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Loss of competitive strength in European conifer species under climate change

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Climate change is expected to alter species assemblages by affecting the outcome of competition between species. Investigating processes of competition remains challenging in tree communities, as they unfold over extensive spatio-temporal scales. Here, we used a deep learning-based meta-model trained on 135 million simulated tree responses to climate across Europe to investigate changes in the competitiveness of nine major tree species under future climate. We harnessed projections from local process models to train a Deep Neural Network of forest state transitions to investigate climate-induced changes in competition at continental scale. We found decreasing competitive strength for evergreen conifers across their distribution, while deciduous broadleaved species increased in competitiveness. Most investigated species lost competitive strength at their warm range edges. Consequently, up to 25% of Europe's forests could experience a change in the dominant tree species until the end of the 21st century, suggesting a profound climate-induced reassembly of Europe's forests.

Competition for limited resources is a fundamental process driving the composition and structure of vegetation around the globe^{1–3}. Competition is a mutual process between co-occurring species striving for the same resources, and its outcome is determined by the competitiveness and sensitivity to competition of the interacting species^{4,5}. In forested ecosystems, competition between tree species is driven by traits that determine the potential to overgrow others (i.e., height growth potential)⁶, the ability to shade out competitors (i.e., high leaf area index (LAI)), tree longevity (i.e., the ability to outlive competitors), and the ability to acquire water and nutrients more efficiently than neighboring trees (e.g., different rooting strategies)^{7,8}. Although facilitation between trees may also occur, competition remains the dominant process of interaction between trees in forest ecosystems^{9,10}. Under stable environmental conditions, highly competitive tree species can maintain their dominance over extended periods of time and cover extensive areas. European beech (*Fagus sylvatica* L.), for instance, is a shade-tolerant late-seral species that can dominate natural forest development in large parts of temperate Europe¹¹.

Changing environmental conditions due to climate change can have profound impacts on the competitiveness of tree species, as they shift the availability and distribution of critical resources in space and time¹². As a consequence, species could lose competitiveness or experience higher sensitivity to competition, resulting in reduced competitive strength relative to other species, and ultimately leading to a change in species assemblages^{13,14}. Therefore, the loss of competitive strength of individual species can serve as an early warning indicator for climate-induced shifts in tree species composition¹⁵. Such shifts could affect the resource use efficiency and carbon uptake of forest ecosystems, as well as other important ecosystem services¹⁶. Losses in competitive strength could also be substantial for biodiversity, e.g., when obligate species lose the resource of a host tree species¹⁷. Consequently, a quantification of potential changes in the competitive strength of tree species is highly relevant for anticipating ecosystem responses to ongoing environmental changes.

Assessing changes in the competitive strength of trees is challenging, as competition occurs over extended periods of time. Furthermore,

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competitive strength can vary throughout the range and life stages of a species, limiting the utility of short-term, local assessments and requiring the consideration of large spatio-temporal extents. Process-based simulation models relying on fundamental principles of forest dynamics are prime tools to overcome these challenges¹⁸. They can be applied to study the outcomes of competition over timeframes of decades to centuries consistently across a range of locations, while explicitly accounting for the effects of changing climatic conditions. A number of process-based forest models have been developed over the past decades, designed to capture local ecosystem characteristics and parametrized and tested with local data. These models thus represent our best available quantitative understanding of how forests in a given region might respond to climate change¹⁹. Yet, this treasure trove of local climate change responses has not been synthesized across locations and models to date, and thus remains underutilized in large-scale assessments and policy considerations. Recent breakthroughs in deep learning (DL) present new opportunities to learn from the nuanced climate change responses observed in local simulation data, e.g., by conducting DL-based model syntheses^{20,21}.

Here, we harnessed a database of harmonized local forest simulations across Europe containing 135 million simulation-years from 17 process-based forest models²² to train a deep neural network (DNN) of state transitions in forest ecosystems. This DNN forms the core of a meta-model of forest dynamics that is able to probabilistically synthesize and scale local process model results to large spatial extents. The resulting meta-modeling framework is then used to investigate how climate change affects competitive strength at large spatial scales. Specifically, we (i) examined the change in competitive strength for nine widely distributed European tree species (i.e., European beech (*Fagus sylvatica* L.), Scots pine (*Pinus sylvestris* L.), silver fir (*Abies alba* Mill.), Norway spruce (*Picea abies* (L.) H. Karst.), European larch (*Larix decidua* Mill.), silver birch (*Betula pendula* Roth), Aleppo pine (*Pinus halepensis* Mill.), pedunculate oak (*Quercus robur* L.), and holm oak (*Quercus ilex* L.)) within their current range limits (represented by their native and naturalized ranges in Europe²³) at the level of individual species, and (ii) highlighted in which geographical regions and sections of their current niche (i.e., warm vs. cold edges of the distribution) species gain or lose competitive strength under climate change. We used height growth and LAI as indicators of competitive strength and combined them into a competitive strength index (CSI). Subsequently, we analyzed (iii) whether the potential loss in competitive strength at the species level also results in a change in species dominance at the community level, i.e., if changes in species-level competitive strength also result in changes in tree species composition (considering a total of 63 tree species). We furthermore (iv) identified hotspots of shifting species dominance, pinpointing areas in which assemblages are likely to change, and which require special attention in forest policy and management.

Results

Change in the competitive strength of major European tree species

We found that six out of nine studied species, including all investigated evergreen species, experienced a decline in competitive strength under climate change (Fig. 1). Under severe climate change (scenario RCP8.5, period 2071–2100), the CSI of Aleppo pine (−23.9%), holm oak (−3.2%), and Norway spruce (−8.0%) decreased across their current distribution ranges, relative to values under current climate (1981–2010). In addition, silver birch (−3.9%), silver fir (−1.2%), and Scots pine (−5.4%) had negative CSI values. In contrast, pedunculate oak (+7.8%), European beech (+5.5%), and European larch (+0.7%) increased their competitive strength under climate change. On average, broadleaved species responded slightly positive to climate change (+2.3%), while the competitive strength of coniferous species decreased (−3.9%). Patterns remained similar also under strong climate change (RCP4.5), yet under moderate climate change (RCP2.6), only the two Mediterranean species, Aleppo pine (−8.2%), holm oak (−2.6%), as well as Scots pine (−2.3%) and Silver birch (−0.5%) decreased in competitive strength. Norway spruce, which showed decreasing competitive

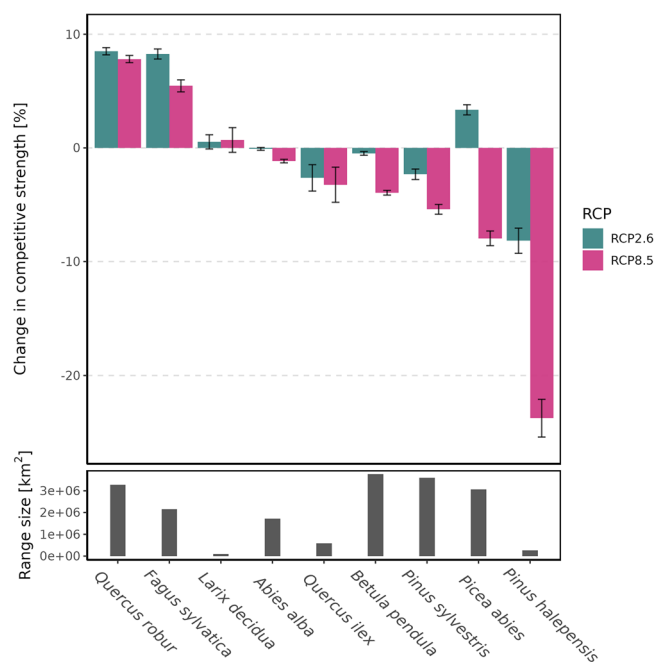


Fig. 1 | Change in competitive strength between current and future climate conditions. Change in competitive strength between current (1981–2010) and future climate conditions (2071–2100) in different climate scenarios (RCP8.5 and RCP2.6). Values represent the weighted mean change in competitive strength index (CSI) across all grid cells (12 × 12 km) within a species' current distribution (range size indicated in the lower panel). Grid cells were weighted according to their relative share on total forest area, following Brus et al.³². Error bars indicate 95% confidence intervals. CSI aggregates across the competition indicators LAI (i.e., the ability to form dense canopies and shade out other species) and height growth (i.e., the ability to overgrow competitors) by means of averaging. Detailed results for the individual components of CSI, as well as values for scenario RCP4.5, can be found in the Supplementary Information (Figs. S1–S3).

strength under RCP4.5 and RCP8.5, benefitted under RCP2.6 (+3.4%). Analyzing the two components of CSI, we found that LAI responded more negatively to climate change than height growth across most species (Figs. S1 and S2).

Spatial patterns of changing competitive strength

Spatial variation was high among and within species, but competitive strength generally decreased in warmer and more water-limited biomes (i.e., Mediterranean and temperate broadleaved forests) and increased in more cold-limited biomes (i.e., temperate coniferous and boreal forests as well as tundra ecosystems) (Fig. 2). European beech, which had an overall increasing competitive strength throughout its distribution, decreased in competitive strength in the Mediterranean parts of its range (−6.8%) while strongly increasing in the temperate coniferous biome (+36.9%) (scenario RCP8.5; Fig. S4). Norway spruce showed an overall decreasing CSI throughout its distribution, which was particularly pronounced in the temperate broadleaved biome (−21.2%). Conversely, it increased its competitive strength in cold-limited areas such as Fennoscandia (+14.3% in boreal forests) and in the temperate coniferous biome (+12.2%). Competitive strength decreased in 78% of the current range of Aleppo pine (i.e., the species with the most pronounced negative response throughout its range), but only in 24% of pedunculate oak (the species with the most pronounced positive response), with values of 33 and 50% for European beech and Norway spruce, respectively. To determine the geographical variation in competitive responses within species, we investigated changes in CSI in different parts of a species' climatic niche. Overall, species responded with increasing competitive strength close to their cold-induced niche edges, while close to the warm niche edges, competitive strength generally decreased (Table 1). Coniferous species responded more negatively than

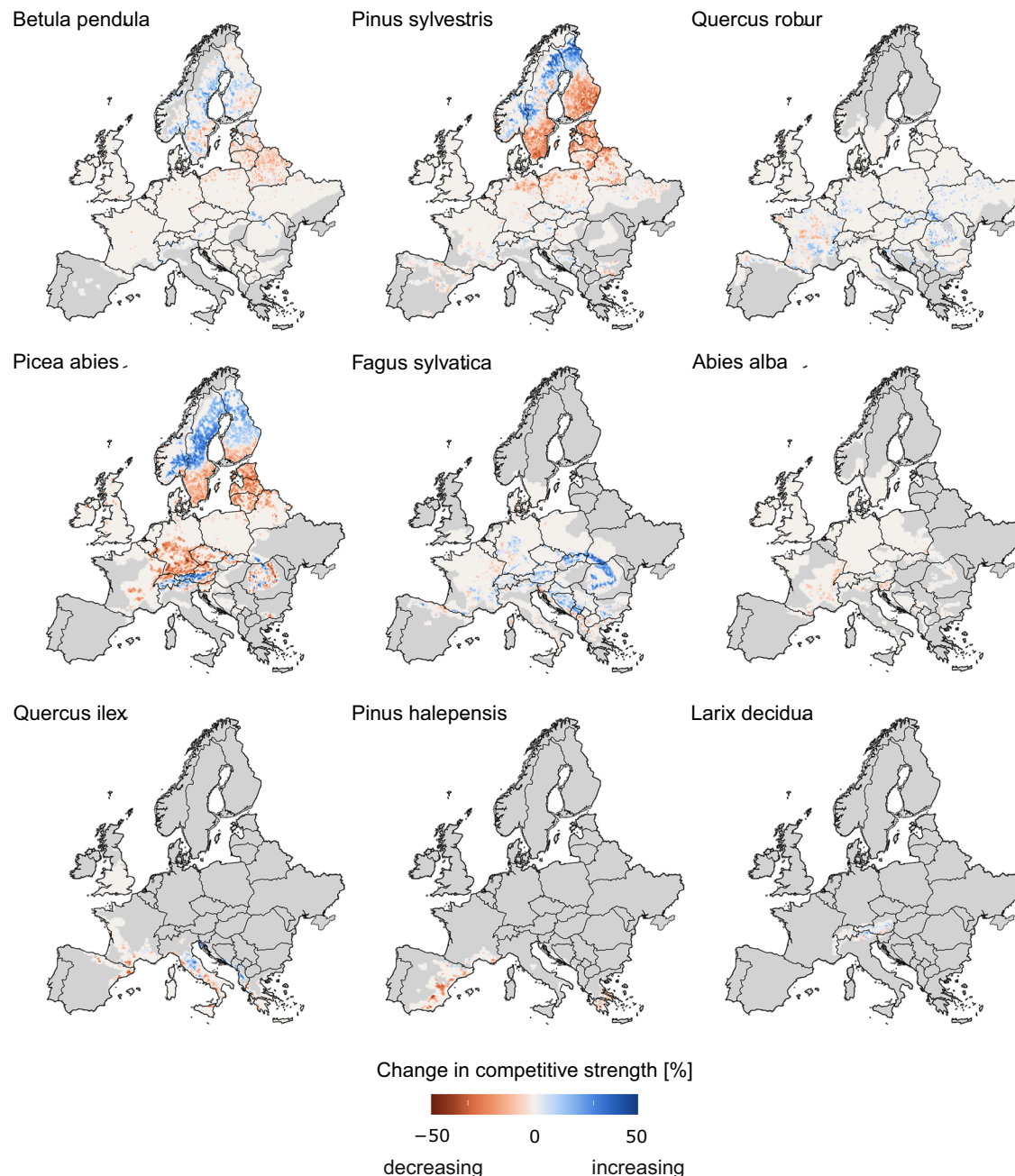


Fig. 2 | Change in competitive strength for nine major European tree species under climate change. The maps show a change in competitive strength for nine major European tree species under severe climate change (RCP8.5) across their current distribution. Maps are in order of decreasing range size from top to bottom. Colors indicate changes in competitive strength index (CSI), from strongly decreasing (red) to strongly increasing (blue) CSI for the period 2071–2100 relative

to 1980–2010. Grid cells where forest cover was below 5% and grid cells where the focal species currently is less than 5% of total forest area were set to zero to aid visual interpretation of results. Maps for other climate scenarios and for the two individual components of CSI are shown in the Supplementary Information (Figs. S5–S12). Uncertainty maps for CSI predictions are also available in the Supplementary Information (Figs. S13–S16).

broadleaved species at their warm niche edges, and were particularly sensitive at their warm and dry niche edges.

Shifts in dominant species

A change in competitive strength only results in a change in tree species if another species can gain in relative competitiveness and outperform the previously dominating species. Here, we used our DNN meta-model to investigate where shifts in the currently dominant species (defined as a species having >66% of stand basal area) are likely under climate change. We found that Norway spruce, holm oak, and silver birch were the species that most frequently lost their current role as dominant species to another

species. Under the RCP8.5 scenario, these species were projected to decrease in dominance by −20.2%, −3.9%, and −4.4% compared to the baseline scenario across the area they currently dominate (Fig. 3a). In contrast, European beech and pedunculate oak were overall able to increase their dominance by +9.9 and +9.2%, respectively. These projected changes in species losing and gaining dominance are largely congruent with the changes in competitive strength at the level of individual species reported above, suggesting that changes in the competitive strength of species are also likely to result in a change in species assemblages. Interestingly, Scots pine and Aleppo pine were projected to slightly increase in dominance under both RCP2.6 (+0.4%; +0.2%) and RCP8.5 (+0.5%; +1.5%), despite

decreasing competitive strength. This suggests that in the very warm and dry region where they occur, their competitors may suffer even more strongly from climate change, allowing them to sustain their presence and even increase in dominance^{24,25}.

We found that for 24.8% of Europe's forest area, where one of the studied species is currently dominant, the dominant species is likely to change under the severe climate change of RCP8.5 due to a changed competitive balance between species. This corresponds to a forest area of 96 million hectares potentially being affected by changes in species dominance.

Table 1 | Climate-induced change in competitive strength at the edges of the current climatic niche of a species compared to the niche core

Niche position	RCP2.6		RCP8.5	
	Broadleaved	Coniferous	Broadleaved	Coniferous
Core	3.2 ± 0.1	−1.9 ± 0.1	1.1 ± 0.1	−8.2 ± 0.1
Cold-dry edge	17.3 ± 0.4	21.0 ± 0.9	19.6 ± 0.4	15.2 ± 0.9
Cold-wet edge	9.5 ± 0.7	5.8 ± 0.9	12.0 ± 0.9	6.9 ± 1.8
Warm-dry edge	0.3 ± 0.2	−3.7 ± 0.3	0.5 ± 0.3	−7.9 ± 0.4
Warm-wet edge	−2.5 ± 1.0	−2.4 ± 0.8	−4.6 ± 0.9	−3.7 ± 0.7

Negative values are shown in bold. Niche edges were defined as areas where the mean annual temperature and the annual precipitation sum were above the 90th and below the 10th percentile of the values of the full niche space of a species, respectively. The niche core was the remaining area of a species' niche. Values are mean CSI ± standard error, calculated from the pooled standard deviation for each group. Values for RCP4.5 are shown in the Supplementary Information (Table S3).

Norway spruce (negative change in 69.7% of the area it currently dominates, corresponding to 57.6 million ha) and silver birch (34.7%, 8.3 million ha) had the highest proportion of the area where dominance decreased (Figs. S19–S21). Pedunculate oak showed the lowest proportion of grid cells with decreasing dominance (0.8, 0.6 million ha). Hotspots of expected competition-induced changes in the dominant tree species were largely located at major ecotones between biomes. One hotspot was in central Europe at the ecotone between the temperate broadleaved and temperate coniferous biomes (e.g., in the mountain regions of the Alps, Fig. 3b). Additional hotspots were at the ecotone between the tundra and boreal forests biomes (e.g., along the Scandes), as well as the ecotone between the boreal and the temperate coniferous biomes (in southern Fennoscandia). Also at the ecotone between the Mediterranean and temperate broadleaved biomes (e.g., in southern France and the Adriatic coast) elevated likelihoods for a shift in the dominant species were recorded.

Discussion

Harnessing a DL-based forest meta-model, we present a continental-scale synthesis of local forest simulations under climate change. Mining more than 135 million simulation-years of data for more than 13,000 unique locations throughout Europe, we show that the competitive strength of major European tree species is likely to change considerably under climate change. Our analyses highlight that evergreen coniferous tree species, currently dominating ~56% of the forest area of Europe, will lose competitiveness under climate change. Conversely, deciduous broadleaved species can partly increase their competitiveness, suggesting a major shift in the dominant clades of tree species in Europe. This finding is generally in line with previous works based on statistical species distribution models^{26–28}. However, we note that our DL-based meta-model—trained on detailed simulation data from locally calibrated forest process models—projects rates of tree species change that are lower than those inferred from correlation-

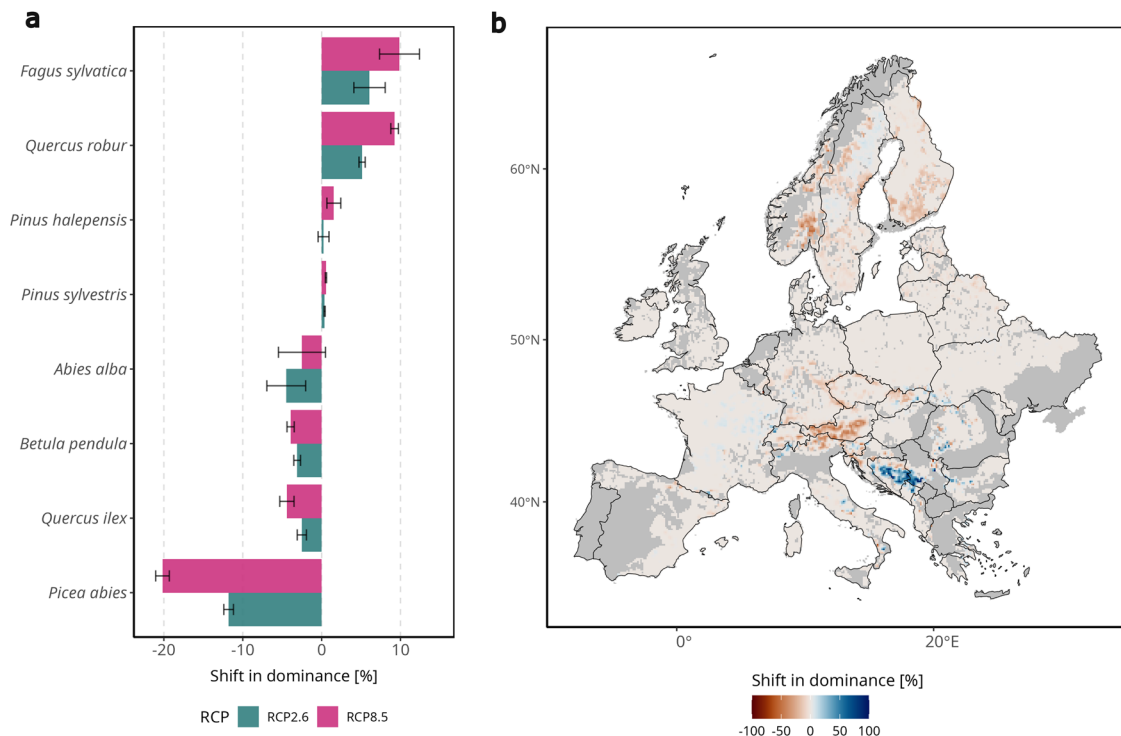


Fig. 3 | Shifts in species dominance under climate change. a Losses and gains in the ability to dominate stand development under climate change across the area where a species currently dominates³². Changes are reported in comparison to baseline climate scenario projections. Error bars indicate 95% confidence intervals. **b** Hotspots of change in the currently dominant species under climate change (severe scenario RCP8.5, see Fig. S17 for RCP4.5 and Fig. S18 for RCP2.6). To map an overall shift in

dominance, we calculated the weighted sum of the individual species shift in dominance. Maps for individual species are shown in the Supplementary Information (Figs. S19–S21). Gray areas show regions where either no projections were available or where none of the nine focal species currently dominate. European larch was excluded from this analysis (see “Methods” for details).

based species distribution models. While species distribution models predict equilibrium states under given climate conditions and do not consider competition between species explicitly, the process-based models underlying our analyses simulate the interactions between trees as an emergent property based on local resource availability and tree species traits^{18,19}. The change in dominant species inferred from our synthesis of process-based simulations is thus likely a more realistic indicator of species change and underlines that major shifts in tree species are particularly expected at the trailing edge of the distribution of species. This is in line with already observed trends at the warm range edges of important European tree species^{29–31}. We note that our assessment of where species dominance could change uses the current species distribution as reference³², and economically important tree species, such as Norway spruce, were historically cultivated outside of the mountainous and northern regions where they were naturally dominant.

Our DL-based meta-modeling approach offers a solution to bridging the gap between detailed local-scale forest modeling and continental-scale analyses of forest dynamics under climate change. Traditional process-based models, while excellent for capturing fine-scale processes such as the competitive interactions between trees (e.g., refs. 33,34), face computational limitations when applied across large spatial scales. Furthermore, these models are usually developed and parameterized for specific focal ecosystems, trading off broad-scale applicability across a diverse range of ecosystems for locally accurate projections. Our DL-based synthesis leverages the strengths of these local models while overcoming their limitations by effectively scaling their responses to the continental scale. We note that the aim of our meta-modeling is not to develop a model that is better than any of the underlying process models, but rather to present a complementary approach to consistently scale local process model results to the continental scale. As the DL-based approach distills the emergent responses to environmental drivers across many models, it also hedges against uncertainties related to the structure and design of individual models, likely resulting in a more robust projection of forest dynamics. We note that our approach allows the assimilation of future local model simulations as well as the inclusion of other, complementary model categories such as genetic-based models³⁵ to further refine simulated continental-scale responses, facilitating collaborative research on forest ecosystems in a changing world.

We explicitly considered height growth and LAI as indicators of competitive strength. Both indicators are specifically relevant in the context of competition for light, with height growth being a crucial strategy in the asymmetric competition of plants for light³⁶ and high LAI indicating the ability to shade out competitors³⁷. While our choice of indicators reflects the fact that light is the dominant constraint for tree growth in large parts of Europe³⁸, we note that other traits such as rooting depth and the tolerance of extremes (e.g., drought, frost) are also important factors for the competitiveness of trees^{39,40}. We found that LAI generally responded more negatively to climate change than height growth, and that only European beech was able to increase LAI under future climate. This finding deviates from large-scale simulation results of Earth system models and dynamic vegetation models, generally projecting a greening of Europe under climate change^{41,42}. As recent observations in Europe are not in line with a general greening of vegetation⁴³, the findings presented here underscore the value of our DL-based process model synthesis. Future work could harness the approach presented here to further elucidate where and under which conditions large-scale earth system models differ from best-available local process models, helping to quantify uncertainties and improve global modeling capabilities^{44,45}.

Inherent limitations of our approach need to be considered when interpreting our findings. Some parts of Europe—both in geographic and climatic space—remain underrepresented in the process model simulations synthesized here. Expanding the database with simulations from these regions (e.g., parts of Eastern Europe, see Figs. S13–S16) could increase the accuracy of and reduce the uncertainty in our predictions. Furthermore, while an important strength of our approach is the synthesis across many different process models—hedging against uncertainties in the structure

and process representation of individual models—the data underlying the current study are not equally distributed across models and species³². For instance, training data for Aleppo pine was obtained from a single process-based model, rendering the strong climate change response reported here more uncertain compared to other, more broadly represented species for which simulations from multiple process models were available. We also note that an inherent downside of meta-modeling is the necessary abstraction⁴⁶, making the DL-based meta-model less traceable than the underlying process models. To shed light into the DNN “black box,” we here used approaches from the field of explainable AI⁴⁷ (see Supplementary Methods, Fig. S23). A further shortcoming of our work is that none of the process-based models used to inform our DL-based meta-model explicitly considered phenotypic plasticity and related acclimation of trees to a changing climate, which could, in some cases, result in an overestimation of climate responses^{48,49}. We also note that extreme climatic events and natural disturbances such as wildfire, wind, and bark beetle outbreaks are important drivers of tree species change^{50–52}; yet, these factors were not considered in our analysis. In addition, the potential spread of insect pests and pathogens, such as oak decline, *Dothistroma* needle blight, or invasive *Phytophthora* species, could be enhanced by climate change^{53–55} and may cause profound shifts in the competitive strength of tree species. Considering the joint effects of abiotic and biotic disturbances more explicitly should thus be a future direction of research. We note that dominance was assessed based on relative basal area shares and did not consider the absolute abundance of a species. Furthermore, changes in dominant tree species reflect changes in the relative competitiveness between species. We studied nine species in detail and included a total of 63 species in our training dataset for the DNN model of dominance. Nonetheless, including an even broader set of species in process model simulations would be desirable, as it could identify local winners and losers under climate change more comprehensively. We note, however, that species that have historically been rare remain difficult to parameterize in process-based models⁵⁶.

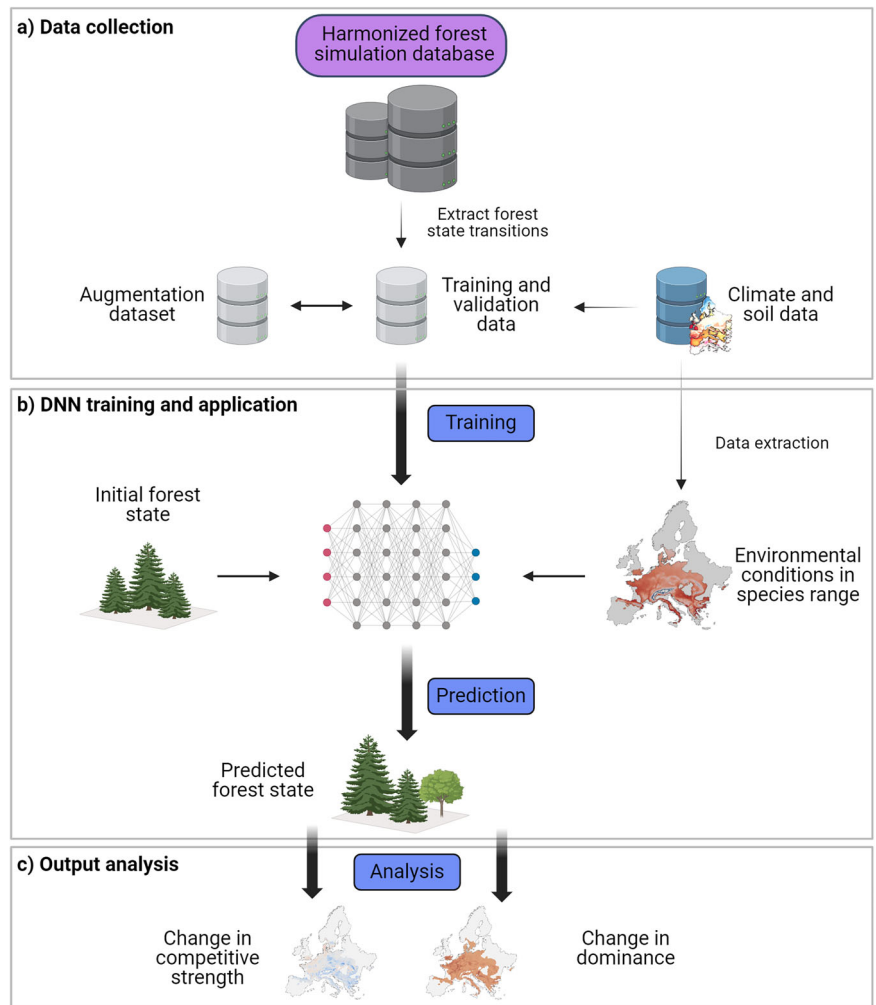
Changes in the competitive strength of tree species and related shifts in dominant vegetation have important implications. The diversity of species communities in forests, for instance, is strongly linked to the dominant tree species⁵⁷. Changes in dominant tree species could thus trigger a turnover in species communities, particularly since climate change could lead to a shift from evergreen coniferous trees to deciduous broadleaved trees, i.e., species groups that diverge strongly in both morphology and phylogeny. The finding that deciduous oaks might increase in competitiveness could have a positive effect on biodiversity, as these species have been found to be associated with highly diverse species communities in previous analyses^{28,58}. Changes in the competitive strength of tree species also have important implications for managing forests for ecosystem services. In plantations for timber production, the loss of competitive strength of a crop species may necessitate increased efforts in tending and thinning. This is particularly relevant as evergreen conifer species represent the majority of plantation forests in Europe. In forests managed for multiple ecosystem functions and services, maintaining diversity in structures and species is an important management approach^{59,60}. This requires an intimate understanding of the competitive relations between trees and their potential changes under climate change. Our spatially explicit analysis of hotspots of potential future changes in dominant tree species can alert managers to areas where changes are likely in the future, highlighting situations in which adjustments of the prevailing silvicultural concepts might be needed to maintain desired tree species mixtures. In conclusion, our study demonstrates a high likelihood that climate change will alter the competitive relationships between trees across Europe. This change can have important implications for biodiversity and the supply of ecosystem services, and should thus be considered more explicitly in forest policy and management.

Materials and methods

Methods overview

To investigate the impact of climate change on the competitive strength of tree species and assess related potential shifts in species dominance, we

Fig. 4 | Analysis workflow. **a** Data collection from a harmonized database of process-based model simulations under climate change²². From the database, forest state transitions were extracted to create training and validation datasets, using a data augmentation approach to increase the number of training data. In parallel, corresponding data on environmental conditions (i.e., climate and soil) were compiled from pan-European datasets to enable linking forest state transitions to environmental conditions. **b** DNN training and application: training data were used to train a DNN to predict (i) the forest state after a transition and (ii) the time until a transition takes place, based on the initial forest state and the prevailing environmental conditions. **c** Output analysis: we analyzed differences between predictions under baseline climate (1981–2010) and future climate (2071–2100) for indicators of competitive strength (objectives (i) and (ii)) and changes in the dominant tree species (objectives (iii) and (iv)). This figure was created with BioRender.com.



trained a DNN on a large dataset of harmonized forest simulations across Europe²², containing data on 135 million simulation-years for 13,599 unique locations throughout Europe. We subsequently applied the trained DNN in a meta-modeling framework to predict forest state changes under different climate scenarios, analyzing a set of indicators of competitiveness at the level of individual species, as well as the DNN-projected changes in species composition (Fig. 4). In a first step, harnessing the dataset of harmonized forest simulations, we converted continuous forest simulation outputs to discrete forest states (based on tree height, LAI, and species composition, see ref. 61) and coupled them with data on climate and environmental conditions to create training data for deep learning. In a second step, we trained a DNN to predict transitions between these states based on driver data (i.e., current state of the system, climate scenario data). Informed by local simulations from the underlying process-based models, the trained DNN served as a meta-model of the underlying process-based models to project climate-induced changes (cf., ref. 20). We used this meta-model to project changes in the three state variables for nine study species under current and future climate conditions across the current distribution range of the species. Based on these results, we investigated how competitive strength (represented by the indicators height growth and LAI) and dominant tree species shifted under future conditions. Figure 4 gives an overview of the workflow of the analysis; all steps are explained in more detail below.

Data on forest dynamics

We used a recently published harmonized database of more than 135 million simulation-years from 1.1 million simulation runs conducted by 17

different models in 13,599 locations across Europe²². This database is a collection of previously conducted local forest simulations under climate change, which were harmonized to a common suite of output variables and standardized metadata (including a vector of common environmental drivers). All simulations in the dataset are based on process-based models operating at the stand- to landscape-scale. Models were run in the absence of natural disturbance, and either represent unmanaged conditions or business-as-usual management for a given location and species. Management signals were filtered out during training dataset preparation (see below). The various output structures of the different forest models were harmonized to three common variables: Canopy height, LAI, and species composition. These three variables were chosen as they describe complementary aspects of forest ecosystems and as they were available from all underlying models.

We converted continuous model outputs to discrete states by binning the three output variables in order to simplify the classification task for the DNN⁶¹. Classes for species composition described the dominant and up to four co-occurring species. A species was considered *dominant* when the proportion of basal area was higher than 66% of the total basal area; other species were considered as admixed species when they exceeded 20% of the simulated basal area. LAI (one-sided or projected) was stratified into three discrete classes: 0–2 m²/m², 2–4 m²/m², and >4 m²/m². Canopy height was binned in 2 m classes, ranging from 0–2 m to 48–50 m, and >50 m. The unique combination of classes in all three dimensions resulted in a potential maximum of 4.1 million forest states. However, only a fraction of these potential states is actually realized in ecosystems, as not all combinations occur in reality.

Next, we identified transitions between these states from the forest simulations in the database. A transition was detected whenever the forest state changed from one year to the next in the underlying simulations. Additionally, we identified “no-change” conditions, i.e., situations where the same state persisted for at least 10 years. State transitions were the primary response variable used for training the DNN; consequently, we henceforth refer to them as “training samples.” Training samples also contained auxiliary information on the environmental conditions under which a state transition occurred. The final training sample comprised information on the forest state prior to transition, its residence time (i.e., the time elapsed since the last transition), the forest state after transition, and the time when the next transition is expected to happen, alongside soil conditions and climate data for the time horizon of the transition. In other words, each training sample contained the current state of a forest as well as information about whether, how, and when the state will change within the next decade, given the prevailing soil and climate drivers.

We expanded our dataset by creating augmentation training samples based on the original training samples. Data augmentation is a widely used and well-established technique to enhance the number of training data for DNNs⁶², enabling models to generalize better without overfitting. We created augmentation training samples leveraging the state transitions from the original training samples. Specifically, we altered the residence time and time until transition by the same number of years, maintaining the absolute duration between state transitions. By doing so, we preserved the integrity of the temporal dynamics of the underlying data, ensuring that the total time for each state transition remained unchanged. This method allowed us to increase the number of training samples meaningfully, without artificially generating new state transitions or introducing redundancy.

We filtered training samples by location, model, and forest state to reduce the bias resulting from multiple contributions from the same model and location to the simulation database. Specifically, the majority of simulations in the database are from two models (i.e., iLand and 4C), and some species were simulated more frequently than others²². To reduce the dominance of a single model and/or species in the training dataset, we downsampled to a maximum of 100,000 training samples per location, while keeping as many different forest states as possible. Furthermore, we filtered out direct management signals from interventions such as thinnings or final harvests (e.g., by detecting and eliminating canopy height reduction by more than 2 m from the data) from the training samples. The resulting dataset comprised 2,750,456 million data points covering 5445 distinct forest states. The number of training samples for the different species ranged from 34,759 (*Betula pendula*) to 250,634 (*Fagus sylvatica*; see Table S1).

Climate and soil data

Pan-European climate change scenarios and soil information were used (i) to provide environmental context information for the state transitions from the underlying simulation database²², and (ii) as driver data for model projections. As environmental context information for state transitions, we used daily climate data for mean temperature, precipitation, solar radiation, and vapor pressure deficit (VPD). We aggregated daily data to annual averages for all four variables and also derived monthly averages for temperature and precipitation. Furthermore, we used a machine learning-based targeted compression to derive a set of climate indices relevant for predicting climate responses of vegetation^{63,64}. This step considerably reduced the amount of data required in processing (by a factor of 30), but retained the information value of high temporal resolution climate data for climate impact simulations. A detailed description of the climate data compression is given in the Supplementary Methods (section Climate compressor approach). The final climate data for each training sample contained mean annual temperature, mean annual precipitation, mean annual solar radiation, mean annual VPD, monthly means for temperature and precipitation, and 24 climate indicators from the climate data compression. (i.e., in total 52 variables) for 10 years. As driver data for model projections, we used climate data for two time slices, baseline climate (1981–2010) and future climate (2071–2100) in 10-year time steps. We used EURO-CORDEX daily climate

data for three Representative Concentration Pathway (RCP) scenarios (RCP2.6, RCP4.5, RCP8.5) as well as historical climate conditions, each simulated with three Global Circulation Models (GCMs) (for details see Supplementary Methods section Climate data). We bias-corrected climate data based on ERA-Interim (ECMWF) data. All climate data was obtained in a $0.11^\circ \times 0.11^\circ$ ($\sim 12 \times 12$ km) spatial resolution from the Copernicus Climate Data Store. (<https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cordex-domains-single-levels?tab=overview>).

We compiled pan-European soil datasets at a 1×1 km resolution to represent the variability of soil conditions within each climate grid cell. For soil depth, soil texture (i.e., sand, silt, and clay content), and water holding capacity, we obtained gridded data from the European Soil Data Center⁶⁵. Furthermore, we approximated plant-available nitrogen based on a pseudo-mineralization rate derived from a continental-scale spatial model in combination with a continental product of soil N stocks from the SoilGrids dataset⁶⁶. For more details, see ref. 22.

Deep neural network architecture and evaluation

DNNs are powerful tools to learn complex relationships in data and are increasingly used in the environmental sciences^{67,68}. The DNN architecture used here consisted of a feed-forward neural network with 6.6 million trainable parameters, arranged in 22 layers with 3 blocks with residual connections. The inputs of the DNN were: the present forest state, the history of the forest state (i.e., the three previous forest states of a cell), its residence time, the residence time history (i.e., the residence times in the previous three states), soil conditions, and climate conditions. The DNN was trained to classify the forest state after a transition and the time until transition, considering 5445 discrete forest states and ten classes of target time (10-year forecasting window). We used TensorFlow⁶⁹ in combination with the Keras API⁷⁰ to implement the model architecture. To check the ability of the DNN to generalize, we performed several cross-validation experiments, including a random five-fold cross-validation, a model selection cross-validation, and a climate scenario cross-validation. The results of these in-depth validation exercises can be found in the Supplementary Methods section, DNN architecture and cross-validations. As expected, data are distributed unequally between states, with many states occurring only rarely, while some occur very frequently. We thus further tested the predictive performance of the DNN relative to state frequency to ensure that our model does not predominantly predict the most frequent states (for details, see Supplementary Methods section DNN architecture and cross-validations). Moreover, we analyzed the importance of individual variables in projections using a variable permutation technique (Fig. S23). The final DNN performed well, correctly predicting the forest state after transition with 86.9% and the time to transition with 61.1% accuracy in the validation dataset (Table S2).

Prediction of forest state transitions with the trained DNN

We used the trained DNN for predicting forest state transitions for the nine study species. To assess competitive strength (objectives (i) and (ii)), we focused on the stem exclusion stage of stand development (i.e., the stage in which competition is highest) as we assumed that changes in competitiveness will be most relevant in this stage of stand development. Initial states for prediction were defined as canopy heights in the stem exclusion stage (i.e., between 15 and 30% of maximum tree height; obtained from ref. 28), and simulations were started from all three LAI classes. To account for the local variability in soil conditions (1×1 km), three soil vectors were sampled for each 12×12 km grid cell. To analyze shifts in tree species dominance (objectives (iii) and (iv)), we used the 10 most common forest states in the dataset in which the focal species currently dominates stand development (>66% of basal area) as a starting point, again focusing on the stem exclusion stage of stand development. We excluded European larch from this part of the analysis because no forest states with admixed species were available for the stem exclusion stage in our simulation database. Only forest states with a minimum of 10 occurrences in our dataset were considered as initial states, ensuring sufficient representation for prediction.

Projections for all species were done for all grid cells within their current range. Species ranges were obtained from the chorological maps of European woody species³³. We combined native and naturalized ranges whenever species occurred outside of their native range, and the information was available. We obtained model projections for each species with several initial states, for six 10-year time steps (three baseline, three future time steps), three GCMs, and three RCPs. For each species, model projections were averaged across the three different time steps of a period (baseline or future), different initial states, and soil conditions. For each of the three forest state variables (canopy height, LAI, and species composition), differences were calculated between simulations under climate change and those under the current climate, with the latter serving as a counterfactual to isolate climate change effects.

Competitive strength

Height growth and LAI were used as indicators for competitive strength. We calculated height growth (i.e., change in canopy height) and change in LAI from DNN-derived state transitions. Specifically, we divided the simulated state change by the predicted time until transition. To overcome the uncertainty of time to transition predictions in the analysis, we used a weighted mean (with prediction probabilities as weights) of the three transition times that were predicted as most probable by the DNN. Changes in the two indicators per grid cell were calculated as differences of percent negative and percent positive changes under climate change relative to projections under the historic climate. We weighted both indicators according to a species' share of total forest area using the data of Brus et al.³². In the calculation of species-level change, we derived the weight of each grid cell by dividing the species' share of total forest area by the mean share of the species across all grid cells within its range. To aggregate across both dimensions, we calculated a CSI per tree species as the mean change in height growth and LAI across all grid cells comprising the range of a species. We note that a potentially complex and context-dependent relationship between tree height and LAI exists in forest ecosystems^{71,72}, yet we here selected the most parsimonious approach to combining them by means of averaging. For visualization purposes, we did not apply the weighting by forest share as described above in the spatial mapping of the CSI. We rather used filters to omit marginal grid cells from the visualization (by setting them to zero), i.e., areas where forest cover was below 5% of the total land area, and areas where the share of the focal species on total forest area was below 5%. To investigate a species' response to climate change at its range edges, we distinguished the core range (between the 10th and 90th percentile of mean annual temperature and mean annual precipitation of the current range of a species) from the niche edges (beyond the 10th and 90th percentile, respectively) in temperature and precipitation space, considering the warm-dry, warm-wet, cold-dry and cold-wet edge of the distribution. The average CSI was calculated across all grid cells within the respective part of the niche.

Species dominance

To assess whether changes in competitive strength actually result in a change in the dominant tree species at the community level, we analyzed the species composition component of our DNN projections. Specifically, we analyzed whether and how frequently a species that currently dominates stand development (i.e., >66% of basal area) loses its dominant position under climate change. We expressed this shift in dominance in percent change under climate change relative to baseline climate conditions. We weighted the contribution of each grid cell where a species currently dominates³² as described above for the calculation of CSI when reporting results at the species level.

To map hotspots of change in the dominant tree species across Europe, we focused on all grid cells in which one of our nine study species currently dominates stand development (based on data from ref. 32). We first calculated the shift in dominance per species in each grid cell where the focal species is currently dominating. Note that for Aleppo pine and holm oak, we masked their distribution range with the area where *miscellaneous pine*,

respectively *miscellaneous oaks*, were mapped as dominant, due to the lack of species-level information. We then aggregated across species by weighing with the proportion of dominance for each grid cell. Specifically, for each grid cell, species-specific change in dominance values were multiplied by a species' corresponding forest share, and the sum of these weighted values was divided by the sum of forest shares across all study species.

Uncertainty estimates

All DNN predictions were probabilistic, i.e., probabilities for the predicted future forest state were obtained from the DNN, and the most probable state was analyzed further in the context of our research questions (see above). To further elucidate uncertainties of our DNN meta-model, we examined the probability of the predicted forest state transitions and times to transition across the range of each species (Figs. S13–S16). These maps indicate the degree of certainty that the DNN has in a projected state transition for a given cell. They highlight that for species where high amounts of training data were available (i.e., European beech, Norway spruce, Scots pine), the DNN tended to be more confident than for species with less training data. The spatial variation in the thus obtained uncertainty maps suggests that regions poorly covered by underlying simulation data had higher uncertainty in DNN predictions. For instance, predictions for silver birch in Eastern Europe had lower confidence due to the limited availability of training data for that species in this region.

Data availability

The data that support the findings of this study are openly available at <https://doi.org/10.5281/zenodo.19161115>⁷³. The underlying forest simulation database is available at <https://doi.org/10.5281/zenodo.10730806>⁷⁴.

Code availability

Code for the data preprocessing, deep neural network, network predictions, and the analysis is available at https://github.com/magrueni/europe_tree_competition_publi.

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Author contributions

M.G., W.R. and R.S. contributed to the conceptualization of the study. R.S. and W.R. supervised the project. Investigation, formal analysis, and coding were done by M.G. with support from W.R. and M.Ba. M.G. prepared the

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Competing interests

The authors declare no competing interests.

Additional information

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