



GAPPARD: a computationally efficient method

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GAPPARD: a computationally efficient method of approximating gap-scale disturbance in vegetation models

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Abstract

Models of vegetation dynamics that are designed for application at spatial scales larger than individual forest gaps suffer from several limitations. Typically, either a population average approximation is used that results in unrealistic tree allometry and forest stand structure, or models have a high computational demand because they need to simulate both a series of age-based cohorts and a number of replicate patches to account for stochastic gap-scale disturbances. The detail required by the latter method increases the number of calculations by two to three orders of magnitude compared to the less realistic population average approach. In an effort to increase the efficiency of dynamic vegetation models without sacrificing realism, and to explore patterns of spatial scaling in forests, we developed a new method for simulating stand-replacing disturbances that is both accurate and 10-50x faster than approaches that use replicate patches. The GAPPARD (approximating GAP model results with a Probabilistic Approach to account for stand Replacing Disturbances) method works by postprocessing the output of deterministic, undisturbed simulations of a cohort-based vegetation model by deriving the distribution of patch ages at any point in time on the basis of a disturbance probability. With this distribution, the expected value of any output variable can be calculated from the output values of the deterministic undisturbed run at the time corresponding to the patch age. To account for temporal changes in model forcing, e.g., as a result of climate change, GAPPARD performs a series of deterministic simulations and interpolates between the results in the postprocessing step. We integrated the GAPPARD method in the forest models LPJ-GUESS and TreeM-LPJ, and evaluated these in a series of simulations along an altitudinal transect of an inner-alpine valley. With GAPPARD applied to LPJ-GUESS results were insignificantly different from the output of the original model LPJ-GUESS using 100 replicate patches, but simulation time was reduced by approximately the factor 10. Our new method is therefore highly suited rapidly approximating LPJ-GUESS results, and provides the opportunity for future studies over large spatial domains, allows easier parameterization of tree species, faster identification of

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areas of interesting simulation results, and comparisons with large-scale datasets and forest models.

1 Introduction

Forests are an important part of the Earth System, at present covering roughly 30 % of the Earth's land surface and responsible for about half of the total terrestrial carbon (Fischlin and Midgley, 2007). Ongoing pressures on forest ecosystems including climate and land use change affect forest structure, composition and carbon storage, and changes in forests may in turn feedback to affect climate and ecosystem services (Fischlin and Midgley, 2007; Purves and Pacala, 2008). In order to assess the importance of forests in the Earth System and understand their sensitivity to ongoing environmental change, it is essential to have forest models that can be applied at continental- to global-scales. Large-scale forest models that can be used to address these questions are complex, as they must include a dynamic representation of forest demography, particularly with respect to forest disturbances and structure-related competition (Quillet et al., 2010; Bonan, 2008). The most widely used tools for assessing the role of plant cover in the Earth System are Dynamic Global Vegetation Models (DGVMs). All DGVMs simulate forest growth and include a representation of plant physiology and vegetation dynamics (Prentice et al., 2007), but the first generation DGVMs did not explicitly simulate forest structure, and showed important limitations in their ability to model competition and disturbances (Quillet et al., 2010). Recently, a second generation of DGVMs has been developed that explicitly account for forest structural characteristics, improve the modeling of competition and small-scale disturbances, and, thus, lead to more realistic simulations of forest growth (e.g., Hickler et al., 2008; Sato et al., 2007; Fisher et al., 2010). These new DGVMs, also called "hybrid" models, have substantial advantages over the original DGVMs in terms of realism, but this typically comes at the cost of computational demand, which puts limits on the spatial domain or maximum resolution that can be simulated in a reasonable amount of time.

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to simulating small-scale disturbances that was both efficient and accurate. Furthermore, we recognized that exploring spatial scaling in forests could lead to the elucidation of near-universal relationships between forest demographics and disturbance at larger scales, a fundamentally interesting ecological problem.

In this paper we describe a new approach to simulating forest dynamics that dispenses with the need to simulate replicate patches in a hybrid DGVM and is both as accurate as and substantially more computationally efficient than traditional models. We compare our new approach to standard LPJ-GUESS and TreeM-LPJ in a series of experiments along an environmental gradient in the Swiss Alps and demonstrate the quality of the new method. We then suggest potential applications for this new, efficient model for addressing large-scale problems on the role of forests in the Earth System.

2 Material and methods

2.1 Base models

LPJ-GUESS is a process-oriented hybrid model to describe vegetation dynamics (Smith et al., 2001; Hickler et al., 2004). It shares characteristics of the dynamic global vegetation model (DGVM) LPJ-DGVM (Sitch et al., 2003) and the individual (cohort) based gap model GUESS (Smith et al., 2001). Plant physiological and biogeochemical processes are based on the formulations in LPJ-DGVM. Plants are either simulated as tree species (Koca et al., 2006; Wolf et al., 2008; Hickler et al., 2012) or aggregated to plant functional types (PFTs).

TreeM-LPJ is a process-oriented height class based forest model (Scherstjanoi et al., 2013). It combines plant physiological functions from LPJ-GUESS with the height class structure from the forest landscape model TreeMig (Lischke et al., 2006b). Thereby, the vertical forest structure represents LPJ-GUESS individuals of different height. TreeM-LPJ is fully deterministic and therefore runs faster than LPJ-GUESS.

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2.2 Stochasticity in gap models

Models relying on the gap approach including LPJ-GUESS simulate the fate of individual trees, determined by growth and death processes and a stochastic establishment, leading to demographic stochasticity. Other stochastic elements can be climatic drivers and in particular stochastically appearing small-scale disturbances (disturbance stochasticity). Due to the stochasticity, individuals and vegetation biomass on each patch develop differently and simulations of many replicate patches have to be averaged to yield the forest dynamics, requiring a lot of computational time. To obtain realistic results, Bugmann et al. (1996) recommended the use of 200 successive repetitions of simulations per stand for gap models. Most commonly 50 or 100 of such replicate patches are used (Koca et al., 2006; Miller et al., 2008; Hickler et al., 2008, 2009; Wramneby et al., 2008), but to save computational time, the number of patches is often smaller (e.g. 20 in Hickler et al., 2012). In LPJ-GUESS, small-scale disturbances have a stronger effect on species composition, forest height, age structure and biomass than the demographic stochasticity (stochastic establishment and mortality). Demographic stochasticity varies the numbers of individuals in cohorts (by drawing from a Poisson distribution in the establishment function and by imposing expected mortality rates as probabilities for stochastic death in the mortality function) and leads only to moderate deviations from the non-stochastic case. Small-scale disturbances, in contrast, have a strong effect on the simulated forest dynamics. They are assumed to destroy all trees in a patch (Fig. 1b₁–b_n), i.e. after a disturbance all living biomass in that patch is removed to the litter (dead organic matter) and growth succession starts again from the bare ground. As a result, the total biomass (mean of all replicate patches) of a disturbance simulation is typically smaller than in an undisturbed run (Fig. 1a).

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2.3 New approach to include small-scale disturbances

2.3.1 Basic assumptions

We maintain the idea that a forest consists of many patches, each of which is affected by disturbance independently. We also maintain patch-destroying disturbances, i.e. living biomass state variables are set to 0 by a disturbance.

Consequently, at a given time T , the patches have different patch ages a that depend on the times $T - a$, when they were affected by a disturbance, and the distribution of patch ages $P(a)$ at time T determines the forest state. A patch of age a has state variables (e.g. numbers per species and height class, sapwood, and heartwood mass...) and output variables (e.g. biomass per height class). Here, we refer to both as output variables $y(a)$ because each state variable can easily be treated as an output variable and because we apply the new method in a postprocessing way.

Our approach is based on the idea that a forest does not necessarily have to be represented by different replicate patches but can be calculated using a small number of undisturbed simulations starting from different time points, using the information of the patch age distribution. This includes a temporal upscaling of the information gained from such undisturbed, deterministic, and thus computationally efficient model runs. We will refer to our new method as the GAPPARD method: approximating GAP model results with a Probabilistic Approach to account for stand Replacing Disturbances.

2.3.2 Constant drivers

If the drivers are constant (e.g. during the spin-up phase of a climate change simulation), we assume that each re-growth following a disturbance leads to the same development of output variables as the initial forest development (Fig. 1b), i.e. $y(a) = y(x)$, with x the time since the start x_0 of the undisturbed simulation and a the time since the last disturbance in the disturbed simulation, i.e. patch age. In our simulations, we do not dynamically update several state variables that in reality would be indirectly

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affected by disturbance, including soil moisture and temperature, and the state of the snowpack.

To have age a at a given time T , a patch of a disturbed forest first must have encountered a disturbance and subsequently survived a yr. Given the probability of a disturbance ρ_{dist} , the probability that a patch afterwards survives a yr without any disturbance is $(1 - \rho_{\text{dist}})^a$. Consequently, the probability that a forest patch has age a is

$$P(a) = \rho_{\text{dist}} (1 - \rho_{\text{dist}})^a \quad (1)$$

A special case is given by the patches surviving from the beginning ($T = 0$) to exactly time T ; they have not encountered any disturbance, but started from bare ground (“were killed”) for sure ($\rho_{\text{dist}} = 1$) at time 0:

$$P(T) = 1 (1 - \rho_{\text{dist}})^T \quad (2)$$

The expectation value Y of simulation result y is then given by:

$$\begin{aligned} Y(T) &= E[y(T)] = P(T) y(T) + \sum_{a=1}^{T-1} P(a) y(a) \\ &= (1 - \rho_{\text{dist}})^T y(T) + \rho_{\text{dist}} \sum_{a=1}^{T-1} (1 - \rho_{\text{dist}})^a y(a) \end{aligned} \quad (3)$$

To calculate the resulting expectation values, we first perform one simulation without disturbances (SWD) leading to $y(x)$ for all time points x . Afterwards, Eq. (3) must be applied in a postprocessing step.

The method presented here is a modified version of the von Foerster equation (von Foerster, 1959), a general age-structured population dynamics approach, in which instead of the patch age distribution the age distribution is constantly changed during the simulation.

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2.3.3 Changing drivers

When drivers change, disturbances occurring at different times have different impacts. For example, under low temperature conditions, succession after a disturbance will most probably be slower than in a warmer climate. In order to account for such transient drivers, we modify the standard method of running only one SWD (described above) by running several SWDs starting at different starting times s_i ("nodes"), $i = 0..n$. This yields different trajectories of the output variables $y_i(s_i + x)$, each starting at a different starting time s_i with $y_i(s_i) = 0$.

For each time point T of the output, $E[y(T)]$ is determined similarly to Eq. (3). However, in this case instead of using one undisturbed y at one time point $x = a$ in the summation, the two values that belong to two subsequent trajectories starting before and after the target time point $T - a$ are used to describe the state of a patch with age a (Fig. 2).

The two output values $y(s_i + a)$ and $y(s_{i+1} + a)$ are then interpolated according to the distance of $T - a$ to the nodes s_i and s_{i+1} , so that the trajectory with the node closer to the target time $T - a$ has more weight than the other one.

$$y_{\text{interpol}}(T, a) = \dots \left\{ \begin{array}{l} y_0(s_0 + a) \quad \forall T - a \leq s_0 \\ \vdots \\ y(s_{i+1} + a) \left(\frac{s_{i+1} - (T - a)}{s_{i+1} - s_i} \right) + y(s_i + a) \left(1 - \frac{s_{i+1} - (T - a)}{s_{i+1} - s_i} \right) \quad \forall s_{i-1} < T - a \leq s_i \\ y(s_n + a) \quad \forall a > s_n \end{array} \right. \quad (4)$$

Substituting Eqs. (4) into (3) yields then:

$$Y(T) = (1 - p_{\text{dist}})^T y_{\text{interpol}}(T, a) + p_{\text{dist}} \sum_{a=1}^{T-1} (1 - p_{\text{dist}})^x y_{\text{interpol}}(T, a) \quad (5)$$

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2.4 Model application and evaluation

To evaluate the GAPPARD method, we applied it to LPJ-GUESS and TreeM-LPJ (LPJ-GUESS-G and TreeM-LPJ-G) and compared the results to the stochastic runs of LPJ-GUESS. The stochastic LPJ-GUESS simulations served as a reference because it is the original model that all used models are based on. For the same reason, we used only LPJ-GUESS to parameterize our tree species: if the parameters are valid for LPJ-GUESS they must be also valid for LPJ-GUESS-G, TreeM-LPJ and TreeM-LPJ-G, because they were all developed as computationally efficient upscaled versions of LPJ-GUESS.

2.4.1 Location and climate data

We selected the Rhone valley in the Swiss canton of Valais to test our new approach. The floor of this valley is one of the driest regions in Switzerland, and the hillsides lead to steep gradients in environmental conditions. In the region, management generally did not effect the species compositions to such extends as in most Swiss regions, so we could use recent forest data to parameterize our modeled tree species. We selected eight stands along a north-facing transect (Fig. 3, Table 2) that cover the vegetation zones where homogeneous forest areas exist (from ca. 150 m above the valley bottom to tree line). Each stand was derived from climate data points of a hundred meter grid so that the altitudinal distances between two stands would be approximately 200 m.

Changing climate is applied after the simulation year 1900. Up to 1900 we used randomly selected values of the first 30 climate data years for the model spinup. For the 1901–1929 simulation period, we used CRU data downscaled to a hundred meter grid (Mitchell et al., 2004). For the 1930–2006 simulation period, we used Swiss weather station data from the Federal Office of Meteorology and Climatology MeteoSwiss interpolated to a hundred meter grid by applying the Daymet method (Thornton et al., 1997). For the 2007–2100 simulation period, we used CRU climate data of the A1b

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climate scenario (Mitchell et al., 2004). Along with that scenario we used CO₂ data that reach 703 ppm in 2100 (IPCC, 2001, Annex II).

Based on the Soil Suitability Map of Switzerland (Frei, 1976), we chose to use a low value of usable volumetric soil water holding capacity of 0.1 (fraction of soil layer depth) and a value for soil thermal diffusivity at 15 % water holding capacity of 0.8 mm² s⁻¹. These values correspond to the poorly developed soils on the slopes of the Rhone valley.

2.4.2 Tree species parameterization

Using LPJ-GUESS, we optimized the parameterization of each tree species present in our study area to obtain the best possible fit to observed forest inventory data. We used LPJ-GUESS for the parameter optimization because this model served as the reference for the subsequent model comparisons, and applied the same optimized parameter set for all of the models we analyzed in this study. The tree species parameters we used are generally based on the existing LPJ-GUESS parameterizations for plant functional types (Hickler et al., 2004; Wolf et al., 2008) and for species (Koca et al., 2006; Miller et al., 2008; Hickler et al., 2012). In our experiments, we used the most abundant Swiss forest species, selected according to the species used in Lischke et al. (2006a), and then analyzed which of them already had been parameterized for LPJ-GUESS. We excluded all LPJ-GUESS species not present in the Swiss Alps, and added parameterizations for three new species that are abundant in our study area: *Larix decidua*, *Pinus cembra* and *Pinus mugo*. For *Larix decidua* we generated an additional function to model its leaf phenology based on results presented by Migliavacca et al. (2008) (Appendix A2).

We further optimized the species-specific parameters used in our experiments so that model results would best match forest inventory data from the Swiss National Forest Inventories NFI1 (EAFV, 1988) and NFI3 (Brändli, 2009). We selected inventory data only from plots located south of the Rhone and within a 30 km distance of our simulation plots, and further stratified the inventory information into eight altitudinal

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classes analogous to the altitudes of the eight simulated stands. At each altitudinal class we calculated the mean and the standard deviation of the biomass of all living tree species and estimated carbon mass assuming that half of a tree's biomass is carbon (IPCC (2003), see Appendix A1 for more details).

5 We used total forest carbon mass (above and belowground) as sole main metric for evaluating the model performance in light of the NFI data. Our aim was to optimize the model parameters so that for each altitudinal class the simulated total and main species carbon mass were similar to the NFI data. The parameters we optimized for all species included minimum soil water content needed for establishment, minimum growing degree day sum, and maximum temperature for establishment (w_{min} , $gdd5min_e$ and t_{max_e} in Table D3 of the appendix). We further adjusted the allometric parameters for some species, in particular the steepness-influencing parameter in diameter to height relation (k_{allom2} in Table D3 of the appendix). Further details on the parameterization, especially for the tree species newly added to LPJ-GUESS, are described in Appendix A2 and Tables D1.

15 We applied one altitude-specific set of LPJ-GUESS average return intervals for generic, patch-destroying disturbances (RID, inverse of p_{dist} in Sect. 2.3.2). We assumed that the stands along the height gradient underlie different disturbances. In general, stands close to the valley bottom are more frequently disturbed by fire in the Valais region (Zumbrunnen et al., 2009). Furthermore, we assumed that more uphill stands are disturbed more frequently by storm events, rock fall and especially avalanches. On the one hand altitude is not a good explanatory characteristic for avalanche appearance, and Schneebeli and Meyer-Grass (1992) found that in spruce- and larch-dominated forests steepness favors the release of avalanches, but on the other hand a thin crown cover, big gap lengths and higher proportions of larches also increase the probability of avalanche release. The steepness is approximately the same for all our simulated stands except the most upper stand, which is on slightly flatter ground. At this highest elevation site however, shade-intolerant larch is very abundant, the trees are exposed to avalanches from higher altitudes, the annual maximum snowpack is

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deeper and trees grow with larger gaps surrounding them. First tests with the same RID values used for all stands, led to less precise results, especially concerning the total modeled carbon mass (not shown). To create an altitude-specific disturbance distribution, we used either an RID value of 65 or 100 for each single stand, depending on which value suits best to predict the total carbon mass (RID in Table 2).

To evaluate the tree species parameterization we used two indices: the Euclidean distance scaled to one and the percentage similarity coefficient (Bugmann, 1994). Details on both indices can be found in the appendix.

2.4.3 Analyzed output variables

For our analysis, we used as investigated output variables (1) the total of the tree carbon mass of a species, and (2) this variable stratified by certain height classes (of 4 m height except the lowest being 2 m high). We examined the course of these variables from an LPJ-GUESS simulation including small-scale disturbances and 400 replicate patches, and compared the outcome to the results of LPJ-GUESS-G and TreeM-LPJ-G.

2.4.4 GAPPARD method versus stochastic LPJ-GUESS model runs

The crucial test of the GAPPARD method is its ability to reproduce the behavior of LPJ-GUESS disturbance runs in terms of total carbon mass, species composition and height structure. To apply the GAPPARD method, we used the RID values of the defined altitude-specific disturbance distribution (RID in Table 2) and took its inverse values for Eqs. (3) and (4). Using the new set of parameters and the altitude-specific disturbances, we simulated forest growth for all eight stands with a spinup time of 800 yr and a total simulation time of 1000 yr covering a simulation period from 1100 to 2100.

Additionally to a full time SWD (including 800 yr spinup), we used four nodes from which we started SWDs that provide the input for the GAPPARD method to account for climate change: 1950, 2000, 2050 and 2080. All simulations ended with the year 2100.

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Without disturbance, as forests become taller the model needs to calculate light interception in an increasing number of foliage layers (Prentice et al., 1993), which consumes computational resources. Therefore, we increased the depth of these layers from two to five meters after 200 yr and to ten meters after 400 yr for the full time SWD.

This change did not lead to a decline in result quality because without disturbances forests become homogenous in such a way that a less detailed light calculation does not have much influence. In addition, such old forests are rather rare so that such a simplification has an even smaller impact.

To examine the analysis, we first tracked the total carbon mass of the different species from the end of the spinup phase until 2080. Second, we mapped the carbon mass results of the different species along height classes for all stands and two time points of simulation: 1900, and 2080. We did not analyze simulation years after 2080 because they do not represent interpolated results between two nodes but a prolonging of 2080 conditions (Eq. 4, case $a > y(s_n)$). Third, to quantify the quality of the results we calculated the root mean square error (RMSE) for each stand and each species, based on simulation results of a 10-yr resolution. The RMSE corresponds to the differences in carbon mass between two models (described in detail in Appendix C), and is calculated out of the sums of all individuals of one species reaching a certain height class and an adjacent height class (tolerance to difference in height classes). For every species, each of these differences enter into the calculation of the RMSE as a fraction of the maximum possible difference appearing in that stand and the calculated simulation period. Hence, the maximum RMSE is one (completely different results). We calculated the RMSEs separately for two time periods: the spinup period and the climate change period. For both, we calculated the RMSE between LPJ-GUESS with 400 replicate patches and (1) LPJ-GUESS with 100, (2) LPJ-GUESS with 25 replicate patches, (3) LPJ-GUESS-G and (4) TreeM-LPJ-G.

To test the model performance we compared the simulation times of stochastic LPJ-GUESS model runs with 400, 100 and 25 replicate patches, and TreeM-LPJ-G and LPJ-GUESS-G. Listed times needed for the simulations using the GAPPARD method

consider only initial runs. The computational time needed for the GAPPARD method is negligibly short. The simulations ran on one core of an AMD Opteron 2439 2.8 GHz processor.

3 Results

3.1 Tree species parameterization

We successfully parameterized the LPJ-GUESS forest model using NFI data of the Rhone valley. We achieved a high accordance between the used NFI data and the simulated data of carbon mass for total living forest and for main species (Table 3).

Combined, the NFI1 and NFI3 data show an increase in forest biomass from the lowest site at 800 m to middle elevations of approximately 150 t ha^{-1} ($100\text{--}265 \text{ t ha}^{-1}$; $5\text{--}13.5 \text{ kgC m}^{-2}$) followed further upslope by a decline in biomass to $130\text{--}170 \text{ t ha}^{-1}$ at the upper alpine vegetation zone ($6.5\text{--}8.75 \text{ kgC m}^{-2}$) (see Tables D4 and D5 in the appendix for more details). In general, we were able to simulate these shifts, although we rather overestimated the NFI1 data and rather underestimated the NFI3 data. Consistent with the data, our simulations also show a small increase in forest carbon at all sites between the years in which the NFI was performed. We have reached percentage similarity coefficients higher than 0.93 and Euclidean distances scaled to 1 of smaller than 0.35 for the comparison of the total carbon mass over all altitudinal classes (T11 in Table 3).

With the new LPJ-GUESS parameters and functions, we were able to simulate the general pattern of a dominant *Pinus sylvestris* at stands closer to the valley bottom, dominant *Picea abies* and *Larix decidua* in forests at a mid-altitudinal elevation, dominant *Pinus cembra* and *Larix decidua* in forests at the upper alpine vegetation zone, and a continuous decrease of the proportion of broad-leaved tree species with altitudinal height (Fig. 4 and 5 and Figs. D1 and D2 in the appendix). The newly parameterized LPJ-GUESS could simulate the NFI distribution of most species with percentage

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similarity coefficient values of over 0.5 and Euclidean distances scaled to 1 of smaller than 1.0 (Table 3). There are only two major exceptions. First, the NFI data, especially at mid-altitudinal elevations, show high biomass of *Larix decidua* that LPJ-GUESS does not capture with the parameterizations, model functions, and initial modeling conditions we used. Concomitantly, the model generally predicts more *Picea abies* than is observed in the NFI data, so the sum of the carbon mass of both species leads to a good coherence to the NFI data. Second, the modeled carbon mass of *Quercus pubescence* exceeds the NFI1 values in stand (a) what is reflected in both used indices. Moreover, although there is basically no *Tilia cordata* and *Carpinus betulus* appearing in the NFI data, both species could establish as minor tree species in lower altitude stands in LPJ-GUESS.

3.2 Development of forest species composition and carbon mass with LPJ-GUESS

The climate change scenario we applied led to several changes in all simulated stands. Over the period from 1900 to 2000, the total carbon mass in most stands slightly increased. During the 21st century the carbon mass increased in all stands with highest increase at the beginning of the 21st century (black solid line in Fig. 8).

At lower stands *Quercus pubescens* and *Picea abies* (stands a and b) or drought tolerant broad-leaved species (stands b to e) profit from a decrease of *Pinus sylvestris*. In all stands, the proportion of broad-leaved species increased. Generally the increase of broad-leaved species was lowest on higher altitudes ($<0.1 \text{ kgCm}^{-2}$ in stand h), and highest on low altitudes (approximately 1 kgCm^{-2} in stand a). Like *Quercus pubescens* and *Pinus sylvestris*, with climate change *Picea abies* could establish on higher altitudes. Although no *Picea abies* appeared in stands (g) and (h) in 1900, in 2080 this species made approximately a third of the total carbon mass in stand (g) and a fifth in stand (h).

The three stochastic LPJ-GUESS model runs (using 400, 100 and 25 of replicate patches) in the long term showed similar results for tree carbon mass

development (Fig. 8). However, it is clearly illustrated, that carbon mass can vary strongly for decades but also for centuries (in the case of 25 replicate patches). A high number of replicate patches minimizes the chances of intensively altering output variables. However, as can be clearly seen in Fig. 8), even the results of the 400 replicates and 100 replicates simulations are quite different. Only for periods with extreme climatic situations all of the three LPJ-GUESS runs were affected equally (e.g. in the beginning of the 1920).

3.3 Development of forest species composition and carbon mass with the GAPPARD method

A comparison among LPJ-GUESS results using 400 replicate patches, LPJ-GUESS-G and TreeM-LPJ-G shows that the GAPPARD method successfully reproduces the stochastic LPJ-GUESS simulations. The overall development of total forest carbon mass was captured in most simulation runs of both TreeM-LPJ-G and LPJ-GUESS-G. However, there are some shortcomings. There was a more pronounced difference between LPJ-GUESS and TreeM-LPJ-G than between LPJ-GUESS and LPJ-GUESS-G (Fig. 6–7 and Fig. D3–D5 and Table D6 in the Appendix).

The total carbon mass produced with LPJ-GUESS-G was in the range of LPJ-GUESS results for each stand and at any simulation time. TreeM-LPJ-G mostly underestimated the biomass (Fig. 8, and Fig. D3–D5 in the Appendix), and in most stands only showed a small increase in total tree carbon mass or none. Both models using the GAPPARD method smooth the results over time so that changes of output variables only occur gradually with the simulation years, which can be seen in total carbon mass results and for single species.

Concerning species composition, LPJ-GUESS-G was successful in reproducing LPJ-GUESS results. Mean RMSE values are in the range of the mean RMSE between LPJ-GUESS using 100 and LPJ-GUESS using 400 replicate patches. The only case where LPJ-GUESS-G produced a different species composition was in stand g). There, *Picea abies* established in the middle of the 20th century in the LPJ-GUESS

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stochastic simulation run, but arrives only about a century later in the LPJ-GUESS-G run. TreeM-LPJ showed the same discontinuity but differs also on a few more points. In general, TreeM-LPJ-G led to a flatter distribution of carbon mass over height classes in stands dominated by *Picea abies* (Fig. 6, and Figs. D6 and D7 in the appendix), while its total carbon mass was underestimated there as well. Furthermore, all *Picea abies* dominated stands, especially stand (c) had a too large proportion of *Pinus sylvestris*. In stand (a) forests consisted only of *Pinus sylvestris* at the beginning of the 20th century, during the 20th century broad-leaved species could establish but not *Picea abies*.

A comparison of simulation times showed that both GAPPARD approaches perform faster than LPJ-GUESS using 100 replicate patches (Table 4). With the GAPPARD method, TreeM-LPJ was almost four times faster and LPJ-GUESS approximately eleven times faster than the standard LPJ-GUESS.

For the spinup period, the mean root mean square error between LPJ-GUESS using 400 replicate patches and (1) LPJ-GUESS-G was approximately 0.1 and (2) TreeM-LPJ-G was 0.15 (mean RMSE, calculated for species that produced at least 0.5 kgCm^{-2} in one of both models). For the simulation period, the mean RMSE between LPJ-GUESS and (1) LPJ-GUESS-G was approximately 0.05 and (2) TreeM-LPJ-G was 0.13. Reducing the numbers of replicate patches in a stochastic LPJ-GUESS run down to 25 resulted in a mean RMSE (between the 400 and the 25 replicates simulation runs) of approximately 0.09 for the spinup period and 0.07 for the simulation period, and was roughly four times faster than the 100 replicates simulation (Table 4).

4 Discussion

This study identified a novel efficient method to run disturbance driven models and also yielded an LPJ-GUESS parameterization and adaptation, and climate change simulations for a region with specific properties.

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4.1 Parameterization

For the first time the alpine mountain forest species *Larix decidua*, *Pinus cembra* and *Pinus mugo* were parameterized for LPJ-GUESS. Both *Pinus* species could be included using existing parameters. One main achievement is the newly added function to model the leaf phenology of *Larix decidua* (see Sect. 2.4.2 and Appendix A2).

We used observed forest biomass from inventory data as the only variable upon which to optimize the LPJ-GUESS species-level parameters. Although this simple approach does not account for the properties influencing forest dynamics, such as tree age, height or width, it led to a considerable similarity between the newly parameterized LPJ-GUESS results and the NFI data. With the NFI data, we could use a relatively dense sample of plots close to the modeled stands, which makes the results highly reliable. Sources of error mainly concern the estimation of the biomass from the NFI data on one side, and the comparison with LPJ-GUESS allometry based simulated values (in all used models) on the other side. Using the LPJ-GUESS allometry function, trees with identical diameter always have the same height and therefore the same mass. As a consequence, it could be possible that the model results might match the carbon mass results of the NFI, but not the diameter at breast height. This may particularly be the case in high mountain settings where tree allometry is strongly influenced by meteorologically imposed constraints (e.g. wind), which we did not consider in our models directly. Such an inconsistency, which might vary for different species, could lead to an unrealistic simulation of the vertical structure of the forest, and thus to further deviations from observations. However, the good agreement between our simulations and the observed biomass data indicates that differences in allometry are compensated in the model, e.g., through changes in stand density controlled by disturbance. Another source of error may be linked to the development of the forests in the used NFI plots. It is not clear in detail how strong the influence of the management in the specific NFI plots is. It is also not exactly known on which stands clear-cuts or big disturbance events have taken place. We assume that the mean state of all used stands

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is representative for the overall disturbance regime, so that the constant probability of disturbance events we use can reproduce it.

Despite of all sources of error, our parameterization results show high consistency between NFI data and simulated values. Furthermore, the simulated carbon mass and forest species distribution in the different stands at the time of the NFI dating are plausible to a great extent.

4.2 Simulation results

Using the altitude-specific disturbance distribution and the new parameters, we were able to simulate total forest carbon mass and a species composition that largely reflects the NFI data. We were able to reproduce forest species composition and tree carbon mass without using a specific disturbance function like the LPJ-GUESS fire function (Thonicke et al., 2001). However, to account for feedback effects between fire and forest growth and the spreading of fire, and both especially in the context of climate change, an appropriate modeling of the fire function is important. However, as our main concern was to present a new modeling technique we accept approximations regarding missing modeling detail of disturbance types.

The few discrepancies between the simulation results and the NFI data are partly due to uncertainties in the interpretation of the data. It is very likely that the situation with the high carbon mass of *Larix decidua* and low one of *Picea abies* in mid-altitudinal stands is to a high degree a result of management practices in the Rhone Valley (Gimmi et al., 2010). In addition, including specific total disturbance years (removal of all living carbon mass of all replicate patches in one pre-defined year) did not lead to a significant increase in the biomass of early successional *Larix decidua* because *Picea abies* completely overgrew it after only 30 yr of succession (results not shown). Although this suggests that succession may occur too quickly in LPJ-GUESS, it can be assumed that in the absence of forest management the real forests analyzed here at altitudes between 1200 m and 1800 m would be strongly dominated by *Picea abies* (Frehner et al., 2005). For the species *Carpinus betulus* and *Tilia cordata* the simulation results

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exceeded the NFI data, which possibly is enhanced by not modeling all here existing broad-leaved summergreen species. It is generally known that *Carpinus betulus* does not exist in this part of the Rhone Valley (Welten and Sutter, 1982), which is also reflected by the NFI data. In contrast, *Tilia cordata* usually exists in this region (Welten and Sutter, 1982; Svejgaard Jensen, 2003), but for unknown reasons is found only on very few plots of the NFI data in the analyzed region.

The increase of tree carbon mass with climate change, also at the lowest site, can mainly be explained by the 20th century increase in atmospheric CO₂ concentrations (Fischlin and Midgley, 2007). Test simulations with a constant level of CO₂ led to a decrease in tree carbon mass in the 21st century in most plots (results not shown). This decrease can be traced back to a drier climate with more pronounced water stress so that growth rates might be reduced and respiration rates increased. With rising CO₂ levels this effect can be compensated, at least to a certain degree, because stomatal regulation maintains high production rates and prevents plant water loss. In our results, the increase of tree carbon mass is more pronounced in stands with more frequent disturbances (close to valley bottom or upper tree line). Two reasons may be responsible for that. First, species more adapted to the new climatic conditions could profit from opening gaps. Second, species adapted to previous climatic conditions (which survive more likely with less disturbances) could be affected negatively by the changing conditions opening space for new species. However, at the lowest stand (ca. 800 m) the increase of carbon mass may be unrealistically large. Closer to the bottom of the Rhone Valley extreme drought events causing forest diebacks are expected to occur more frequently in the near future (Rebetez and Dobbertin, 2004). But the modeled future carbon stock does not show the effect of such extreme events (compare with the dry year 1921 in Fig. 8) suggesting that the climate data that we used may underestimate drought events or that the CO₂-effect is too strong. In addition, the north-facing aspect of all the sites we simulated means that they may be relatively less sensitive to interannual climate variability than the inner-Alpine region as a whole. However, the carbon mass of LPJ-GUESS results does not continuously increase over time, mainly

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due to stochastic variances, so that long-term trends are much more significant than changes in carbon mass over decades. This is one reason why a quantitative analysis of the carbon mass development between NFI1 and NFI3 is not fully reliable. However, the limited sample size of the NFI data does not allow the strict quantitative analysis of changes in carbon stocks.

With climate change, the occurrence of *Pinus sylvestris* at stands closer to the Rhone valley bottom will most probably be reduced and exchanged by broad-leaved drought resistant species like *Quercus pubescens* (Rebetez and Dobbertin, 2004; Bigler et al., 2006). This is well reflected in our modeling results. But it is not entirely clear why in our simulations with LPJ-GUESS the carbon mass of *Picea abies* increases at the lowest stand, while the mass of *Pinus sylvestris* decreases, especially because the latter is more drought resistant than *Picea abies*. We assume that the simulated decrease in *Pinus sylvestris* biomass is partly because, using LPJ plant physiological functions, it profits far less from increased CO₂ levels in comparison with broad-leaved summer-green tree species (Cheaib et al., 2012). Another reason for the decrease in *Pinus sylvestris* biomass might be that the lowest stand is still roughly 150 m above the valley bottom, so that conditions are still good enough for *Picea abies*. This is also reflected in the NFI data where the carbon mass of *Picea abies* at the lowest stand approximately doubled between NFI1 and NFI3 (Fig. 7, upper row). The general increase from the NFI1 to the NFI3 biomass confirms the increase of forest biomass, although this change also can be due to past forest management and the prevention of disturbance events.

It is unclear whether the modeled shift of species to higher altitudes as a consequence of climate change happened in a reasonable amount of time. In all models used here, tree establishment of new species only depends on the environment but does not consider changes in and feedbacks to the seed pool. It is well known that modeling seed pools and the dispersal of seeds have a large potential to change simulation results (Lischke, 2005; Lischke et al., 2006b; Epstein et al., 2007; Neilson et al.,

2005). Incorporation of seed dispersal and migration into the models presented here remains an open problem for future research.

4.3 GAPPARD method

We developed and successfully applied a new method to include the effect of small-scale disturbances in a postprocessing way. We utilized a modified version of the von Foerster equation (see Sect. 2.3.2, Eq. 3) to account for stand-replacing disturbances by using only undisturbed simulation runs. Furthermore, we were able to calculate output variables under changing climate conditions, using a linear interpolation between the results of selected SWDs. Several other approaches also used von Foerster types but during the simulations for each year and without using computationally efficient interpolation methods (Kohyama, 1993; Moorcroft et al., 2001; Falster et al., 2010).

The GAPPARD method is clearly a step towards a computationally more efficient modeling of forest carbon mass and species distributions. Despite this success, there are some limitations. With the method presented here, it is currently not possible to include any spatial interactions between neighboring grid cells or patch-to-patch interactions. Therefore, seed dispersal as applied in TreeMig or the spatial mass effect of LPJ-GUESS (establishment in a patch depends on carbon mass of other patches in a stand) cannot be applied so far. The stochastic mortality and establishment functions of LPJ-GUESS seem to have a much smaller effect on forest carbon mass and species composition than do stochastic small-scale disturbances. With a more significant impact on demographic stochasticity, LPJ-GUESS might lead to results that could not be reproduced with the GAPPARD method as adequately as we show here. In this case, the methods used in TreeMig (Lischke et al., 2006b) or TreeM-LPJ (Scherstjanoi et al., 2013) to model vertical and horizontal heterogeneity could provide possible solutions. Although it might not have an influence on the stands modeled here, one additional limitation of the GAPPARD method could be that the influence of climatic extreme events is not visible in the model output because of the linear interpolation between different initial undisturbed runs (see Sect. 2.3.2, Eq. 4) and because of the preset node

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positions. Thus, a central question for future applications would be the number and setup of starting points of SWDs. Especially if a disturbance has happened before an extreme climatic event (e.g. extreme dry years) the following succession may show large differences to the mean calculated with our new method. Hence, nodes must be set such that long term trends and short term variabilities are depicted. Here, we use pre-defined starting points for the SWDs (nodes) chosen independently from climate data. However, this simplification concerning extreme climatic events still led to results of acceptable quality in LPJ-GUESS-G, also because unresolved spatial heterogeneity, e.g. microhabitats, implies that not all patches respond the same way to extreme climate variability and extreme events. Still, this simplification might be the reason for the underestimation of *Picea abies* growth in stand g). Our first SWD starts in 1950. An additional SWD starting 1900 did not substantially change the model results (not shown). Hence, the combination of suitable establishment conditions in one or more certain years in the beginning of the 20th century in combination with disturbance events must be the reason why *Picea abies* establishes earlier in LPJ-GUESS.

Furthermore, it remains unclear whether a different interpolation method (e.g. spline interpolation) between two nodes could lead to even better results. In addition, errors may result from ignoring that some state variables are not set to 0 after a disturbance event in stochastic LPJ-GUESS simulations (e.g. amount of litter, soil water and snow layer) but were treated as if they were. Another source of error can be explained by the smaller stochastic variability in our method during the spinup phase compared to the gap approach of LPJ-GUESS: while in LPJ-GUESS in every spinup year again the same potential exists to randomly draw more extreme values out of the reference period (first 30 yr of 20th century), which then can influence succession after disturbances, with our method only conditions of the first year of the SWD are responsible for the establishment.

In most stands, simulations with TreeM-LPJ-G and LPJ-GUESS led to different total biomass and different species composition. However, the original TreeM-LPJ model does not include a gap approach and does not account for disturbance effects, and

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therefore these models should not be compared directly, and TreeM-LPJ-G should only be compared with the standard LPJ-GUESS results. It is hard to distinguish how much of the deviations between TreeM-LPJ-G and LPJ-GUESS originate from the GAPPARD method and how much from the height class approximations in TreeM-LPJ. However, we expected the model's results to be closer to LPJ-GUESS. In contrast, we were surprised that the results of LPJ-GUESS-G were so close to the LPJ-GUESS results, particularly given all the uncertainties mentioned before.

It is important to note that at the moment the new method cannot serve to track output variables in the same way as the original LPJ-GUESS can. However, the method presented here is not designed to model carbon or nutrient cycles. Furthermore, the method is best applicable if state variables that are typically reset by disturbances do not influence the subsequent tree establishment.

5 Conclusions and outlook

With GAPPARD, we provided a new method of efficiently simulating the dynamics of tree biomass and forest species composition. It can be used for any output variable that can be produced with the deterministic run and that is reset by disturbance. GAPPARD can further be applied for any model that uses a gap approach and that applies disturbances as stand replacing events. Our simulations demonstrated that the GAPPARD method can also be used for simulations that consider the transient effects of changes in climate and atmospheric CO₂ concentrations. Moreover, the principle of the method can be applied to newly implement the effect of stand-replacing disturbances in any dynamic forest or vegetation model.

The GAPPARD method is particularly suitable for simulating a great number of stands in a fast way, and hence is applicable on larger scales. The results can be used to make first estimations about the development of output variables (e.g. species composition) or to identify hot spots of unusual or interesting simulation results which than can be analyzed in more detail with the original models.

As a next step, we plan to apply the efficient method developed here in combination with the optimized species-level parameter set for Swiss tree taxa in Swiss- and Europe-wide simulations on a 1 km grid. Furthermore, we plan to extend the method by implementing effects of demographic stochasticity, non-stand-replacing disturbances and spatial interactions.

Appendix A

Parameterization details

A1 Adaptation of NFI data

The selection of the NFI plots is based on the distance to the simulated stands, on the stand type, and topographical considerations. We used only NFI plots that were classified as accessible forest areas, and that are all located south of the Rhone, at most 30 km westward or eastward from the simulated stands, and at most 30 km southward from the southernmost stand. We also classified the chosen NFI plots according to their exposition but the results were not sensitive to it (results not shown).

The NFI1 and NFI3 data of all plots are split into two parts. One part comprehends trees with diameter at breast height (DBH) higher than 12 cm (older trees), the other trees with DBH lower than 12 cm (young trees). For the older trees, the biomass per area is estimated for each occurring species. The young trees in the NFI1 are classified into DBH classes of 0–4 cm, 4–8 cm or 8–12 cm, or are classified as 30–130 cm high. The young trees in the NFI3 are classified into height classes of 10–40 cm or 40–130 cm, or are classified as having a DBH of 0–12 cm. To estimate their biomass we used the mean values of the classes, applied it to the LPJ-GUESS allometry function and calculated the biomass considering wood density (Assmann, 1962).

For the parameter tuning, we utilized a set of simulation runs that all used 800 yr of spinup period and simulated forest developments from 1900 up to the years the NFI

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data was estimated. To widely smooth stochastic variations, we used a number of 400 replicate patches for the final parameter fine-tuning simulation runs.

A2 New plant physiological functions and parameters

We added three new tree species to LPJ-GUESS that have not been included before: *Larix decidua*, *Pinus cembra* and *Pinus mugo*. Hence, we had to parameterize them from scratch. Both *Pinus* species were applicable to existing functions of LPJ-GUESS. But first plausibility tests showed that these functions were not sufficient for *Larix decidua*, mainly due to the tree species' specific phenology. In LPJ-GUESS, the foliage of summergreen species is transferred to litter all at once on one simulation day (typically in fall) when the maximum number of equivalent days with full leaf cover per growing season exceeds a certain value. For most species, this approximation has no significant negative influence because photosynthetic efficiency in general is reduced more suddenly. But especially for larches, leaf senescence can be a process lasting for months during which photosynthetic intensity is reduced stepwise. Based on Migliavacca et al. (2008), we included this physiological trait by defining a new phenology type for *Larix decidua*. It will be modeled like a summergreen species, but in autumn the phenological state of the larches will decrease with an s-shaped curve, in dependency of the number of days since the start of fall of leaves (sd) and the number of days with full leaf cover this year (md):

$$\text{phen}(t) = \begin{cases} \frac{\text{phen}(t-1)}{1+e^{(0.15(sd-50))}} & ; md > 120 \\ \frac{\text{phen}(t-1)}{1+e^{(0.15(sd-(50+\frac{md-120}{8})))}} & ; \text{else} \end{cases} \quad (\text{A1})$$

We determined the other parameters of *Larix decidua* oriented on expert knowledge and literature about the species (Table D3). We defined it as a shade intolerant species with a high ratio of leaf area to sapwood cross-sectional area (Oren et al., 1995). Although it is a boreal species that also grows under very cold conditions, it can establish

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under warmer conditions, too. Furthermore, saplings do not need much soil water for establishment. The parameters of the new *Pinus* species are mainly based on *Pinus sylvestris* parameters. However, both new *Pinus* species are more cold resistant, have seeds that are less drought resistant and their needles have a higher longevity. Moreover, *Pinus mugo* was defined as shade intolerant.

An important issue was the parameterization of the minimum soil water content needed for establishment (WMIN) of the three new species. Referring to Ellenberg (1986), Bugmann (1996) defined *Larix decidua* as a rather drought intolerant species. However, he also listed other authors that had defined intermediate values for it. Eilmann and Rigling (2012) could show that *Larix decidua* is, in comparison to e.g. *Pinus sylvestris*, strongly affected by drought events. On the other hand, Lischke et al. (2006b) and Shuman et al. (2011) defined it as a very drought tolerant species. Yan and Shugart (2005) used different larch species but also defined them as drought tolerant. Matras and Pâques (2008) noted that the response of *Larix decidua* to drought can vary strongly depending on stand conditions. Klimek et al. (2011) discussed the water consumption of *Larix decidua* seedlings compared to other conifers, and reported different observations ranging from same water uptake rates among all conifers to studies that show that *Larix decidua* consumes ten times more than other conifers. If soil conditions allow it, this species can survive dry years better than other species that are more drought adapted because its root system is very deep (Anfodillo et al., 1998; Valentini et al., 1994). Considering all this, we determined *Larix decidua* having a high proportion of fine roots in the deeper soil layer and a moderately low WMIN value (Table D3). Based on Bugmann (1996) and Lischke et al. (2006b), we also used a moderately low WMIN value for *Pinus cembra* and *Pinus mugo*. According to (Valentini et al., 1994) *Pinus cembra* with its root system is also able to use groundwater from deeper layers, which is also in line with general knowledge. Thus, we determined a high proportion of fine roots in the deeper soil layer for both new *Pinus* species.

We modified several values of the latest existing LPJ-GUESS species parameterization (Hickler et al., 2012) (Table D3). Main changes address the soil water content

needed for establishment, which we increased for *Fagus sylvatica*, *Abies alba* and *Quercus robur*, and decreased for *Betula pendula* and *Picea abies*. Furthermore, we introduced a new shade tolerance class, particularly for *Picea abies* (column “ns” in Table D1). With this, we contribute to *Picea abies* being less shade tolerant than *Fagus sylvatica* or *Abies alba* but more shade tolerant than intermediate shade tolerant species (Bugmann, 1994; Roloff, 2010).

Based on the Swiss-wide applied forest models ForClim (Bugmann et al., 1997) and TreeMig (Lischke et al., 2006b), we additionally adapted the allometry parameters. As a result, *Betula Pendula*, *Pinus cembra* and *Pinus mugo* have a higher stem diameter to tree height ratio than the other species. As another important issue, we changed the parameter of needed growing degree sum required for full leaf cover of *Betula Pendula* and *Larix decidua* to account for their comparatively fast budburst (Murray et al., 1989).

Another important change concerns the parameter of maximum 20-year coldest month mean temperature for establishment ($TMAX_{est}$). This limit is not associated with plant physiological functions, but rather represents a surrogate for functions not implemented in LPJ-GUESS that are responsible for outcompeting cold adapted species under warmer climates. We removed this limit for all species but *Pinus cembra*. In a previous version, the implementation of $TMAX_{est}$ values of -1.5 (Miller et al., 2008; Hickler et al., 2012) or -2 (Koca et al., 2006) for *Picea abies*, and of -1 (Koca et al., 2006; Miller et al., 2008; Hickler et al., 2012) for *Pinus sylvestris* led to two discontinuities (results not shown). First, both species should have been able to establish in the lowest of the analyzed elevations (ca. 800 m), which is reflected by the NFI data. But maintaining the limits led to a prevention of establishment of both because the climate is “too warm”. Second, if the climate in a stand was near to the limit of the $TMAX_{est}$, a species did not grow during the spinup (1901–1930 climate) but established in the slightly colder 1940s. Although it became much warmer afterwards the cold-adapted species, once established, did not become extinct (despite of e.g. drought stress). This created the inverse picture of cold adapted species that grow better under warmer climates. A future

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application of this parameterization in regions with warmer winters might need further tests and possibly a re-implementation of $TMAX_{est}$ for some species.

Similarly, WMIN covers only a part of plant physiological responses to drought. There is a high risk that its values will be defined varying from realistic values to also cover other plant related effects that are not included in LPJ-GUESS (e.g. plant water storage, plant water conduction traits, certain stomata closure effects or absence caused by dispersal barriers). This complicated the parameterization of WMIN. In accordance with the occurrence of species in the NFI data and Bugmann (1996) and Lischke et al. (2006b), *Picea abies* and *Betula pendula* are more drought resistant than the WMIN values of Hickler et al. (2012) might reflect. Consequently, we decreased the WMIN of *Picea abies* and *Betula pendula*. For the same reason we increased the WMIN values of *Abies alba*, *Quercus robur* and *Fagus sylvatica* (Table D3).

We included C3 grass as a plant functional type into our modeling of LPJ-GUESS, LPJ-GUESS-G and TreeM-LPJ-G without changes to the existing LPJ-GUESS functions.

We did not use a bole height to calculate the daily fraction of incoming photosynthetically active radiation. In other words, leaves of all species are equally distributed vertically. This could be a problem for the modeling of species that produce foliage high above the ground (e.g. *Pinus sylvestris*), and by that might have an advantage because they are less shaded. However, the bole height of LPJ-GUESS is still a parameter but should be dependent on stand density and tree age, and, thus, be treated as a state variable, to model this issue realistically.

Appendix B

Used similarity measures for the evaluation of the parameterization

The Euclidean distance

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$$ed = \sqrt{\sum (x_i - y_i)^2} \quad (\text{B1})$$

is proportional to the sum of the squared distances of all data points. For this reason, a lower value stands for better results. To be able to compare results of different dimensions, we scaled the data of each elevation class, giving the highest of all occurring values of one altitudinal height class the value one and normalized the other values to the highest value.

The percentage similarity coefficient

$$sc = 1 - \frac{\sum |x_i - y_i|}{\sum (x_i + y_i)} \quad (\text{B2})$$

is as minimum zero when the distances of the data points equals their sum, and one, if the two data sets are equal (Bugmann, 1994).

Appendix C

Calculation of the Root Mean Square Error

The differences in carbon mass of one species between the two model outputs to compare (C_{m1} , C_{m2}) are summed up for each year between y_{start} and y_{end} (10-yr resolution), and for each height class (htcl) up to the number of height classes (nhtcl), also considering neighboring height classes (htcln). These differences

$$C_{m,\text{diff}} = \left| \sum_{\text{htcln}=\max(\text{htcl}-1,1)}^{\min(\text{htcl}+1,\text{nhtcl})} C_{m1,\text{htcln},\text{yr}} - \sum_{\text{htcln}=\max(\text{htcl}-1,1)}^{\min(\text{htcl}+1,\text{nhtcl})} C_{m2,\text{htcln},\text{yr}} \right| \quad (\text{C1})$$

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are scaled by the maximum carbon mass appearing in that period:

$$C_{m,\max} = \max((C_{m1,\text{htcl},\text{yr}}) + (C_{m1,\text{htcln},\text{yr}}), (C_{m2,\text{htcl},\text{yr}}) + (C_{m2,\text{htcln},\text{yr}})). \quad (\text{C2})$$

Then its square is summed up and divided by the number of elements to sum up. The root of it is the Root Mean Square Error:

$$\text{rmse} = \sqrt{\frac{\sum_{\text{htcl}=1}^{\text{nhtcl}} \sum_{\text{yr}=\text{y}_{\text{start}}}^{\text{y}_{\text{end}}} \left(\frac{C_{m,\text{diff}}}{C_{m,\max}} \right)^2}{\text{nhtcl} \frac{\text{y}_{\text{end}} - \text{y}_{\text{start}}}{10}}} \quad (\text{C3})$$

Acknowledgements. This study is part of the project SER-C07.00123 (MEPHYSTO) funded by the Swiss COST office at the Swiss State Secretariat for Research and Education SBF and of the COST action FP0603 “Forest models for research and decision support in sustainable forest management”. Jed O. Kaplan was supported by the Swiss National Science Foundation (grants PP0022_119049 and PP00P2_139193). We thank Thomas Wuest for IT support and Dirk Schmatz for providing the downscaled climate data, Matthias Dobbertin and Andreas Rigling for information on forests in the Rhone Valley and numerous colleagues who produced and provided the NFI data. The method development was inspired by discussions with Julia Nabel (Swiss National Science Foundation-project 315200_122434).

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**Table 1.** Variables appearing in the equations.

variable	description
T	Time in final, postprocessed results (for simplicity of notation we set initial time $T_0 = 0$)
x	Simulation time in undisturbed simulation
a	Patch age
$P(a)$	Probability that a patch has age a
$y(T)$	Output variable of non-disturbed simulation at time T
p_{dist}	Disturbance probability
s_i	Node, i.e. starting point of non-disturbed simulation with changing drivers, $i = 0..n$
$y_i(s_i + a)$	State or output variable of non-disturbed simulation starting from node i with age a

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Table 2. Specific characteristics for stands a to h. Lat: Latitude in Swiss coordinates (Longitude is 638 300 for all stands); Alt: Altitude above sea level; Temp: Mean annual temperature; Prec: Sum of precipitation of main growing period (April–September); NFI-alt: Altitudinal range set for NFI plots associated with the modeled stands; NFI1, NFI3: numbers of plots per altitudinal range; RID: return intervals for generic, patch-destroying disturbances.

	a	b	c	d	e	f	g	h
Lat	127 400	127 100	126 800	126 500	126 200	125 900	125 500	124 800
Alt in m	795	1003	1214	1415	1588	1793	1990	2190
Temp in °C	9.5	8.5	7.3	6.2	5.3	4.3	3.2	2.1
Prec in mm	385	436	486	535	576	624	670	719
NFI-alt in m	700– 900	900– 1100	1100– 1300	1300– 1500	1500– 1700	1700– 1900	1900– 2100	2100– 2300
NFI1	15	19	29	32	50	54	30	12
NFI3	8	14	21	14	34	24	22	6
RID	65	65	100	100	100	65	65	65

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Table 3. Evaluation of model parameterization. T1: *Picea abies*; T2: *Larix decidua*; T3: *Pinus sylvestris*; T4: *Pinus cembra*; T5: *Abies alba*; T6: *Pinus mugo*; T7: *Quercus spec.*; T8: *Betula pubescens*; T9: *Fraxinus excelsior*; T10: other broad-leaved species; T11: all tree species; NFI1: model results for simulation year 1985 compared with NFI1 data; NFI3: model results for simulation year 2006 compared with NFI3 data; V1: Euclidean distance scaled to 1 (lower values are better), values smaller than 0.67 are written in bold. V2: percentage similarity coefficient (higher values are better), values higher than 0.67 are written in bold.

		T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11
NFI1	V1	0.63	1.39	0.37	0.56	0.6	0.7	1.07	0.83	0.64	0.88	0.19
	V2	0.78	0.5	0.8	0.66	0.72	0.69	0.05	0.71	0.69	0.65	0.96
NFI3	V1	0.76	1.37	0.51	0.59	0.53	0.74	0.67	0.86	0.72	0.85	0.34
	V2	0.7	0.47	0.77	0.69	0.74	0.66	0.54	0.68	0.5	0.63	0.94

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Table 4. Simulation times and mean RMSE. Sum of simulation times of all 8 simulated stands for 800 yr of spinup and simulation from 1900–2100 with LPJ-GUESS using replicate patches and using the new GAPPARD method. RMSE for model spinup of 800 yr (RMSI SPI) and for the simulation time 1900–2080 (RMSI SIM). The mean RMSE is calculated using all species that produced at least 0.5 kgC m^{-2} in one of both models at any point in time during the simulation. The reference to RMSE calculation is always LPJ-GUESS with 400 replicate patches. The 400 replicates run was done once, the others shown as means of 10 simulation runs that use the same random number seed for stochasticity (thereby producing the same output) to account for the different loads of the processor nodes. Simulations were run on one core of an AMD Opteron 2439 2.8 GHz processor.

	LPJ-GUESS			GAPPARD	
	400 replicates	100 replicates	25 replicates	LPJ-GUESS-G	Treem-LPJ-G
simulation times	7 h 31 min 11 s	1 h 15 min 33 s	17 min 58 s	6 min 56 s	20 min 21 s
mean RMSE SPI	–	0.10	0.09	0.10	0.16
mean RMSE SIM	–	0.05	0.07	0.05	0.13

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Table D1. Shade tolerance parameters. The affiliations to species are given in Table D3. st: shade tolerant; ns: nearly shade tolerant; ist: intermediate shade tolerant; si: shade intolerant.

	st	ns	ist	si
Minimum forest-floor PAR for establishment ($\text{MJ m}^{-2} \text{ day}^{-1}$)	1.25	1.625	2	2.5
Growth efficiency threshold ($\text{kgC leaf m}^{-2} \text{ yr}^{-1}$)	0.04	0.06	0.08	0.1
Maximum establishment rate (saplings $\text{m}^{-2} \text{ yr}^{-1}$)	0.05	0.075	0.1	0.2
Recruitment shape parameter after Fulton (1991)	2	4	6	10
Annual sapwood to heartwood turnover rate (yr^{-1})	0.05	0.0575	0.065	0.08

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**Table D2.** Climatic range parameters. The affiliations to species are shown in Table D3.

	boreal	temperate
Optimal temperature range for photosynthesis (°C)	10–25	15–25
Maximum temperature range for photosynthesis (°C)	–4–38	–2–38

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Table D3. Specific tree parameters. b: boreal; t: temperate; st: shade tolerant; ns: nearly shade tolerant; ist: intermediate shade tolerant; si: shade intolerant; e: evergreen; s: summergreen; f: summergreen with fading senescence; phenramp: growing degree sum on 5 degree base required for full leaf cover; k_latosa: ratio of leaf area to sapwood cross-sectional area; rootdist_u and rootdist_l: proportion of roots extending into upper and lower soil layer; chill_b: changed chilling parameter (Sykes et al., 1996); w_min: minimum soil water content (averaged over the growing season and expressed as a fraction of available water holding capacity) needed for establishment; gdd5min: minimum growing degree day sum on 5°C base, tmax_e and tmin_e: minimum and maximum 20-yr coldest month mean temperature for establishment; tmin_s: maximum 20-yr coldest month mean temperature for survival; k_allom2: steepness-influencing parameter in diameter to height relation: longevity and leaf longevity in year: Lar dec: *Larix decidua*; Pic abi: *Picea Abies*; Pin cem: *Pinus cembra*; Pin mug: *Pinus mugo*; Pin syl: *Pinus sylvestris*; Abi alb: *Abies Alba*; Bet pen: *Betula pendula*; Car bet: *Carpinus betulus*; Cor ave: *Coryllus avelanna*; Fag syl: *Fagus sylvatica*; Fra exc: *Fraxinus excelsior*; Que rob: *Quercus robur*; Que pub: *Quercus pubescens*; Til cor: *Tilia cordata*; * newly added species.

	Lar dec *	Pic abi	Pin cem *	Pin mug *	Pin syl	Abi alb	Bet pen
climatic range	b	b	b	b	b	t	t
shade tolerance	si	ns	ist	si	ist	st	si
phenology type	f	e	e	e	e	e	s
phenramp	100	–	–	–	–	–	100
k_latosa	5000	4000	2000	2000	2000	4000	5000
rootdist_u	0.6	0.8	0.6	0.6	0.6	0.8	0.8
rootdist_l	0.4	0.2	0.4	0.4	0.4	0.2	0.2
leaf longevity	0.5	4	4	4	2	4	0.5
chill_b	100	100	100	100	100	100	400
longevity	500	500	500	500	500	350	200
w_min	0.3	0.35	0.3	0.3	0.25	0.4	0.3
gdd5min	300	600	300	400	600	900	700
tmax_e	–	–	–3	–	–	–	–
tmin_e	–29	–29	–29	–29	–29	–3.5	–29
tmin_s	–30	–30	–30	–30	–30	–4.5	–30
k_allom2	40	40	22	30	40	40	30

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Table D3. Continued.

	Car bet	Cor ave	Fag syl	Fra exc	Que rob	Que pub	Til cor
climatic range	t	t	t	t	t	t	t
shade tolerance	ist	si	st	ist	ist	ist	ist
phenology type	s	s	s	s	s	s	s
phenramp	200	200	200	200	200	200	200
k_latosa	5000	4000	5000	5000	4500	4000	5000
rootdist_u	0.7	0.7	0.8	0.8	0.6	0.6	0.8
rootdist_l	0.3	0.3	0.2	0.2	0.4	0.4	0.2
leaf longevity	0.5	0.5	0.5	0.5	0.5	0.5	0.5
chill_b	600	400	600	100	100	100	600
longevity	350	300	500	350	500	500	350
w_min	0.33	0.3	0.5	0.4	0.4	0.2	0.33
gdd5min	1200	800	1300	1100	1100	1900	1000
tcm _{max_e}	–	–	–	–	–	–	–
tcm _{in_e}	–7	–10	–2.5	–15	–15	–5	–17
tcm _{in_s}	–8	–11	–3.5	–16	–16	–6	–18
k_allom2	40	40	40	40	40	40	40

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Table D4. Forest biomass of the NFI1 inventory and LPJ-GUESS results for the simulation year 1985 (all in tha^{-1}). T1: *Picea abies*; T2: *Larix decidua*; T3: *Pinus sylvestris*; T4: *Pinus cembra*; T5: *Pinus mugo*; T6: *Abies alba*; T7: *Quercus spec.*; T8: *Betula pubescens*; T9: *Fraxinus excelsior*; T10: other broad-leaved species; T11: all tree species; SIM: LPJ-GUESS results (400 replicate patches).

		T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11
a	NFI	11.95	15.59	63.08	0	0	0	0.24	3.79	0	8.31	103.19
	SIM	12.77	1.58	74.92	0	2.61	3.42	10.6	6.85	0.68	16	129.44
b	NFI	68.62	18.83	29.59	0	6.51	1.63	0.12	4.85	2.55	6.38	139.3
	SIM	48.61	3.28	34.43	0	11.28	2.02	3.06	8.27	1.74	26.62	139.31
c	NFI	91.64	95.99	19.18	0	14.27	0	0.09	3.08	1.34	19.42	245.03
	SIM	118.05	5.06	17.44	1.31	33.25	1.29	3.78	7.12	2.8	26.1	216.19
d	NFI	113.89	63.11	25.49	0.38	19.14	0.24	0	4.53	0.26	2.93	232.39
	SIM	173.49	12.49	5.83	1.22	20.15	1.11	0.44	7.54	0.3	8.74	231.31
e	NFI	120.49	85	16.15	2.62	3.45	2.61	0	1.01	0	0.84	232.8
	SIM	217.51	25.56	2.19	0.91	0	0.9	0	1.81	0	0.29	249.18
f	NFI	72.01	106.45	5.01	14.37	0	3.3	0	0.27	0	0	201.41
	SIM	139.97	35.61	1.12	2.54	0	1.94	0	0.11	0	0	181.29
g	NFI	18.54	74.72	2.16	31.9	0	6.58	0	0	0	0	133.89
	SIM	15.77	61.06	0.08	56.4	0	5.22	0	0	0	0	138.53
h	NFI	0	78.9	0	50.14	0	1.69	0	0	0	0	130.73
	SIM	0.69	37.15	0	97.23	0	1.62	0	0	0	0	136.69

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Table D5. Forest biomass of the NFI3 inventory and LPJ-GUESS results for the simulation year 2006 (all in tha^{-1}). See Table D4 for descriptions.

		T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11
a	NFI	30.59	0.78	49.87	0	0	0	6.05	12.57	0	8.33	114.86
	SIM	14.95	1.14	72.14	0	3.96	2.12	15.37	8.59	0.71	19.95	138.94
b	NFI	63.84	29.21	32.8	0	10.89	0.81	2.82	3.83	5.31	17.71	167.23
	SIM	47.91	2.78	32.56	0	12.31	1.53	4.35	11.54	2.07	31.7	146.76
c	NFI	65.56	148.39	20.1	0	22.56	1.12	0.48	4.02	1.06	9.6	273.08
	SIM	113.01	5.87	19.34	0.43	41.06	0.92	4.52	8.51	2.88	27.36	223.91
d	NFI	66.83	97.49	26.65	0	28.7	2.1	0	5.25	0	17.81	247.29
	SIM	177.44	17.54	4.85	0.73	21.12	0.71	0.78	9.26	0.52	8.85	241.79
e	NFI	130.08	101.2	20.58	2.3	7.69	0.65	0	0.64	0	1.54	265.2
	SIM	227.29	29.93	1.72	0.62	0	0.62	0	2.83	0	0.67	263.67
f	NFI	74.81	169.62	0	18.58	0	0	0	0.98	0	0	266.23
	SIM	147.41	44.55	1.07	2.33	0	1.42	0	1.01	0	0.01	197.82
g	NFI	28.34	89.99	0	47.21	0	4.68	0	0	0	0	170.39
	SIM	23.16	79.06	0.22	59.96	0	4.81	0	0	0	0	167.21
h	NFI	0	131.13	0	44.18	0	0	0	0	0	0	179.87
	SIM	0.54	57.83	0.01	97.31	0	1.92	0	0	0	0	157.6

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Table D6. Root mean square error (RMSE) between LPJ-GUESS using 400 replicate patches and (I) TreeM-LPJ-G and (II) LPJ-GUESS-G model runs for stands a to h. All values were calculated with a temporal resolution of 10 yr. spi: RMSE for simulation spinup time (800 yr); sim: RMSE for simulation years 1900–2100; yr: only actual year difference considered; p: period of 50 yr considered. Numbers in italic indicate that in both models less than 0.5 kgCm² of that species were produced at any one point during the simulation. Bold numbers indicate values less than 0.2.

(1) *Larix decidua*; (2) *Picea abies*; (3) *Pinus cembra*; (4) *Pinus mugo*; (5) *Pinus sylvestris*; (6) *Abies alba*; (7) *Betula pendula*; (8) *Carpinus betulus*; (9) *Coryllus avelanna*; (10) *Fagus sylvatica*; (11) *Fraxinus excelsior*; (12) *Quercus robur*; (13) *Quercus pubescens*; (14) *Tilia cordata*.

		(I)															
		(a)		(b)		(c)		(d)		(e)		(f)		(g)		(h)	
		spi	sim	spi	sim	spi	sim	spi	sim	spi	sim	spi	sim	spi	sim	spi	sim
1)		0.13	0.13	0.06	0.13	0.12	0.17	0.08	0.18	0.09	0.08	0.06	0.07	0.09	0.07	0.1	0.1
2)		0.36	0.21	0.13	0.1	0.17	0.16	0.17	0.14	0.23	0.23	0.23	0.26	–	0.23	–	0.14
3)		–	–	–	–	–	<i>0.11</i>	–	<i>0.1</i>	0.05	0.11	0.09	0.17	0.14	0.16	0.12	0.13
4)		0.17	0.18	0.07	0.18	0.04	0.21	0.07	0.22	0.05	0.14	0.03	0.19	0.2	0.16	–	0.16
5)		0.05	0.13	0.11	0.16	0.24	0.23	0.12	0.22	0.15	0.27	0.23	0.22	–	0.13	–	0.1
6)		0.29	0.18	0.23	0.24	0.12	0.18	0.23	0.23	0.13	0.09	–	0.1	–	0.09	–	0.13
7)		0.18	0.23	0.08	0.12	0.09	0.11	0.07	0.12	0.04	0.08	0.09	0.09	–	0.07	–	0.1
8)		0.25	0.16	0.08	0.14	0.1	0.15	–	0.12	–	0.11	–	0.1	–	0.1	–	0.1
9)		0.18	0.2	0.07	0.11	0.07	0.13	0.06	0.14	0.03	0.12	–	0.09	–	0.09	–	0.1
10)		–	0.18	0.18	0.19	0.1	0.21	–	0.13	–	0.1	–	0.1	–	0.11	–	–
11)		0.25	0.2	0.09	0.15	0.12	0.21	–	0.12	–	0.06	–	0.1	–	0.1	–	0.1
12)		0.27	0.18	0.11	0.13	0.16	0.17	–	0.21	–	0.07	–	0.1	–	0.1	–	0.1
13)		–	0.09	–	0.11	–	0.1	–	0.1	–	0.1	–	–	–	–	–	–
14)		0.23	0.15	0.08	0.13	0.07	0.15	0.11	0.18	–	0.09	–	0.1	–	0.1	–	0.1

		(II)															
		(a)		(b)		(c)		(d)		(e)		(f)		(g)		(h)	
		spi	sim	spi	sim	spi	sim	spi	sim	spi	sim	spi	sim	spi	sim	spi	sim
1)		0.03	0.1	0.03	0.12	0.02	0.14	0.03	0.13	0.03	0.05	0.02	0.05	0.03	0.09	0.04	0.07
2)		0.04	0.08	0.08	0.1	0.04	0.11	0.03	0.14	0.03	0.09	0.03	0.08	–	0.19	–	0.06
3)		–	–	–	–	–	<i>0.08</i>	–	<i>0.07</i>	<i>0.01</i>	<i>0.08</i>	<i>0.01</i>	0.13	0.06	0.05	0.03	0.07
4)		0.04	0.1	0.04	0.07	0.02	0.08	0.01	0.07	0.01	0.07	0.01	0.09	0.02	0.08	–	0.25
5)		0.07	0.09	0.18	0.16	0.09	0.23	0.04	0.18	0.03	0.1	0.01	0.06	–	0.07	–	0.08
6)		0.23	0.15	0.12	0.18	0.11	0.18	0.05	0.1	0.13	0.07	–	0.1	–	0.1	–	0.11
7)		0.04	0.13	0.02	0.07	0.02	0.05	0.03	0.07	0.02	0.05	0.09	0.07	–	0.06	–	0.1
8)		0.05	0.09	0.04	0.06	0.03	0.06	–	0.05	–	0.06	–	0.1	–	0.1	–	0.1
9)		0.03	0.11	0.02	0.06	0.03	0.1	0.02	0.08	0.01	0.07	–	0.05	–	0.07	–	0.1
10)		–	0.09	0.18	0.1	0.1	0.21	–	0.12	–	0.1	–	0.11	–	0.11	–	–
11)		0.25	0.16	0.06	0.09	0.05	0.14	–	0.12	–	0.03	–	0.11	–	0.1	–	0.1
12)		0.27	0.14	0.11	0.09	0.06	0.09	–	0.16	–	0.03	–	0.11	–	0.1	–	0.1
13)		–	0.07	–	0.05	–	0.1	–	0.1	–	0.1	–	–	–	–	–	–
14)		0.05	0.1	0.03	0.06	0.04	0.08	0.04	0.12	–	0.03	–	0.09	–	0.1	–	0.1

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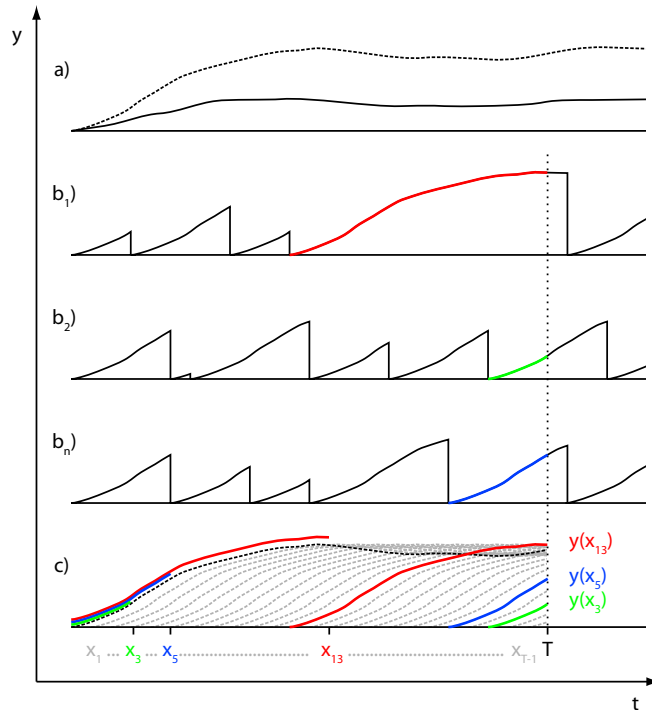


Fig. 1. Principle of GAPPARD. Development of any vegetation state variable (e.g. biomass of a species) y over time t . **(a)** solid line: average development with disturbances, dashed line: development without disturbances; **(b₁–b_n)** development of the state variable for patch 1 to n , stand-replacing disturbances appear with disturbance probability p ; **(c)** necessary information to calculate y with the GAPPARD method at time T , for years x_1 to x_{T-1} the same development of y is applied.

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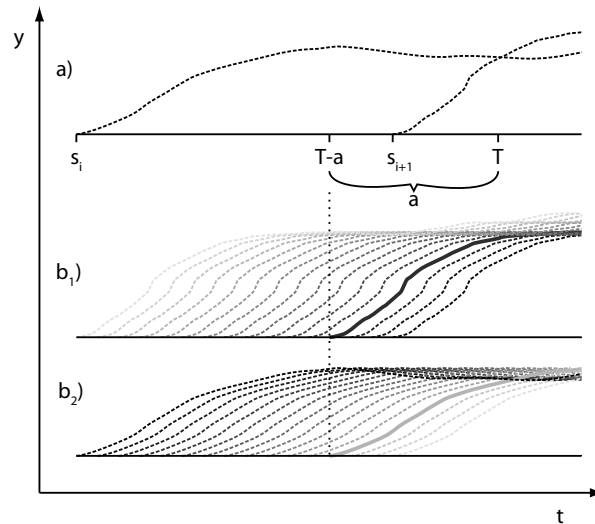


Fig. 2. Principle of GAPPARD applying changing drivers. **(a)** developments of two subsequent trajectories starting from s_i and s_{i+1} ; **(b₁)**, **(b₂)** weight of the trajectory on the calculation of a state variable at time point T with age a for all $T - a$ that are between s_i and s_{i+1} , where T is a year after s_i to which the output variable is calculated and a is the patch age (time since last disturbance). A darker trajectory stands for a bigger influence. The solid lines characterize the weight of the trajectories for $T - a$. Here, the trajectory starting from s_{i+1} has a higher weight because $T - a$ is closer to s_{i+1} than to s_i .

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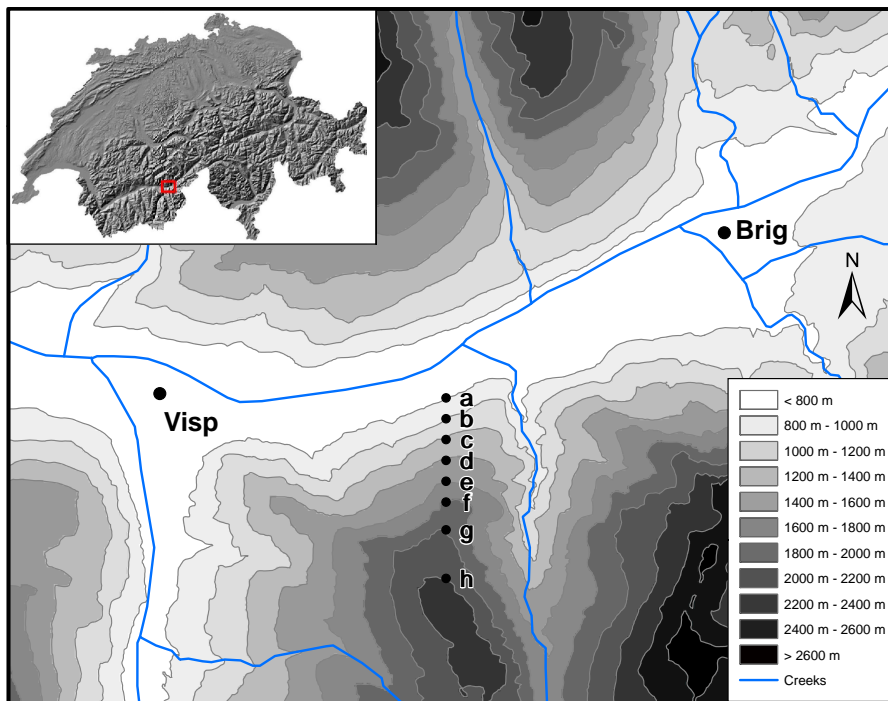


Fig. 3. Terrain around and location of the modeled stands a–h. See Table 2 for detailed values of the stands' altitude.

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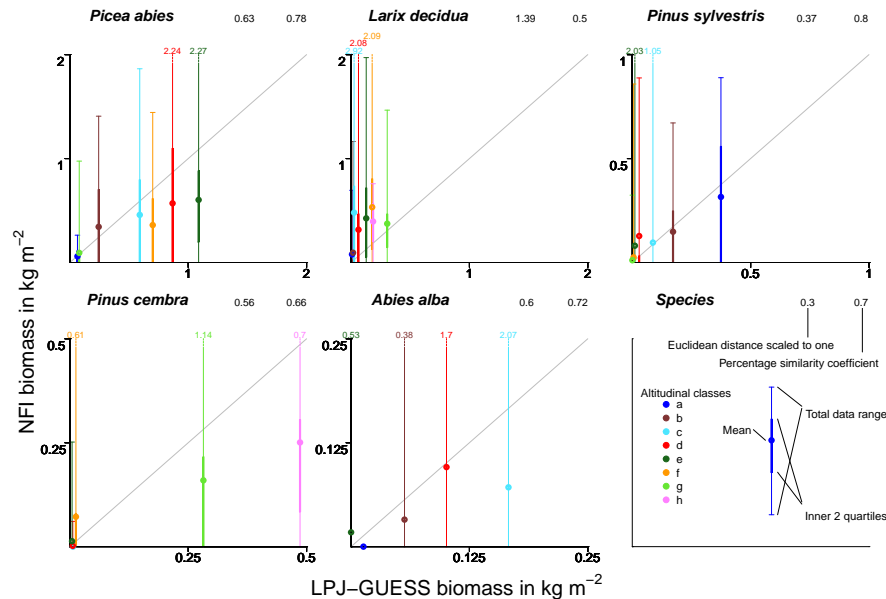


Fig. 4. Comparison of the NFI1 data with LPJ-GUESS runs for main tree species. LPJ-GUESS results were produced using 400 replicate patches and altitude specific disturbances (see RID in Table 2). See the lower right chart for descriptions.

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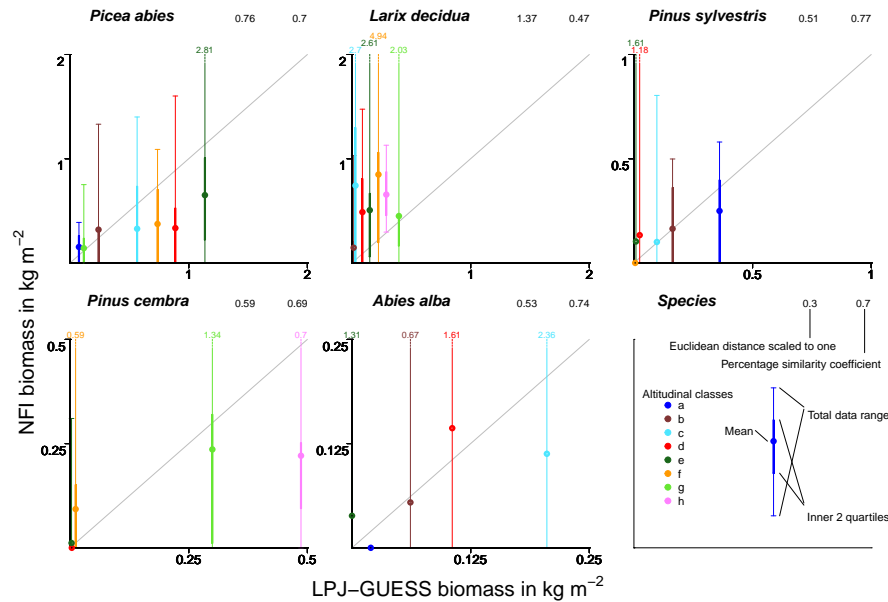


Fig. 5. Comparison of the NFI3 data with LPJ-GUESS runs for main tree species. See Fig. 4 for description.

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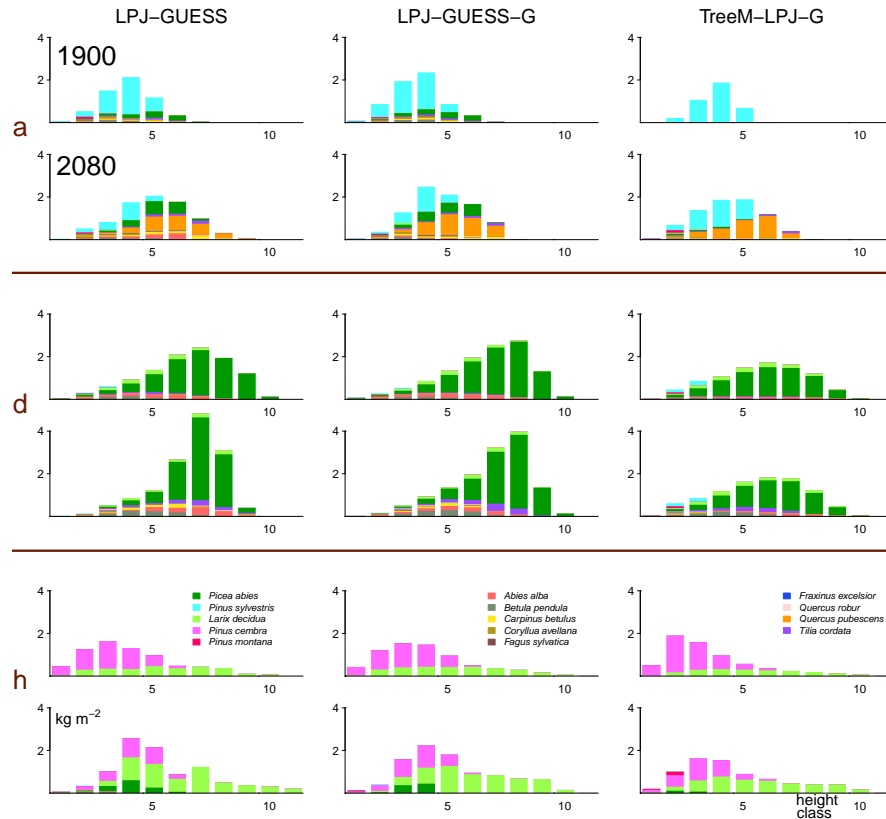


Fig. 6. Simulation results for stands a, d and h for the simulation years 1900 and 2080. Carbon mass per tree species is plotted against tree height classes for LPJ-GUESS using 400 replicate patches (left row), LPJ-GUESS-G (GAPPARD method used on LPJ-GUESS) and TreeM-LPJ-G (GAPPARD method used on TreeM-LPJ). Height class 1: trees 2 m – 6 m height, height class 2: 6 m – 10 m, and so on.

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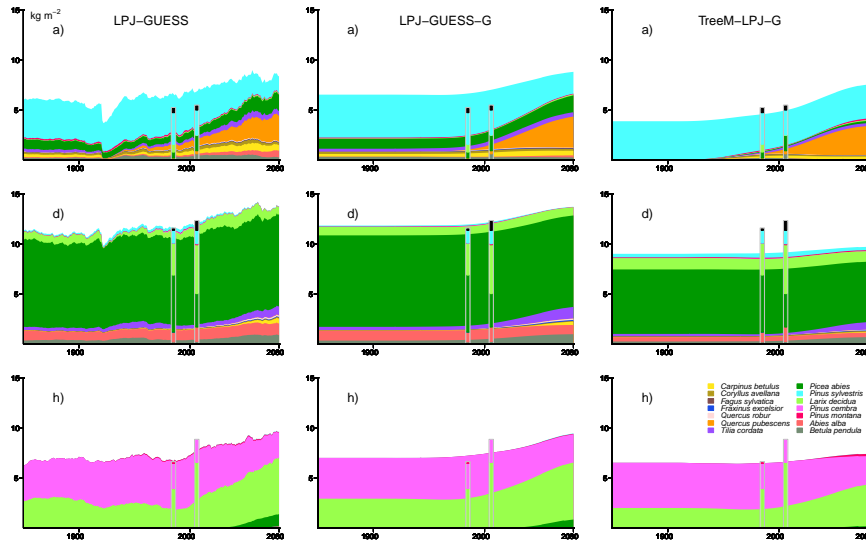


Fig. 7. Single species carbon mass with LPJ-GUESS, LPJ-GUESS-G and TreeM-LPJ-G. LPJ-GUESS: stochastic simulation run using 400 replicate patches, LPJ-GUESS-G and TreeM-LPJ-G: GAPPARD applied to LPJ-GUESS and TreeM-LPJ. Development of carbon mass until 2080. Bars indicate the NFI1 (1985) and NFI3 (2006) data. Black bar sections stand for broad-leaved species that were not modeled.

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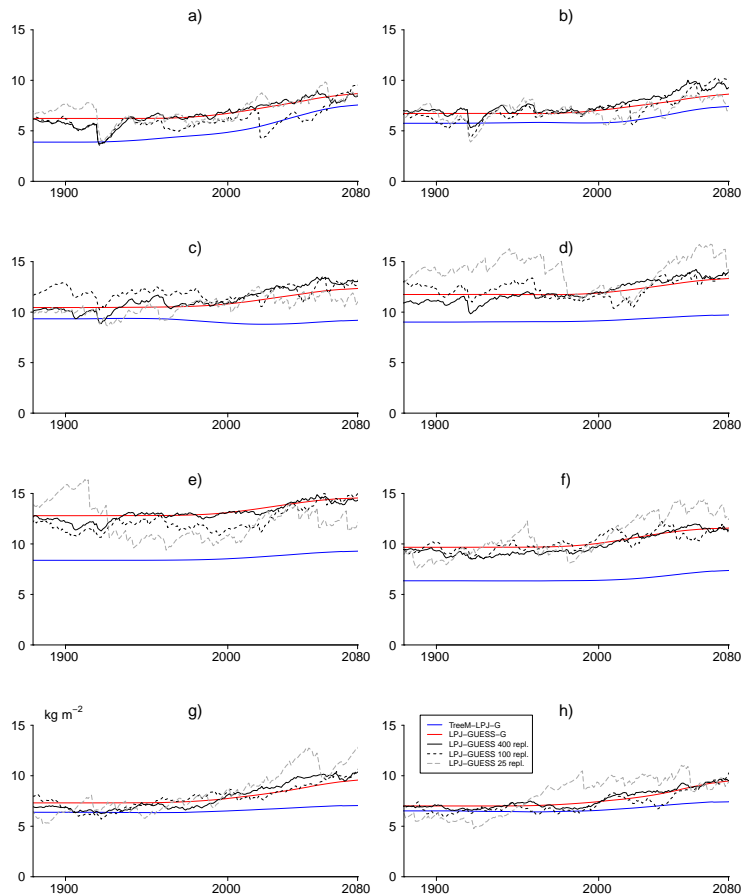


Fig. 8. Tree carbon mass development. Tree carbon mass from spinup time (before 1900) until 2080 with the new GAPPARD method used with TreeM-LPJ (TreeM-LPJ-G) and LPJ-GUESS (LPJ-GUESS-G), and for LPJ-GUESS using 400, 100 and 25 replicate patches.

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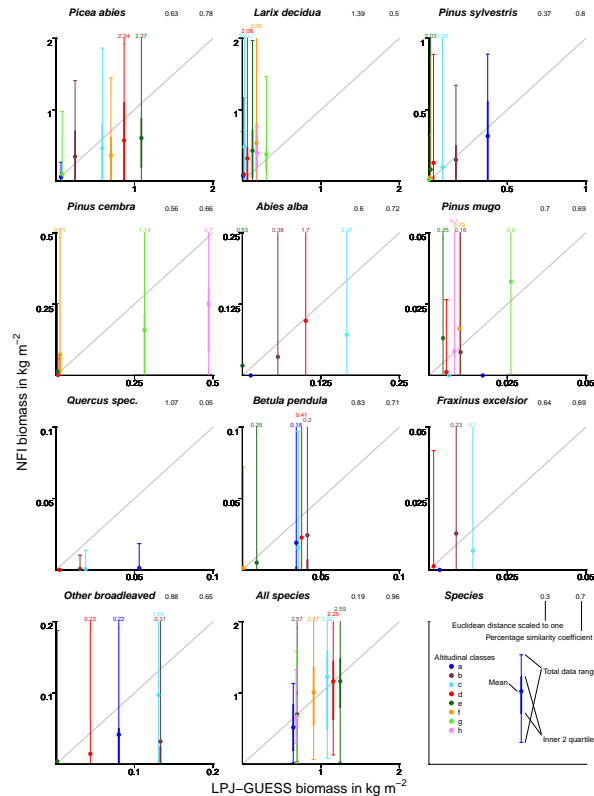


Fig. D1. Comparison of the NFI1 data with LPJ-GUESS runs. LPJ-GUESS results were produced using 400 replicate patches and altitude specific disturbances (see RID in Table 2). See the lower right chart for descriptions.

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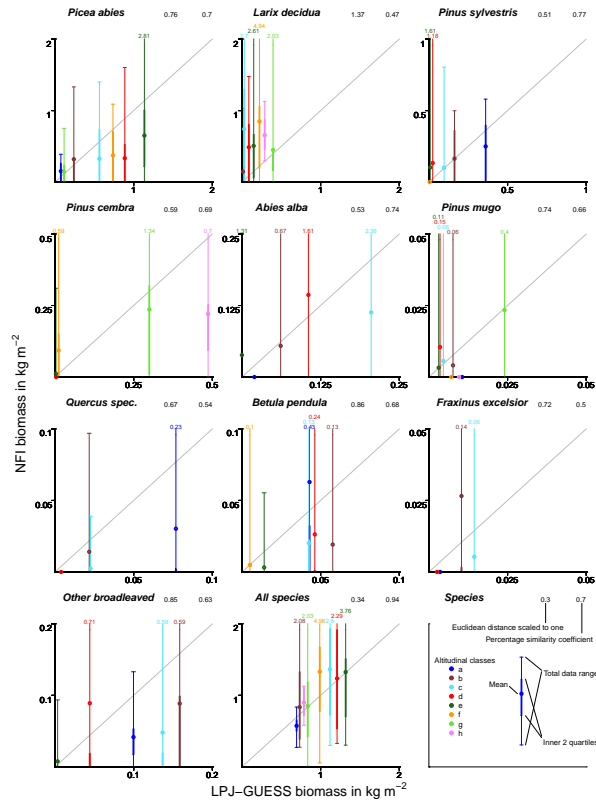


Fig. D2. Comparison of the NFI3 data with LPJ-GUESS runs. See Fig. D1 for description.

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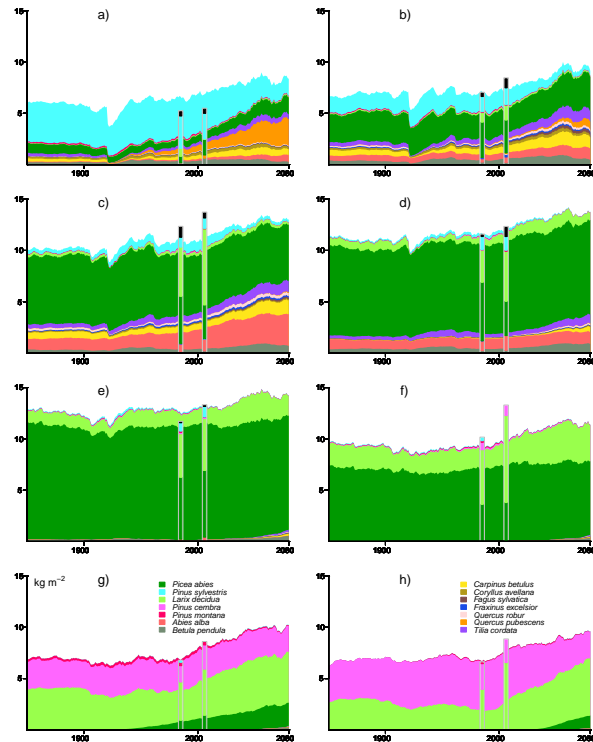


Fig. D3. Single species carbon mass with LPJ-GUESS using 400 replicate patches. Development of carbon mass until 2080. Bars indicate the NFI1 (1985) and NFI3 (2006) data. Black bar sections stand for broad-leaved species that were not modeled.

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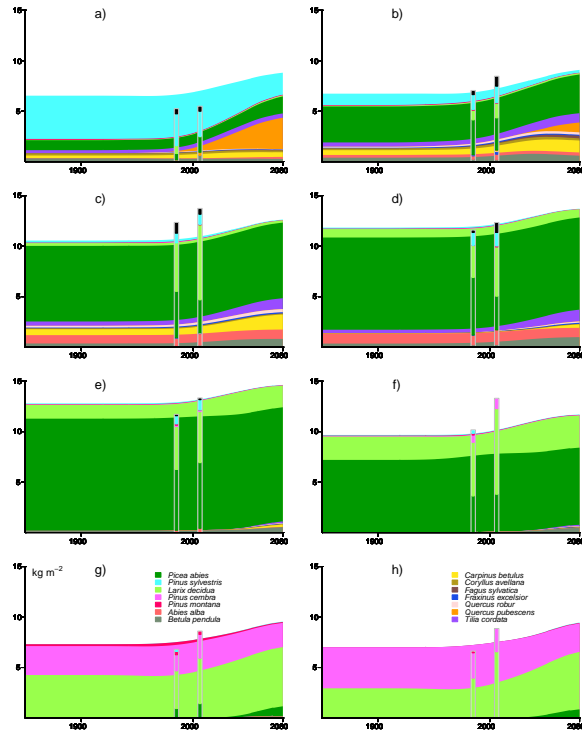


Fig. D4. Single species carbon mass with TreeM-LPJ applying the GAPPARD method. See Fig. D3 for descriptions.

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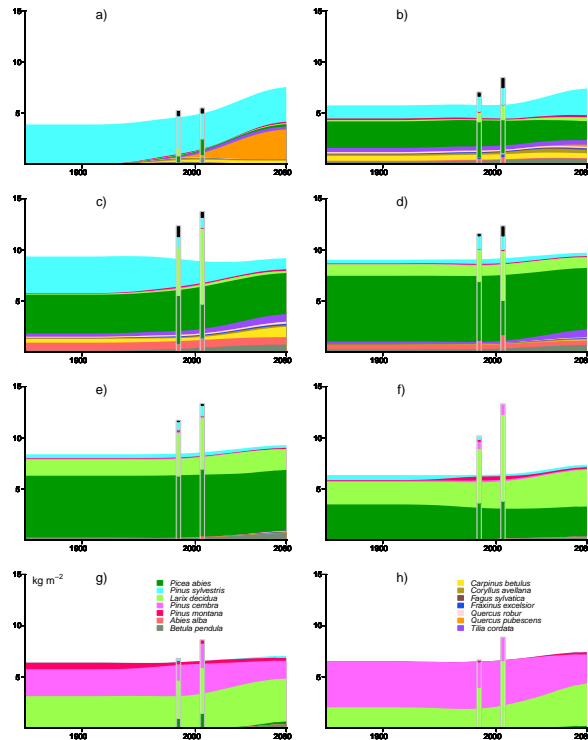


Fig. D5. Single species carbon mass with TreeM-LPJ applying the GAPPARD method. See Fig. D3 for descriptions.

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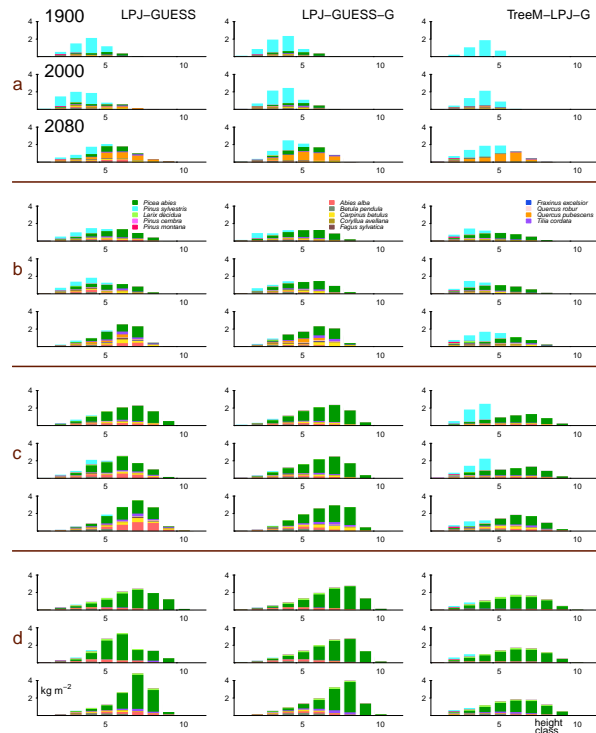


Fig. D6. Simulation results for stands a to d for the simulation years 1900, 2000 and 2080. Carbon mass per tree species is plotted against tree height classes for LPJ-GUESS using 400 replicate patches (left row), and using the new GAPPARD method against LPJ-GUESS (middle row) and against TreeM-LPJ (right row). Height class 1: trees 2 m – 6 m height, height class 2: 6 m – 10 m, and so on.

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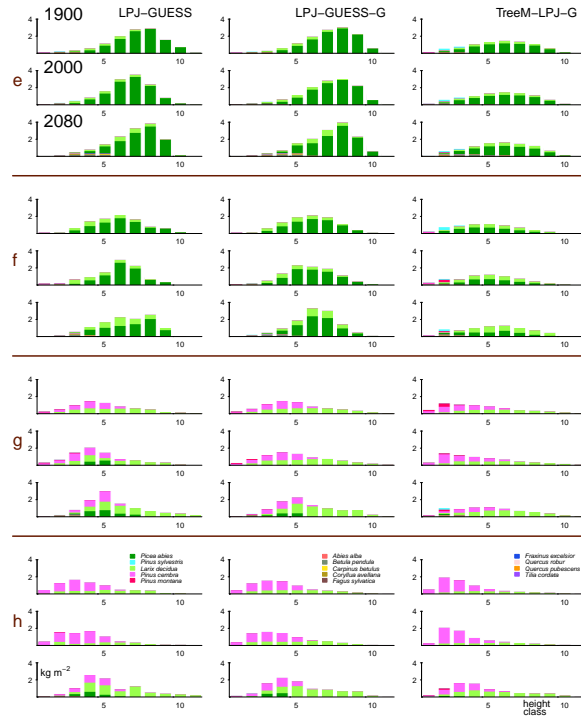


Fig. D7. Simulation results for stands e to h for the simulation years 1900, 2000 and 2080. See Fig. D6 for descriptions.

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