, **16**, 257–260.

Gottfried, M., Pauli, H., Futschik, A., Akhalkatsi, M., Barančok, P., Benito Alonso,

 J.L., … Grabherr, G. (2012) Continent-wide response of mountain vegetation to climate change. *Nature Climate Change*, **2**, 111–115.

 Nakagawa, S. & Schielzeth, H. (2013) A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution*, **4**, 133–142.

 Nicolas, M., Jolivet, C. & Jonard, M. (2014) How monitoring networks contribute to the understanding and to the management of soil and forest ecosystems? *Revue forestière française*.

L., Callaghan, T., Hulme, P.E., Oksane
bit climate-driven shrub expansion on
81–2693.
3., Bell, J.D., Blanchard, J., Bonebrake,
3iodiversity redistribution under clima
1 well-being. *Science (New York, N.Y.)*,
nple Feature Olofsson, J., Oksanen, L., Callaghan, T., Hulme, P.E., Oksanen, T. & Suominen, O. (2009) Herbivores inhibit climate-driven shrub expansion on the tundra. *Global Change Biology*, **15**, 2681–2693.

Pecl, G.T., Araújo, M.B., Bell, J.D., Blanchard, J., Bonebrake, T.C., Chen, I.-C., …

 Williams, S.E. (2017) Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. *Science (New York, N.Y.)*, **355**, eaai9214.

Pebesma, E. (2018) Simple Features for R: Standardized Support for Spatial Vector

Data. *The R Journal*, 10, 439–446.

Perring, M.P., Bernhardt-Römermann, M., Baeten, L., Midolo, G., Blondeel, H.,

Depauw, L., … Verheyen, K. (2018) Global environmental change effects on plant

community composition trajectories depend upon management legacies. *Global*

Change Biology, **24**, 1722–1740.

 Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D. & R Core Team (2019) nlme: Linear and Nonlinear Mixed Effects Models.

Figures

List and captions

Figure 1.

Example 18 (MAT) and the communival

For more details, s

datasets separately. For more details, s

ean annual temperature (MAT) and th

T) in (a) the five-year dataset from 199

95 to 2017. Linear trends (dashed lines

MA Workflow implemented in the study. The 102 plots of the RENECOFOR network are mapped, and the two datasets used in our analyses are represented in color (in red and blue for the five-year and yearly datasets, respectively). Analyses of temporal trends in mean annual temperature (MAT) and the community temperature index (CTI) and factors contributing to the lag between MAT and CTI (MAT-CTI) are conducted on the two datasets separately. For more details, see the Materials and Methods section.

Figure 2.

 Temporal trends for mean annual temperature (MAT) and the community temperature index (CTI) in (a) the five-year dataset from 1995 to 2015 and (b) the yearly dataset from 1995 to 2017. Linear trends (dashed lines) with standard errors (ribbons) of estimated MAT or CTI values are shown. For CTI, the values for exclosure or enclosure are plotted separately. Observed values for temperatures (MAT or CTI) are represented with their associated standard errors and symbol sizes are proportional to sample size (number of plots).

Figure 3.

 Coefficient estimates and 95% confidence intervals extracted from linear mixed- effects models testing the relative contribution of several potential abiotic and biotic determinants on the magnitude and direction of the lag between mean annual

9 temperature (MAT) and the community temperature index (CTI) values in (a) the five-year dataset and (b) yearly dataset. Points (with 95% confidence intervals) 821 represent the standardized mean coefficients averaged from the selected models (Δ) AICc \leq 2) in the model-averaging procedure. Colors show the magnitude and significance of effects (red: significant amplification of the lag; blue: significant mitigation of the lag; light grey: non-significant).

Figure 4.

lls illustrating the contribution of three
ection of the lag between mean annual
mperature index (CTI) for the yearly da
each of the three factors when all other
set to their mean value for quantitative
eciduous stands and Plots of partial residuals illustrating the contribution of three factors in explaining ⁷ the magnitude and direction of the lag between mean annual temperature (MAT) 8 and the community temperature index (CTI) for the yearly dataset. These plots indicate the effects of each of the three factors when all others factors in the model are accounted for and set to their mean value for quantitative variables. Qualitative variables were set to deciduous stands and to outside the fence area here. The factors (a) 'Years', (b) 'Stand Basal Area' and (c) 'Stand Age in 1995' were extracted from the best model (in the model-averaging procedure) explaining the lagged responses of forest plant communities in the yearly dataset. Solid lines and ribbons represent the linear trend and associated standard errors, respectively.

 $\overline{6}$ $\overline{7}$ $\overline{8}$

 $\mathbf{1}$ \overline{c} $\begin{array}{c} 3 \\ 4 \end{array}$

 $\overline{7}$

 $\mathbf{1}$ $\overline{2}$

 $\overline{6}$ $\overline{7}$ $\overline{8}$

 $\mathbf{1}$ \overline{c} $\begin{array}{c} 3 \\ 4 \end{array}$

-
-
-
-
-
-

Figure 1. Workflow implemented in the study. The 102 plots of the RENECOFOR network are mapped, and the two datasets used in our analyses are represented in color (in red and blue for the five-year and yearly datasets, respectively). Analyses of temporal trends in mean annual temperature (MAT) and the community temperature index (CTI) and factors contributing to the lag between MAT and CTI (MAT-CTI) are conducted on the two datasets separately. For more details, see the Materials and Methods section.

Figure 2. Temporal trends for mean annual temperature (MAT) and the community temperature index (CTI) in (a) the five-year dataset from 1995 to 2015 and (b) the yearly dataset from 1995 to 2017. Linear trends (dashed lines) with standard errors (ribbons) of estimated MAT or CTI values are shown. For CTI, the values for exclosure or enclosure are plotted separately. Observed values for temperatures (MAT or CTI) are represented with their associated standard errors and symbol sizes are proportional to sample size (number of plots).

926x1296mm (72 x 72 DPI)

Figure 3. Coefficient estimates and 95% confidence intervals extracted from linear mixed-effects models testing the relative contribution of several potential abiotic and biotic determinants on the magnitude and direction of the lag between mean annual temperature (MAT) and the community temperature index (CTI) values in (a) the five-year dataset and (b) yearly dataset. Points (with 95% confidence intervals) represent the standardized mean coefficients averaged from the selected models (ΔAICc < 2) in the model-averaging procedure. Colors show the magnitude and significance of effects (red: significant amplification of the lag; blue: significant mitigation of the lag; light grey: non-significant).

987x1234mm (72 x 72 DPI)

Figure 4. Plots of partial residuals illustrating the contribution of three factors in explaining the magnitude and direction of the lag between mean annual temperature (MAT) and the community temperature index (CTI) for the yearly dataset. These plots indicate the effects of each of the three factors when all others factors in the model are accounted for and set to their mean value for quantitative variables. Qualitative variables were set to deciduous stands and to outside the fence area here. The factors (a) 'Years', (b) 'Stand Basal Area' and (c) 'Stand Age in 1995' were extracted from the best model (in the model-averaging procedure) explaining the lagged responses of forest plant communities in the yearly dataset. Solid lines and ribbons represent the linear trend and associated standard errors, respectively.

740x1358mm (72 x 72 DPI)

 $\mathbf{1}$

$\overline{2}$ $\overline{7}$

Captions:

Ex. The baseline TerraClimate temperat

ed as background raster.

risons between three sources of time-se

imate, CHELSA and local meteorologic

ites from the RENECOFOR network w

al stations nearby. a) Location of t **App. Figure 1.** Location of the monitored plots throughout France (a) and the time-43 sequence plot for the repeated surveys (b). The two datasets are distinguished by 44 color (in black and light blue for the five-year dataset and yearly dataset, 45 respectively). Seasonal relevés are represented by different symbols (\circ , Spring; +, 46 Summer; \times , Autumn) and grouped by year. Labels refer to the names of plots in the 47 RENECOFOR network. The baseline TerraClimate temperature conditions over the 48 1960–1990 period is used as background raster. **App. Figure 2.** Comparisons between three sources of time-series for macroclimate 50 temperatures (TerraClimate, CHELSA and local meteorological stations). For 51 comparisons, only 13 sites from the RENECOFOR network were used because they 52 had local meteorological stations nearby. a) Location of the 13 sites from the 53 RENECOFOR network used for comparisons. b) Time-series of macroclimate 54 temperatures provided by TerraClimate, CHELSA, and the meteorological stations. 55 Shaded ribbon (in grey) and dotted line show the beginning of vegetation surveys in 56 the RENECOFOR monitoring program.

 App. Figure 3. Trends in mean annual temperatures anomalies from 1958 to 2017 in 58 the 44 permanent plots studied. Temperature anomalies are computed for each 59 permanent plot as the difference between yearly temperatures and the mean 60 temperature over the period 1958–2017. The black line depicts a 5-year moving 61 average of MAT. Mean of temperature anomalies and standard errors are

but (1) to warm (b) environments. Will
nost all of the species sampled in the RE
e 877 species recorded within all strata
timated with these species IVs are unit
roclimatic temperatures are not possibl
mputation of CTI val 82 relationship of two databases : CATMINAT (Julve, 1998) and EcoPlant (Gégout et 83 al., 2005). These two databases were chosen, because CATMINAT contains almost 84 all of species recorded in our dataset and EcoPlant, poorer in species, has the 85 advantage to allow the direct computation of CTI values in degrees Celsius. 86 CATMINAT (Julve, 1998) is based on expert knowledge similarly to Ellenberg IVs 87 (Ellenberg et al., 1992), with temperature preferences of plant species coded along 88 an ordinal scale from cold (1) to warm (9) environments. While the CATMINAT 89 database contains almost all of the species sampled in the RENECOFOR monitoring 90 program (858 out of the 877 species recorded within all strata of vegetation; **App. Fig. 5a**), CTI values estimated with these species IVs are unitless and direct 92 comparisons with macroclimatic temperatures are not possible. On the other hand, 93 EcoPlant allows the computation of CTI values in degrees Celsius. EcoPlant is a 94 phyto-ecological database which provides information about ecological optimum for 95 key variables of forest plant species based on their distribution over the French 96 territory. In EcoPlant, species IV for temperature are expressed in degrees Celsius 97 as they are estimated using logistic regression models based on climatic data from AURELHY dataset for the historical period (1961–1990). Nevertheless, the EcoPlant 99 database covers much less species from our dataset (396 out of 877 species). 100 Therefore, we calibrated a transfer function to transform the unitless CTI values 101 from the CATMINAT database into a CTI value expressed in degrees Celsius. By 102 regressing CTI values from EcoPlant against CTI values from CATMINAT, we can 103 obtain predicted CTI values from CATMINAT expressed in degrees Celsius (see

124 respectively). The final GAM was adjusted with $\lambda = 6$ (model with the lowest 125 RMSE) and it explained 72.9% of the total deviance (**App. Fig. 5d**).

ar, we recorded informations about : (i)
ber of disturbance known in a forest st
r its nature (anthropogenic or natural
nic or natural event); (iii) Anteriority, a
ance whatever its nature; (iv) the Cum
(v) the Cumulated d **App. Figure 6.** Illustrative examples of the indices created to account for disturbance 127 and forest management. Two cases are presented $: a \in A$ site with two anthropogenic 128 events that occurred during several vegetation surveys ; and b) A site with one 129 anthropogenic event and two natural events that occurred during several vegetation 130 surveys. For survey year, we recorded informations about $:(i)$ Cumulated disturb., 131 as the cumulative number of disturbance known in a forest stand since the plot 132 etablishment, whatever its nature (anthropogenic or natural event); (ii) the Type of 133 last event (anthropogenic or natural event); (iii) Anteriority, as the anteriority in 134 year of the last disturbance whatever its nature; (iv) the Cumulated disturb. of 135 anthropogenic events $:(v)$ the Cumulated disturb. of natural events. Only the 136 columns filled in grey were used in our analyses. Anthropogenic events include 137 mainly silvicultural operations such as thinning, logging, tree extraction, cleaning 138 brush and forestry machine passage. Natural events include for example, windfalls 139 and tree uprooting after a storm event.

 App. Figure 7. Cumulative number of disturbance events along time for each studied 141 plot. The type of disturbance is distinguished by different symbols, and the 142 anteriority (in years) of the last disturbance is shown by a color scale.

 App. Figure 8. Correlation matrix plots between explanatory variables used in our 144 analyses, showing scatterplots, density curves and Pearson correlation coefficients 145 for the explanatory variables tested in the models. 'lags': difference $\text{MAT} - \text{CTI}$;

146 'Years': Year of survey; 'Baseline T°C': the baseline temperature conditions during 147 the 1961–1990 period; 'Age in 1995': Age of forest stand in 1995 (year of the first 148 field campaign); 'Disturb. anterior': Anteriority (in years) of the last disturbance 149 which occurred in the plot ; 'Cum.anthr.disturb.': cumulative sum of the number of 150 annual anthropogenic disturbances; 'Cum.nat.disturb.': cumulative sum of the 151 number of natural disturbances ; 'Basal area': forest stand basal area. See Materials 152 and methods for further details.

residuals plots for factors contributing
model averaging procedure in the five-y
uals that remain after removing the eff
l.
l.
presiduals plots for factors contributing
model averaging procedure in the yearl
uals that rema **App. Figure 9.** Partial residuals plots for factors contributing to lags in the best 154 model selected by the model averaging procedure in the five-year dataset. Partial 155 residuals are the residuals that remain after removing the effect of all other 156 covariates in the model.

 App. Figure 10. Partial residuals plots for factors contributing to lags in the best 158 model selected by the model averaging procedure in the yearly dataset. Partial 159 residuals are the residuals that remain after removing the effect of all other 160 covariates in the model.

 App. Figure 11. Species richness changes over time (a), Number of species gained or 162 lost between survey years (b), and Temporal changes over time for averages of IVs 163 for Temperature within the group of species gained or lost between survey years (c). 164 Points and error bars correspond to the average of values between the 44 studied 165 sites and the standard errors, respectively. For the temporal changes, we compared 166 the species lists between the first survey in 1995 and the later surveys of each plot 167 to identify the pools of species gained and lost between each pair of surveys. In

agesperso-orange.fr/catminat.htm). Spe
n pourcentage of the total species richnes
near regressions are displayed ($P < 0.05$
ions on sites characteristics detailing the
near regressions are displayed ($P < 0.05$
ions on site 168 particular, these two pools are used to calculate temporal β -diversity between two 169 surveys of a given plot (Legendre, 2019). Then, we computed the average of IVs for 170 Temperature within the gained and lost species. **App. Figure 12.** Temporal changes over time in species richness within each class of 172 IV for Temperature, Light and Nitrogen (from CATMINAT, Julve, 1998). Each class 173 of IV are detailed in the online version of CATMINAT 174 (http://philippe.julve.pagesperso-orange.fr/catminat.htm). Species richness per 175 classes are expressed in pourcentage of the total species richness in a given plot. 176 Points correspond to the average of species richness between the 44 studied sites, 177 and only significant linear regressions are displayed $(P < 0.05)$. **App. Table 1** Informations on sites characteristics detailing the name of 179 RENECOFOR plots, the dominant tree species in the forest stands, the altitude, the 80 geographical coordinates (latitude and longitude in WGS84), and the dataset (s) in 181 which they occurred (see Materials and Methods for details on the yearly or five-82 year datasets). **App. Table 2** List of 751 forest species inventoried in the herbaceous layer. Species 184 retained for analyses are marked with a "1" in the éponymous column. **App. Tables 3 & 4** Results of the model-averaging procedures and selected models 186 for the studyy of the effects of different variables on lag (difference between MAT 187 and CTI). Only the top 20 models are presented. Coefficients of variables were

- 188 estimated using linear mixed-effects models (LMMs including 'plot' and 'nested
	-

189 subplots' as random effects) in a model-averaging procedure. All variables were

190 standardized (*z*-score) to interpret estimates as relative effect sizes. Coefficient

192 and R^2c describe the variation explained by fixed effects only and variation

194 values < 2 were used to estimate coefficients.

193 explained by the fixed and random effects, respectively. Only models with AICc

App. Table 5 Review of some scientific publications studying the thermophilization

196 rates (expressed in °C/decade) in different ecosystems and taxonomic groups.

191 estimates for predictor variables, marginal R^2 m and conditional R^2 c are shown. R^2 m

FOR PROLL

 $\mathbf{1}$ $\overline{2}$

App. Figure 8.

 $\overline{7}$

 $\mathbf{1}$ $\overline{2}$

-
-

 $\overline{\mathcal{A}}$

 $\mathbf{1}$ $\overline{2}$ $\overline{\mathbf{3}}$

-
-
-
-
-
-
-
-

 $\overline{7}$

 $\overline{\mathcal{A}}$

 $\mathbf{1}$ $\overline{2}$ $\overline{\mathbf{3}}$

-
-
-
-
-

- 252 Dahlberg, C. J., Decocq, G., Diekmann, M., Dynesius, M., Ejrnæs, R., Grytnes, J. A.,
- 253 Hylander, K., Klanderud, K., … Svenning, J. C. (2013). Local temperatures inferred
- 254 from plant communities suggest strong spatial buffering of climate warming across
- 255 Northern Europe. *Global Change Biology*, *19*(5), 1470–1481.
- https://doi.org/10.1111/gcb.12129

 $\overline{2}$

 \overline{a}

 \overline{a}

22 4636.016 5.309 0.015 0.32

9 4636.592 5.884 0.011 0.32

55 4639.41 8.703 0.003 0.3

9 4640.008 9.301 0.002 0.32

9 4640.939 10.232 0.001 0.32

3 4640.978 10.271 0.001 0.3

 $\mathbf{1}$ $\overline{2}$ $\overline{3}$ $\overline{\mathbf{4}}$ 5 6 $\overline{7}$ $\bf 8$ $\mathsf 9$

