On the role of nutrients, climate and anthropogenic impacts on spatio-temporal variability of forest productivity

PhD Thesis

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to be eligible for the Doctor degree

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Universitat Autònoma de Barcelona, November 2015

Block 3

New methodologies

Chapter 9

The consecutive disparity index, *D*: a new measure of temporal variability in ecological studies

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Under review in *Ecology*, (2015)

Abstract

Temporal variability in ecological processes has attracted the attention of many disciplines in ecology, which has resulted in the development of several quantitative indices. The coefficient of variation (CV = standard deviation · mean^{-1}) is one of the most commonly used indices to assess variability in a broad range of fields in ecology but has several drawbacks when applied to temporal variability: i) it does not take into account the chronological order of the values in a time series and ii) it is negatively dependent on the mean. In this paper we propose the consecutive disparity index (D), a new index to assess temporal variability in ecological studies. We used computer simulations and empirical data for fruit production in trees, bird counts, and rodent captures to compare the performances of D and the CV. We also used computer simulations to test the reliability of D as an early warning signal of abrupt shifts. D was more sensitive to changes in temporal autocorrelation in the negative autocorrelation range, and the CV was more sensitive in the positive autocorrelation range. The CV, however, was highly dependent on the mean of the time series, but D was not. Furthermore, D seemed to act as an early warning signal earlier than other indices such as autocorrelation at lag 1, standard deviation, and the CV. Our results demonstrate that the mathematical and statistical features of D make it a suitable index for analysing temporal variability in a wide range of ecological studies. The advantages of D over the CV (temporal information, lower dependence on the mean) makes this index an ideal complement or even substitute for the CV in studies focused on temporal variability.

1. Introduction

Temporal variability is one of the most intriguing features of natural systems. Knowing how and why systems fluctuate with time is of paramount importance for a better understanding of how they work. The study of temporal variability has, therefore, attracted the attention of a wide variety of empirical and theoretical ecologists, who have studied in various systems using very different approaches among subdisciplines, such as resource pulse ecology (Yang et al. 2008), the study of temporal variability in ecosystemic productivity (Knapp and Smith 2001), the study of chaotic fluctuations of ecosystems (Hastings et al. 1993), the study of population abundances (Heath 2006), or studies of *masting* (Norton and Kelly 1988). Obtaining reliable measures of temporal variability is, therefore, of major importance in these fields of ecology.

Masting is a reproductive phenomenon that occurs at the population or community level. It is the erratic and extremely variable production of fruits, combining years with very large fruit crops and years with very low fruit production, occurring synchronously among individuals (Kelly and Sork 2002, Koenig and Knops 2005). Masting thus serves as an example of interannual variability. Masting behaviour has been numerically described mostly using the indices of the coefficient of variation (CV = standard deviation · mean^{-1}) and temporal autocorrelation (AR, i.e. correlation with previous values at different lags) (Kelly and Sork 2002, Fernández-Martínez et al. 2015). Temporal variability in population abundances has also been extensively discussed (Mcardle et al. 1990, McArdle and Gaston 1995, Leirs et al. 1997, Heath 2006) because of its implications in evolutionary ecology, population dynamics, the transmission of infectious diseases to humans, and the evaluation of extinction risks (Heath 2006). Temporal variability in the field of population dynamics has been mostly assessed using the CV or the standard deviation (SD) of log-transformed time series (i.e. SD[log(N+1)]). A mean fluctuation of 100 individuals represents low variability in a mean population of one million but huge variability in a population of 200. The CV has thus been used more often than the SD.

Temporal variability and autocorrelation have been suggested to increase prior to an abrupt shift in a system (Scheffer et al. 2001, Dakos et al. 2008). These increases in variability and autocorrelation have thus been identified as early warning signals of ecosystems approaching an abrupt shift, so the correct assessment of temporal variability is a very important issue in this field, which is why a large array of indices, such as variance, SD, CV, kurtosis, and skewness (Dakos et al. 2012), has been used to assess changes in temporal variability, but none of them takes into account the chronological order of the time series.

The CV has some limitations describing temporal variability, despite being the most common index for assessing variability (Martín-Vide 1986, Mcardle et al. 1990). First, the CV is, by definition, negatively dependent on the mean of the time series. Comparing time series with very different means may thus lead to biases in temporal variability. Second, two time series with identical means and SDs can have completely different temporal behaviours and hence completely different biological consequences. In Figure 9.1, both time series have the same CV but completely opposite temporal behaviours. The first time series is stable during the first half and shifts to a second state of stability, but the second time series fluctuates every year. This insensitivity of the CV to temporal autocorrelation is the main motivation for the development of the consecutive disparity index, D. D assesses the consecutive variations in a time series and so is sensitive to real time-step to time-step variations.

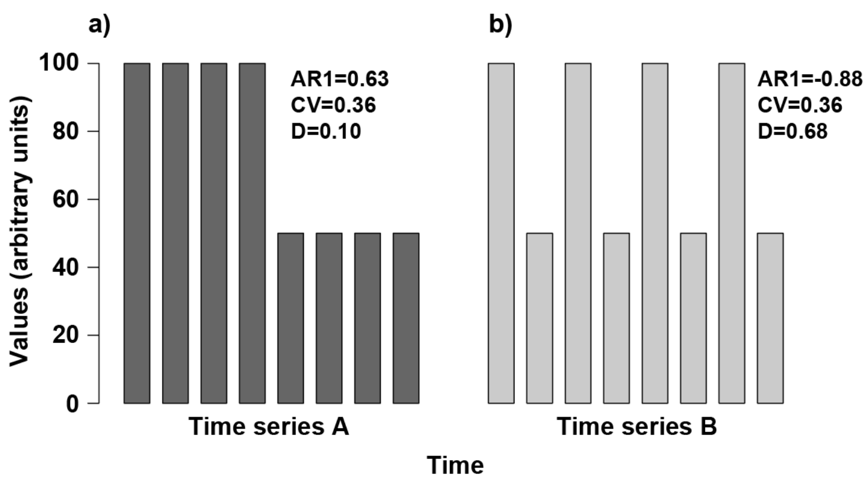

Figure 9.1: Comparison of two time series with equal means and standard deviations but different autocorrelation structures. AR1, autocorrelation coefficient for lag 1; CV, coefficient of variation (standard deviation · mean^{-1}); and D, disparity index (see Eqs. 1 and 2).

D has been used in climate research to better assess interannual variability in the highly irregular precipitation time series of the Iberian Peninsula (Martín-Vide 1986) and is calculated as:

$$D = \frac{1}{n-1} \cdot \sum_{i=1}^{n-1} \left| ln \frac{p_{i+1}}{p_i} \right| \quad \text{Equation 1}$$

where p_i is the series value and n is the series length. To avoid numerical indetermination (division by 0) when a time series contains zeros (which is common in biological data), we can sum a constant (k, usually a unit) to the entire time series as:

$$D = \frac{1}{n-1} \cdot \sum_{i=1}^{n-1} \left| ln \frac{p_{i+1}+k}{p_i+k} \right| \quad \text{Equation 2}$$

The core of D lies in the assessment of the variability by taking into account the consecutive changes in a time series (see Eqs. 1 and 2).

The aim of this study is to demonstrate the advantages of D over the CV for capturing temporal variability in different ecological time series and for different types of studies, focusing the analyses on interannual and intra-annual variability and on the early warning signals in time series approaching an abrupt shift. We thus first performed a computer simulation to demonstrate the different behaviours of the D and CV indices relative to that of temporal autocorrelation. We then validated the simulation using time series of annual fruit production from different species of trees in European forests derived from the ICP Forests dataset on litterfall (http://icp-forest.net/), annual bird counts of several species from Quebec (Canada) for 1966–2014 (Pardieck et al. 2015), and a monthly time series of rodent captures from an experimental manipulation in the Chihuahuan desert (Morgan Ernest et al. 2009). Finally, we used computer simulations to compare the behaviour of D to that of the autocorrelation coefficient at lag 1 (AR1), the SD, and the CV in the study of early warning signals in systems approaching an abrupt shift.

2. Materials and methods

2.1. Simulations

To study the responses of the CV and D indices to different chronological orderings of the time series, we investigated the relationships of the D and CV indices with AR1. We simulated autocorrelated time series with an AR1 autoregressive structure (autoregressive [p] and moving average [q]: ARMA [p=1, q=0] and autocorrelation for lag 1: φ_1 = -0.95 to 0.95) using the "*arima.sim*" function in R (R Core Team 2015). The function was programmed to simulate time series of 100 000 random numbers using a negative binomial distribution with a mean (μ) of 100 and a size (or inverse of the dispersion) of 1 and removing the first 100 simulated values to stabilise the values. Negatively autocorrelated time series generated negative numbers, which have no biological meaning for fruit production, so negative values were transformed to 0. We then calculated the D and the CV indices for each value of φ_1.

To explore the suitability of D to detect early warning signals before critical transitions, we simulated time series that shifted abruptly using a similar approach to previous studies (Dakos et al. 2012, 2013). We simulated a time series with 1500 time steps in which AR1 increased from φ = 0.1 to 0.95, the mean decreased by 0.1 per time step, and the SD increased by 0.025 per time step. We then analysed the evolution of the time series in terms of AR1, SD, and CV to compare it with the evolution of D, using a moving window of 500 time steps. We first fitted a locally weighted regression (Cleveland 1979) to the simulated data using the "*loess*" function in R (R Core Team 2015). We chose a bandwidth that did not overfit our data but removed the trends within the time series. We then used the residuals to calculate several indicators of early warning signals such as the AR1, SD, and CV (Scheffer et al. 2009, Dakos et al. 2012) to compare it with the performance of D. Negative or null values can be problematic for calculating the CV and D indices, so we summed a constant (the highest absolute value) to the residuals to make the entire time series positive. This modification in the time series changed the mean values of CV and D in the time series (otherwise D could not be calculated) but not the temporal evolution of the indices, which was the objective for studying the suitability of the CV and D indices as early warning signals of abrupt shifts. The global trend of the indices was calculated using Kendall's rank correlation, τ (Kendall 1938).

2.2. Data for fruit productions, bird counts, and rodent captures

To validate the computer simulation of the relationships of AR1 with the D and CV indices, we downloaded litterfall data from the ICP forests database (International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forest, operated under the UNECE Convention on Long-range Transboundary Air Pollution, http://icp-forest.net/), containing data for fruit production for several forest tree species in Europe. The database contained data from 210 plots, for which only 113 could be used in models (only plots with at least five consecutive years of data were used). fruit production was summarized per plot and year in g C m^{-2} y^{-1}. We calculated the D, CV, and AR1 indices and the average value of the time series for each plot.

We also used data from the North American Breeding Bird Survey Dataset 1966–2014 (Pardieck *et al.* 2015, www.pwrc.usgs.gov/BBS/RawData). Bird-count data per year and species were downloaded for Quebec (Canada) for 242 species. Similarly to the fruit-production data, we calculated the D, CV, and AR1 indices and the average counts for each species.

We obtained rodent data from a long-term (1978–2002) monitoring and experimental-manipulation study in the Chihuahuan Desert ecosystem (Morgan Ernest et al. 2009) and calculated monthly captures and annual mean monthly captures. We then calculated the annual D and CV indices as an example of an assessment of intra-annual variability.

2.3. Statistical analyses

We performed linear regressions using ordinary least squares to correlate the D and CV metrics to AR1 for the data for fruit production and bird counts. We also constructed models in which D and CV were to be predicted by AR1, the log-transformed mean of the time series, and the CV or D metrics, respectively, to determine which part of the variance in the D and CV indices is explained by the chronological order (AR1) of the time series, the variability (CV and D), and the mean. We next used the relaimpo package (Grömping 2006, 2007) in R (R Core Team 2015) to assess the variance explained by the predictors using the proportional marginal variance decomposition (PMVD metric).

3. Results

Our simulation showed that the scaled (mean = 0, SD = 1) D and CV indices behaved differently than temporal autocorrelation at the first lag (AR1, Figure 9.2). D strongly decreased from very negative to neutral AR1 values, and the CV decreased very slowly. The behaviours of both indices, however, were reversed for positive values of AR1: the CV decreased steeply with increasing AR1, and D decreased slightly. The characteristic exponential-like distribution of the data of the negative binomial distribution (e.g. the fruit-production data, histogram in Figure 9.3), though, became a Gaussian-like distribution for positive AR1.

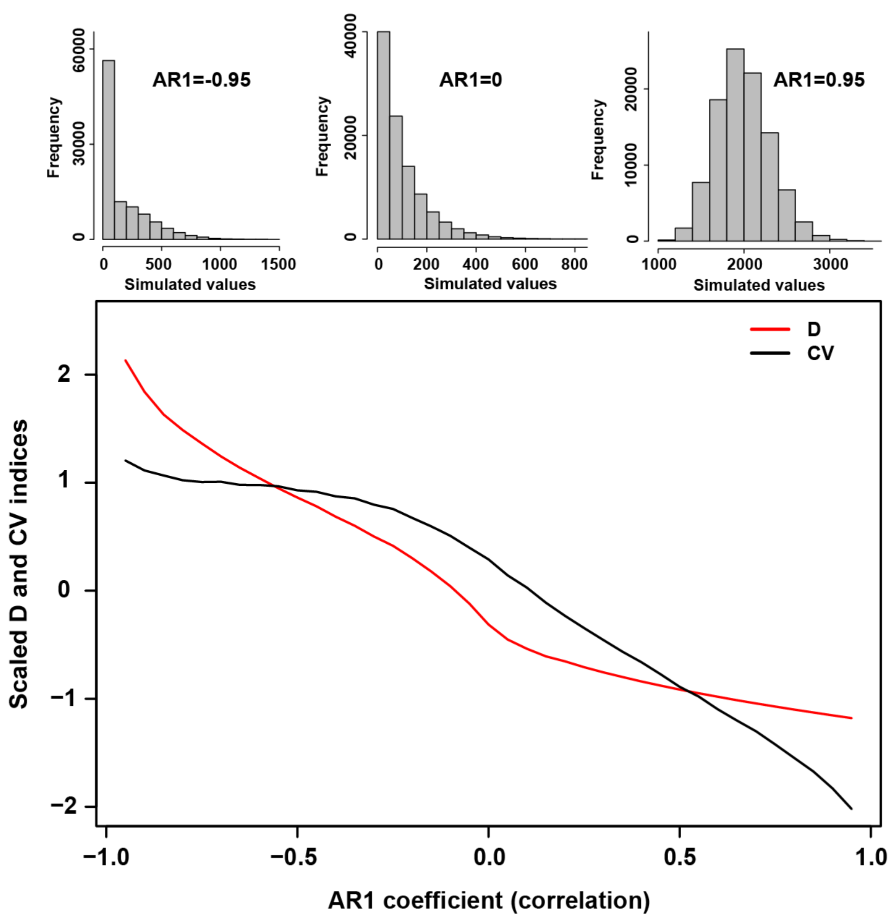

Figure 9.2: Simulated changes in scaled (mean = 0, SD = 1) disparity (D) and CV indices with changing temporal autocorrelation structures for lag 1 (AR1). The three histograms indicate the distribution of the data for autocorrelation coefficients of -0.95, 0, and 0.95.

The fruit-production data were mostly negatively autocorrelated (Figure 9.3) and indicated that D had a logarithmic negative association with AR1 (R^2=0.26, P<0.001), but the CV was not correlated even weakly (Figure 9.3). The D and CV metrics differed most for negative AR1 values. Linear models predicting D for the fruit-production data using CV and AR1 metrics and the log-transformed mean of the time series as predictors explained 63% of the variance in D. AR1 and CV were negatively and positively correlated with D and accounted for 21 and 34% of the variance in D, respectively, and the mean was positively correlated with D and explained only 8% of the variance (Table 9.1). The model correlating the fruit-production CV with AR1, D, and the mean accounted for 79% of the variance in the CV. AR1 explained only 4% of the variance in the CV, and D accounted for 50% of the variance (both AR1 and D were positively correlated with the CV), and the mean, which was negatively correlated with CV, explained 25% of the variance in the CV (Table 9.1).

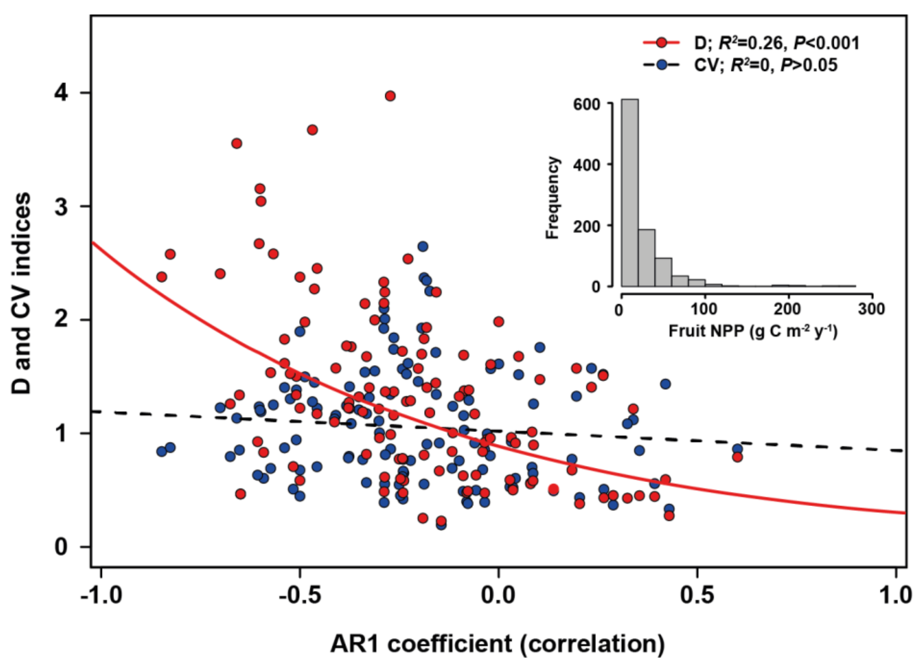

Figure 9.3: Relationships between AR1 and the D and CV indices for fruit production. The inset shows the distribution of the fruit-production data. NPP, net primary production.

In contrast to the fruit-production data, the bird-count data were mostly positively autocorrelated (Figure 9.4). D was not significantly associated with AR1, and the CV was negatively correlated with AR1 (R^2=0.41, P<0.001, Figure 9.3). Linear models predicting D for the bird-count data explained 31% of the variance in D. Both AR1 and CV were negatively correlated with D and accounted for 10 and 14% of the variance in D, respectively. The mean of the time series was positively correlated with D and explained 7% of the variance (Table 9.1). The model correlating the fruit-production CV with AR1, D, and the mean accounted for 69% of the variance in the CV, and AR1, D, and the mean explained 10, 4, and 55% of the variance, respectively, and all were negatively correlated with the CV (Table 9.1). These results indicate that the CV is highly dependent on the mean of the time series, but D is weakly dependent on the mean.

Table 9.1: Summary of models correlating the D and CV indices with AR1, D or CV, and the natural logarithm of the mean (Ln mean) of the time series. The regression coefficients are beta weights (β, standardised coefficients) ± standard error (SE). The proportional marginal variance decomposition (PMVD) metric (Grömping 2007) is also shown as a measure of the explained variance (R^2). All coefficients were significant at the 0.001 level. D was log-transformed for the CV model for fruit production.

	D			**CV**	
	β ± SE	***R²***		**β ± SE**	***R²***
Fruit production					
AR1	-0.40 ± 0.06	0.21	**AR1**	0.22 ± 0.05	0.04
CV	0.71 ± 0.07	0.34	**D**	0.83 ± 0.05	0.50
Ln mean	0.34 ± 0.07	0.08	**Ln mean**	-0.49 ± 0.04	0.25
Bird counts					
AR1	-0.69 ± 0.08	0.10	**AR1**	-0.32 ± 0.06	0.10
CV	-0.50 ± 0.09	0.14	**D**	-0.23 ± 0.04	0.04
Ln mean	0.40 ± 0.10	0.07	**Ln mean**	-0.49 ± 0.06	0.55

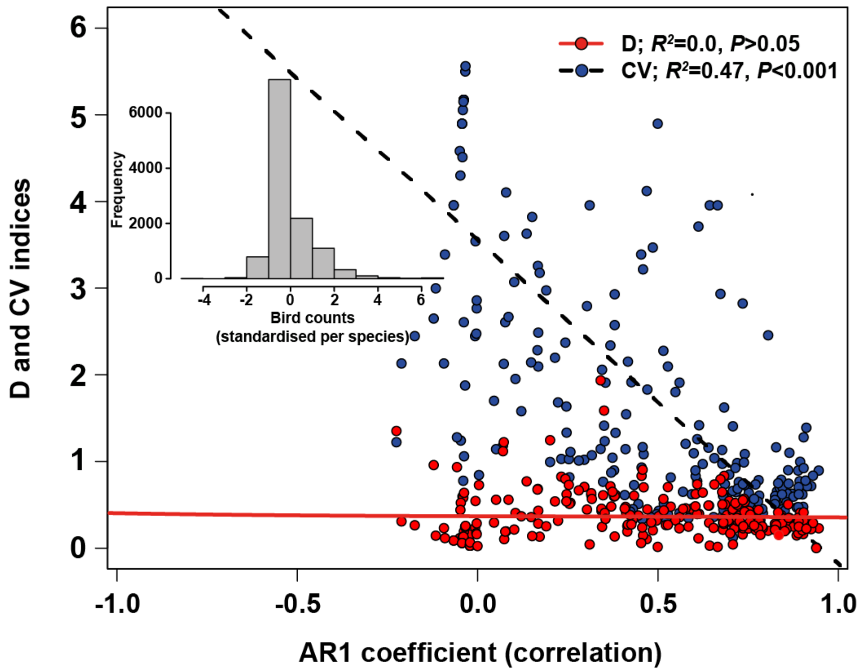

Figure 9.4: Relationships between AR1 and the D and CV indices for bird counts per species. The inset shows the distribution of the bird-count data.

Both indices can also be used to assess intra-annual variability (Figure 9.5). The D and CV indices behaved similarly (R=0.78; P<0.001) when assessing intra-annual variability using the monthly rodent data (Figure 9.5, a). The intra-annual index values, however, can be quite similar or dissimilar, even independently of the AR1 index, depending on the behaviour of the captures within a year (Figure 9.5, a and b). Both indices provided the same value for captures in 1978, which peaked twice during the year (Figure 9.5, b). Rodent captures in 1990 mostly declined from January to September and then increased until December (Figure 9.5, c). The progressive evolution of rodent captures led to higher CVs than D values. These results highlight the different behaviours of the CV and D indices with the chronological order of the values within a time series.

D was also useful for detecting early warning signals in time series approaching critical transitions. Figure 9.6 shows the analyses of a simulated time series with progressively increasing AR1 and variance and decreasing mean, which is typical of a system approaching an abrupt shift (Scheffer et al. 2009). D (Figure 9.6, d) responded as well as the other indices to the proximity of a critical transition for calculations of the AR1, SD, D, and CV indices for a window of 500 time steps (Figure 9.6, c–f). Interestingly, D had a higher slope (t-test, P<0.001) than the AR1, SD, and CV at the beginning of the time series (using the first 200 time steps) of the evolution of the indices. Further simulations with different initial autocorrelation values (increasing initial φ_1 [autocorrelation] from -0.85 to 0.85 and ending at 0.95) produced identical results. D may thus have the potential to act as a warning signal earlier than the AR1, SD, and CV indices. Nonetheless, D had a slight deceleration in the increasing trend, as predicted by our simulations and inversely to the SD and CV indices, which increased more steeply when AR1 increased to very positive values (Figure 9.2). The result was steeper increases in the SD and CV indices immediately before the abrupt shift, in contrast to D which tended towards stabilisation.

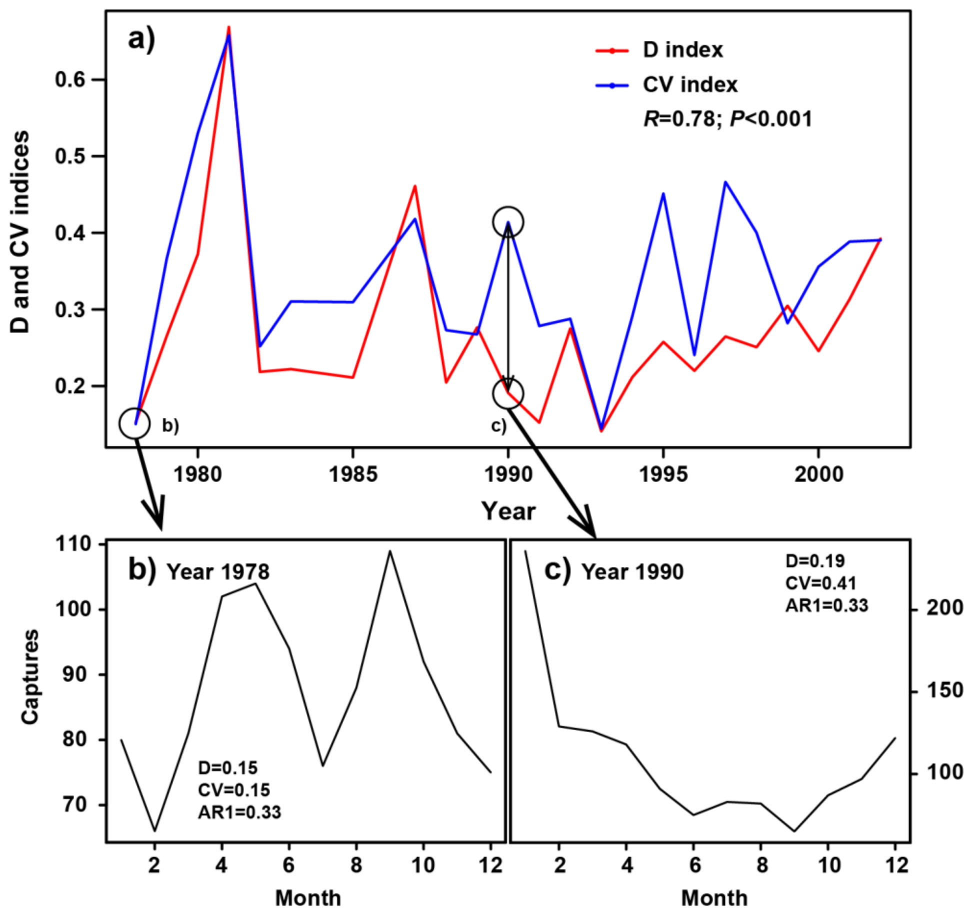

Figure 9.5: a) Intra-annual variability of rodent captures measured with the D and CV indices. The years with the minimum and maximum differences between the D and the CV indices are marked with a circle (1978 and 1990, respectively). Panels b) and c) show the monthly captures for 1978 and 1990.

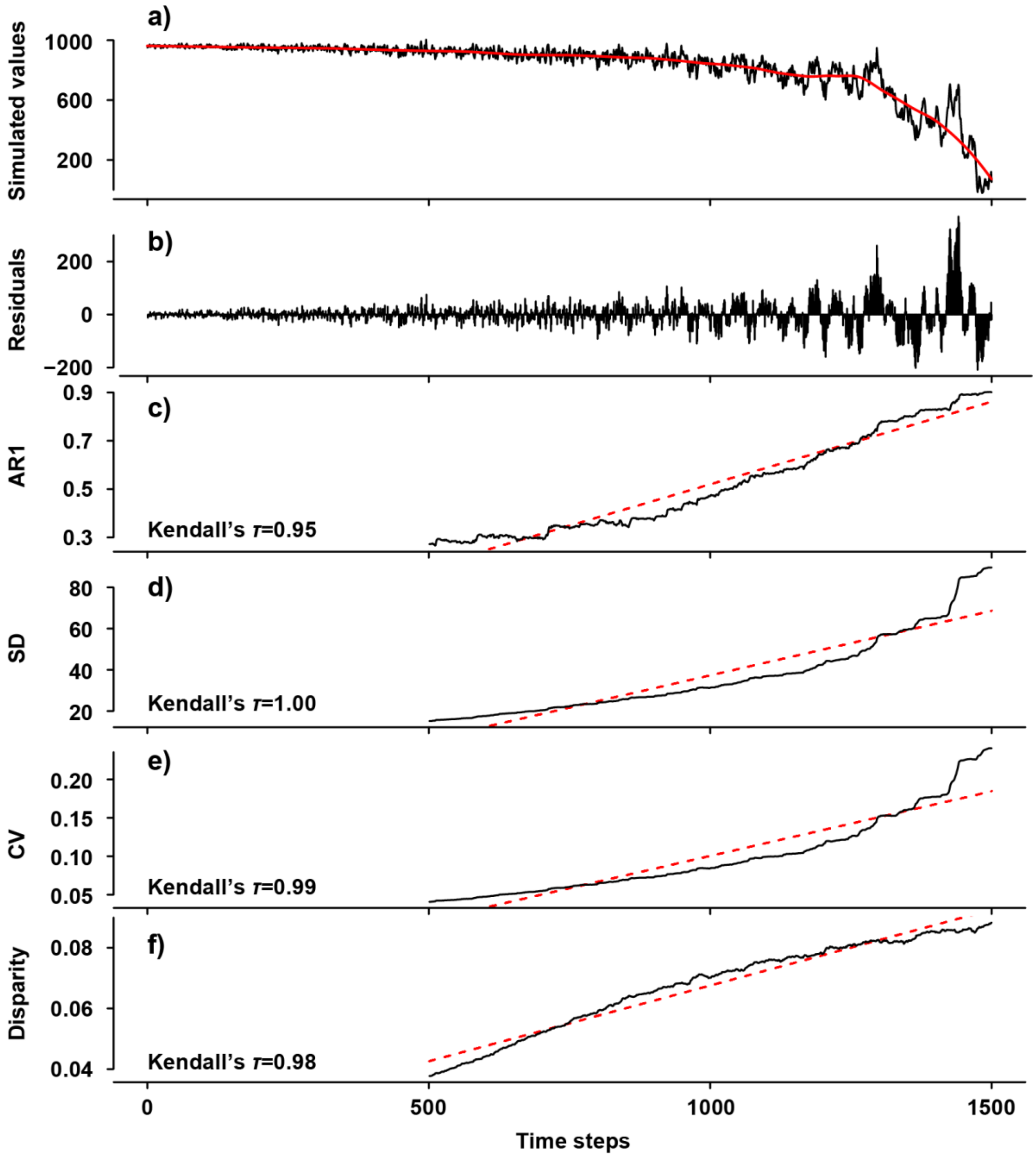

Figure 6: Analysis of early warning signals in a simulated time series approaching an abrupt shift. a) The simulated time series (see methods for further details on the simulation). The red line indicates the trend calculated using a locally weighted regression (Cleveland 1979). b) The residuals of the trend. The evolution of the early warning indicators c) AR1, d) SD, e) CV, and f) D. All indicators were calculated for 500 time steps. The trend of the indicators is shown with dashed red lines, and the Kendall's rank correlation (τ) is also shown.

4. Discussion

The analyses of the fruit-production and bird-count datasets confirmed the results of our simulation suggesting that D was more sensitive to changes in time series with negative temporal autocorrelations, whereas the CV was more variable when comparing positively autocorrelated time series. This opposite behaviour is because D calculates temporal variability within each time step (see Eqs. 1 and 2) and is thus sensitive to the chronological order of the time series, whereas the CV is blind to the order. Our results also confirmed the higher dependence on the mean of the CV compared to D, which carries important implications for the correct assessment of temporal variability. D was also reliable as an early warning signal in time series approaching an abrupt shift. In light of these results, the application of D in the field of ecology is justified.

4.1 Possible applications of D in ecology

A broad range of ecological subdisciplines involves temporal variability, such as resource pulse ecology, population ecology, or the study of non-linear dynamics in ecosystems. Any field needing to evaluate temporal variability can thus potentially benefit from the use of D, as shown by our analyses. Masting studies have particularly often relied on describing the behaviour of fruit production using CVs and temporal autocorrelation (Sork et al. 1993, Herrera et al. 1998, Kelly and Sork 2002). D may represent an opportunity to explore masting with an aggregated index combining the information of both CVs and temporal autocorrelation, which would help to better characterize the interannual variability in fruit production (i.e. the higher the D index, the stronger the masting behaviour because of the higher interannual variability and stronger negative autocorrelation for lag 1). Nonetheless, the most interesting advantage of D compared to the CV may be its much reduced dependence on the mean (Table 9.1). Large differences in the mean of fruit production might occur when comparing the reproductive behaviour of different species (or populations), fruit which might result in underestimates of temporal variability in species with large means, given the negative relationship between the mean and the CV (Table 9.1), which could lead to erroneous biological conclusions. This potential bias applies also for population ecology (e.g. bird counts). Comparing temporal variability for species or populations with very different means could lead to erroneous conclusions, because the variance explained by the mean of the time series can be as high as 55% (Table 9.1). We therefore recommend that these types of studies support their analyses with other indices whose values do not strongly rely on the mean of the time series. D would be a good choice for avoiding this drawback of the CV.

D could be useful in the study of resource ecology to characterise different temporal patterns of resource pulses. Biologically, it has different implications if a population, a species, or a community produces pulses of resources with low or high disparity (time series A and B in Figure 9.1). In time series A with low D (Figure 9.1, a), the system shifts from one state with large resource availability to another with fewer resources to which populations of fruit consumers must adapt, but only once during the time series. In time series B with high D, (Figure 9.1, b) the pulses of resources are intermittent, so the population of consumers will fluctuate with the pulses with a time delay (Clotfelter et al. 2007). The biological strategies and evolutionary or behavioural adaptations of organisms living under these two regimes of resource pulses would necessarily differ (Owen-Smith 2008, Yang et al. 2008). D combined with the CV might then be used to assess the kind of behaviour of the system and allow comparisons among systems.

Several indices have been used to detect early warning signals in systems approaching an abrupt shift, such as variance, AR1, SD, CV, kurtosis, and skewness (Scheffer et al. 2009, Dakos et al. 2012, 2013), but D has not yet been used. Our results demonstrate that D can be as reliable for detecting early warning signals as the more commonly used indices. Our analyses also indicate that using D might identify the proximity of an abrupt shift in the state of a system even earlier than the AR1, SD, and CV indices (Figure 9.6), which represents an advantage over the other indices. In contrast to the SD and CV indices, D saturates immediately before an abrupt shift. This more distant proximity to critical transitions suggests that D could have practical applications for anticipating critical scenarios when managing endangered species or ecosystems or in the study of early warning signals.

D is an easy metric to obtain and has a large potential use in the field of ecology that could help to mitigate some of the drawbacks of the other indices that have traditionally been used to assess temporal variability (e.g. the CV).

6. Conclusions

Our results, based on numerical simulations and empirical data, indicate that D can, in most cases, be more suitable than the CV for assessing temporal variability. D would be more suitable when time series are negatively autocorrelated (as is often the case when analysing fruit-production data such as in masting studies). D varies not only with temporal variability but also with the degree of autocorrelation, so using only one index (D) would allow the capture of both variability and temporal autocorrelation in similar proportions, which could be useful for example in masting studies. D would be more suitable when comparing temporal variability in time series with very different means or when assessing the evolution of the temporal variability of a time series and changes in the mean. D would also be more suitable in the study of early warning signals; our results suggest that D can detect a future abrupt shift earlier than the common indices (AR1, SD, and CV). D behaved similarly to or better than the CV in all the situations we tested. Given the information D provides and the lower dependence on the mean compared to the CV, we recommend that D should be introduced in ecological studies with temporal variation, at least, as a support for the CV.

Acknowledgements

This research was supported by the European Research Council Synergy grant ERC-2013-SyG 610028-IMBALANCE-P, the Spanish Government grant CGL2013-48074-P, and the Catalan Government projects SGR 2014-274 and FI-2013. SV is a Postdoctoral Fellow of the Research Foundation – Flanders (FWO).

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10. General discussion

Across the chapters of this thesis we have tried to improve our knowledge on the features and functionality of forests on the responses of forest ecosystems to multiple endogenous and exogenous factors. We have specially focused our research on the effects of climate, weather variability and nutrient availability on vegetative and reproductive forest productivity. Although some of our research has provided further support to previous results and well known and pre-established theories, we have also developed new hypotheses that have enlightened poorly explored mechanisms that surely deserve to be studied further. The results of this thesis open the door to a wide range of new ideas and hypotheses worth to test in the near future. This thesis is also a good example of what the so called "*big data*" can offer to ecologists and environmental scientists.

What we have learnt

At the beginning of the thesis (Chapter 1) we provide a global synthesis of what forest ecosystems are and how they function. We found that stand age, water availability, and length of the warm period were the main factors controlling forest structure and functionality. However, resource-use efficiency (of light and water) were rather constant across different biomes. Standing biomass and carbon fluxes were strongly correlated to each other at the global scale and both were controlled by climate (mainly water availability and temperature) and stand characteristics such as the age of the stand or leaf type. Additionally, the interaction between temperature and precipitation was the main climatic driver of gross primary production and ecosystem respiration. However, carbon sequestration was mainly correlated to nitrogen deposition and that triggered our second chapter.

The scientific community already knew that tropical forests, which are usually nutrient limited, do not sequester most of the carbon they photosynthesize and that forests receiving high loads of nitrogen deposition sequestered more carbon than those growing under lower rates of nitrogen deposition (Chapter 1). Previous research also pointed out that fertile forests produce biomass more efficiently (Vicca et al. 2012) while soils subjected to high loads of nitrogen deposition respire less than those subjected to lower rates of nitrogen deposition (Janssens et al. 2010). We therefore checked whether nutrient-rich forests sequestered more carbon than nutrient-poor forests. We found that, indeed, nutrient-rich forests sequester 33 ± 4% of photosynthesized carbon while nutrient-poor forests only sequester 6 ± 4% of it (Chapter 2). At the ecosystem level, this effect of nutrient availability was independent of climate, stand age or the management of the stand.

And we started analyzing the signal of nutrient availability at a closer scale, looking at different forest compartments such as foliage, branches, stems and coarse and fine roots. We found that, once the effect of stand age was removed, nutrient availability and climate played a crucial role in determining the biomass-to-net primary production ratio (B:NPP, as a surrogate of mean residence time of carbon) of woody and non-woody tissues (Chapter 3). But nutrient availability had a different effect depending on the forest compartment. Whereas the B:NPPs of woody tissues (branches, stems, and coarse roots) were positively influenced by nutrient availability, it had a negative effect on the fine root fraction. B:NPP of the fine foot fraction was also positively correlated to thermal amplitude and precipitation seasonality.

The first three chapters were focused on average values per ecosystem. However, ecosystems usually lie in a sort of *dynamic equilibrium state* (Begon et al. 1996, Hougthon 2009) and therefore, are constantly modulating their functionality to better fit the environment including anthropogenic impacts. Hence, in Chapter 4 we looked for the effects of increasing atmospheric CO_2 concentrations, changing nitrogen and sulphur atmospheric deposition rates and the changing climate on gross primary production, respiration and net primary production. We found that increasing CO_2 has increased gross primary production and carbon sequestration, on average, by 1% annually from 1995 to 2011. We also found that the reduction of sulphur deposition in Europe and the USA involves a higher recovery in ecosystem respiration than in gross primary production, limiting the increase of carbon sequestration. By contrast, trends in climate and nitrogen deposition barely contributed to changing carbon fluxes.

Despite vegetative productivity plays the key role on forest carbon balance, the production of fruits demands a fraction of the photosynthesized resources that greatly varies among years (Herbst et al. 2015). In Chapter 5 we found that fruit production ranges from 10 to 40 g C m^{-2} y^{-1} and uses around 0.5 - 3% of the photosynthesized carbon in European forests. We also found that forests enriched with foliar zinc and phosphorous concentrations, produced larger fruit crops and presented less irregularity in interannual fruit crop size than those limited in zinc and phosphorous. However, foliar nitrogen concentration, associated to broadleaved species, the C:P ratio and temporal variability in annual precipitation were aligned with higher temporal variability in fruit crop size. Our results, highlighted, for the first time, that foliar nutrient concentration of N, P and Zn and foliar nutrient stoichiometries determine the percentage of photosynthates allocated into reproduction, fruit net primary production and its temporal behaviour in European forests.

In Chapter 6, we found that interannual variability and synchrony in fruit production (*masting*) was controlled by the interannual variability of the North Atlantic Oscillation, having a more prominent importance than local weather variables in predicting it. The relationships emerged from these analyses supported both the *resource matching* and the *pollination efficiency* hypotheses. On the other hand, synchrony in fruit production between forests was mainly controlled by the degree of synchrony of forests to the winter NAO rather than to weather variables. Our results pointed out the Moran effect as the most likely mechanism for synchronization of fruit production at large geographical scales although we could not discard the possibility that *pollen coupling* plays a role in synchronizing fruit production at local scales.

In Chapter 7, we continued testing *masting* hypotheses, at the local scale, in *Quercus ilex* and *Quercus pubescens* stands. We found that spring water deficit was the most relevant factor in explaining inter-annual variability in acorn production in both species and that inter-annual differences in pollen production did not influence acorn crop size. These results provided evidences supporting the *resource matching* hypothesis for the two species. Spring water deficit was also the main factor affecting synchrony in fruit production among forests supporting the Moran effect.

However, not only weather variability can be used to predict fruit crop size or *masting* behavior. In Chapter 8 we demonstrated that fruit production can also be predicted using remotely sensed vegetation indices, such as the enhanced vegetation index (EVI). Our results suggested that fruit crop size in *Quercus ilex* was driven by a combination of two factors, i.e. good and improving vegetation conditions (detected via EVI several months prior to fruit harvest), and the need of wet weather conditions during spring. Results from Chapters 6 and 8 call for a renewed point of view of weather variability driving *masting* in forests.

Finally, in Chapter 9 we introduce the consecutive disparity index, D, as a measure of temporal variability for ecological studies. We demonstrate the usefulness of the index and the advantages with respect to the coefficient of variation (CV). We found the D index to be less dependent on the mean than the coefficient of variation and to take into account the autocorrelation of the time series. Further, the D index responded early than the CV index to time series approaching an abrupt shift (with increasing variance and autocorrelation). Overall, the D index seems to be a good candidate to substitute, or at least to complement, the CV index in studies focused on the evaluation of temporal variability.

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Supplementary material

Supplementary Material

Chapter 1
Spatial variability and controls over biomass stocks, carbon fluxes, and resource-use efficiencies across forest ecosystems

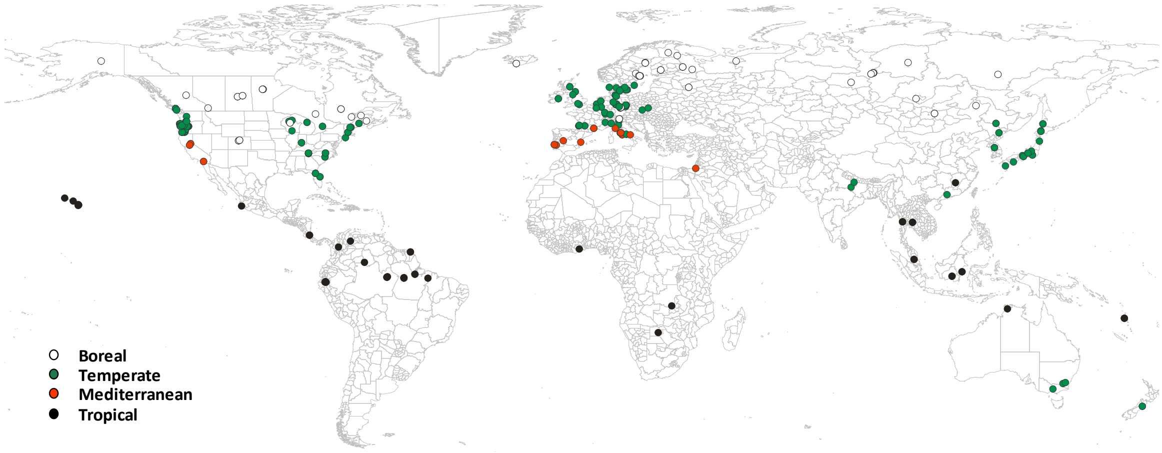

Figure S1.1: Global map of the forest sites in the study containing estimates for stand biomass, carbon flux, or both.

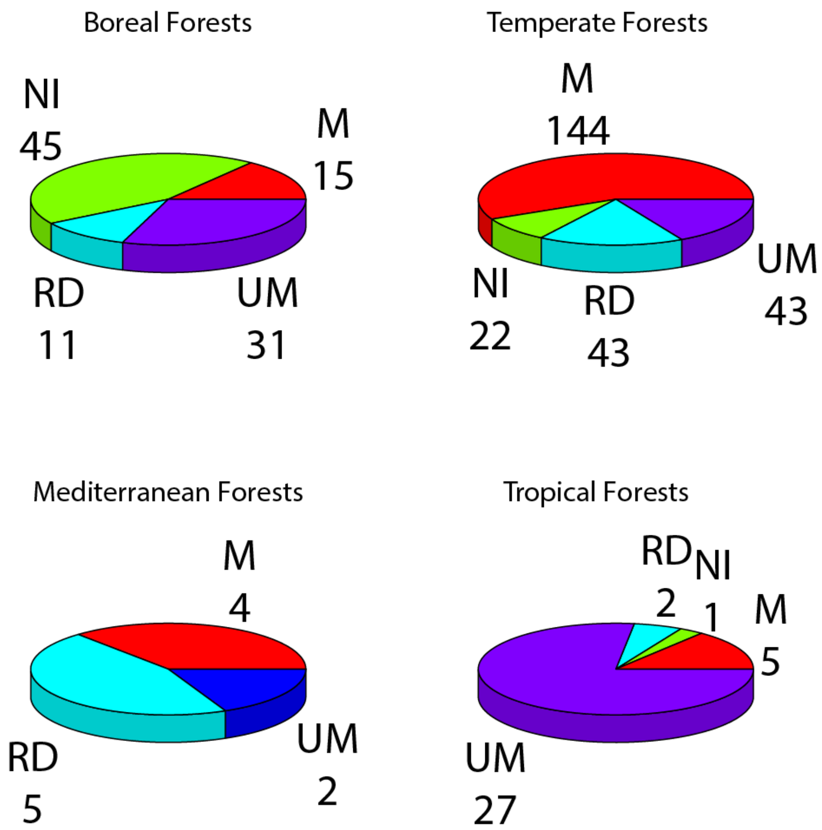

Figure S1.2: Pie plots showing the number and percentage (graphic) of forests per management regime in each one of the biomes of our final dataset. **Abbreviations:** managed forests (M), unmanaged (UM), recently disturbed (RD) and forests without available information on management (NI).

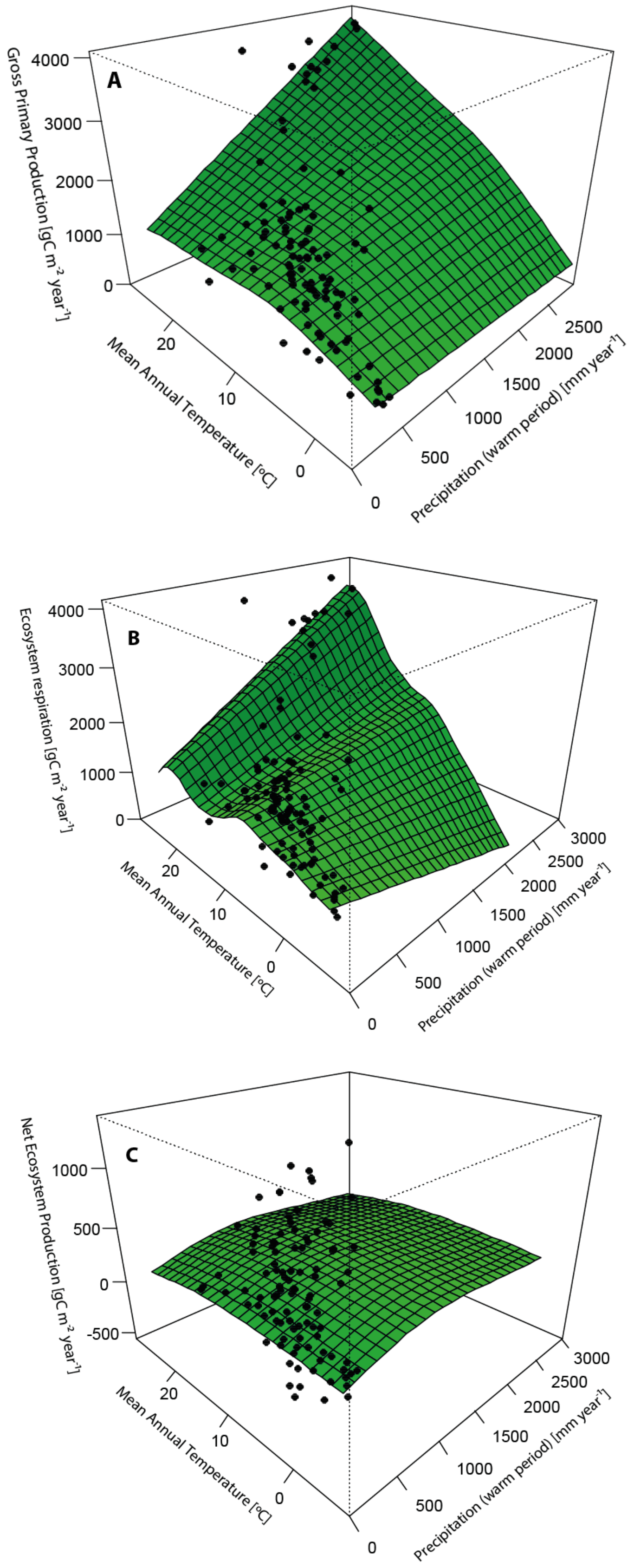

Figure S1.3: Relationship of GPP, Re and NEP (plots A, B and C respectively) with MAT and MAP of the warm period. The response surface was obtained using spline functions to smooth the data within a Generalized Additive Models (GAM).

Table S1.1: Pearson correlation coefficients for climatic variables, stand age and nitrogen deposition. Bold coefficients are significant at the 0.05 level. **Abbreviations:** mean annual actual evapotranspiration (AET), mean annual potential evapotranspiration (PET), mean annual percentage of water deficit (WD), mean annual temperature (MAT), mean annual precipitation (MAP), mean annual thermal amplitude (ThA), mean precipitation seasonality (PS), mean temperature of the warm period (TWP), mean length of the warm period (LWP), mean precipitation of the warm period (PWP), actual evapotranspiration of the warm period (AET WP), mean potential evapotranspiration of the warm period (PET WP), mean percentage of water deficit of the warm period (WD WP), mean annual nitrogen deposition (ND).

	AET	PET	WD	MAT	MAP	ThA	PS	TWP	PWP	LWP	AET WP	PET WP	WD WP	Age	ND
AET		**0.24**	**-0.62**	**0.77**	**0.74**	**-0.54**	0.11	**0.80**	**0.81**	**0.62**	**1.00**	**0.28**	**-0.59**	-0.04	0.05
PET	**0.24**		**0.50**	**0.58**	0.09	**-0.24**	**0.54**	**0.48**	**0.23**	**0.65**	**0.26**	**0.99**	**0.51**	-0.15	-0.13
WD	**-0.62**	**0.50**		**-0.25**	**-0.52**	**0.32**	**0.29**	**-0.33**	**-0.49**	-0.05	**-0.61**	**0.44**	**0.99**	-0.08	**-0.18**
MAT	**0.77**	**0.58**	**-0.25**		**0.62**	**-0.76**	**0.22**	**0.88**	**0.79**	**0.91**	**0.80**	**0.64**	**-0.20**	**-0.23**	0.01
MAP	**0.74**	0.09	**-0.52**	**0.62**		**-0.55**	0.05	**0.65**	**0.91**	**0.40**	**0.72**	0.11	**-0.49**	0.04	-0.12
ThA	**-0.54**	**-0.24**	**0.32**	**-0.76**	**-0.55**		0.10	**-0.49**	**-0.59**	**-0.65**	**-0.56**	**-0.30**	**0.25**	**0.21**	-0.11
PS	0.11	**0.54**	**0.29**	**0.22**	0.05	0.10		**0.34**	0.13	**0.22**	0.12	**0.52**	**0.28**	0.14	**-0.42**
TWP	**0.80**	**0.48**	**-0.33**	**0.88**	**0.65**	**-0.49**	**0.34**		**0.84**	**0.71**	**0.82**	**0.52**	**-0.31**	-0.10	-0.13
PWP	**0.81**	**0.23**	**-0.49**	**0.79**	**0.91**	**-0.59**	0.13	**0.84**		**0.63**	**0.82**	**0.28**	**-0.45**	-0.06	-0.10
LWP	**0.62**	**0.65**	-0.05	**0.91**	**0.40**	**-0.65**	**0.22**	**0.71**	**0.63**		**0.67**	**0.72**	0.01	**-0.26**	0.01
AET WP	**1.00**	**0.26**	**-0.61**	**0.80**	**0.72**	**-0.56**	0.12	**0.82**	**0.82**	**0.67**		**0.30**	**-0.58**	-0.07	0.05
PET WP	**0.28**	**0.99**	**0.44**	**0.64**	0.11	**-0.30**	**0.52**	**0.52**	**0.28**	**0.72**	**0.30**		**0.47**	**-0.20**	-0.12
WD WP	**-0.59**	**0.51**	**0.99**	**-0.20**	**-0.49**	**0.25**	**0.28**	**-0.31**	**-0.45**	0.01	**-0.58**	**0.47**		-0.10	**-0.21**
Age	-0.04	-0.15	-0.08	**-0.23**	0.04	**0.21**	0.14	-0.10	-0.06	**-0.26**	-0.07	**-0.20**	-0.10		-0.08
ND	0.05	-0.13	**-0.18**	0.01	-0.12	-0.11	**-0.42**	-0.13	-0.10	0.01	0.05	-0.12	-0.21	-0.08	

Table S1.2: Stand age, mean biomass and its distribution among boreal, temperate, Mediterranean, and tropical biomes, separating forests by leaf type. The table shows the mean value (in g C · m^{-2}, except for LAI and SLA, whose units are $m^2 m^{-2}$ and $m^2 kg^{-1}$, respectively) followed by the lower and upper 95% bootstrapped (bias accelerated) confidence intervals and the number of replicates (in parentheses). "NA" indicates not available data. Notice that the percentages of foliar, woody, and belowground biomasses are calculated relative to total biomass. Mixed forests were excluded.

	Boreal		**Temperate**		**Mediterranean**		**Tropical**
	Needleleaved	**Broadleaved**	**Needleleaved**	**Broadleaved**	**Needleleaved**	**Broadleaved**	**Broadleaved**
Stand Age	84.9	69.5	84.6	75.3	24.0	32.0	78.5
	73.8 – 98.3 (81)	47.5 – 103.9 (10)	68.7 – 106.1 (157)	63.2 - 95.1 (74)	NA - NA (2)	11.9 - 54.7 (7)	60.2 – 95.6 (22)
LAI	3.9	3.5	6.6	5.6	4.1	2.1	4.9
	3.3 - 4.8 (56)	2.8 - 4.5 (9)	6.0 - 7.1 (151)	5.0 - 6.6 (73)	NA - NA (2)	1.4 - 2.7 (9)	4.3 - 5.4 (22)
SLA	12.6	35.9	18.9	26.2	6.9	20.3	13.5
	10.4 - 15.3 (21)	33.9 - 37.1 (3)	12.9 - 41.3 (118)	21.7 - 30.9 (20)	NA - NA (1)	11.0 - 28.5 (4)	10.7 - 18.7 (9)
Foliar Biomass	292	103	629	223	800	152	458
	254 - 335 (40)	76 - 125 (3)	558 - 700 (124)	188 - 276 (21)	NA - NA (1)	40 - 248 (4)	341 - 705 (11)
Woody Biomass	4310	7359	14727	11907	7100	2351	15294
	3240 - 5936 (26)	NA - NA (2)	12331 - 17518 (109)	10609 - 13428 (9)	NA - NA (1)	667 - 3483 (3)	9839 - 18302 (4)
Aboveground B.	5332	6699	13630	10557	7960	3245	10256
	4511 - 6239 (67)	4286 - 8667 (7)	11652 - 15717 (141)	9146 - 12170 (51)	NA - NA (1)	1120 - 4941 (4)	8396 - 12348 (27)
Belowground B.	1353	1120	4047	2568	2640	2704	2210
	1155 - 1583 (63)	735 - 1663 (7)	3124 - 5153 (69)	2130 - 3878 (49)	NA - NA (1)	1613 - 4747 (4)	1659 - 3372 (14)
Total Biomass	6900	7818	17724	13162	10600	5950	11923
	5988 - 7980 (63)	5094 - 10119 (7)	14062 - 22452 (69)	11285 - 15506 (48)	NA - NA (1)	3351 - 9417 (4)	9095 - 15090 (13)
% Foliar	5.8%	1.1%	5.7%	2.2%	7.5%	2.3%	5.2%
	4.2% - 8.6% (35)	0.7% - 1.5% (3)	4.6% - 7.1% (57)	1.6% - 3.4% (18)	NA - NA (1)	1.2% - 3.2% (4)	3.0% - 10.3% (10)
% Woody	68.1%	67.8%	69.3%	85.1%	67.0%	50.0%	72.2%
	59.0% - 74.0% (23)	NA - NA (2)	65.4% - 72.8% (47)	71.5% - 111.2% (9)	NA - NA (1)	26.5% - 64.2% (3)	67.2% - 75.1% (3)
% Belowground	20.1%	15.2%	24.0%	19.4%	24.9%	47.9%	19.9%
	18.8% - 21.7% (63)	11.4% - 20.6% (7)	22.3% - 26.3% (69)	17.6% - 23.3% (48)	NA - NA (1)	28.9% - 61.9% (4)	15.5% - 24.7% (13)

Table S1.3: Weighted values of mean carbon flux and partitioning percentages for boreal, temperate, Mediterranean, and tropical biomes, grouping forests according to leaf type. The table shows the mean value (in g C · m^{-2} $year^{-1}$) followed by the lower and upper 95% bootstrapped (bias accelerated) confidence intervals and the number of replicates (in parentheses). "NA" indicates not available data The ABP%, BBP%, FNPP%, and WNPP% percentages are NPP fluxes relative to GPP. The weighting factor was calculated as the inverse of the uncertainty. Mixed forests were excluded.

	Boreal		**Temperate**		**Mediterranean**		**Tropical**
	Needleleaved	**Broadleaved**	**Needleleaved**	**Broadleaved**	**Needleleaved**	**Broadleaved**	**Broadleaved**
GPP	892 788 - 1027 (17)	1041 769 - 1200 (5)	1609 1419 - 1743 (24)	1403 1283 - 1533 (22)	1354 813 - 1647 (4)	1359 1152 - 1560 (9)	3106 2596 - 3414 (14)
TBP	349 255 - 506 (5)	500 NA - NA (2)	775 581 - 1077 (9)	797 703 - 939 (13)	NA NA - NA (NA)	NA NA - NA (NA)	1232 1055 -1444 (5)
ABP	130 107 - 148 (5)	285 NA - NA (2)	504 311 - 870 (9)	434 363 - 522 (13)	NA NA - NA (NA)	NA NA - NA (NA)	718 514 - 948 (6)
FNPP	48 45 - 52 (4)	120 NA - NA (2)	184 106 - 370 (8)	167 146 - 190 (12)	NA NA - NA (NA)	NA NA - NA (NA)	382 319 - 551 (6)
WNPP	76 57 - 98 (4)	166 NA - NA (2)	281 163 - 556 (8)	260 192 - 353 (11)	NA NA - NA (NA)	NA NA - NA (NA)	299 164 - 380 (6)
BBP	133 103 - 201 (5)	133 NA - NA (2)	232 188 - 300 (9)	255 210 - 318 (13)	NA NA - NA (NA)	NA NA - NA (NA)	266 232 - 314 (6)
Re	828 704 - 1040 (16)	870 586 - 1002 (5)	1234 1097 - 1348 (25)	1090 965 - 1238 (22)	1124 567 - 1305 (4)	1063 925 - 1243 (9)	2964 2396 - 3289 (14)
NEP	99 16 - 216 (18)	196 154 - 265 (5)	343 254 - 431 (25)	317 239 - 416 (25)	271 175 - 411 (4)	305 120 - 478 (9)	118 -23 - 304 (15)
ABP%	17.3% 16.1% – 20.7% (5)	23.4% NA - NA (2)	26.0% 17.3% - 50.2% (7)	31.1% 24.5% – 39.3% (12)	NA NA - NA (NA)	NA NA - NA (NA)	24.2% 15.0% – 31.8% (6)
BBP%	16.1% 14.1% – 20.1% (5)	7.7% NA - NA (2)	17.1% 11.8% – 29.2% (7)	18.2% 14.2% – 22.7% (12)	NA NA - NA (NA)	NA NA - NA (NA)	8.0% 7.0% – 9.1% (6)
FNPP%	6.3% 4.9% – 6.8% (4)	9.2% NA - NA (2)	9.5% 6.0%- 23.4% (6)	11.8% 11.0% – 12.6% (12)	NA NA - NA (NA)	NA NA - NA (NA)	12.7% 9.2% – 19.0% (6)
WNPP%	9.5% 8.8% – 10.1% (4)	14.1% NA - NA (2)	15.2% 9.4% – 33.2% (6)	15.9% 11.2% – 22.2% (11)	NA NA - NA (NA)	NA NA - NA (NA)	9.9% 4.4% – 12.8% (6)

Table S1.4: Weighted mean values of resource-use efficiency for boreal, temperate, Mediterranean, and tropical biomes, grouping forests according to leaf type. The table shows the mean value of each efficiency variable, followed by the lower and upper 95% bootstrapped (bias accelerated) confidence intervals and the number of replicates (in parentheses). "NA" indicates not available data. The CUEe and BPE percentages correspond to the ratio of NEP to GPP and of TBP to GPP, respectively. LUE units are gC MJ^{-1}, and WUE units are gC L^{-1}. The weighting factor was calculated as the inverse of the uncertainty. Mixed forests were excluded.

	Boreal		**Temperate**		**Mediterranean**		**Tropical**
	Needleleaved	**Broadleaved**	**Needleleaved**	**Broadleaved**	**Needleleaved**	**Broadleaved**	**Broadleaved**
CUEe%	9.7% -0.2% - 21.3% (16)	17.9% 14.5% - 25.6% (5)	21.8% 17.0% - 26.0% (24)	21.7% 16.9% - 27.9% (22)	19.4% 12.3% - 23.6% (4)	20.8% 8.9% - 30.0% (9)	3.3% -2.0% - 9.1% (14)
BPE%	43.7% 35.5% - 54.7% (5)	40.6% NA - NA (2)	50.8% 41.4% - 72.0% (7)	54.8% 46.3% - 64.0% (12)	NA NA - NA (NA)	NA NA - NA (NA)	38.2% 33.0% - 48.2% (5)
LUE	2.2 1.7 - 2.6 (9)	NA NA - NA (NA)	2.6 2.4 - 2.9 (10)	2.0 1.7 - 2.3 (11)	2.3 NA - NA (2)	2.0 1.6 - 2.2 (7)	NA NA - NA (NA)
$LUE\%_{APAR}$	9.4% 7.1% - 11.0% (9)	NA NA - NA (NA)	11.1% 10.1% - 12.5% (10)	8.5% 7.0% - 9.9% (11)	9.8% NA - NA (2)	8.5% 7.2% - 9.7% (7)	NA NA - NA (NA)
$LUE\%_{PAR}$	6.2% 4.2% - 7.5% (9)	NA NA - NA (NA)	7.6% 6.7% - 8.6% (10)	5.8% 4.9% - 6.8% (11)	5.8% 4.0% - 7.1% (2)	5.5% 4.2% - 6.4% (7)	NA NA - NA (NA)
$LUE\%_{TRad}$	2.8% 2.0% - 3.4% (9)	NA NA - NA (NA)	3.4% 3.0% - 3.8% (10)	2.6% 2.2% - 3.1% (11)	2.6% 1.8% - 2.6% (2)	2.5% 1.9% - 2.9% (7)	NA NA - NA (NA)
WUE	2.6 2.3 - 2.9 (17)	2.5 2.0 - 2.9 (5)	2.8 2.5 - 3.2 (24)	2.3 1.9 - 2.7 (22)	3.1 2.3 - 4.3 (4)	2.1 1.7 - 2.5 (9)	2.7 2.4 - 2.8 (14)

Table S1.5: β coefficients (± SE) of the stepwise regressions for the a) structural, b) functional, and c) efficiency variables studied. The adjusted R^2 of the entire model and the number of replicates are also noted. "Ln" after a dependent variable indicates that a logarithmic transformation was required to achieve the model's assumptions. "Ln" after a β coefficient indicates the variable entered the model in its logarithmic form. For management, leaf habit, and leaf type, a capital letter is designated to express differences between levels (management: U = unmanaged, M = managed, D = disturbed; leaf habit: E = evergreen, D = deciduous; leaf type: N = needleleaved, B = broadleaved). All regression models were significant at the 0.001 level or lower. **Abbreviations:** mean annual actual evapotranspiration (AET), mean annual potential evapotranspiration (PET), mean annual percentage of water deficit (WD), mean annual temperature (MAT), mean annual precipitation (MAP), mean annual thermal amplitude (ThA), mean precipitation seasonality (PS), mean temperature of the warm period (TWP), mean length of the warm period (LWP), mean precipitation of the warm period (PWP), actual evapotranspiration of the warm period (AET WP), mean potential evapotranspiration of the warm period (PET WP), mean percentage of water deficit of the warm period (WD WP), mean annual nitrogen deposition (ND).

a) Biomass	LAI	SLA	Foliar	Woody (Ln)	Aboveground (Ln)	Belowground	Total Biomass	% Foliar	% Woody	% Belowground
R^2 adj	0.36		0.23	0.67	0.55	0.54	0.66	0.45	0.35	0.22
N	195		143	116	169	107	106	76	60	106
AET									0.80±0.16	
PET									-0.35±0.16	
WD			-0.39±0.08							
MAT										
MAP	0.43±0.07Ln			0.23±0.06Ln	0.25±0.06Ln	0.23±0.08	0.35±0.07			
ThA										
PS								-0.41±0.13		
TWP	-0.19±0.08Ln					-0.39±0.09	-0.36±0.07			
LWP				0.34±0.06Ln	0.21±0.06Ln	0.50±0.10Ln	0.40±0.08Ln			0.29±0.13
PWP										-0.40±0.13
AET WP	0.19±0.08Ln									
PET WP										
WD WP								-0.27±0.10		
Stand Age	0.21±0.06Ln			0.79±0.06Ln	0.70±0.05Ln	0.56±0.07Ln	0.64±0.06Ln	-0.57±0.09Ln	0.21±0.11Ln	0.27±0.09Ln
ND	0.24±0.07							-0.28±0.14		
Leaf Habit								E>D		E>D
Leaf Type	N>B		N>B			N>B				
Management										

b) Fluxes	GPP	TBP	ABP (Ln)	FNPP	WNPP (Ln)	BBP	Re	NEP	ABP%	BBP%	FNPP%	WNPP%
R^2 adj	0.81	0.76	0.73	0.64	0.47	0.28	0.76	0.18	0.22	0.30	0.42	0.24
N	83	30	34	32	30	30	103	109	32	28	29	29
AET												
PET												
WD		-0.33 ± 0.12					-0.28 ± 0.06Ln					
MAT							0.22 ± 0.09					
MAP												
ThA	-0.33 ± 0.06					-0.39 ± 0.16					1.12 ± 0.29Ln	
PS												
TWP												
LWP		0.56 ± 0.12Ln	0.45 ± 0.13	0.80 ± 0.11							1.36 ± 0.29Ln	
PWP	0.40 ± 0.09						0.49 ± 0.10			-0.53 ± 0.16Ln		
AET WP	0.36 ± 0.10											
PET WP												
WD WP			-0.34 ± 0.14		-0.48 ± 0.14							
Stand Age	0.23 ± 0.05 Ln	-0.32 ± 0.09Ln				-0.37 ± 0.16Ln				-0.41 ± 0.16Ln		
ND			0.41 ± 0.10		0.41 ± 0.14			0.23 ± 0.10	0.50 ± 0.16Ln			0.51 ± 0.16Ln
Leaf Habit												
Leaf Type												
Management								M > UM - M > D				

c) Efficiencies	CUEe	BPE	LUE	WUE
R^2 adj	0.18	0.33	0.13	0.43
N	82	27	42	83
AET				
PET				-0.41 ± 0.10Ln
WD				
MAT				
MAP				
ThA				-0.66 ± 0.10
PS		-0.40 ± 0.16		
TWP			-0.39 ± 0.15Ln	
LWP				
PWP				
AET WP				
PET WP				
WD WP				0.60 ± 0.10
Stand Age	0.39 ± 0.15Ln	-0.42 ± 0.16Ln		0.35 ± 0.09Ln
ND				
Leaf Habit				
Leaf Type				
Management	M > UM			

Supplementary Material

Chapter 2
Nutrient availability as the key regulator of global forest carbon balance

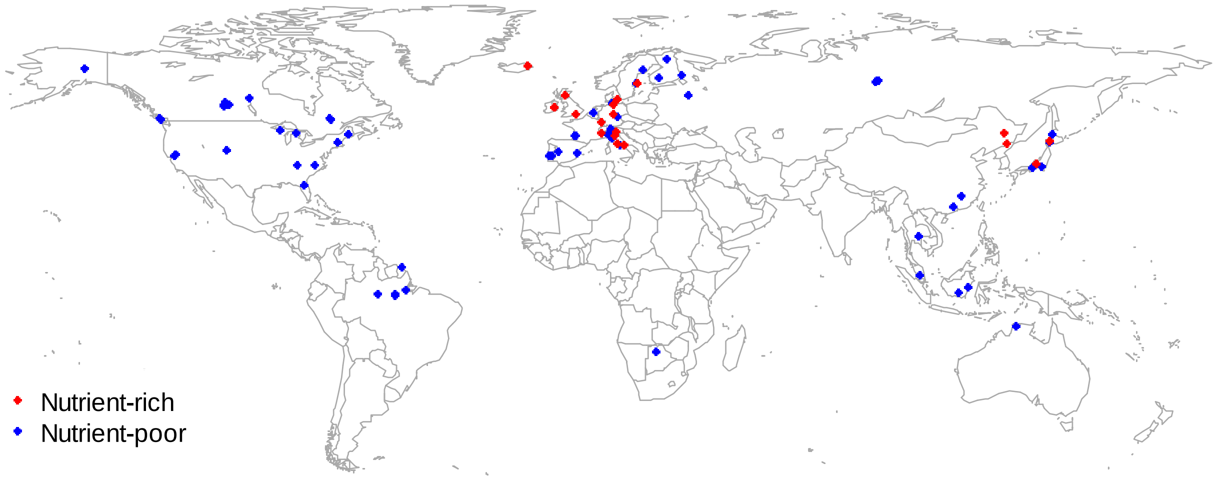

Figure S2.1. Global map of the forests used in this study. Forests have been coded according to their nutrient status: red indicates nutrient-rich forests whereas blue indicates nutrient-poor forests.

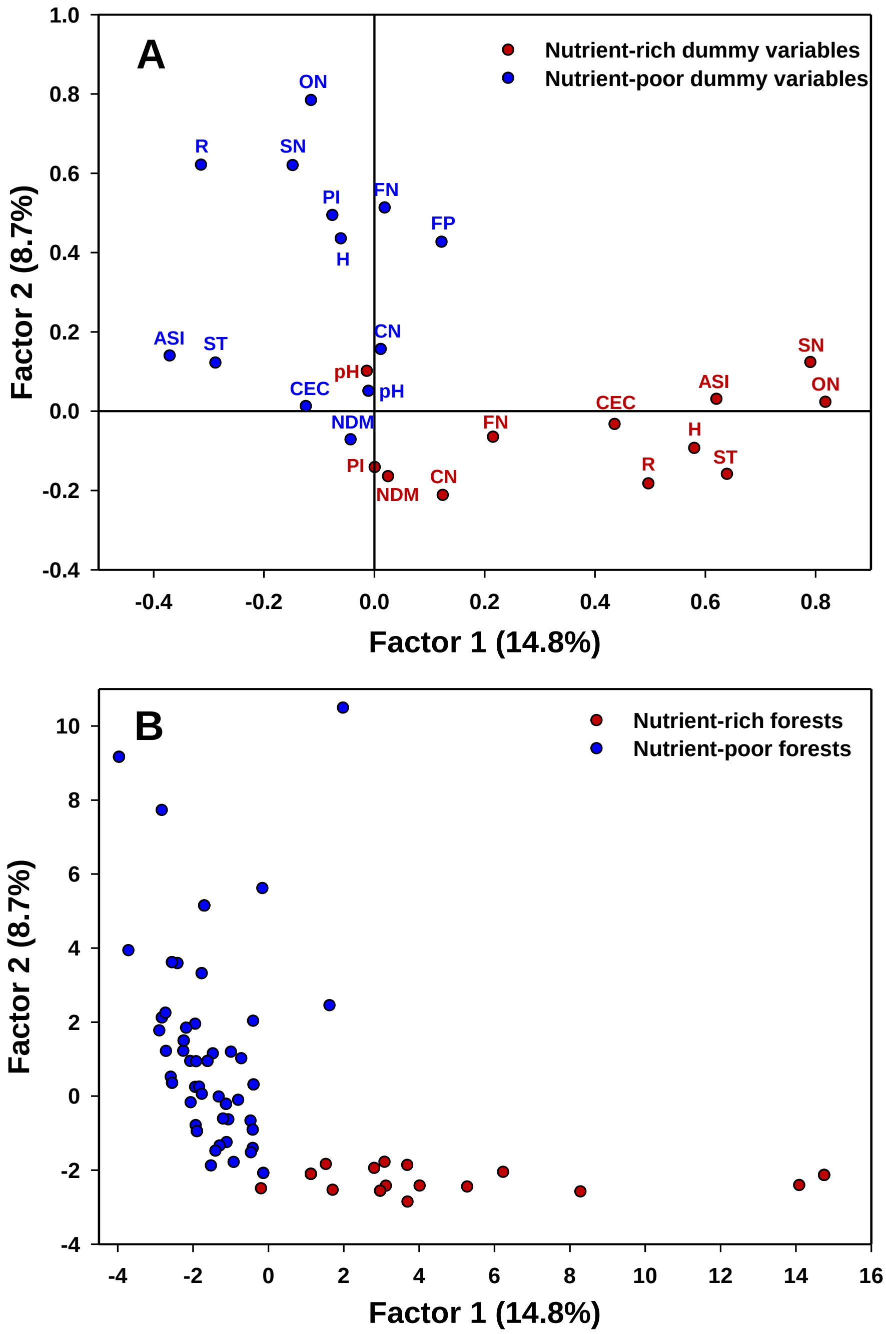

Figure S2.2. Summary of the factor analysis performed to evaluate nutrient availability. Graph A shows the factor loadings of the variables used in the analysis following the criteria presented in Supplementary Table S2.3. A clear separation can be seen between those indicating high (correlated with Factor 1, F1) and low (correlated with Factor 2, F2) nutrient availability. Graph B shows the factor scores of the studied forests aggregated according to the nutrient status. Note that in graph A FP is missing because no forest presented high values of FP. Note also that in graph B some forests might present equal factor scores, resulting in fewer points than expected. Abbreviations: ASI (additional soil information), CEC (cation exchange capacity), CN (soil C:N ratio), FN (foliar nitrogen concentration), FP (foliar phosphorus concentration), H (history of the stand), NDM (nitrogen deposition or mineralization), ST (soil type), ON (other soil nutrients), PI (assessment by the principal investigator of the forest), R (report about nutrient availability), SN (soil nitrogen concentration).

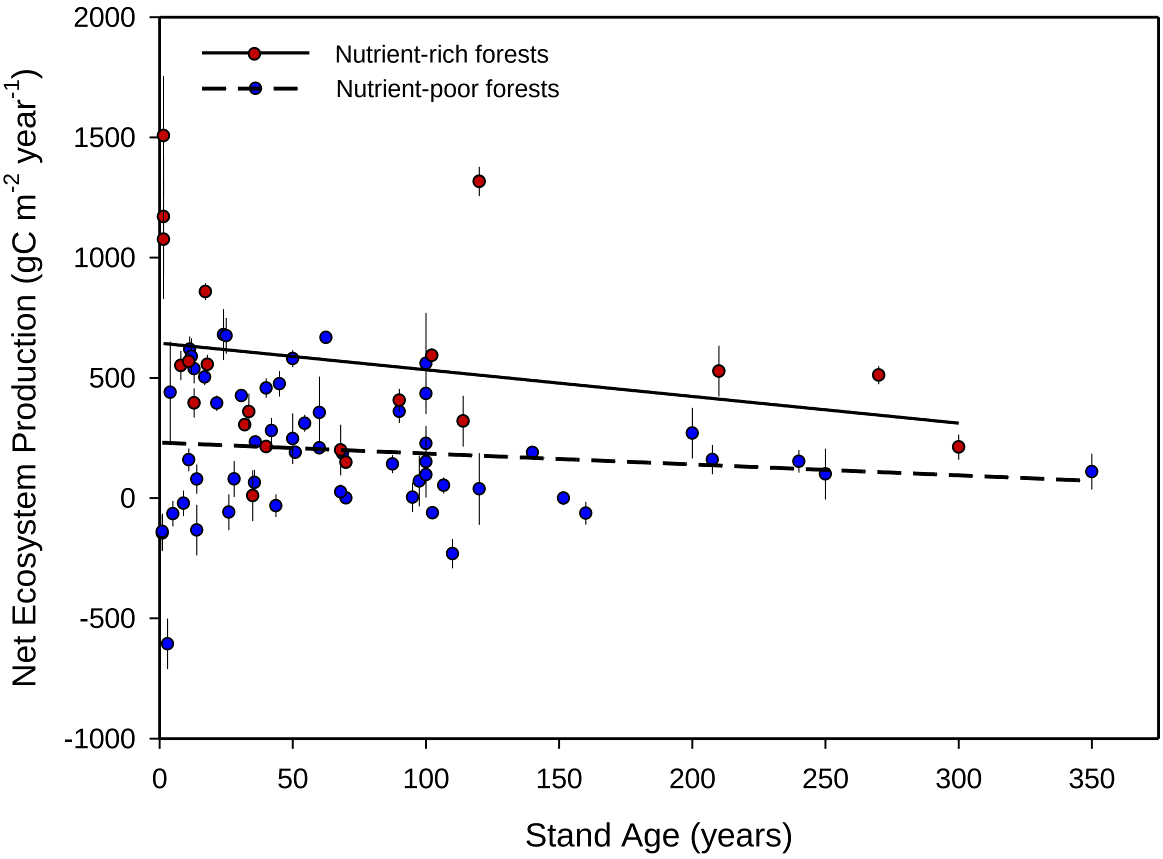

Figure S2.3. Influence of stand age and nutrient availability on NEP. Nutrient availability clearly influences NEP (P < 0.0001), but stand age has no significant effect (P = 0.14) when GPP is not considered. Neither interaction between nutrient availability and stand age is significant (P = 0.50).

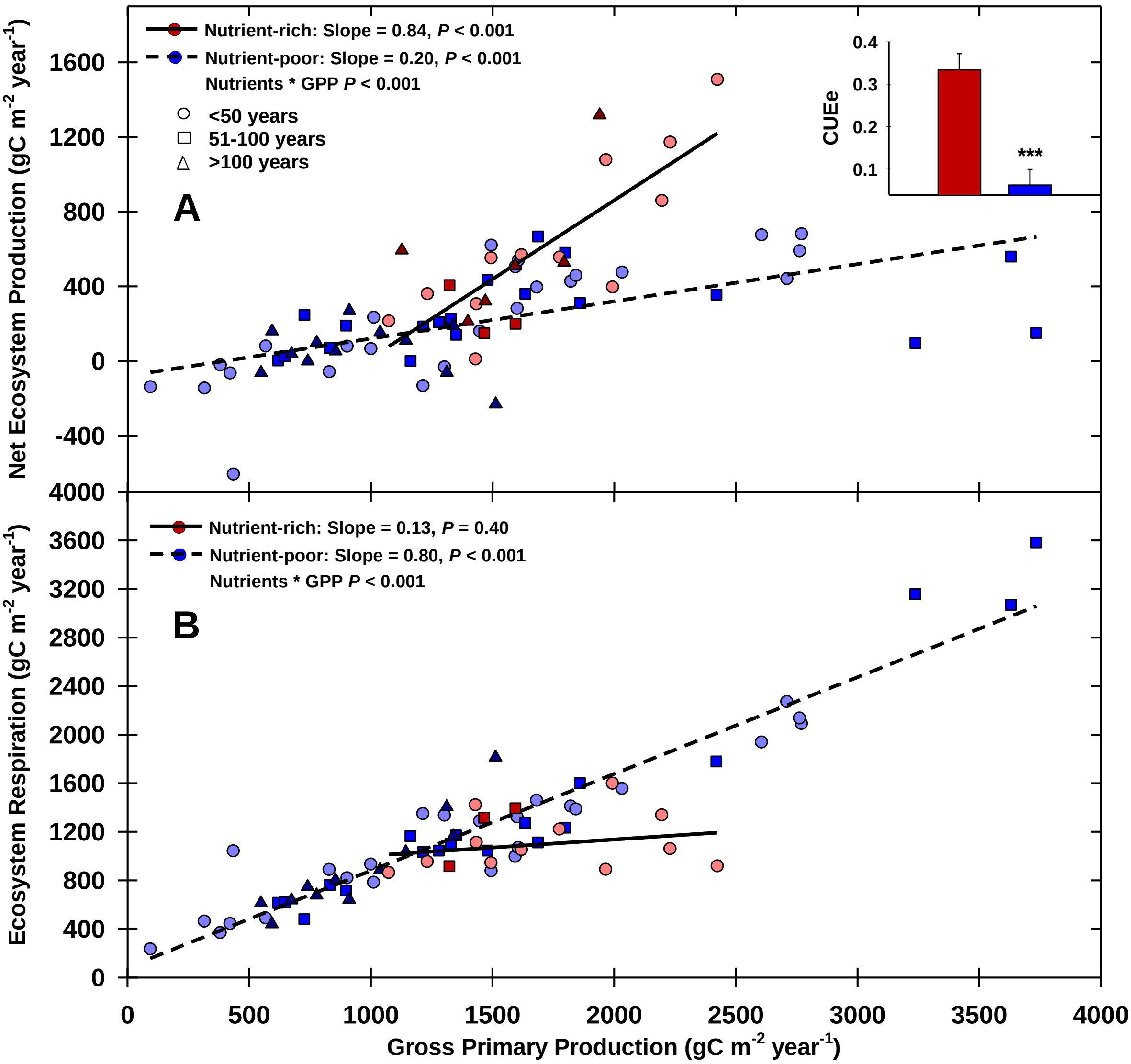

Figure S4. Relationships of NEP (A) and Re (B) with GPP in nutrient-rich and nutrient-poor forests indicating the age category of each stand. The age of the stand did not affect the relationships of NEP (graphs **A**, **C**, **E**) and Re (graphs **B**, **D**, **F**) with GPP. The bar charts inside the NEP graphs show the average CUEe of nutrient-rich and nutrient-poor forests. Graphs **C** and **D** show forests older than 50 years old and graphs **E** and **F** show forests younger than 50 years old. Red-like points indicate nutrient-rich forests and blue-like points represent the nutrient-poor ones.

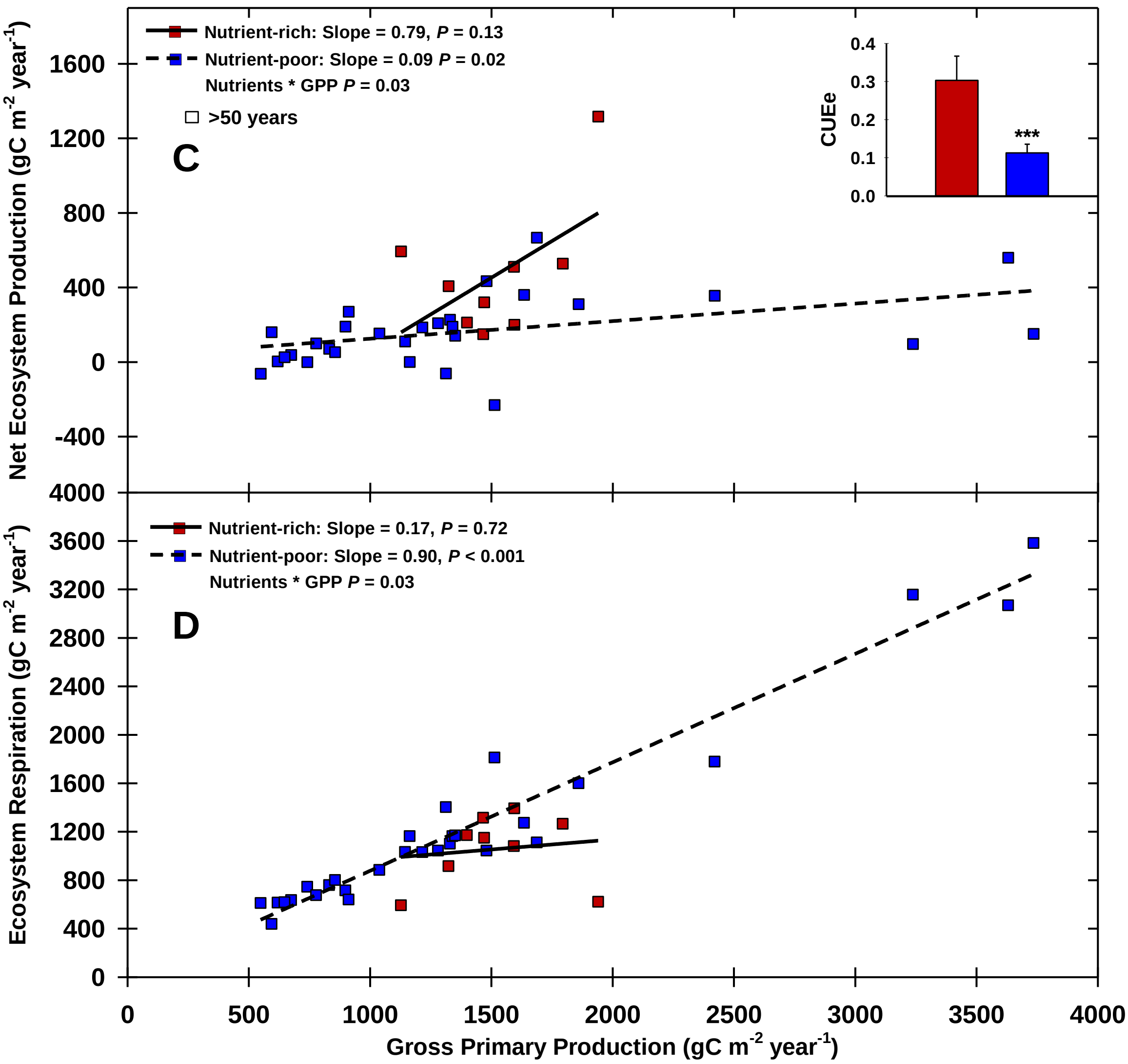

Figure S4. Relationships of NEP (A) and Re (B) with GPP in nutrient-rich and nutrient-poor forests indicating the age category of each stand. The age of the stand did not affect the relationships of NEP (graphs **A**, **C**, **E**) and Re (graphs **B**, **D**, **F**) with GPP. The bar charts inside the NEP graphs show the average CUEe of nutrient-rich and nutrient-poor forests. Graphs **C** and **D** show forests older than 50 years old and graphs **E** and **F** show forests younger than 50 years old. Red-like points indicate nutrient-rich forests and blue-like points represent the nutrient-poor ones.

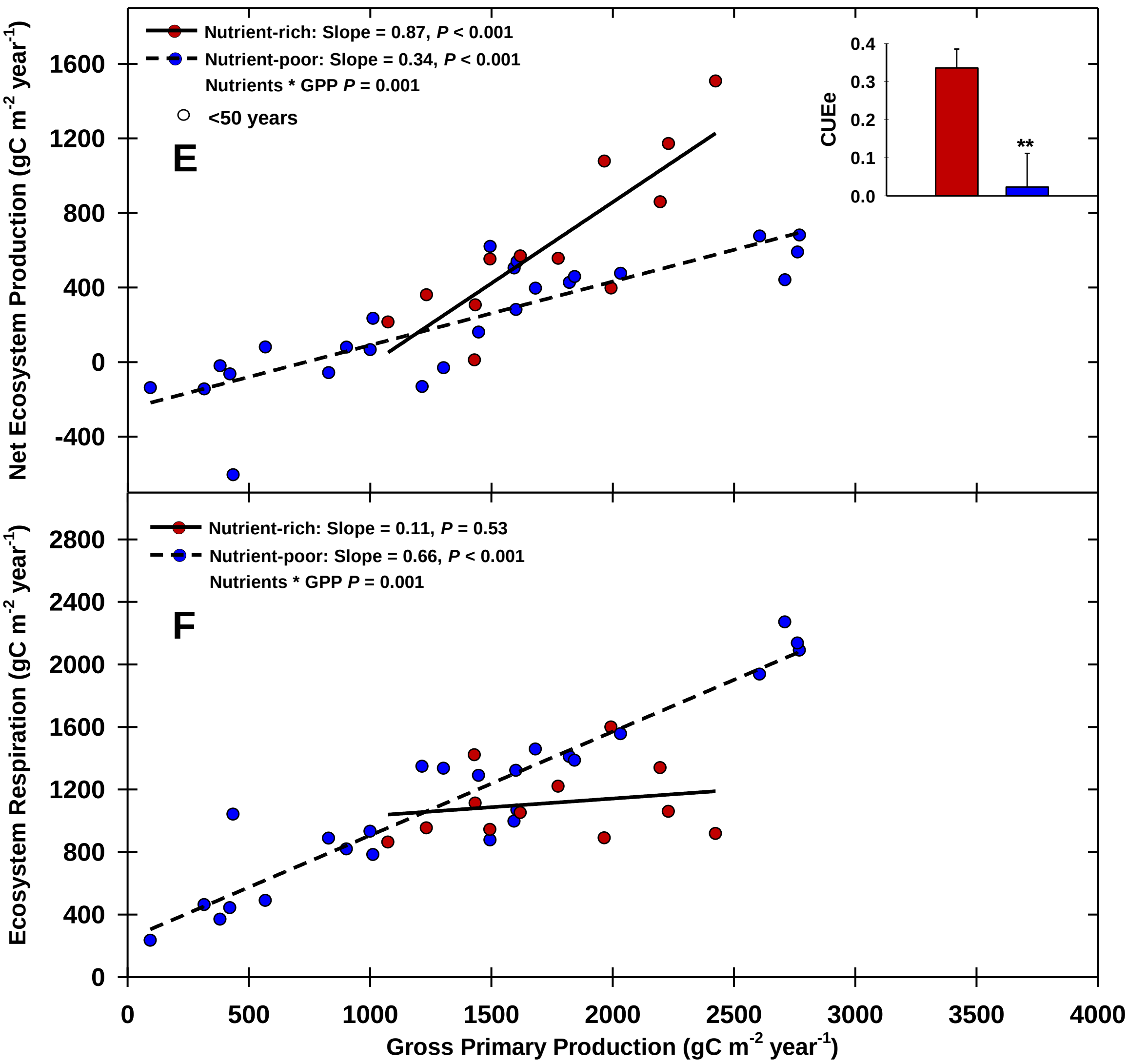

Figure S4. Relationships of NEP (A) and Re (B) with GPP in nutrient-rich and nutrient-poor forests indicating the age category of each stand. The age of the stand did not affect the relationships of NEP (graphs **A**, **C**, **E**) and Re (graphs **B**, **D**, **F**) with GPP. The bar charts inside the NEP graphs show the average CUEe of nutrient-rich and nutrient-poor forests. Graphs **C** and **D** show forests older than 50 years old and graphs **E** and **F** show forests younger than 50 years old. Red-like points indicate nutrient-rich forests and blue-like points represent the nutrient-poor ones.

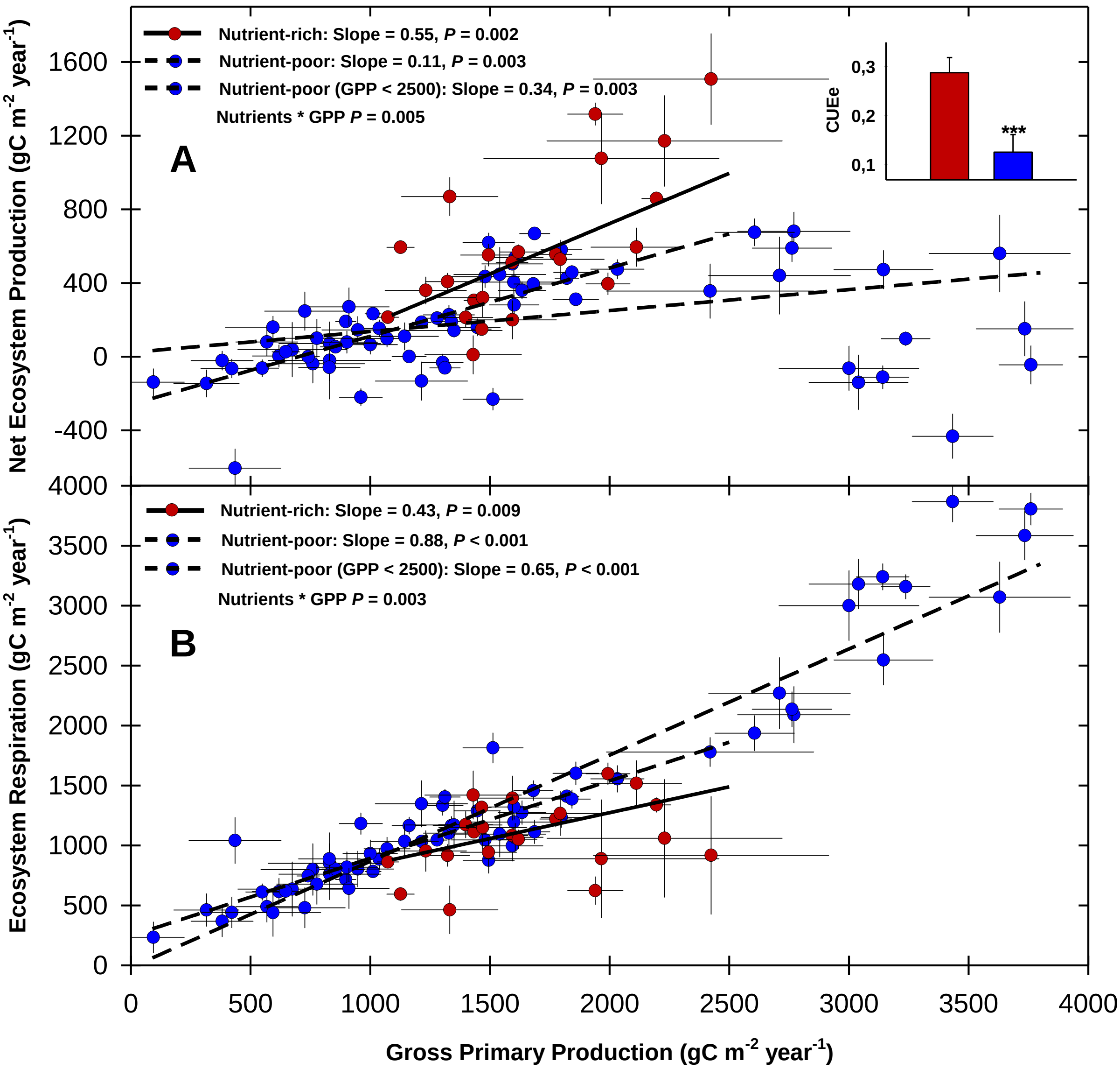

Figure S2.5. Relationships of NEP (A) and Re (B) with GPP in nutrient-rich and nutrient-poor forests weighted using the inverse of the uncertainty as a weighting factor. The uncertainty of the estimates did not change the results. Thus, as in Figure 2.1, nutrient-poor forests do not increase NEP when rates of carbon uptake increase. The bar chart inside graph **A** shows the average CUEe of nutrient-rich and nutrient-poor forests. Error bars indicate the uncertainty of the estimate on both the x- and y-axes (SE). In forests with GPP < 2500, Nutrients*GPP (where Nutrients = nutrient availability) interactions are not significant at the 0.05 level.

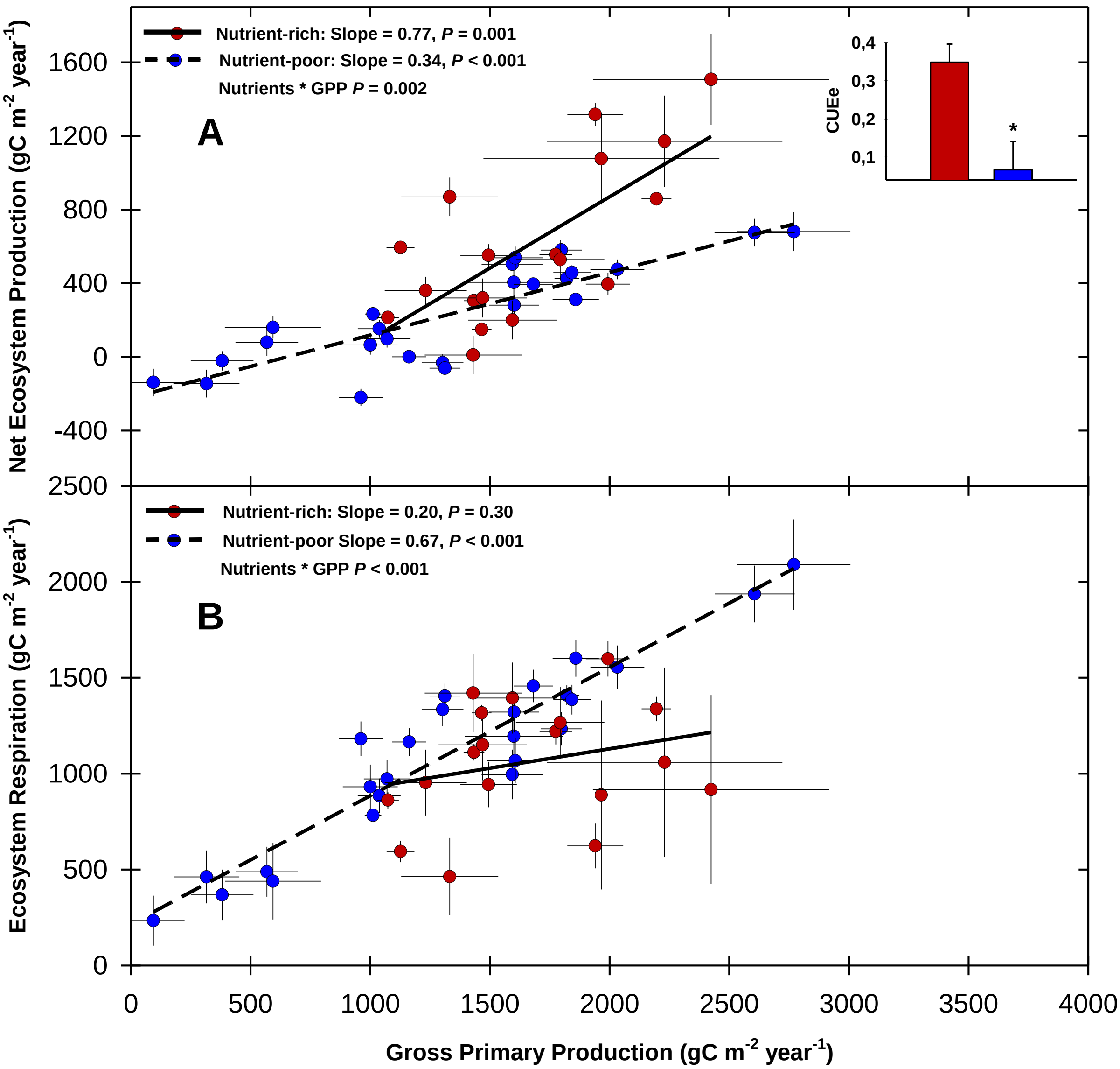

Figure S2.6. Relationships of NEP (A) and Re (B) with GPP in nutrient-rich and nutrient-poor managed forests. The general pattern for NEP and Re versus GPP shown for nutrient-rich forests was also evident here. Nutrients = nutrient availability.

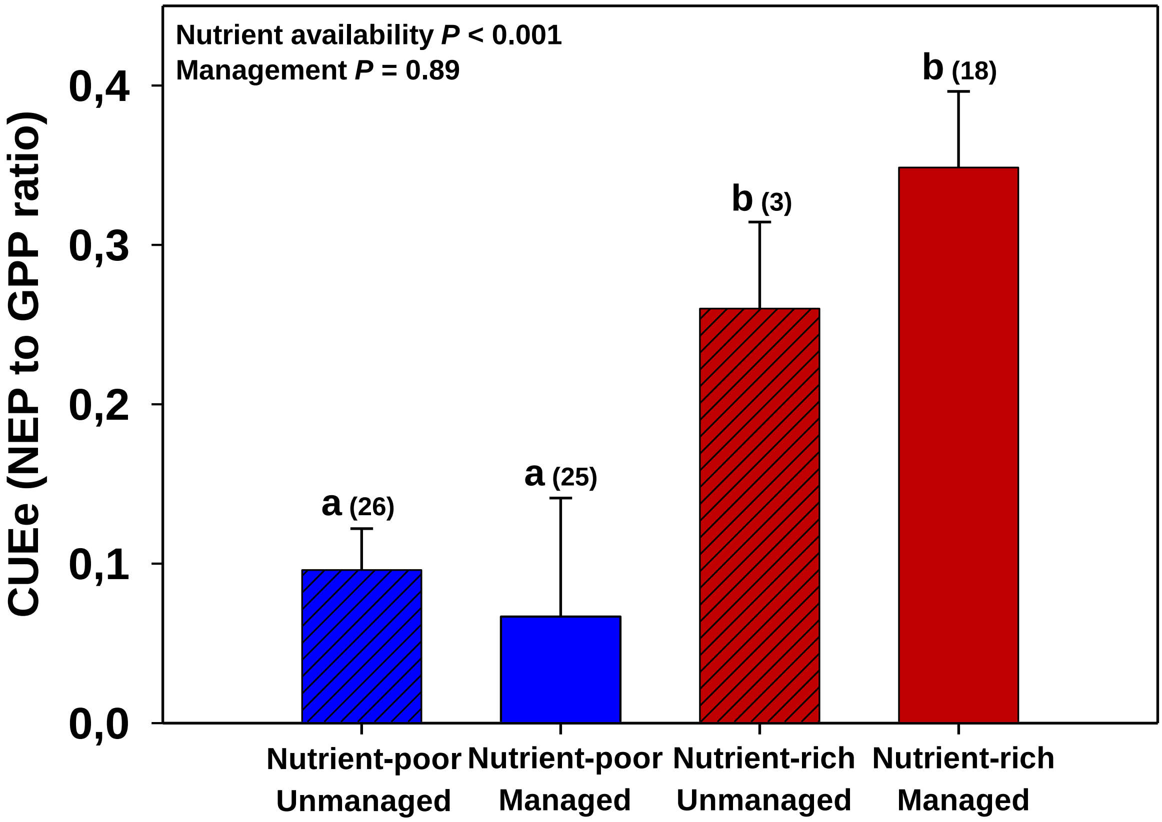

Figure S2.7. NEP to GPP ratio (CUEe) is influenced by nutrient availability but not by management. Different letters indicate significant differences between groups (Tukey's HSD). The numbers beside the letters indicate the number of forest sites in the data base.

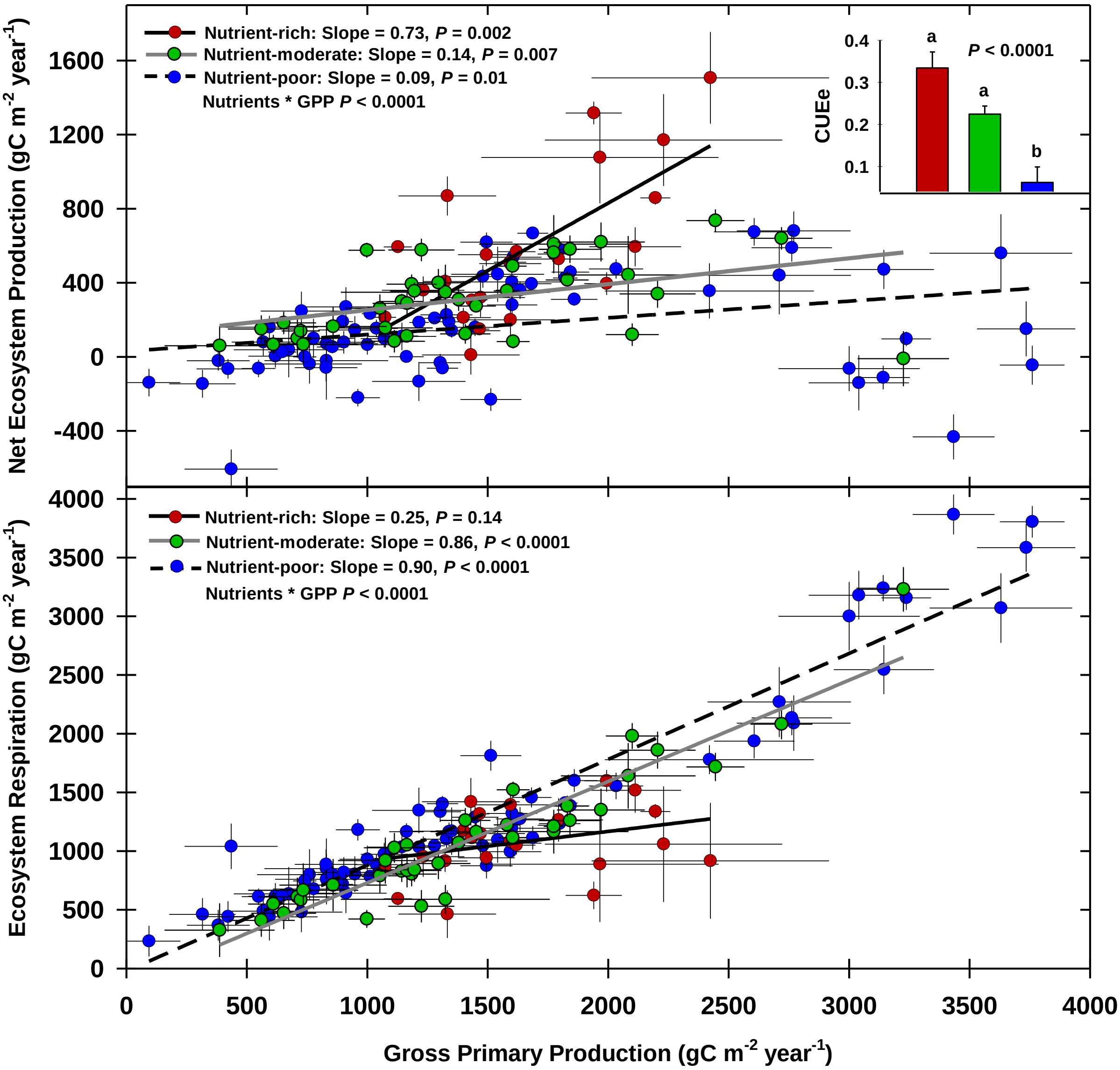

Figure S2.8. Relationships of NEP (A) and Re (B) with GPP showing also the medium nutrient availability category. The general pattern for NEP and Re versus GPP in medium nutrient availability forests fits between the patterns shown by the nutrient-rich and the nutrient-poor forests. Nutrients = nutrient availability.

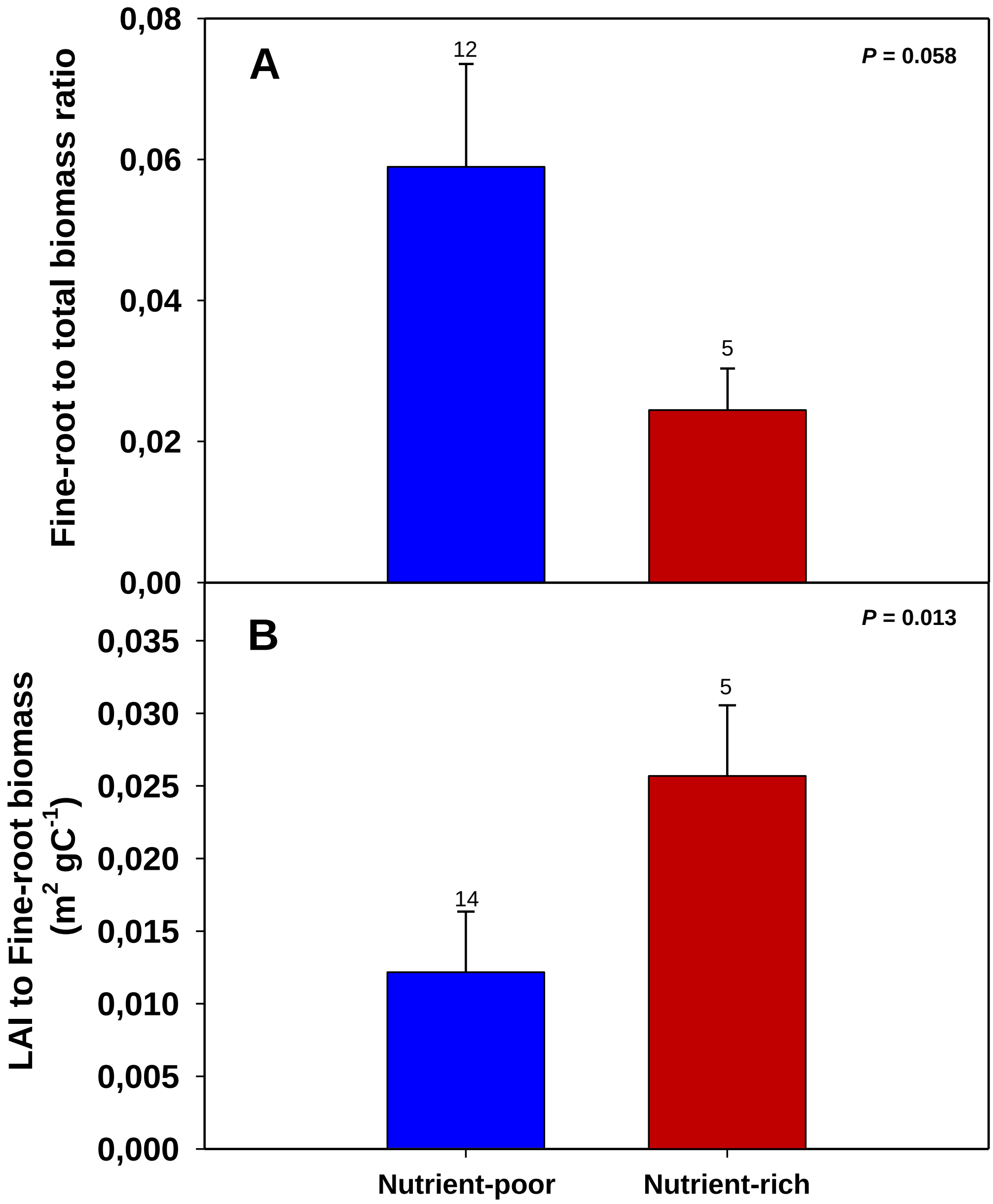

Figure S2.9. Nutrient-rich forests have a lower fine-root to total biomass ratio and a higher ratio of leaf area index (LAI) per unit of fine-root biomass. Error bars indicate standard errors. The numbers above the bars indicate the number of forest sites in the data base. Significance was tested with ANOVA.

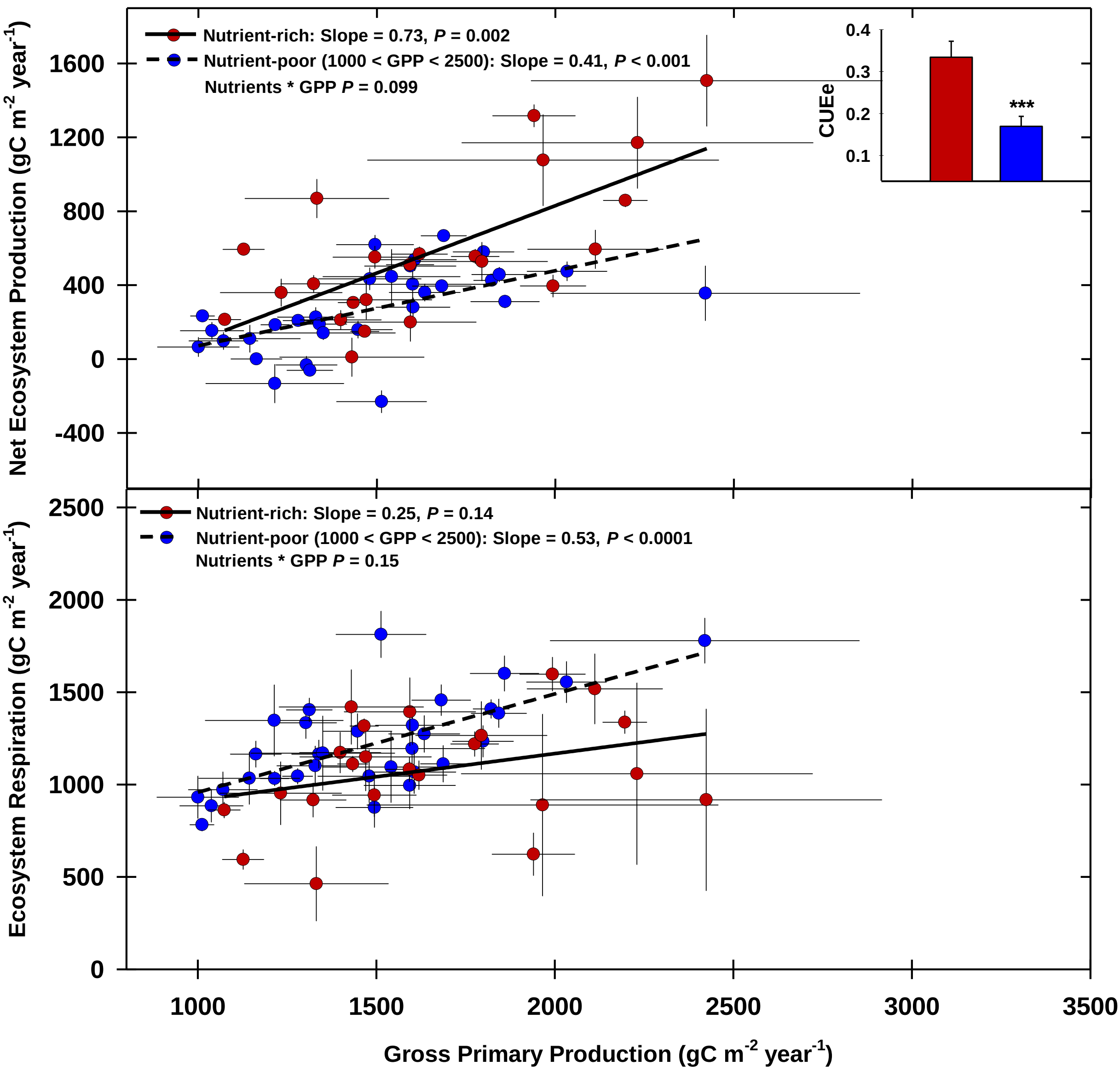

Figure S2.10. Relationships of NEP (A) and Re (B) with GPP showing only forests presenting 1000 < GPP < 2500. The results for this range of GPP indicate that the interaction between GPP*nutrient availability is not significant neither for NEP nor for Re. However, nutrient availability significantly increases the mean in NEP and reduces Re (P = 0.0026 and P = 0.0036 respectively). On the other hand, differences in CUEe between nutrient-rich and nutrient-poor forests remained significant at the < 0.001 level (CUEe nutrient-rich = 0.33, nutrient-poor = 0.17). Nutrients = nutrient availability.

Table S2.1: Information on the nutrient availability of the forests studied. The term id indicates the number of the site, referenced at the bottom of the table. NA indicates our classification of nutrient status according to the provided information [high (H), medium (M) or low (L) nutrient availability]. PI indicates the nutrient status suggested by the principal investigators of the forests. The other columns provide information on nutrient availability as follows: soil type, additional soil information, soil pH, soil carbon content (kg m^{-2}) or concentration (per dry mass %), soil nitrogen content or concentration, carbon-to-nitrogen ratio (C:N), information on other soil nutrients, cation exchange capacity (CEC), nitrogen deposition (D) or mineralisation (M), foliar nutrient concentration (N: nitrogen, P: phosphorus), history of the forest and reports in the published literature on soil or forest nutrient availability. Units: Carbon (C) and nitrogen (N) in percentage of dry mass (when indicated by %) or in kg m^{-2}; CEC in meq 100 g^{-1}; nitrogen deposition and mineralization in kg ha^{-1} $year^{-1}$; foliar nutrient concentration in percentage of dry mass. Additional abbreviations: L (lower soil horizons), Lt (litterfall), U (upper soil horizons).

Site id	NA	PI	Soil type	Additional soil info	pH	C	N	C:N	Other Nutrients	CEC	N D/M	Fol N	History	Report
1	H										D:10		Fertilized with 350 kg urea ha^{-1}, 46% N	
2	L	L	Spodosol (ultic alaquods)	Poorly drained, argilic horizon										Nutrient limited
3	M			Stony sandy loam										Adequate nutrient supply
4	M							24			M:65			
5	L		Dystric, podzolic brown soils or Gleysols	Sandy to loamy sandy texture, organic layer mod/moder	3 to 5					Low (Ca, Mg)	D: high			
6	L		Hydromorphic podzol	Sandy, surface water table in winter										
7	M	M	Haplic and Entic podzols				U: 1.53% L: 0.13%	U: 30 L: 21						
8	L		Mixed, mesic, ultic haploxeralf (Cohasset series)	Fine-loamy, clay-loam	5.5	U: 6.9%	U: 0.17%	U: 41						

9	L		Fibric Histosol	Very wet, waterlogged										Nutrient-poor
10	M		Dystri-cambic Arenosol, near id 10	Not waterlogged							D: high			
11	L		Haplic podzol	wet sandy soil with humus and/or iron B horizon (Al buffer region).	4					Low	D: 35			Poor in Mg and P foliar concentrations. Good N foliar concentration.
12	L		Ultisol											
13	M	M	Brown podzolic	well drained, stone free, fine sandy loam materials										Good potato production when fertilized.
14	L			Sandy, hummus rich in calcium carbonate	5.8	U: 1.9% L: 0.7%		U: 66 L: 100						
15	L								Low P	Low				Extremely nutrient limited
16	H		Brown forest earth	Deep and nutrient-rich soil layer										
17	L		Ferro-humic or humic podzols	Good drainage			0.01%	135				N:0.79%		
18	L													Similar to id 17
19	M		Histosol (Belhaven series)	Loamy mixed dysis thermic terric Haplosaprists (peat soils)	<4.5								Previously farmed; F at planting: 28–50 kg ha^{-1} (N and P); F mid-rotation: 140–195 kg ha^{-1} N and 28 kg ha^{-1}P	
20	H		Humic alfisol	Silty loam-silty clay	5.2		Very high			Very high	D: high			
21	L		Oxisol	80% clay, high porosity (50-80%), low water capacity, highly	4.3									Low nutrient content

				weathered										
22	L		Rustic podsol, Chromic cambisol	Reddish soils	4			U: 29			D: 13			
23	L		Lateritic red or yellow soil	63% clay, 19% silt	3.8									
24	H												Former agricultural land regularly fertilized	Nutrient rich
25	L		Ultic alfisol	Mixed clay mineralogy, poorly drained from fall to spring	5.8									
26	L		Arenosol	Dune system										
27	L		Dystric cambisols		4.8	0.35%	0.03%		P: 9 ppm			N: 1.17% P: 0.07%		
28	L		Gelisol	Loamy sand to loam, thick organic horizon (30cm)		U: 40% L: 3%	U: 0.7% L: 0.17%	U: 50 L: 20				N: 0.84%		
29	L													Strongly nutrient limited
30	L						Low				D: 5.7			Immature and nutrient-rich lava soil (64% N deficit)
31	L			Peat soil	<4.7									Nutrient limited
32	M		Orthic Gleysol									N: 0.7 - 2.1%		
33	M		Andosol	Silty loam	5.8	U: 2.1%	Low			19				Nitrogen limited
34	L	L	Acrisol and ultisols	Sandy										Nutrient-poor

35	M		Brown alfisol	Sandy loam or loam										
36	H		Cambisol	4% sand, 56% lime, 44% clay										Nutrient-rich
37	H	H	Gleysol				U: 1.3%	U: 19 L: 30						
38	M		Gleysol	Peaty, seasonally waterlogged, black organic horizon									Fertilized 40 ago.	N increased after clear cutting
39	M		Gleysol	Peaty, seasonally waterlogged, black organic horizon									Fertilized 40 ago.	N increased after clear cutting
40	L			well drained, acidic sandy loam with some poorly drained peat soils							M: 34			Nutrient-poor
41	H		Luvisol or Stagnic luvisol											Typically very nutrient-rich soils
42	L	L		Well drained lateritic red and yellow earth soils with highly weathered sands	5.5		0.10%							Nutrient-poor
43	L	L			3.5			35				N: 1.06%		
44	L	M L	Haplic podzol				Low				M: low D: low			>99.9% soil N is unavailable for plants. Nitrogen limitation.
45	L			Sandy loam with limited water capacity	acid		Low		Low P					Bogs and peatland poor in N and very P limited
46	L	L	Lithic haploxerepts	Very rocky silt loam		1.1%	0.11%	10						
47	L			Heavily leached					Low P	Low				Nutrient-poor

48	H										Very nutrient-rich soil
49	H										Very nutrient-rich soil
50	H										Very nutrient-rich soil
51	M		Spodosol (or cryosol)	Coarse texture, highly leached, gray		2.2%	0.50%	4.4			
52	L		Entisol								
53	L		Dystric cambisol	90 cm depth, low water capacity, rocky and sandy (80%)	5.6	2.6%		14			
54	H	M	Typic Fragiudalf (Alfisol)	fine-silty	U: 3.7 L: 6.7	U: 6.2%	U: 0.5%	U: 12.6			
55	M		Haplic cambisol and rendzic leptosols (rendzina)	Very shallow	4 to 7.5	6.5	0.47	U: 15	D: 26		
56	H		Alfisol	Dark-brown							
57	H	H	Humic Umbrisol		6.1			15.8			
58	L		Hydromorphic podzol	Sandy, waterlogged in winter				26			
59	M			Sand dunes.					D: high		Nutrient-poor under natural conditions
60	M		Kandiustalfs		6.5						Relatively nutrient rich
61	L	L M	Kalahari sands	Presents a calcrete duricrust						N: 1 to 3%	Nutrient-poor
62	M			Sandy soils			Low				N-fixing shrubs increase N availability
63	M			Sandy soils			Low				N-fixing shrubs

														increase N availability
64	L	L		83% sand, 9% silt and 8% clay	5.6	1.6%	0.12%	133						
65	M		Typic Dystrochrept								M: 122			
66	M	M	Mollic Eutroboralf and Typic Argiboroll	Loam	5.3	2.5%	0.14	17.9	High P					Although N might be limiting, P is highly available
67	L	M L										N: 0.95%		
68	H		Eutric Vertisol	60% clay		5.6%	3.80%	8.5	P: 98ppm	27		N: 3%	Former fertilized agricultural land	
69	L		Podzolic glacial till	Sandy										Nutrient-poor
70	L	L	Ombrotrophic peat dome		<3	39%	1.30%	30	Low			P: very low N: low		Low availability of essential nutrients
71	L	L		58% sand, 32% silt, 10% clay	U: 6.4 L: 6.3	U: 1.2 L: 1.6	U: 0.08 L: 0.08	U: 15 L: 20				N: 0.71%		
72	L		Durian Series	Band of laterite, highly leached	3.5 to 4.8				Low P	Low				
73	H		Xeric Alfisol	Loam texture			High		High				Former agricultural land	Characterized by its high nutrient availability
74	H		Xeric Alfisol	Loam texture			High		High				Former agricultural land	Characterized by its high nutrient availability
75	H		Xeric Alfisol	Loam texture			High		High				Former agricultural land	Characterized by its high nutrient availability

76	L			Waterlogged								Nutrient availability restricted by slow decomposition rates
77	L			Waterlogged								Nutrient availability restricted by slow decomposition rates
78	L			Waterlogged								Nutrient availability restricted by slow decomposition rates
79	M	H		75% rocks, stone-free fraction is silty-clay loam (39% clay, 35% silt, 26% sand)		7.40%	0.48%	U: 15 L: 11			N: 1.26%	
80	L		Red earth				Low		Low			Very poor nutrient status
81	M				U: 3.9 L: 4.1	U: 27% L: 9%	U: 1.3% L: 0.4%	U: 20 L: 24	U: 0.08% L: 0.03%		N Lt: 1% P lt: 0.07%	
82	H		Luvisol	100 cm depth, 52% sand, 12% silt, 35% clay	5.7			12.6				
83	L		Utisol	Stony	5.1		Low		Low	Low		Nutrient-poor, especially P
84	L	L		93% sand, 3% silt, 4% clay	6.5 to >7.9	U: 0.9 L: 0.4	U: 0.03 L: 0.03	U: 30 L: 14	Low		N: 0.70%	Poor sandy soil
85	H			Loam, from volcanic ashes.							N: 2.30%	
86	M	M				U: 4.2%	U: 0.4%	10.5				
87	L			Sandy to sandy loam		3.1	0.14	22.0			N: 0.95%	
88	L			Sandy to sandy loam		2.3	0.19	12.1			N:1.07%	

89	L			Sandy to sandy loam		3.3	0.17	19.4				N:1.35%		
90	L			Sandy to sandy loam		1.7	0.08	21.3				N:1.36%		
91	L			Sandy		1.8	0.1	18.0				N:1.20%		HJP75 could be more nutrient limited due to higher tree competition
92	L			Sandy to sandy loam		1.4	0.1	14.0				N:1.55%		
93	M	M												
94	M	M												
95	H													Fertilized
96	L	L	Ultic alaquods	Sandy, siliceous, thermic		Low	Low		Low				Trees responded drastically to fertilization experiment	Low in available nutrients
97	L	L	Ultic alaquods	Sandy, siliceous, thermic		Low	Low		Low				Trees responded drastically to fertilization experiment	Low in available nutrients
98	L		Haplic podzol				Low		Low					Nutrient-poor soil
99	M				Low					Low				Nutrients are sufficiently available in this forest
100	H		Luvisol				High							Very nutrient rich
101	L	M		57% sand, 36% silt and 6% clay			0.18%				M: 4.4			
102	H		Brown soil											Very nutrient rich
103	M		Dystric Cambisol	Clay loam, from volcanic ash deposit										

104	L		Belterra clay Ferralsols				Low		Low			Nutrient-poor
105	L		Belterra clay Ferralsols				Low		Low			Nutrient-poor
106	L		Gleyic Cambisol							D: 5		Stream water chemistry revealed very low N concentrations
107	M		Dystric Cambisol									Less nutrient rich than a eutric Cambisol
108	L			Drained, peat-rich			Low		Low			Severely nutrient limited
109	L		Volcanogenous regosol	Well drained			Low		Low			Nutrient-poor
110	M	M	Brunicolic grey brown luvisol	Sandy to loamy sand soil, low-to-moderate water-holding capacity	6.3	0.56%	U: 0.06%	L: 11.4		D: 7.5	Planted on former agricultural land	Have higher amounts of soil macronutrients (i.e. P, K, Ca, Mg) than id 111 and 112
111	M	M	Gleyed brunisolic luvisol	Sandy to loamy sand soil, low-to-moderate water-holding capacity	4.1	0.61%	U: 0.05%	L: 15.4		D: 7.5	Planted on cleared oak-savannah land	
112	M	M	Brunicolic grey brown luvisol	Sandy to loamy sand soil, low-to-moderate water-holding capacity	3.7	0.60%	U: 0.06%	L: 19.4		D: 7.5	Planted on cleared oak-savannah land	
113	M	M	Gleyed brunisolic luvisol	Sandy to loamy sand soil, low-to-moderate water-holding capacity	4.3	0.51%	U: 0.07%	L: 14.2		D: 7.5	Planted on former agricultural land	Same as id 110
114	L		Entic Haplothod	Sandy, well drained			Low					Nitrogen limited
115	H		Brown Andosol			U: 8.1% L: 3.0%	U: 0.4% L: 0.2%.	U: 20 L: 15			Grazed heathland pasture prior to afforestation	

116	L	L M		Gravelly loamy sand, 19 cm depth	U: 39% L: 4.6%	U: 0.9% L: 0.3%	U: 43 L: 15					Presents low nitrogen availability
117	L	L M		Gravelly loamy sand to sand, 19 cm depth	U: 45% L: 6.9%	U: 1% L: 0.2%	U: 45 L: 35					
118	L	L M		Gravelly loamy sand, 19 cm depth	U: 46% L: 18%	U: 1% L: 0.8%	U: 46 L: 23					
119	M	M										Fertilization stimulated tree growth
120	L		Typic Paleudult	Highly weathered, acidic		Low		low P	Low			
121	M		Podzols and Cambisols									Moderately nutrient-rich soils
122	M		Enthic Haplorthod							M: > id 114		Nutrient-poor soil similar to id 114
123	M		Stagni-vertic Cambisol	Some areas of arenihaplic Luvisols and calcaric Cambisols								Vegetation is typical for relatively nutrient-rich soils
124	M		Rendzina	Above chalk and limestone			11					Poor soil conditions
125	M		Brown	Loam		Low		Low				Nutrient limitations
126	L		Cambisols	Sandy silt		Low		Low			see report	Nutrient limited: extremely low nutrient concentrations were reported in *Pinus* and *Larix* trees
127	L		Cambisols	Sandy silt		Low		Low			Idem id 126	Nutrient limited
128	L		Cambisols	Sandy silt		Low		Low			Idem id 126	Nutrient limited
129	L		Cambisols	Sandy silt		Low		Low			Idem id 126	Nutrient limited

Site id: 1. Aberfeldy/Griffins; **2.** Austin; 3. Balmoral; 4. Barlett; 5. Bayreuth/Weiden Brunnen; **6.** Bilos; **7.** Bily Kriz Forest; **8.** Blodgett Forest; **9.** Bornhoved Alder; **10.** Bornhoved Beech; **11.** Brasschaat; **12.** Bukit Soeharto; **13.** Camp Borden; **14.** Castelporziano; **15.** Caxiuana; **16.** Changbai Mountains; **17.** Chibougamau EOBS; **18.** Chibougamau HBS00; **19.** Coastal plain North Carolina; **20.** Collelongo; **21.** Cuieiras/C14; **22.** Davos; **23.** Dinghushan DHS; **24.** Dooary; **25.** Duke Forest; **26.** El Saler; **27.** Espirra; **28.** Fairbanks; **29.** Flakaliden C; **30.** Fujiyoshida; **31.** Fyedorovskoye; **32.** Groundhog; **33.** Gunnarsholt; **34.** Guyaflux; **35.** Gwangneung; **36.** Hainich; **37.** Hampshire; **38.** Hardwood; **39.** Hardwood_21; **40.** Harvard; **41.** Hesse; **42.** Howards spring; **43.** Howland; **44.** Hyytiala; **45.** Ilomantsi Mekrijärvi; **46.** Ione; **47.** Jacaranda/K34; **48.** Kannenbruch Alder/Ash; **49.** Kannenbruch Beech; **50.** Kannenbruch Oak; **51.** Khentei Taiga; **52.** Kiryu; **53.** La Majadas del Tietar; **54.** La Mandria; **55.** Lägeren; **56.** Laoshan; **57.** Lavarone; **58.** Le Bray; **59.** Loobos; **60.** Mae Klong; **61.** Maun Mopane; **62.** Metolius; **63.** Metolius young; **64.** Mitra; **65.** Morgan Monroe; **66.** NAU Centennial; **67.** Niwot Ridge; **68.** Nonantola; **69.** Norunda; **70.** Palangkaraya; **71.** Parco Ticino; **72.** Pasoh; **73.** Popface alba; **74.** Popface euamericana; **75.** Popface nigra; **76.** Prince Albert SSA (SOAS); **77.** Prince Albert SSA (SOBS); **78.** Prince Albert SSA (SOJP); **79.** Puechabon; **80.** Qianyanzhou Ecological Station; **81.** Renon; **82.** Roccarespampami 2; **83.** Sakaerat; **84.** San Rossore; **85.** Sapporo; **86.** Sardinilla; **87.** Saskatchewan F77; **88.** Saskatchewan F89; **89.** Saskatchewan F98; **90.** Saskatchewan HJP02; **91.** Saskatchewan HJP75; **92.** Saskatchewan HJP94; **93.** Sky Oaks old; **94.** Sky Oaks young; **95.** Skyttorp2; **96.** Slash pine Florida Mid; **97.** Slash pine Florida old; **98.** Sodankylä; **99.** Solling; **100.** Soroe; **101.** Sylvania; **102.** Takayama; **103.** Takayama 2; **104.** Tapajos 67; **105.** Tapajos 83; **106.** Teshio CC-LaG; **107.** Tharandt; **108.** Thompson NSA (NOBS); **109.** Tomakomai; **110.** Turkey Point TP02; **111.** Turkey Point TP39; **112.** Turkey Point TP74; **113.** Turkey Point TP89; **114.** University of Michigan; **115.** Vallanes; **116.** Vancouver Island DF49; **117.** Vancouver Island HDF00; **118.** Vancouver Island HDF88; **119.** Vielsalm; **120.** Walker Branch; **121.** Wet-T-57; **122.** Willow Creek; **123.** Wytham Woods; **124.** Yatir; **125.** Yellow River Xiaolangdi; **126.** Yenisey Abies; **127.** Yenisey Betula; **128.** Yenisey Mixed; **129.** Yenisey/Zotino.

Table S2.2. Analysis of sensitivity to a possible misclassification of nutrient availability. The table contains those forests for which information assessing nutrient status could lead to a wrong classification. Each shows its values for CUEe, the uncertainty of this estimate (SE), the original and most plausible classification of nutrient status and an alternative nutrient classification. The *P*-values of the significant variables and the β weights of the covariates, using the original and the alternative nutrient classification with stepwise backward regressions, are shown at the bottom of the table. Possible predictors were GPP, nutrient availability, stand age and management, including their interactions up to the second order, MAT, MAP and WD. Significance levels: * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$. H high, M medium and L low nutrient availability.

Forest name	CUEe	SE	Original Classification		Alternative Classification	
Bayreuth/Weiden Brunnen	-0.02	0.04	L		M	
Bilos	0.25	0.07	L		M	
Blodgett Forest	0.11	0.03	L		M	
Bornhoved Alder	0.15	0.07	L		M	
Brasschaat	0.00	0.02	L		M	
Camp Borden	0.12	0.05	M		L	
Castelporziano	0.32	0.02	L		M	
Guyaflux	0.04	0.04	L		M	
Hampshire	0.28	0.06	H		M	
Hardwood	0.32	0.05	M		H	
Hardwood_21	0.31	0.06	M		H	
Lägeren	0.23	0.03	M		H	
Lavarone	0.68	0.05	H		M	
Loobos	0.23	0.02	M		L	
Maun Mopane	-0.03	0.25	L		M	
Prince Albert SSA (SOAS)	0.15	0.02	L		M	
Prince Albert SSA (SOBS)	0.06	0.06	L		M	
Prince Albert SSA (SOJP)	0.05	0.08	L		M	
Sylvania	0.10	0.07	L		M	
Teshio CC-LaG	0.05	0.08	L		M	
Vielsalm	0.31	0.02	M		L	
Wet-T-57	-0.03	0.04	M		H	
Willow Creek	0.25	0.06	M		H	
Yatir	0.28	0.11	M		L	
Yellow River Xiaolangdi	0.30	0.05	M		L	
			Effect (β)	***R*²**	**Effect (β)**	***R*²**
Nutrient availability			H>L; -0.32**	0.12	H>L; -0.29**	0.07
GPP			0.91***	0.14	0.59**	0.12
Age			1.13***	<0.01	1.22***	0.01
GPP*Age			-1.17***	0.17	-1.18***	0.18
MAT			-	-	0.39*	0.06
Adjusted *R*²			**0.40**		**0.39**	

NOTE: Depending on the classification, the number of replicates varies (because the number of forests of medium nutrient availability changes).

Table S2.3: Followed criteria for evaluating nutrient availability. The table shows the code assigned to the forests according to the values of the variables used for the nutrient availability assessment.

Variable	Code	Variable	Code
Soil Additional Info		**Soil type**	
Poorly drained, argilic horizon	Low	Acrisol and ultisols	Low
100 cm depth, 52% sand, 12% silt, 35% clay	Medium	Alfisol	High
4% sand, 56% lime, 44% clay	Medium	Andosol	Medium
57% sand, 36% silt and 6% clay	Low	Arenosol	Low
58% sand, 32% silt, 10% clay	Medium	Belterra clay Ferralsols	Low
60% clay	Medium	Brown Andosol	High
63% clay, 19% silt	Low	Brown podzolic	Low
75% rocks, stone free fraction is silty-clay loam (39% clay, 35% silt, 26% sand)	Medium	Brown soil	High
80% clay, high porosity (50-80%), low water capacity, highly weathered	Low	Brunicolic grey brown luvisol	High
83% sand, 9% silt and 8% clay	Low	Cambisol	Medium
90 cm depth, low water capacity, roky and sandy (80%)	Low	Dystric cambisol	Medium
93% sand, 3% silt, 4% clay	Low	Enthic Haplorthod	Low
Above chalk and limestone	Low	Entisol	Low
Band of laterite, highly leached	Low	Eutric Vertisol	Low
Clay loam, from volcanic ash deposit	Medium	Fibric Histosol	Low
Coarse texture, highly leached, gray	Low	Gleyed brunisolic luvisol	High
Dark-brown	High	Gleyic Cambisol	Medium
Deep and fertile soil layer	High	Gleysol	Medium
Drained, peat-rich	Low	Haplic cambisol and rendzic leptosols	Medium
Dune system	Low	Histosol	Low
Fine-loamy, clay-loam	Medium	Humic umbrisol	Medium
Fine-silty	Medium	Kalahari sands	Low
Good drainage	High	Kandiustalfs	Medium
Gravelly loamy sand to sand, 19 cm depth	Medium	Lateritic red or yellow soil	Low
Gravelly loamy sand, 19 cm depth	Medium	Lithic haploxerepts	Low
Heavily leached	Low	Luvisols	High
Highly weathered, acidic	Low	Mixed mesic ultic haploxeralf	Low
Loam	High	Mollic Eutroboralf and Typic Argiboroll	Medium
Loam, from volcanic ashes.	High	Ombrotrophic peat dome	Low
Loamy mixed dysis thermic terric Haplosaprists (peat soils)	Low	Orthic Gleysol	Medium
Loamy sand to loam, thick organiz horizon (30cm)	Medium	Oxisol	Low
Mixed clay mineralogy, poorly drained from fall to spring	Low	Podzol	Low
Not waterlogged	Medium	Red earths	Low
Peat soil	Low	Spodosol	Low
Peaty, seasonally waterlogged, black organic horizon	Low	Stagni-vertic Cambisol	Medium
Peaty, seasonally waterlogged, black organic horizon	Low	Typic Dystrochrept	Medium
Presents a calcrete duricrust	Low	Typic Paleudult	Low
Sand dunes	Low	Ultic alaquods	Low
Sandy	Low	Ultic alfisol	Low

Sandy loam or loam	Medium
Sandy loam with limited water capacity	Low
Sandy silt	Medium
Sandy to loamy sand soil, low-to-moderate water holding capacity	Medium
Sandy to loamy sandy texture, organic layer mod/moder	Medium
Sandy to sandy loam	Medium
Sandy, hummus rich in calcium carbonate	Low
Sandy, siliceous, thermic	Low
Sandy, surface water table in winter	Low
Sandy, waterlogged in winter	Low
Sandy, well drained	Low
Silty loam	Medium
Silty loam-silty clay	Medium
Some areas of arenihaplic Luvisols and calcaric Cambisols	Medium
Stony	Low
Stony sandy loam	Medium
Very rocky silt loam	Low
Very shallow	Low
Very wet, waterlogged	Low
Waterlogged	Low
Well drained	Medium
Well drained lateritic red and yellow earth soils with highly weathered sands	Low
Well drained, acidic sandy loam with some poorly drained peat soils	Low
Well drained, stonefree, fine sandy loam materials	Medium
Wet sandy soil with humus and/or iron B horizon (Al buffer region).	Medium

Soil pH

0 - 5	Low
5.1 - 6	Medium
6.1 - 8	High

Soil N%

>0.8%	High
>0.1%	Medium
<0.1%	Low

Ultisol	Low
Volcanogenous regosol	Medium

Other Nutrients (soil P)

9 ppm	Low
98 ppm	High
0.08-0.03%	Medium

C:N ratio

> 30	Low
30 - 20	Medium
<20	High

CEC (meq L^{-1})

>20	High
>10	Medium
<10	Low

N deposition (kg ha^{-1} $year^{-1}$)

>20	High
20 - 10	Medium
<10	Low

N mineralization (kg ha^{-1} $year^{-1}$)

4.4	Low
34	Low
65	Medium
122	High

Foliar N%

>2%	High
2 - 1%	Medium
<1%	Low

Foliar P%

0.07%	Low

Table S2.4. Validation of the nutrient classification. Summary of the percentage of successfully classified forests of the different logit models used to validate the nutrient classification. In general terms, our nutrient classification was successfully predicted with the available data for nutrient status that, in turn, achieved a good percentage of successful predictions of the reports found in the literature on the nutrient status of the forests.

Dependent variable	Model selection	AIC	Correct cases	Failed cases	Success (%)
Nutrient status	Saturated	110	92	0	100%
Nutrient status	Stepwise	37	91	1	99%
Report	Saturated	130	55	3	95%
Report	Stepwise	37	54	4	93%

List of Models

Here, we present the minimum adequate models exposed in Table 1 followed by its homologous final model achieved by the model averaging procedure. Predictor variables were: GPP, Nutrient availability (NA), Age, Management (MNG), and its interactions up to second order, MAT, MAP and WD. Forests whose category of management was not managed or unmanaged were excluded. In model averaging summaries, R imp indicates the relative importance of the variables in the final model.

General Model

NEP (Figure 1)

	Estimate	**Std.Err**	**t value**	**Pr(>|t|)**	
Intercept	-1056	219.8	-4.803	0.0000124	***
gpp	0.8679	0.1235	7.029	3.38E-09	***
age	4.76	1.319	3.609	0.000664	***
nutrient.classLOW	934.9	229.4	4.076	0.000149	***
mat	20.67	6.186	3.342	0.001502	**
gpp:age	-0.00293	0.0007656	-3.828	0.000333	***
gpp:nutrient.classLOW	-0.6802	0.1318	-5.162	0.00000346	***
age:nutrient.classLOW	-1.862	0.7679	-2.425	0.018614	*

***R^2*=** 0.7356 **adj *R^2*=** 0.702

ANOVA table (type III)

	SumSq	**DF**	**F value**	**Pr(>F)**		***R^2***
(Intercept)	809163	1	23.0691	0.00001244	***	
gpp	1732864	1	49.4036	3.384E-09	***	0.18
age	456867	1	13.0252	0.0006645	***	0.03
nutrient.class	582787	1	16.6151	0.0001486	***	0.19
mat	391717	1	11.1678	0.0015015	**	0.09
gpp:age	513890	1	14.6509	0.0003332	***	0.09
gpp:nutrient.class	934745	1	26.6494	3.465E-06	***	0.15
age:nutrient.class	206289	1	5.8813	0.0186138	*	0.01
Residuals	1929161	55				

NEP model averaging

	Estimate	**SE**	**Adj SE**	**z val**	**Pr(>|z|)**		**Variables**	**R Imp**
(Intercept)	-935.8	239.8	244.1	3.833	0.00013	***	(Intercept)	1.00
age	3.947	2.058	2.075	1.902	0.05715	.	gpp	1.00
gpp	0.7856	0.1379	0.1404	5.597	<0.00001	***	gpp:NA	1.00
mat	18.69	6.871	7.011	2.667	0.00766	**	NA	1.00
NA.LOW	731.9	287.5	291.9	2.507	0.01217	*	mat	0.97
age:gpp	-0.00284	0.00081	0.000824	3.445	0.00057	***	MNG	0.62
age:NA.LOW	-1.865	0.7762	0.7939	2.349	0.01881	*	gpp:MNG	0.55
gpp:NA.LOW	-0.5897	0.164	0.1668	3.536	0.00041	***	age	0.53
MNG.UM	280.4	156.1	158.2	1.773	0.07628	.	wd	0.50
wd	2.738	1.733	1.768	1.549	0.12146		age:gpp	0.45
gpp:MNG.UM	-0.2451	0.0736	0.07525	3.257	0.00112	**	age:NA	0.42
MNG.UM:NA.LOW	-72.39	136	139.1	0.52	0.60276		map	0.15
map	-0.0281	0.09175	0.0938	0.3	0.76454		MNG:NA	0.08
							age:MNG	0.00

16 models Δ < 4

Re (Figure 2)

	Estimate	Std.Err	t value	Pr(>|t|)	
(Intercept)	1097	228.8	4.794	0.0000129	***
gpp	0.09329	0.1285	0.726	0.471097	
age	-4.788	1.373	-3.487	0.000968	***
nutrient.classLOW	-955.6	238.8	-4.002	0.00019	***
mat	-17.02	6.44	-2.643	0.010676	*
gpp:age	0.00294	0.000797	3.688	0.000519	***
gpp:nutrient.classLOW	0.6805	0.1372	4.961	0.00000712	***
age:nutrient.classLOW	1.967	0.7995	2.46	0.017077	*

R^2= 0.9108 adj R^2= 0.8995

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	873556	1	22.9785	0.00001286	***	
gpp	20021	1	0.5266	0.4710968		0.64
age	462225	1	12.1587	0.0009684	***	0.01
nutrient.class	608864	1	16.0159	0.0001896	***	0.03
mat	265614	1	6.9869	0.0106758	*	0.16
gpp:age	517154	1	13.6035	0.0005186	***	0.03
gpp:nutrient.class	935495	1	24.6078	7.125E-06	***	0.05
age:nutrient.class	230005	1	6.0502	0.0170767	*	0.01
Residuals	2090888	55				

Re model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	1028	252.1	256.7	4.004	6.2E-05	***	(Intercept)	1.00
age	-4.61	1.463	1.492	3.089	0.00201	**	gpp	1.00
gpp	0.1505	0.1434	0.146	1.031	0.30247		NA	1.00
mat	-15.27	7.095	7.242	2.108	0.03502	*	gpp:NA	1.00
NA.LOW	-765.2	303.2	307.8	2.486	0.01293	*	mat	0.85
age:gpp	0.00283	0.00083	0.00085	3.332	0.00086	***	age	0.71
age:NA.LOW	1.971	0.8094	0.8277	2.382	0.01723	*	age:gpp	0.71
gpp:NA.LOW	0.5838	0.1719	0.1747	3.342	0.00083	***	age:NA	0.68
wd	-3.12	1.809	1.845	1.691	0.09077	.	wd	0.59
MNG.UM	-214.4	164.1	165.9	1.292	0.1963		MNG	0.39
gpp:MNG.UM	0.2253	0.07724	0.07896	2.853	0.00434	**	gpp:MNG	0.29
map	0.05755	0.09505	0.09721	0.592	0.55382		map	0.15
MNG.UM:NA.LOW	76.51	142	145.3	0.527	0.59841		MNG:NA	0.03
							age:MNG	0.00

13 models Δ < 4

Models weighted by the uncertainty of the estimates (Supplementary Figure 5)

NEP

	Estimate	Std.Err	t value	Pr(>|t|)	
(Intercept)	-848.4	226.4	-3.747	0.000431	***
gpp	0.7368	0.1328	5.548	8.53E-07	***
age	5.099	1.522	3.349	0.001468	**
nutrient.classLOW	719.1	240.9	2.985	0.004221	**
mat	17.79	6.842	2.6	0.011953	*
gpp:age	-0.00308	0.0009198	-3.346	0.001484	**
gpp:nutrient.classLOW	-0.515	0.1536	-3.352	0.001457	**
age:nutrient.classLOW	-2.288	0.8235	-2.778	0.007462	**

***R^2*=** 0.614 **adj *R^2*=** 0.5648

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	15401	1	14.0377	0.0004313	***	
gpp	33773	1	30.783	8.532E-07	***	0.20
age	12308	1	11.2187	0.0014678	**	0.02
nutrient.class	9778	1	8.9126	0.0042208	**	0.14
mat	7416	1	6.7591	0.011953	*	0.08
gpp:age	12281	1	11.1935	0.0014844	**	0.06
gpp:nutrient.class	12327	1	11.2351	0.001457	**	0.08
age:nutrient.class	8469	1	7.7187	0.0074616	**	0.03
Residuals	60343	55				

NEP model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	1028	252.1	256.7	4.004	6.2E-05	***	(Intercept)	1.00
age	-4.61	1.463	1.492	3.089	0.00201	**	gpp	1.00
gpp	0.1505	0.1434	0.146	1.031	0.30247		NA	1.00
mat	-15.27	7.095	7.242	2.108	0.03502	*	gpp:NA	1.00
NA.LOW	-765.2	303.2	307.8	2.486	0.01293	*	mat	0.85
age:gpp	0.002829	0.00083	0.000849	3.332	0.00086	***	age	0.71
age:NA.LOW	1.971	0.8094	0.8277	2.382	0.01723	*	age:gpp	0.71
gpp:NA.LOW	0.5838	0.1719	0.1747	3.342	0.00083	***	age:NA	0.68
wd	-3.12	1.809	1.845	1.691	0.09077	.	wd	0.59
MNG.UM	-214.4	164.1	165.9	1.292	0.1963		MNG	0.39
gpp:MNG.UM	0.2253	0.07724	0.07896	2.853	0.00434	**	gpp:MNG	0.29
map	0.05755	0.09505	0.09721	0.592	0.55382		map	0.15
MNG.UM:NA.LOW	76.51	142	145.3	0.527	0.59841		MNG:NA	0.03
							age:MNG	0.00

13 models Δ < 4

Re

	Estimate	Std.Err	t value	Pr(>|t|)	
(Intercept)	843.6	226	3.733	0.000451	***
gpp	0.257	0.1309	1.963	0.054717	.
age	-4.752	1.544	-3.078	0.003249	**
nutrient.classLOW	-710.6	240.3	-2.957	0.004569	**
mat	-14.44	6.942	-2.08	0.042228	*
gpp:age	0.002832	0.0009312	3.041	0.003608	**
gpp:nutrient.classLOW	0.5055	0.1522	3.321	0.001596	**
age:nutrient.classLOW	2.252	0.8341	2.7	0.009199	**

R^2= 0.8781 **adj R^2=** 0.8626

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	10232	1	13.9334	0.0004507	***	
gpp	2830	1	3.8532	0.0547171	.	0.65
age	6956	1	9.4726	0.0032495	**	0.00
nutrient.class	6421	1	8.7445	0.0045687	**	0.02
mat	3176	1	4.3251	0.0422277	*	0.15
gpp:age	6791	1	9.2477	0.0036078	**	0.02
gpp:nutrient.class	8101	1	11.032	0.0015956	**	0.03
age:nutrient.class	5353	1	7.2893	0.009199	**	0.01
Residuals	40389	55				

Re model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	787.1	271	275.3	2.858	0.00426	**	(Intercept)	1.00
age	-4.66	1.566	1.602	2.91	0.00362	**	gpp	1.00
gpp	0.2976	0.1511	0.1536	1.937	0.05273	.	NA	1.00
mat	-13.85	7.181	7.34	1.887	0.05921	.	gpp:NA	0.97
NA.LOW	-557	302.8	307	1.814	0.06964	.	mat	0.73
age:gpp	0.00279	0.00094	0.00097	2.889	0.00387	**	age	0.70
age:NA.LOW	2.252	0.8484	0.8675	2.596	0.00942	**	age:gpp	0.70
gpp:NA.LOW	0.4508	0.1705	0.1735	2.598	0.00938	**	age:NA	0.70
wd	-2.856	1.872	1.913	1.493	0.1354		wd	0.51
MNG.UM	-185.5	162	163.9	1.132	0.25761		MNG	0.30
gpp:MNG.UM	0.2135	0.09021	0.09213	2.317	0.02049	*	gpp:MNG	0.22
map	-0.03157	0.08994	0.09188	0.344	0.73117		map	0.11
							age:MNG	0.00
							MNG:NA	0.00

15 models Δ < 4

Models forests Eddy Covariance data

NEP

	Estimate	Std.Err	t value	Pr(>|t|)	
(Intercept)	-575.607	257.70547	-2.234	0.029924	*
gpp	0.58016	0.1567	3.702	0.000525	***
nutrient.classLOW	468.7595	281.1306	1.667	0.101563	
managementUM	321.0978	119.82562	2.68	0.009896	**
mat	18.41545	7.09241	2.597	0.012274	*
gpp:nutrient.classLOW	-0.43306	0.18555	-2.334	0.02358	*
gpp:managementUM	-0.25613	0.07463	-3.432	0.001197	**

R^2= 0.58 adj R^2= 0.5306

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	181821	1	4.9889	0.029924	*	
gpp	499578	1	13.7077	0.000525	***	0.18
nutrient.class	101326	1	2.7803	0.101563		0.11
management	261706	1	7.1808	0.009896	**	0.04
mat	245706	1	6.7418	0.012274	*	0.09
gpp:nutrient.class	198516	1	5.447	0.02358	*	0.06
gpp:management	429267	1	11.7785	0.001197	**	0.11
Residuals	1858698	51				

NEP model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	-541.6	328.6	333.1	1.626	0.10396		(Intercept)	1.00
gpp	0.5573	0.1879	0.1907	2.922	0.00348	**	gpp	1.00
MNG.UM	328.7	130.2	133.2	2.467	0.01361	*	NA	1.00
mat	17.67	7.436	7.606	2.323	0.02018	*	MNG	0.91
NA.LOW	391.7	370.2	374.8	1.045	0.29596		gpp:MNG	0.91
gpp:MNG.UM	-0.2623	0.07625	0.07807	3.36	0.00078	***	mat	0.90
gpp:NA.LOW	-0.4468	0.1904	0.1948	2.293	0.02183	*	gpp:NA	0.83
wd	1.995	1.977	2.023	0.986	0.32403		age	0.18
MNG.UM:NA.LOW	-91.61	138.1	141.5	0.648	0.51729		wd	0.18
age	2.343	2.424	2.434	0.963	0.33564		MNG:NA	0.11
age:gpp	-0.00275	0.0008	0.000822	3.341	0.00083	***	age:gpp	0.09
age:NA.LOW	-1.928	0.799	0.8188	2.354	0.01855	*	age:NA	0.09
map	0.02251	0.09908	0.1015	0.222	0.82458		map	0.08
							age:MNG	0.00

9 models Δ < 4

Re

	Estimate	Std.Err	t value	Pr(>|t|)	
(Intercept)	627.57583	260.16476	2.412	0.01949	*
gpp	0.38836	0.1582	2.455	0.01754	*
nutrient.classLOW	-522.60114	283.81343	-1.841	0.07139	.
managementUM	-314.55694	120.96911	-2.6	0.01215	*
mat	-17.83373	7.16009	-2.491	0.01605	*
gpp:nutrient.classLOW	0.46899	0.18732	2.504	0.01554	*
gpp:managementUM	0.2495	0.07534	3.311	0.00171	**

R^2= 0.9163 **adj R^2=** 0.9065

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	216134	1	5.8188	0.01949	*	
gpp	223853	1	6.0266	0.01754	*	0.67
nutrient.class	125940	1	3.3906	0.07139	.	0.01
management	251153	1	6.7616	0.01215	*	0.01
mat	230428	1	6.2036	0.01605	*	0.19
gpp:nutrient.class	232822	1	6.2681	0.01554	*	0.01
gpp:management	407320	1	10.966	0.00171	**	0.02
Residuals	1894342	51				

Re model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	643	310.3	315.7	2.037	0.04166	*	(Intercept)	1.00
gpp	0.3806	0.1769	0.1803	2.111	0.03475	*	gpp	1.00
MNG.UM	-321.6	134.1	137.2	2.344	0.01908	*	NA	1.00
mat	-17.6	7.308	7.486	2.351	0.01871	*	gpp:NA	0.95
NA.LOW	-509.2	338.6	344.3	1.479	0.1391		mat	0.90
gpp:MNG.UM	0.2514	0.07647	0.07833	3.21	0.00133	**	MNG	0.89
gpp:NA.LOW	0.4727	0.1973	0.2017	2.344	0.01908	*	gpp:MNG	0.89
wd	-1.792	1.933	1.981	0.905	0.36569		age	0.20
MNG.UM:NA.LOW	109.1	139.1	142.6	0.765	0.44426		wd	0.14
age	-2.459	2.41	2.421	1.016	0.3098		MNG:NA	0.12
age:gpp	0.00268	0.00081	0.00083	3.236	0.00121	**	age:gpp	0.11
age:NA.LOW	1.953	0.8048	0.8247	2.367	0.01791	*	age:NA	0.11
map	-0.01641	0.1001	0.1025	0.16	0.87287		map	0.09
							age:MNG	0.00

8 models Δ < 4

Models without nutrient status

NEP

	Estimate	Std.Err	t	Pr(>|t|)	
(Intercept)	-594.399	133.86874	-4.44	4.1E-05	***
gpp	0.511744	0.0616439	8.302	1.9E-11	***
managementUM	355.4655	131.84313	2.696	0.00917	**
wd	5.280222	1.6748899	3.153	0.00256	**
gpp:managementUM	-0.36777	0.0796442	-4.62	2.2E-05	***

R^2= 0.5974 **adj** R^2= 0.5697

ANOVA table (type

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	998461	1	19.7151	4.09E-05	***	
gpp	3490265	1	68.9169	1.92E-11	***	0.31
management	368140	1	7.2691	0.009166	**	0.08
wd	503344	1	9.9388	0.002562	**	0.05
gpp:management	1079913	1	21.3234	2.20E-05	***	0.15
Residuals	2937383	58				

NEP model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R
(Intercept)	-571.522	154.13	157.1015	3.638	0.00028	***	(Intercept)	1.00
gpp	0.51726	0.06999	0.07143	7.241	2.0E-16	***	gpp	1.00
MNG.UM	331.4987	138.953	141.85	2.337	0.01944	*	MNG	1.00
wd	5.23634	1.73593	1.7725	2.954	0.00314	**	gpp:MNG	1.00
gpp:MNG.UM	-0.3526	0.08492	0.08666	4.069	4.7E-05	***	wd	1.00
map	-0.11618	0.09751	0.09959	1.167	0.24337		map	0.38
age	0.3439	0.45327	0.46312	0.743	0.45774		age	0.22
mat	3.80219	7.9414	8.10027	0.469	0.63879		mat	0.19
							age:gpp	0.00
6 models Δ < 4							age:MNG	0.00

Re

	Estimate	Std.Err	t	Pr(>|t|)	
(Intercept)	608.429056	137.84864	4.414	0.0000448	***
gpp	0.4893964	0.0634765	7.71	1.88E-10	***
managementUM	-	135.7628	-2.567	0.01287	*
wd	-5.4720214	1.7246841	-3.173	0.00242	**
gpp:managementUM	0.3532584	0.082012	4.307	0.0000646	***

R^2= 0.8672 **adj** R^2= 0.858

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	1046150	1	19.481	4.48E-05	***	
gpp	3192086	1	59.442	1.88E-10	***	0.70
management	353779	1	6.588	0.01287	*	0.02
wd	540575	1	10.066	0.002415	**	0.11
gpp:management	996345	1	18.554	6.46E-05	***	0.04
Residuals	3114635	58				

Re model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R
(Intercept)	553.652	163.49	166.527	3.325	0.00089	***	(Intercept)	1.00
gpp	0.46987	0.07201	0.07349	6.393	2.0E-16	***	gpp	1.00
MNG.UM	-301.36	144.967	147.921	2.037	0.04162	*	MNG	1.00
map	0.16497	0.09806	0.10018	1.647	0.09961	.	gpp:MNG	1.00
wd	-5.33181	1.77344	1.811	2.944	0.00324	**	wd	1.00
gpp:MNG.UM	0.31923	0.0905	0.09226	3.46	0.00054	***	map	0.57
mat	-1.60924	8.40043	8.56236	0.188	0.85092		mat	0.18
age	-0.27027	0.46671	0.47681	0.567	0.57084		age	0.20
							age:gpp	0.00
6 models Δ < 4							age:MNG	0.00

Models excluding forests with GPP>2500

NEP (Figure 1)

	Estimate	Std.Err	t value	Pr(>|t|)	
Intercept)	-862.685	196.8156	-4.383	0.0000557	***
gpp	0.7604	0.1203	6.32	5.59E-08	***
nutrient.classLOW	441.8157	226.904	1.947	0.05682	.
wd	4.2971	1.5516	2.77	0.00772	**
gpp:nutrient.classLOW	-0.4184	0.1396	-2.998	0.00413	**

R^2= 0.7179 adj R^2= 0.6966

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	706098	1	19.2125	0.00005568	***	
gpp	1467744	1	39.9365	5.592E-08	***	0.44
nutrient.class	139341	1	3.7914	0.056824	.	0.17
wd	281899	1	7.6703	0.007721	**	0.05
gpp:nutrient.class	330378	1	8.9894	0.004128	**	0.06
Residuals	1947852	53				

NEP model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	-869.3	197.7	202.4	4.295	1.7E-05	***	(Intercept)	1.00
gpp	0.7416	0.1187	0.1215	6.105	<0.00001	***	gpp	1.00
mat	17.13	6.702	6.847	2.502	0.01233	*	NA	1.00
NA.LOW	700.2	250.3	255.2	2.744	0.00607	**	gpp:NA	1.00
wd	2.96	1.667	1.705	1.737	0.08247	.	mat	0.95
gpp:NA.LOW	-0.5919	0.1571	0.1602	3.696	0.00022	***	wd	0.63
age	0.4008	0.6631	0.6738	0.595	0.55191		age	0.20
MNG.UM	28.78	57.71	59.08	0.487	0.6262		MNG	0.15
map	0.003563	0.09553	0.09778	0.036	0.97093		map	0.13
age:gpp	-0.00076	0.00076	0.000778	0.982	0.32601		age:gpp	0.04
							age:MNG	0.00
							age:NA	0.00
							gpp:MNG	0.00
10 models Δ < 4							MNG:NA	0.00

Re (Figure 2)

	Estimate	Std.Err	t value	Pr(>|t|)	
(Intercept)	904.8063	195.6001	4.626	0.0000244	***
gpp	0.2193	0.1196	1.834	0.07224	.
nutrient.classLOW	-460.8056	225.5027	-2.043	0.04599	*
wd	-4.3754	1.542	-2.838	0.00643	**
gpp:nutrient.classLOW	0.4221	0.1387	3.043	0.00364	**

R^2= 0.7411 **adj** R^2= 0.7215

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	776734	1	21.398	0.00002441	***	
gpp	122124	1	3.3644	0.072238	.	0.55
nutrient.class	151576	1	4.1757	0.045992	*	0.03
wd	292264	1	8.0515	0.006429	**	0.10
gpp:nutrient.class	336102	1	9.2592	0.003641	**	0.06
Residuals	1923867	53				

Re model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	911.146	200.906	205.649	4.431	9.4E-06	***	(Intercept)	1.00
gpp	0.22852	0.12099	0.12381	1.846	0.06494	.	gpp	1.00
mat	-12.4522	6.86698	7.01552	1.775	0.07591	.	NA	1.00
NA.LOW	-586.236	259.596	264.532	2.216	0.02668	*	gpp:NA	1.00
wd	-3.77785	1.69819	1.73473	2.178	0.02942	*	wd	0.86
gpp:NA.LOW	0.50671	0.16353	0.16657	3.042	0.00235	**	mat	0.63
age	-0.14644	0.34228	0.35019	0.418	0.67582		MNG	0.17
MNG.UM	-24.049	60.7591	62.0809	0.387	0.69847		age	0.14
map	-0.01268	0.09794	0.10008	0.127	0.89922		map	0.13
							age:gpp	0.00
							age:MNG	0.00
							age:NA	0.00
							gpp:MNG	0.00
10 models Δ < 4							MNG:NA	0.00

Weighted models excluding forests with GPP>2500

NEP

	Estimate	Std.Err	t value	Pr(>|t|)	
Intercept)	-567.832	201.3927	-2.82	0.00675	**
gpp	0.5898	0.1245	4.737	0.0000167	***
nutrient.classLOW	484.8521	235.3754	2.06	0.04433	*
mat	16.0388	6.577	2.439	0.01813	*
gpp:nutrient.classLOW	-0.4356	0.1585	-2.748	0.00818	**

R^2= 0.6143 adj R^2= 0.5852

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	8623	1	7.9497	0.00675	**	
gpp	24335	1	22.435	0.00001666	***	0.34
nutrient.class	4603	1	4.2432	0.044333	*	0.11
mat	6450	1	5.9468	0.018128	*	0.12
gpp:nutrient.class	8191	1	7.5515	0.008178	**	0.05
Residuals	57488	53				

NEP model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	-630.542	240.08	244.2723	2.581	0.00984	**	(Intercept)	1.00
gpp	0.58475	0.13469	0.13717	4.263	2E-05	***	gpp	1.00
mat	13.9113	7.15618	7.30633	1.904	0.05691	.	NA	1.00
NA.LOW	313.3486	302.626	306.4643	1.022	0.30656		gpp:NA	0.87
wd	3.69658	1.81166	1.85251	1.995	0.04599	*	wd	0.76
gpp:NA.LOW	-0.37807	0.17028	0.17373	2.176	0.02954	*	mat	0.75
map	0.07223	0.08776	0.08967	0.806	0.4205		map	0.19
MNG.UM	29.63878	54.6654	55.95706	0.53	0.59634		MNG	0.12
age	0.11882	0.35025	0.35868	0.331	0.74045		age	0.10
							age:gpp	0.00
							age:MNG	0.00
							age:NA	0.00
							gpp:MNG	0.00
12 models Δ < 4							MNG:NA	0.00

Re

	Estimate	Std.Err	t value	Pr(>|t|)	
(Intercept)	330.71463	132.59705	2.494	0.01572	*
gpp	0.58081	0.05895	9.852	1.16E-13	***
nutrient.classLOW	170.1716	56.38605	3.018	0.00388	**
wd	-3.91987	1.78531	-2.196	0.03243	*

R^2= 0.7128 adj R^2= 0.6968

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	4639	1	6.2207	0.01572	*	
gpp	72381	1	97.0636	1.156E-13	***	0.58
nutrient.class	6792	1	9.1082	0.003878	**	0.03
wd	3595	1	4.8208	0.032435	*	0.11
Residuals	40268	54				

Re model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	614.725	234.124	238.326	2.579	0.0099	**	(Intercept)	1.00
gpp	0.40001	0.13299	0.13544	2.953	0.00314	**	gpp	1.00
mat	-11.4335	7.2117	7.36514	1.552	0.12057		NA	1.00
NA.LOW	-303.751	284.67	288.541	1.053	0.29247		gpp:NA	0.90
wd	-3.46331	1.80117	1.8424	1.88	0.06014	.	wd	0.72
gpp:NA.LOW	0.35391	0.16485	0.16807	2.106	0.03523	*	mat	0.56
map	-0.04307	0.08784	0.08976	0.48	0.63136		MNG	0.14
MNG.UM	-19.3384	58.1629	59.4065	0.326	0.74478		map	0.14
age	-0.05802	0.34906	0.35716	0.162	0.87094		age	0.12
							age:gpp	0.00
							age:MNG	0.00
							age:NA	0.00
							gpp:MNG	0.00
15 models Δ < 4							MNG:NA	0.00

Models using only managed forests

NEP

	Estimate	Std.Err	t value	Pr(>|t|)	
(Intercept)	-857.573	205.9132	-4.165	0.000201	***
gpp	0.7092	0.1253	5.661	0.00000237	***
nutrient.classLOW	257.9824	249.5965	1.034	0.308621	
wd	6.39	1.8149	3.521	0.001247	**
gpp:nutrient.classLOW	-0.2955	0.1474	-2.005	0.053009	.

R^2= 0.7857 **adj** R^2= 0.7605

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	619836	1	17.345	0.0002014	***	
gpp	1145367	1	32.0511	2.372E-06	***	0.52
nutrient.class	38177	1	1.0683	0.3086206		0.14
wd	443006	1	12.3967	0.0012471	**	0.09
gpp:nutrient.class	143617	1	4.0189	0.0530094	.	0.04
Residuals	1215014	34				

NEP model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	-872.4	254.7	261.1	3.341	0.00083	***	(Intercept)	1.00
gpp	0.6644	0.1388	0.1426	4.66	3.2E-06	***	gpp	1.00
mat	16.51	9.362	9.723	1.698	0.08957	.	NA.	1.00
NA.LOW	282.1	334.3	341	0.827	0.408		wd	1.00
wd	6.396	2.165	2.229	2.869	0.00412	**	gpp:NA	0.85
gpp:NA.LOW	-0.3741	0.172	0.1776	2.107	0.03516	*	mat	0.49
age	0.9862	0.8297	0.8554	1.153	0.24892		age	0.46
age:NA.LOW	-1.362	1.124	1.168	1.166	0.24349		map	0.13
map	-0.02869	0.118	0.1222	0.235	0.81435		age:NA	0.11
age:gpp	0.00027	0.00105	0.001097	0.246	0.80581		age:gpp	0.03

13 models Δ < 4

Re

	Estimate	Std.Err	t value	Pr(>|t|)	
(Intercept)	909.3045	208.0546	4.371	0.000111	***
gpp	0.2617	0.1266	2.067	0.04639	*
nutrient.classLOW	-323.2086	252.1922	-1.282	0.208656	
wd	-6.2747	1.8337	-3.422	0.001636	**
gpp:nutrient.classLOW	0.3361	0.1489	2.257	0.03055	*

R^2= 0.8121 **adj** R^2= 0.79

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	696872	1	19.1014	0.0001107	***	
gpp	155911	1	4.2735	0.0463903	*	0.57
nutrient.class	59923	1	1.6425	0.2086559		0.03
wd	427173	1	11.7089	0.0016363	**	0.17
gpp:nutrient.class	185837	1	5.0938	0.0305504	*	0.05
Residuals	1240417	34				

Re model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	928.819	249.516	256.331	3.624	0.00029	***	(Intercept)	1.00
gpp	0.29454	0.14175	0.14572	2.021	0.04325	*	gpp	1.00
NA.LOW	-353.056	325.228	332.658	1.061	0.28855		NA	1.00
wd	-6.27146	2.166	2.23117	2.811	0.00494	**	wd	1.00
gpp:NA.LOW	0.3958	0.17112	0.17674	2.239	0.02513	*	gpp:NA	0.90
mat	-15.2377	9.50801	9.87347	1.543	0.12276		mat	0.44
age	-1.00995	0.8149	0.83836	1.205	0.22833		age	0.41
age:NA.LOW	1.42601	1.14127	1.18605	1.202	0.22924		age:NA	0.12
map	0.03553	0.11456	0.11897	0.299	0.76523		map	0.10
							age:gpp	0.00

10 models Δ < 4

Models using an alternative nutrient availability classification

NEP

	Estimate	Std.Err	t value	Pr(>|t|)	
Intercept)	-926.2	195.4	-4.74	0.0000165	***
gpp	0.7644	0.1093	6.994	4.6E-09	***
age	5.143	1.253	4.104	0.000141	***
alternutrLOW	769.5	203	3.79	0.000387	***
mat	20.21	5.225	3.869	0.000302	***
gpp:age	-0.00337	0.0007395	-4.557	0.0000309	***
gpp:alternutrLOW	-0.5263	0.1166	-4.515	0.0000357	***
age:alternutrLOW	-1.918	0.7773	-2.468	0.016854	*

R^2= 0.7553 adj R^2= 0.723

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
Intercept)	623153	1	22.4697	0.00001645	***	
gpp	1356752	1	48.9219	4.604E-09	***	0.25
age	467161	1	16.8449	0.0001407	***	0.04
alternutr	398366	1	14.3643	0.000387	***	0.12
mat	415043	1	14.9657	0.0003016	***	0.11
gpp:age	575924	1	20.7667	0.00003088	***	0.1
gpp:alternutr	565233	1	20.3812	0.0000357	***	0.11
age:alternutr	168904	1	6.0903	0.0168544	*	0.02
Residuals	1469850	53				

NEP model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
Intercept	-924.6	208.3	212.8	4.344	1.4E-05	***	(Intercept)	1.00
age	5	1.387	1.413	3.539	0.0004	***	age	1.00
alternutrLOW	761.1	213.8	218.6	3.482	0.0005	***	alternutr	1.00
gpp	0.7599	0.1127	0.1152	6.598	2E-16	***	gpp	1.00
mat	20.18	5.445	5.572	3.622	0.00029	***	mat	1.00
age:alternutrLOW	-1.943	0.7858	0.8042	2.416	0.01571	*	age:gpp	1.00
age:gpp	-0.00331	0.0008	0.000812	4.077	4.6E-05	***	alternutr:gpp	1.00
alternutrLOW:gpp	-0.5283	0.1217	0.1245	4.244	2.2E-05	***	age:alternutr	0.93
map	0.05238	0.08533	0.08736	0.6	0.54879		map	0.15
MNG.UM	25.84	60.62	62.06	0.416	0.67716		MNG	0.14
wd	0.508	1.615	1.653	0.307	0.7586		wd	0.13
							age:MNG	0.00
							alternutr:MNG	0.00
5 models Δ < 4							gpp:MNG	0.00

Re

	Estimate	Std.Err	t value	Pr(>|t|)	
(Intercept)	977.7	198	4.939	0.00000824	***
gpp	0.2071	0.1107	1.87	0.067002	.
age	-5.106	1.27	-4.022	0.000184	***
alternutrLOW	-828.8	205.7	-4.029	0.00018	***
mat	-19.72	5.294	-3.725	0.000475	***
gpp:age	0.003305	0.0007492	4.41	0.0000508	***
gpp:alternutrLOW	0.5626	0.1181	4.763	0.0000152	***
age:alternutrLOW	1.975	0.7876	2.508	0.015246	*

R^2= 0.9122 **adj *R^2*=** 0.9006

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	694393	1	24.3888	8.243E-06	***	
gpp	99570	1	3.4971	0.0670024	.	0.67
age	460518	1	16.1745	0.0001841	***	0.01
alternutr	462143	1	16.2316	0.0001799	***	0.02
mat	395084	1	13.8763	0.0004749	***	0.13
gpp:age	553836	1	19.4521	0.0000508	***	0.04
gpp:alternutr	645866	1	22.6844	0.00001521	***	0.04
age:alternutr	179061	1	6.2891	0.0152462	*	0.01
Residuals	1509004	53				

Re model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	988.9	205.1	209.8	4.713	2.4E-06	***	(Intercept)	1.00
age	-5.131	1.284	1.314	3.905	9.4E-05	***	age	1.00
alternutrLOW	-830.8	212.8	217.7	3.815	0.00014	***	alternutr	1.00
gpp	0.2053	0.1117	0.1143	1.796	0.07251	.	gpp	1.00
mat	-19.53	5.501	5.63	3.469	0.00052	***	mat	1.00
age:alternutrLOW	1.996	0.7959	0.8146	2.451	0.01425	*	age:alternutr	1.00
age:gpp	0.00332	0.00076	0.00078	4.272	1.9E-05	***	age:gpp	1.00
alternutrLOW:gpp	0.5642	0.1231	0.126	4.479	7.5E-06	***	alternutr:gpp	1.00
map	-0.04651	**0.08653**	0.08859	**0.525**	0.59959		map	0.16
MNG.UM	-24.53	61.43	62.9	0.39	0.69654		MNG	0.15
wd	-0.5608	1.636	1.675	0.335	0.7377		wd	0.14
							age:MNG	0.00
							alternutr:MNG	0.00
4 models Δ < 4							gpp:MNG	0.00

Models with the factors extracted from the nutrient classification

NEP

	Estimate	Std.Err	β	β Std.Err	t value	Pr(>|t|)	
(Intercept)	-269.131	88.209304	0	0	-3.051	0.00346	**
f1	-27.8263	25.151078	-0.358	0.3235612	-1.106	0.27322	
gpp	0.414041	0.0556693	0.87959	0.1182636	7.438	<.0001	***
managementUM	269.0477	124.50198	0.38392	0.1776568	2.161	0.03491	*
f1:gpp	0.030442	0.0129536	0.7639	0.3250582	2.35	0.02226	*
gpp:managementUM	-0.2593	0.0770538	-0.6833	0.2030509	-3.365	0.00137	**
R^2=	0.6811	**adj R^2=**	0.6532				

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	379989	1	9.3089	0.003459	**	
f1	49966	1	1.224	0.273216		0.23008
gpp	2258026	1	55.3167	5.93E-10	***	0.25579
management	190625	1	4.6699	0.034912	*	0.05029
f1:gpp	225437	1	5.5227	0.022257	*	0.05242
gpp:management	462245	1	11.324	0.001374	**	0.09254
Residuals	2326737	57				

NEP model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	-283.9	117.3	119.3	2.38	0.01733	*	(Intercept)	1.00
f1	-23.95	29.63	30.08	0.796	0.42587		F1	1.00
gpp	0.3949	0.0736	0.07487	5.274	1.00E-07	***	gpp	1.00
managementUM	287.8	129	131.8	2.184	0.02897	*	MNG	1.00
f1:gpp	0.03079	0.01348	0.01376	2.236	0.02532	*	F1:GPP	0.91
gpp:managementUM	-0.2697	0.07942	0.08109	3.326	0.00088	***	gpp:MNG	1.00
mat	8.61	6.457	6.599	1.305	0.19198		mat	0.40
wd	1.836	1.88	1.917	0.958	0.33831		wd	0.23
f1:managementUM	10.99	24.14	24.68	0.445	0.65613		age	0.14
age	0.1778	0.4022	0.411	0.433	0.66526		f1:MNG	0.11
map	-0.00703	0.09706	0.09907	0.071	0.94347		map	0.11

13 models Δ < 4

Re

	Estimate	Std.Err	β	β Std.Err	t value	Pr(>|t|)	
(Intercept)	262.962863	95.062739	0	0	2.766	0.007595	**
f1	-29.580566	6.7969963	-0.2122776	0.04877697	-4.352	5.54E-05	***
gpp	0.592046	0.0600396	0.7015992	0.0711494	9.861	5.20E-14	***
managementUM	-354.527459	127.54614	-0.2821977	0.10152452	-2.78	0.007325	**
gpp:managementUM	0.3044804	0.0785227	0.4475773	0.11542614	3.878	0.000272	***
R^2=	0.8825	**adj R^2=**	0.8744				

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	363520	1	7.6519	0.0075953	**	
f1	899786	1	18.94	5.54E-05	***	0.04064662
gpp	4619512	1	97.2379	5.20E-14	***	0.79499854
management	367050	1	7.7262	0.0073248	**	0.01205423
gpp:management	714312	1	15.0358	0.0002716	***	0.03479453
Residuals	2755424	58				

Re model averaging

	Estimate	SE	Adj SE	z val	Pr(>|z|)		Variables	R Imp
(Intercept)	304.659	129.075	131.275	2.321	0.0203	*	(Intercept)	1.00
f1	23.8269	30.8621	31.3221	0.761	0.4468		F1	1.00
gpp	0.5864	0.06759	0.06894	8.506	<2e-16	***	gpp	1.00
managementUM	-269.56	134.21	137.027	1.967	0.0492	*	MNG	1.00
f1:gpp	-0.03089	0.01409	0.01439	2.146	0.0319	*	F1:GPP	0.89
gpp:managementUM	0.24987	0.08332	0.08504	2.938	0.0033	**	gpp:MNG	1.00
wd	-2.08056	1.89952	1.93923	1.073	0.2833		wd	0.30
mat	-5.51703	6.9059	7.05402	0.782	0.4341		mat	0.18
map	0.05393	0.09743	0.09953	0.542	0.5879		map	0.15
f1:managementUM	-10.2502	25.1642	25.7219	0.398	0.6903		f1:MNG	0.11
age	-0.10723	0.41819	0.42727	0.251	0.8018		age	0.11

13 models Δ < 4

Models using the "medium" nutrient availability category

NEP

	Estimate	Std.Err	β	β Std.Err	t value	Pr(>|t|)	
(Intercept)	-650.147	207.74185	0	0	-3.13	0.00221	**
gpp	0.689827	0.1239448	1.68764	0.30322786	5.566	1.66E-07	***
nutrient.classLOW	258.9967	227.36606	0.41185	0.36154805	1.139	0.25696	
nutrient.classMEDIUM	391.1855	238.17323	0.56405	0.34342186	1.642	0.10316	
managementOTHR	110.4697	116.18876	0.13705	0.14414666	0.951	0.34366	
managementUM	270.503	103.77753	0.38345	0.14710976	2.607	0.01032	*
wd	3.125687	1.1435189	0.20683	0.07566875	2.733	0.00723	**
gpp:nutrient.classLOW	-0.32062	0.1365047	-1.0328	0.43971008	-2.349	0.0205	*
gpp:nutrient.classMEDIUM	-0.37808	0.1422941	-0.8666	0.32615306	-2.657	0.00898	**
gpp:managementOTHR	-0.20223	0.0766118	-0.3909	0.14808735	-2.64	0.00942	**
gpp:managementUM	-0.3007	0.0626977	-0.8944	0.18649016	-4.796	4.77E-06	***

***R*²=**	0.5834	**adj *R*²=**	0.548	

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	438923	1	9.7943	2.21E-03	**	
gpp	1388151	1	30.9759	1.66E-07	***	0.12
nutrient.class	149973	2	1.6733	0.192051		0.17
management	312383	2	3.4853	0.033835	*	0.10
wd	334825	1	7.4714	7.23E-03	**	0.03
gpp:nutrient.class	316390	2	3.53	0.032437	*	0.05
gpp:management	1030957	2	11.5026	2.73E-05	***	0.10
Residuals	5288049	118				

Re

	Estimate	Std.Err	β	β Std.Err	t	Pr(>|t|)	
(Intercept)	946.1472	225.7538	0	0	4.191	6.42E-05	***
gpp	0.1500605	0.1312338	0.17799832	0.15566652	1.143	0.255847	
nutrient.classLOW	-598.9845	238.7771	-0.49483793	0.19726044	-2.509	0.013893	*
nutrient.classMEDIUM	-769.0284	254.6037	-0.57940296	0.19182404	-3.02	0.003276	**
age	-2.345405	0.7963151	-0.25679676	0.08718799	-2.945	0.004096	**
managementOTHR	112.3993	62.51324	0.06759027	0.03759176	1.798	0.075492	.
managementUM	171.6502	60.24119	0.12208751	0.04284699	2.849	0.005417	**
wd	-2.910387	1.324959	-0.09620986	0.04379972	-2.197	0.030591	*
gpp:nutrient.classLOW	0.5007344	0.1411159	0.75653774	0.21320593	3.548	0.000615	***
gpp:nutrient.classMEDIUM	0.5897503	0.1492076	0.7248549	0.18338927	3.953	0.000153	***
gpp:age	0.00160319	0.0005973	0.24371494	0.09080813	2.684	0.008647	**

***R*²=**	0.8971	**adj *R*²=**	0.8858	

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	741158	1	17.565	6.42E-05	***	
gpp	55170	1	1.3075	2.56E-01		0.71958764
nutrient.class	393809	2	4.6665	0.0117675	*	0.01904361
age	366040	1	8.6749	4.10E-03	**	0.00879914
management	397873	2	4.7147	1.13E-02	*	0.01802822
wd	203592	1	4.825	0.0305909	*	0.09880494
gpp:nutrient.class	659885	2	7.8194	0.0007349	***	0.02221301
gpp:age	303933	1	7.203	8.65E-03	**	0.01059682

CUEe

	Estimate	Std.Err	β	β Std.Err	t value	Pr(>|t|)	
(Intercept)	-0.05665285	0.0929213	0	0	-0.61	0.5435	
gpp	0.00030991	5.251E-05	0.79007388	0.1338564	5.902	5.51E-08	***
nutrient.classLOW	-0.173781	0.064971	-0.3085533	0.1153579	-2.675	0.0088	**
nutrient.classMEDIUM	-0.02722514	0.0697433	-0.04408481	0.1129332	-0.39	0.6971	
age	0.00290722	0.0008546	0.68411616	0.2010993	3.402	0.001	***
map	-0.00016161	6.121E-05	-0.29530044	0.1118445	-2.64	0.0097	**
gpp:age	-1.9465E-06	6.354E-07	-0.63595917	0.2076081	-3.063	0.0028	**
R^2=	0.3763	**adj R^2=**	0.3369				

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	0.0197	1	0.3717	0.5435249		
gpp	1.8473	1	34.8383	5.51E-08	***	0.1446
nutrient.class	0.5977	2	5.6359	0.0048644	**	0.1056
age	0.6137	1	11.5728	9.81E-04	***	0.0117
map	0.3696	1	6.9711	0.0096844	**	0.0468
gpp:age	0.4976	1	9.3836	0.0028486	**	0.0677
Residuals	5.0375	95				

GPP Models

General

		Estimate	Std.Err	t value	Pr(>|t|)		R^2
(Intercept)		1306.23	137.051	9.531	1.28E-13	***	
mat		74.397	6.163	12.072	2E-16	***	0.65
wd		-8.874	2.581	-3.438	0.00107	**	0.1
	R^2=	0.7514	**adj R^2=**	0.7432			

Weighted

		Estimate	Std.Err	t value	Pr(>|t|)		R^2
(Intercept)		1379.807	140.646	9.811	4.39E-14	***	
mat		63.475	6.473	9.805	4.47E-14	***	0.56
wd		-10.171	2.751	-3.697	0.000474	***	0.15
	R^2=	0.7056	**adj R^2=**	0.6958			

GPP < 2500

		Estimate	Std.Err	t value	Pr(>|t|)		R^2
(Intercept)		1406.357	135.555	10.375	1.83E-14	***	
NA.LOW		-263.7	97.152	-2.714	0.0089	**	0.11
mat		56.63	7.272	7.787	2.18E-10	***	0.47
wd		-5.408	2.517	-2.149	0.0362	*	0.04
	R^2=	0.6223	**adj R^2=**	0.6013			

GPP < 2500 Weighted

	Estimate	Std.Err	t value	Pr(>|t|)		R^2
(Intercept)	1386.784	133.901	10.357	1.57E-14	***	
mat	51.652	7.161	7.213	1.69E-09	***	0.44
wd	-9.159	2.644	-3.464	0.00104	**	0.14
R^2=	0.5799	adj R^2=	0.5646			

Only Managed forests

	Estimate	Std.Err	t value	Pr(>|t|)		R^2
(Intercept)	1048.172	119.347	8.783	1.77E-10	***	
NA.LOW	-309.188	117.171	-2.639	0.0122	*	0.07
mat	74.979	9.498	7.894	2.29E-09	***	0.59
R^2=	0.6598	adj R^2=	0.6409			

Only Eddy covariance data

	Estimate	Std.Err	t value	Pr(>|t|)		R^2
Intercept)	1223.0939	167.9484	7.283	1.43E-09	***	
mat	51.4191	8.761	5.869	2.76E-07	***	0.38
map	0.363	0.1423	2.551	0.0136	*	0.27
wd	-12.0537	2.6356	-4.573	0.0000284	***	0.16
R^2=	0.811	adj R^2=	0.8005			

Alternative Classification

	Estimate	Std.Err	t value	Pr(>|t|)		R^2
(Intercept)	1569.856	123.786	12.682	2E-16	***	
alternutrLOW	-216.12	90.99	-2.375	0.0209	*	0.04
mat	67.954	5.944	11.433	2E-16	***	0.58
wd	-11.626	2.252	-5.163	0.00000321	***	0.13
R^2=	0.7514	adj R^2=	0.7384			

CUE Models

General

	Estimate	Std.Err	t value	$Pr(>\lvert t\rvert)$	
(Intercept)	-0.2251	0.113	-1.993	0.050969	.
gpp	0.0003517	0.0000645	5.452	0.00000107	***
age	0.004071	0.0009644	4.221	0.0000866	***
NA.LOW	-0.1956	0.05992	-3.264	0.001843	**
gpp:age	-2.944E-06	7.065E-07	-4.168	0.000104	***
***R*²=**	0.4349	**adj *R*²=**	0.3959		

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	0.1901	1	3.9722	0.050969	.	
gpp	1.42266	1	29.7273	1.068E-06	***	0.14
age	0.85283	1	17.8204	0.00008656	***	0.004
NA.	0.50995	1	10.6556	0.0018432	**	0.12
gpp:age	0.83122	1	17.3688	0.0001038	***	0.17
Residuals	2.7757	58				

Weighted

	Estimate	Std.Err	t value	$Pr(>\lvert t\rvert)$	
(Intercept)	-0.03192	0.1037	-0.308	0.75943	
gpp	0.0001887	0.0000578	3.265	0.00185	**
age	0.003124	0.001041	3.001	0.00398	**
NA.LOW	-0.03051	0.05347	-0.571	0.57044	
gpp:age	-1.967E-06	6.16E-07	-3.193	0.0023	**
age:NA.LOW	-0.001373	0.0005272	-2.604	0.01173	*
***R*²=**	0.3448	**adj *R*²=**	0.2873		

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	0.043	1	0.0947	0.759431		
gpp	4.8367	1	10.6612	0.001854	**	0.01
age	4.087	1	9.0088	0.003982	**	0.03
NA.	0.1478	1	0.3257	0.570442		0.16
gpp:age	4.6239	1	10.1922	0.002296	**	0.09
age:NA.	3.0765	1	6.7813	0.011726	*	0.05
Residuals	25.8594	57				

GPP<2500

	Estimate	Std.Err	t value	$Pr(>\lvert t\rvert)$	
(Intercept)	-0.504	0.1096	-4.598	0.0000261	***
gpp	0.0004657	7.229E-05	6.442	3.31E-08	***
age	0.003238	0.001097	2.952	0.00466	**
gpp:age	-2.172E-06	8.525E-07	-2.548	0.01371	*
***R*²=**	0.4552	**adj *R*²=**	0.4249		

ANOVA table (type III)

	SumSq	DF	F value	Pr(>F)		R^2
(Intercept)	1.03712	1	21.1416	0.00002612	***	
gpp	2.03587	1	41.5013	3.308E-08	***	0.38
age	0.42758	1	8.7162	0.00466	**	0.01
gpp:age	0.31848	1	6.4922	0.01371	*	0.07
Residuals	2.64901	54				

GPP<2500 weighted

	Estimate	Std.Err	t value	Pr(>|t|)		R^2
(Intercept)	0.187674	0.036618	5.125	0.00000396	***	
NA.LOW	-0.126927	0.035287	-3.597	0.00069	***	0.15
mat	0.012343	0.003086	4	0.000191	***	0.19
R^2=	0.3397	adj R^2=	0.3157			

Only Managed

	Estimate	Std.Err	t value	Pr(>|t|)		R^2
(Intercept)	-0.3887	0.1444	-2.693	0.0109	*	
gpp	0.0004172	7.783E-05	5.36	0.00000585	***	0.37
age	0.00461	0.001737	2.655	0.012	*	0.03
NA.LOW	-0.171	0.08213	-2.082	0.0449	*	0.09
gpp:age	-2.712E-06	1.304E-06	-2.079	0.0452	*	0.05
R^2=	0.5477	adj R^2=	0.4945			

Eddy covariance

	Estimate	Std.Err	t value	Pr(>|t|)		R^2
(Intercept)	-0.2325	0.1195	-1.945	0.057055	.	
gpp	0.0003537	7.426E-05	4.763	0.0000152	***	0.12
age	0.004067	0.001055	3.857	0.000313	***	0.02
NA.LOW	-0.1892	0.06651	-2.845	0.006295	**	0.09
gpp:age	-2.933E-06	8.006E-07	-3.663	0.000576	***	0.15
R^2=	0.3728	adj R^2=	0.3255			

Alternative Classification

	Estimate	Std.Err	t value	Pr(>|t|)		R^2
Intercept)	-0.2209	0.115	-1.921	0.05998	.	
gpp	0.0002462	7.852E-05	3.136	0.00275	**	0.12
age	0.004683	0.001057	4.43	0.0000453	***	0.01
alternutrLOW	-0.1627	0.06088	-2.672	0.0099	**	0.07
mat	0.01454	0.006533	2.225	0.03017	*	0.06
gpp:age	-3.202E-06	7.429E-07	-4.31	0.000068	***	0.18
R^2=	0.4426	adj R^2=	0.392			

Using Factor 1 and 2 from the nutrient classification analysis

	Estimate	**Std.Err**	**t value**	**Pr(>|t|)**	
(Intercept)	-0.09955499	0.0714464	-1.393	0.17	
f1	0.01556442	0.0053638	2.902	0.01	**
f2	0.04844199	0.0200583	2.415	0.02	*
gpp	0.00020052	4.541E-05	4.416	<0.0001	***
managementUM	0.1584173	0.0931077	1.701	**0.09**	.
f2:gpp	-2.6022E-05	1.143E-05	-2.277	0.03	*
gpp:managementUM	-0.0001458	5.589E-05	-2.609	0.01	*
R^2=	0.4812	**adj R^2=**	0.4246		

ANOVA table (type III)

	SumSq	**DF**	**F value**	**Pr(>F)**		**R^2**
(Intercept)	0.03965	1	1.9416	0.169098		
f1	0.17194	1	8.4201	0.005328	**	0.18
f2	0.1191	1	5.8325	1.91E-02	*	0.02
gpp	0.39819	1	19.4996	4.76E-05	***	0.09
management	0.05912	1	2.8949	0.094507	.	0.04
f2:gpp	0.1059	1	5.186	0.02668	*	0.07
gpp:management	0.13899	1	6.8064	0.011675	*	0.09
Residuals	1.12313	55				

Supplementary Material

Chapter 3

Nutrient availability and climate as the main determinants of the ratio of biomass to NPP in woody and non-woody forest compartments

Table S3.1: B:NPPs (mean years ± standard error) of leaves, branches, stems, and coarse and fine roots across species and biomes. The B:NPPs were not adjusted to the stationary state. The number of forests is shown in parentheses.

Species	Foliage	Branches	Stems	Coarse roots	Fine roots
Cocos nucifera	2.5 (1)				
Fagus sylvatica	1.1 ± 0.1 (12)	20.3 ± 3.1 (5)	87.4 ± 18.1 (5)	66.4 ± 17.2 (8)	1.1 ± 0.04 (8)
Larix gmelinii		19.3 (1)	65.2 (1)	28.6 (1)	
Picea abies	4.4 ± 0.4 (11)	26.0 ± 17.9 (5)	42.9 ± 11.1 (5)	35.5 ± 10.8 (7)	1.4 ± 0.4 (7)
Picea mariana	9.5 (2)			162.8 (2)	5.5 (1)
Pinus banksiana	2.0 (1)			133.3 (1)	3.4 (1)
Pinus ponderosa	4.1 ± 0.5 (13)	84.7 ± 37.0 (12)	62.4 ± 23.2 (12)	62.3 (2)	2.0 (2)
Pinus radiata	5.3 (1)		8.2 (1)	10.4 (1)	0.7 (1)
Pinus strobus				24.1 ± 11.5 (4)	
Pinus sylvestris	4.4 ± 1.1 (6)	41.9 ± 9.7 (3)	71.0 ± 39.8 (3)	118.0 ± 67.9 (3)	2.1 ± 0.6 (3)
Pinus taeda				7.6 (1)	
Pseudotsuga menziesii	3.5 ± 0.5 (12)	26.8 ± 7.2 (12)	62.8 ± 20.9 (12)	62.6 ± 20.2 (12)	6.1 ± 0.6 (11)
Biomes					
Boreal Evergreen	5.4 ± 1.1 (9)	41.9 ± 9.7 (3)	71.0 ± 39.8 (3)	132.1 ± 35.2 (6)	3.0 ± 0.7 (5)
Boreal Deciduous	1.0 (2)	19.3 (1)	65.2 (1)	28.6 (1)	2.2 (1)
Temperate Evergreen	4.1 ± 0.3 (41)	66.3 ± 19.4 (32)	64.5 ± 13.8 (32)	56.2 ± 11.8 (31)	3.7 ± 0.6 (24)
Temperate Deciduous	1.1 ± 0.1 (15)	25.8 ± 4.8 (7)	75.4 ± 15.0 (7)	81.1 ± 18.6 (12)	1.4 ± 0.2 (12)

Table S3.2: B:NPPs, biomasses, and net primary productions (NPPs) of foliage, branches, stems, and coarse and fine roots grouped by leaf type (foliage) and nutrient availability. The B:NPPs and mean biomasses of branches, stems, and coarse roots were adjusted to the theoretical stationary state (200 y, see Figure 1). N indicates the number of forests. Different letters within a column and compartment indicate differences between groups using Tukey's test for multiple comparisons at the 0.05 level.

Compartment		B:NPP (years)	Biomass (gC m^{-2})	NPP (gC m^{-2} y^{-1})		N
	Leaf habit					
Foliage	Evergreen	4.3 ± 0.4^{a}	499.8 ± 90.9^{a}	129.6	± 22.7^{a}	53
	Deciduous	1.1 ± 0.1^{b}	198.2 ± 22.3^{b}	180.4	± 16.7^{b}	18
	Nutrient availability					
Branches	High	295.8 ± 49.9^{a}	6965.1 ± 1402.9^{a}	32.7	± 5.8^{a}	4
	Medium	80.2 ± 42.9^{b}	1918.6 ± 287.6^{b}	106.4	± 21.4^{a}	7
	Low	60.8 ± 21.3^{b}	2065.9 ± 328.3^{b}	69.5	± 11.5^{a}	22
Stems	High	349.3 ± 54.3^{a}	36740.9 ± 7075.4^{a}	177.8	± 12.4^{ab}	4
	Medium	128.2 ± 14.2^{b}	9085.9 ± 1063.6^{b}	135.1	± 22.5^{b}	7
	Low	104.7 ± 12.8^{b}	16902.2 ± 3555.6^{b}	293.2	± 44.6^{a}	24
Coarse roots	High	294.4 ± 101.7^{a}	5541.7 ± 1319.9^{a}	60.8	± 9.3^{a}	8
	Medium	125.1 ± 13.1^{b}	5426.4 ± 2343.3^{a}	58.8	± 12.4^{a}	17
	Low	115.8 ± 18.5^{b}	4360.6 ± 1088.1^{a}	76.2	± 13.8^{a}	26
Fine roots	High	1.6 ± 0.2^{a}	311.1 ± 27.4^{a}	197.8	± 9.5^{a}	7
	Medium	1.5 ± 0.2^{a}	274.6 ± 52.2^{a}	173.6	± 28.8^{a}	11
	Low	3.9 ± 0.7^{b}	447.6 ± 69.6^{a}	138.2	± 19.0^{a}	25

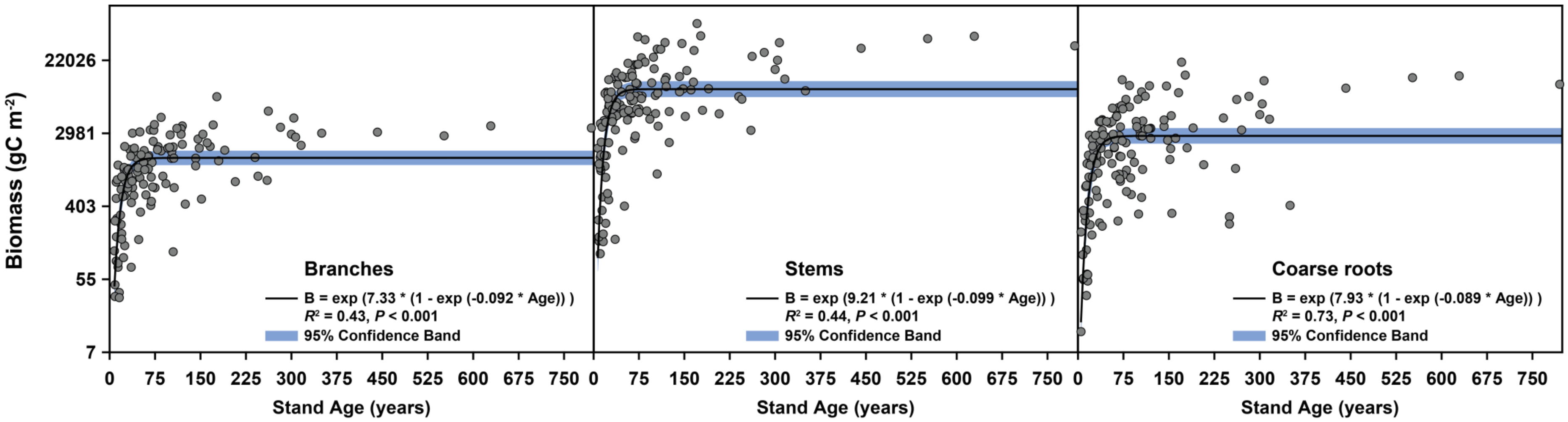

Figure S3.1. Relationships between biomass and stand age for branches, stems, and coarse roots. Data were fitted using an asymptotic exponential function.

Supplementary Material

Chapter 4

Atmospheric deposition, CO_2, and change in the land carbon sink

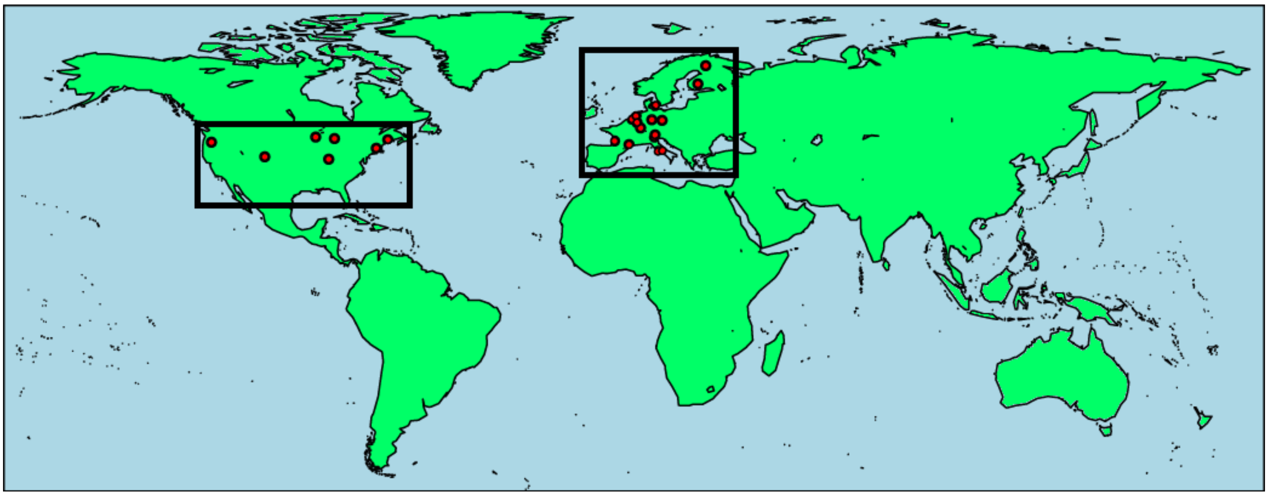

Figure S4.1. Map indicating the locations of the 23 forest sites with eddy-covariance data. The forests were located in temperate and boreal biomes across Europe and the USA. The boxes indicate the extent of the regional analysis (Europe and the USA).

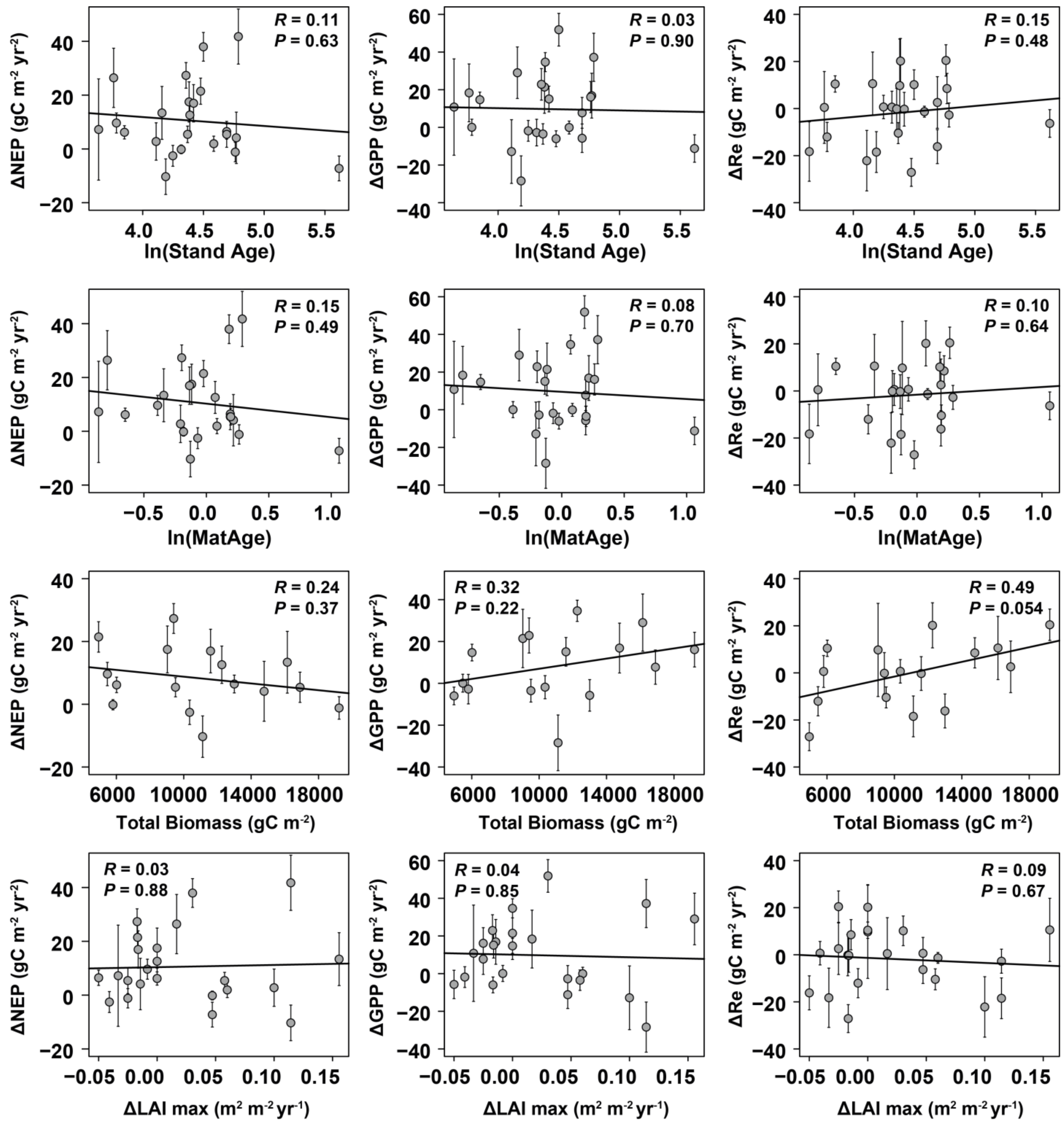

Figure S4.2. Relationships between C-flux trends in the 23 forests (ΔNEP/Δt, ΔGPP/Δt and ΔRe/Δt) and stand age, corrected logging maturity age (MatAge), total standing biomass and LAI trends. Error bars indicate standard errors and "t" indicates time in units of years. Corrected maturity age was calculated by dividing the mean stand age by the logging maturity tree age as described by Stokland *et al.* (Stokland *et al.*, 2003) for average productivity classes. See Methods for more information on the calculation of the corrected logging maturity age.

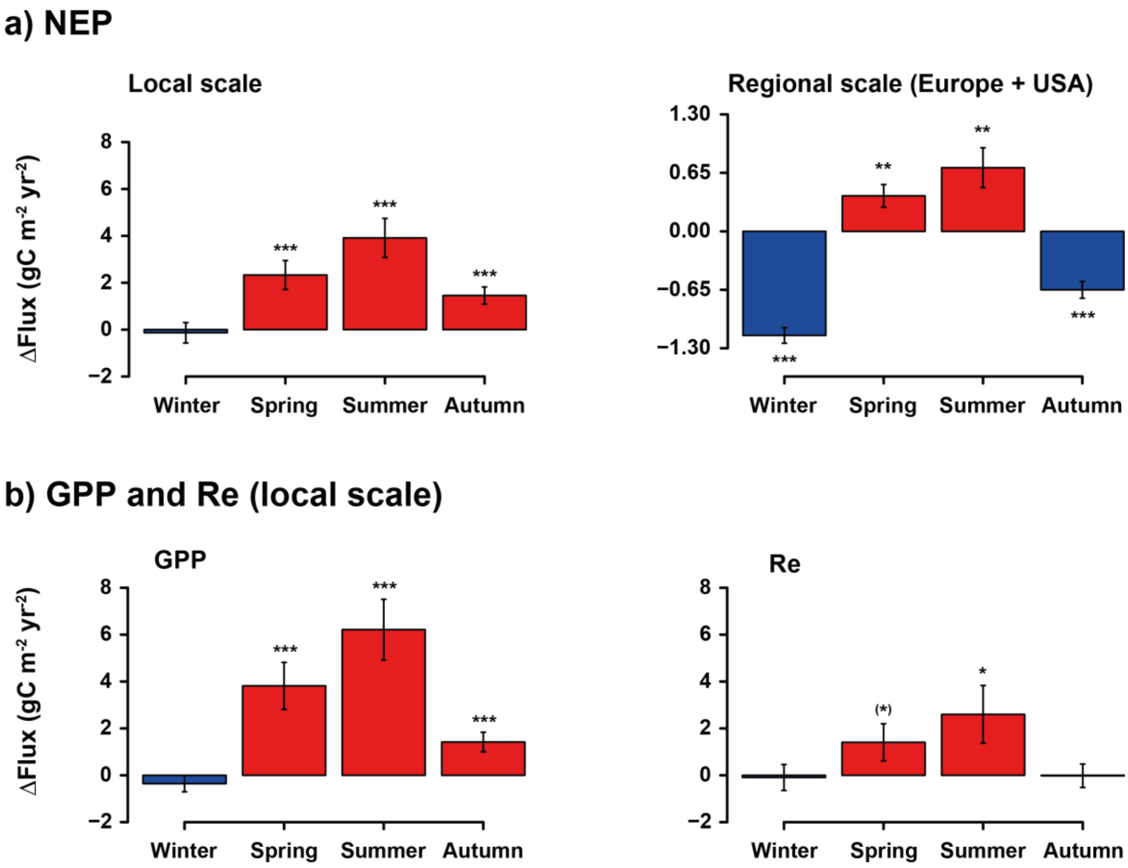

Figure S4.3. Mean change in: (a) NEP and (b) GPP and Re during winter, spring, summer and autumn from 1995 to 2011. Seasonal trends were calculated using mixed models with random slopes. Seasons were calculated as: winter, January–March; spring, April–June; summer, July–September; autumn, October–December for the local and regional scales. Error bars indicate standard errors. Units are ppm for CO_2, kg ha^{-1} yr^{-1} for S and N deposition, °C for temperature and standard deviations for SPEI. Error bars indicate standard errors. Significance levels: $^{(*)}$, $P < 0.1$; *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$.

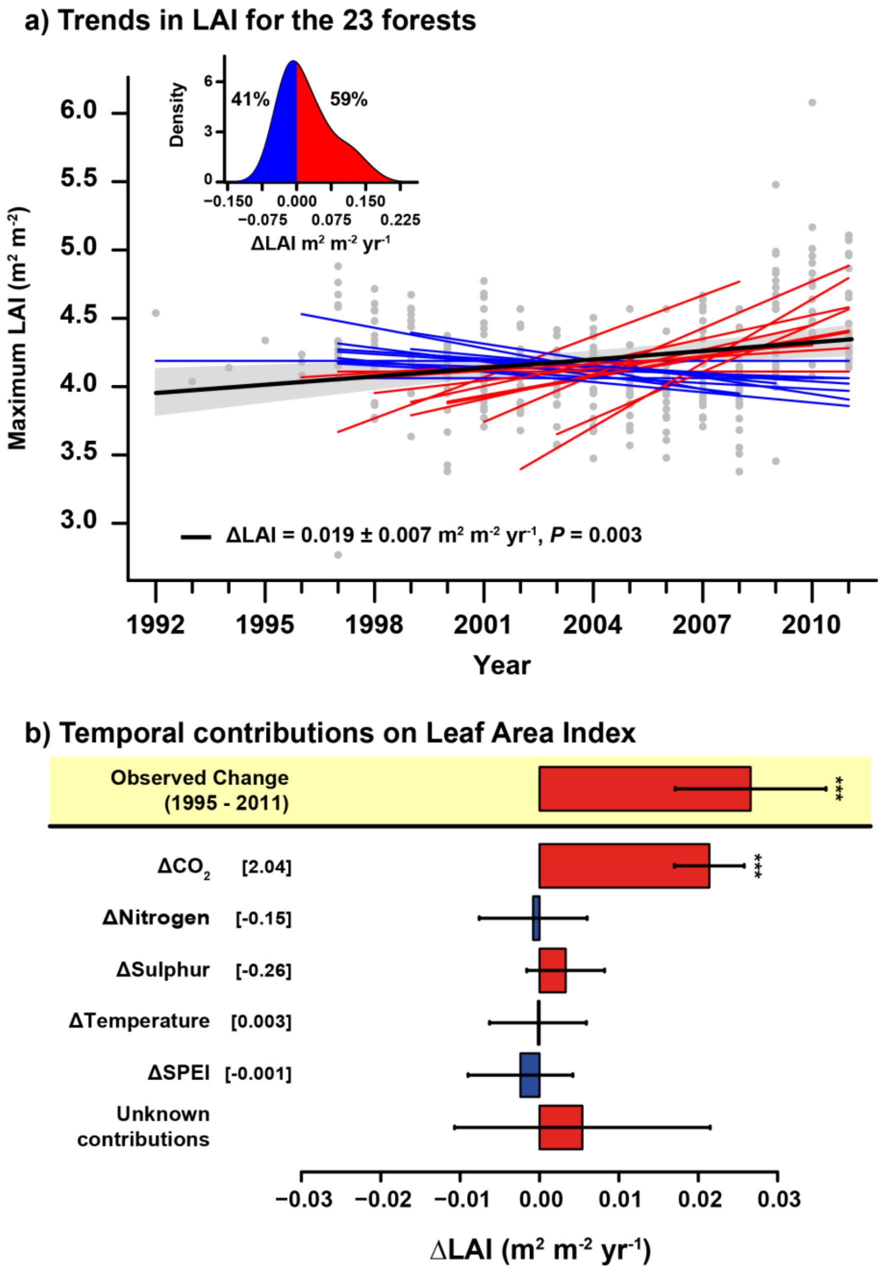

Figure S4.4. Trends in (a) forest maximum LAI and (b) temporal contribution of the predictor variables. a) Red and blue lines indicate forests with increasing and decreasing trends, respectively, and the thick black line indicates the average slope. The shaded area indicates the standard error of the average slope. Grey dots indicate site-year observations, and all values were adjusted to the same mean to remove site-specific variability. The inset shows the modelled distribution of the trends using kernel-density estimation. b) The model (Supplementary Information) suggested that increasing CO_2 is the main contributor to the observed increases in LAI. The difference between the modelled contributions and the observed trends has been considered as an unknown contribution to the temporal variation in C fluxes. The temporal variations of the predictors are shown in square brackets. Error bars indicate standard errors. Units are ppm for CO_2, kg ha^{-1} yr^{-1} for S and N deposition, °C for temperature and standard deviations for SPEI. Error bars indicate standard errors. See Methods for information about the methodology used to calculate the contributions. All data came from eddy-covariance towers. Significance levels: $^{(*)}$, $P < 0.1$; *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$.

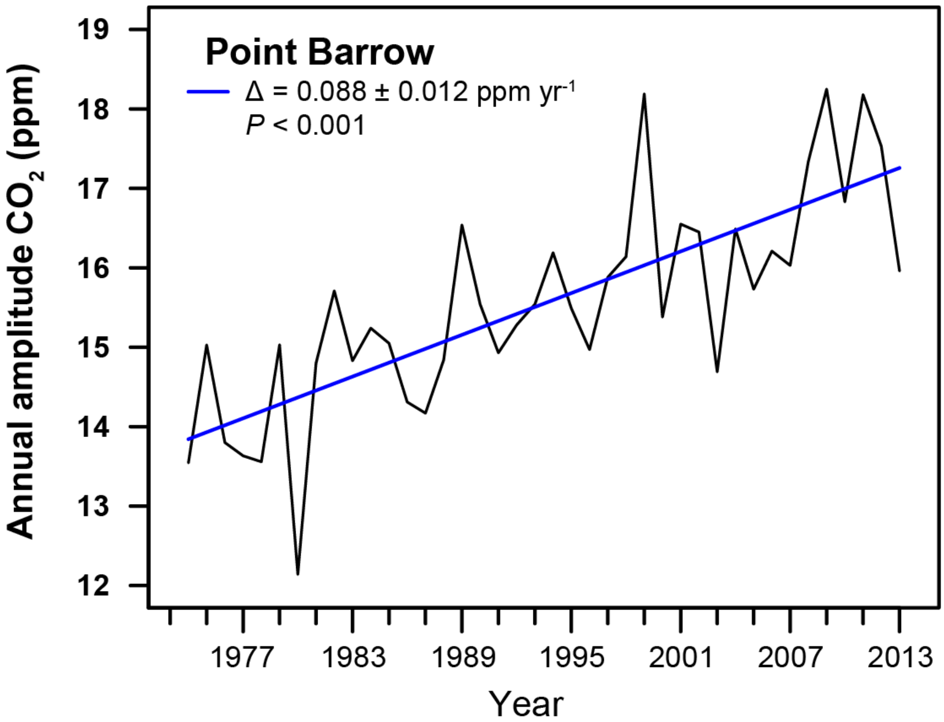

Figure S4.5. Trend in the amplitude of annual atmospheric CO_2 concentration at Point Barrow (1975–2013).

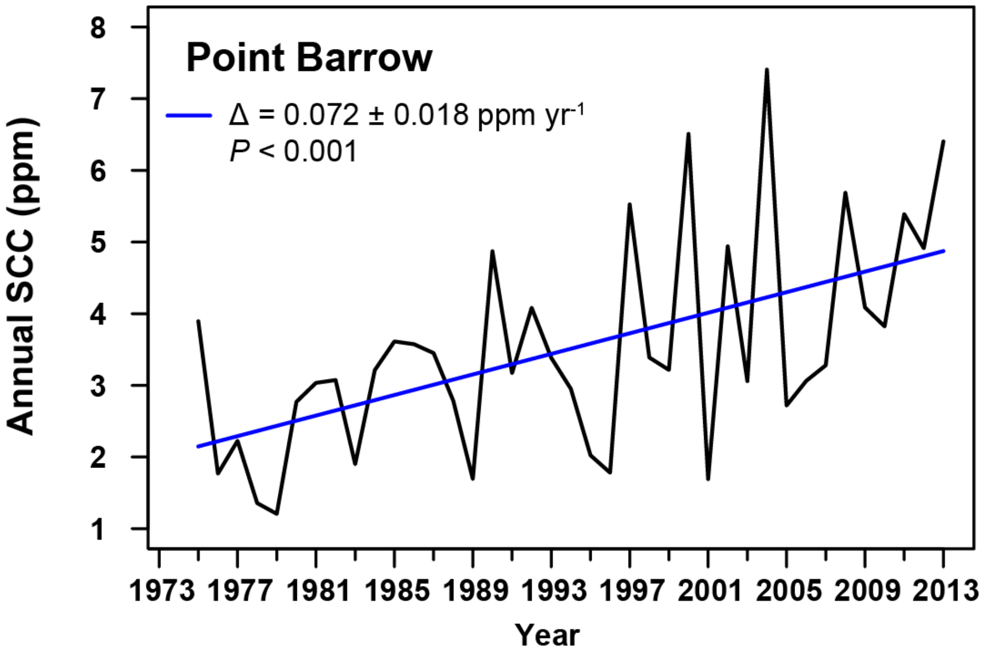

Figure S4.6. Trends in the SCC index at Point Barrow (1975–2013). The SCC index is calculated as the difference between CO_2 concentrations in the first week of May and in the last week of June, providing information on the carbon sink strength during spring.

Table. S4.1. Summary of the main characteristics of the forests and the slopes presented by NEP, GPP and Re. Slopes were computed using the robust Theil-Sen slope estimator. *P* indicates a one-tailed *P* (H1: slope >0). Corrected maturity age was calculated by dividing the mean stand age by the logging maturity tree age as described by Stokland *et al.* (2003) for average productivity classes. Abbreviations: for Climate, Temp, temperate; Bor, boreal; for Forest type, M, mixed; E, evergreen; D, deciduous; B, broadleaved; C, coniferous; for CO_2 source, ML, Mauna Loa; EC, eddy covariance.

Forest	Code	Climate	Forest	Age	Maturity	Corrected	Years	CO_2	ΔCO_2	NEP	*P*	GPP	*P*	Re	*P*	LAI	*P*
Brasschaat	BE-Bra	Temp	M	80	90	0.89	14	ML	27.9	17.5 ± 7.5	0.0773	21.4 ± 13.9	0.0313	9.7 ± 19.8	0.2556	0.000	0.6329
Castelporziano	IT-Cpz	Temp	EB	61	75	0.81	10	EC	18.9	2.8 ± 6.9	0.3603	-12.8 ± 16.9	0.7629	-22.1 ± 12.8	0.8145	0.100	0.0173
Collelongo	IT-Col	Temp	DB	118	95	1.24	12	ML	30.1	4.1 ± 9.6	0.2686	16.8 ± 11.9	0.1219	8.5 ± 6.4	0.0574	-0.014	0.8299
Hainich	DE-Hai	Temp	DB	275	95	2.89	13	EC	31.7	-7.3 ± 4.6	0.9197	-11.2 ± 7.3	0.8502	-6.3 ± 5.9	0.7489	0.047	0.0466
Harvard	US-Ha1	Temp	DB	81	75	1.07	20	EC	36.3	12.6 ± 5.9	0.0372	34.7 ± 5.1	<0.0001	20.2 ± 9.6	0.0075	0.000	0.6539
Hesse	FR-Hes	Temp	DB	43	95	0.45	15	EC	35.2	26.4 ± 11.0	0.0374	18.3 ± 15.4	0.1381	0.5 ± 15.3	0.5000	0.017	0.2737
Howland MT	US-Ho1	Temp	EC	109	90	1.21	13	EC	22.6	6.5 ± 2.8	0.0293	-5.8 ± 7.5	0.7489	-16.2 ± 7.2	0.9364	-0.050	0.9934
Howland F	US-Ho2	Temp	EC	109	90	1.21	11	EC	14.4	5.4 ± 4.8	0.1751	7.7 ± 8.2	0.2667	2.6 ± 11.0	0.3202	-0.025	0.7621
Hyytiala	FI-Hyy	Bor	EC	47	90	0.52	16	EC	37.4	6.2 ± 2.5	0.0172	14.7 ± 4.0	0.0017	10.4 ± 3.5	0.0051	0.000	0.5201
Lavarone	IT-Lav	Temp	EC	120	90	1.33	10	EC	47.2	41.8 ± 10.3	0.0100	37.2 ± 12.8	0.0159	-2.7 ± 5.1	0.7042	0.114	0.1008
Le Bray	FR-LBr	Temp	EC	38	90	0.42	11	EC	13.2	7.2 ± 18.8	0.4381	10.8 ± 25.6	0.3777	-18.3 ± 12.6	0.8935	-0.033	0.8465
Loobos	NL-Loo	Temp	EC	88	90	0.98	16	EC	32.7	21.5 ± 4.9	0.0009	-6.0 ± 4.2	0.9186	-27.1 ± 5.9	0.9991	-0.017	0.6559
Metolius	US-Me2	Temp	EC	64	90	0.71	11	EC	28.1	13.4 ± 9.8	0.1379	29.0 ± 13.7	0.0806	10.6 ± 13.4	0.2667	0.156	0.0866
Morgan Monroe	US-MMS	Temp	DB	70	75	0.93	15	EC	25.1	-2.6 ± 3.9	0.8619	-1.8 ± 5.5	0.6897	0.7 ± 5.0	0.5000	-0.041	0.8677
Niwot ridge	US-NR1	Bor	EC	98	90	1.09	12	ML	21.5	1.9 ± 2.8	0.4185	-0.1 ± 3.4	0.5000	-1.3 ± 2.3	0.6341	0.060	0.0166
Park Falls	US-PFa	Temp	DB	44	65	0.68	16	EC	31.2	9.6 ± 3.7	0.0172	0.1 ± 4.3	0.4820	-12.1 ± 6.2	0.9425	-0.008	0.5873
Puechabon	FR-Pue	Temp	EB	66	75	0.88	13	ML	25.4	-10.3 ± 6.6	0.9197	-28.4 ± 13.3	0.9502	-18.5 ± 8.7	0.9880	0.114	0.0108
Renon	IT-Ren	Bor	EC	90	75	1.20	13	EC	33.8	37.9 ± 5.3	0.0001	51.9 ± 8.7	0.0006	10.2 ± 6.3	0.0636	0.030	0.1202
Sodankyla	FI-Sod	Bor	EC	75	90	0.83	13	EC	28.8	-0.2 ± 1.6	0.5000	-2.8 ± 7.1	0.5243	0.6 ± 6.8	0.4757	0.047	0.1346
Soroe	DK-Sor	Temp	DB	78	95	0.82	13	EC	38.7	27.3 ± 4.8	0.0004	22.9 ± 8.4	0.0164	-0.2 ± 8.8	0.5000	-0.017	0.7336
Tharandt	DE-Tha	Temp	EC	117	90	1.30	17	EC	27.2	-1.2 ± 3.6	0.6446	16.1 ± 8.3	0.0383	20.4 ± 6.7	0.0178	-0.025	0.6730
UMBS	US-UMB	Temp	DB	79	65	1.22	14	EC	26.7	5.4 ± 3.1	0.0080	-3.5 ± 5.4	0.7444	-10.4 ± 4.5	0.9373	0.058	0.0017
Vielsalm	BE-Vie	Temp	M	83	95	0.87	13	ML	23.0	17.0 ± 6.9	0.0062	15.1 ± 6.8	0.0120	-0.3 ± 7.2	0.5243	0.017	0.2330

Table S4.2. Mean annual and seasonal trends for the 23 forests for NEP, GPP, Re and maximum LAI. Weighted slopes were calculated using the number of years as the weighting factor. t*P* indicates *P* for the *t*-test and z*P* indicates *P* for the combined z-transformed probability test. *P* was calculated using the alternative hypothesis (H_1) of slopes >0 for both analyses. Units are in g C m^{-2} yr^{-2} for C fluxes and m^2 m^{-2} yr^{-1} for LAI.

Variable	Period	Mean slope	Weighted slope	t*P* (H_1 >0)	z*P* (H_1 >0)
NEP	**Annual**	10.56 ± 2.79	10.39 ± 2.70	0.0005	<0.0001
	Winter	1.31 ± 0.84	0.95 ± 0.77	0.19	0.0674
	Spring	2.43 ± 1.13	2.39 ± 1.12	0.0004	0.0213
	Summer	3.68 ± 1.16	3.86 ± 1.15	0.0023	<0.0001
	Autumn	1.82 ± 0.60	1.79 ± 0.57	0.0004	0.0029
GPP	**Annual**	9.75 ± 3.88	10.02 ± 3.83	0.0098	<0.0001
	Winter	-0.35 ± 0.71	-0.37 ± 0.64	0.87	0.69
	Spring	3.11 ± 1.64	3.29 ± 1.63	0.0004	0.0354
	Summer	4.90 ± 1.96	5.07 ± 1.91	0.0102	<0.0001
	Autumn	1.20 ± 0.94	1.26 ± 0.88	0.1084	<0.0001
Re	**Annual**	-1.79 ± 2.71	-1.02 ± 2.82	0.74	0.64
	Winter	-1.48 ± 0.72	-1.22 ± 0.69	0.88	0.97
	Spring	0.51 ± 0.92	0.77 ± 0.97	0.25	0.29
	Summer	0.57 ± 1.65	0.86 ± 1.62	0.37	0.15
	Autumn	-0.40 ± 0.73	-0.36 ± 0.71	0.38	0.70
Max Lai	**Annual**	0.023 ± 0.012	-1.02 ± 2.82	0.0302	0.0359

Table S4.3. Rates of change in predictors for 1995–2011. For a) the 23 forests and b) Europe and the USA. Trends were calculated using GLMMs with random slopes, with the forest or the pixel as a random effect and year as a fixed effect. Models also used an ARMA (1,0) autocorrelation structure. See Methods further details. Trend units are ppm yr^{-1} for CO_2, kg ha^{-1} yr^{-2} for N and S deposition, K yr^{-1} for temperature and standard deviation yr^{-1} for SPEI.

	Mean	**SE**	**Total change 1995–2011**	**SE**	***P***
a) 23 sites					
CO_2	2.043	0.139	34.731	2.370	<0.001
Nitrogen	-0.153	0.042	-2.608	0.710	<0.001
Sulphur	-0.257	0.025	-4.366	0.427	<0.001
Temperature	0.003	0.008	0.047	0.136	0.73
SPEI	-0.001	0.005	-0.011	0.091	0.91
b) Regional, Europe + USA					
Nitrogen	-0.083	0.008	-1.405	0.143	<0.001
Sulphur	-0.151	0.010	-2.560	0.164	<0.001
Temperature	0.058	0.002	0.981	0.031	<0.001
SPEI	-0.010	0.001	-0.163	0.017	<0.001

Summary of models and statistical analyses

1. Relationships between annual trends in carbon fluxes and predictors

1.1 Using trends extracted by the Theil-Sen slope estimator

Correlations of observed trends in C fluxes with trends in mean annual temperature, spei, N and S wet deposition, the difference in carbon dioxide concentration from the beginning to the end of the study period (deltacdioxide), and site characteristics such as climate (mean annual temperature and precipitation), mean annual N and S wet deposition, soil ph, age of the stand, leaf type and habit. Models were adjusted using stepwise forward models using the following saturated model: C flux trend ~ MATc + MAPc + Age + corrected maturity age + leaf type + (ph + n.wet.t + s.wet.t)^2 + (n.wet.t + deltacdioxide)^2 + mat.t + spei.t + lai.max.t + total.biomass. Models were weighted for the n years of the plots. ".t" suffixes in variables indicate the trends of the variable. Significance levels: (*), $P < 0.1$; *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$.

GPP

	Estimate	SE	Beta	SE	*t*	Pr(>|t|)	
(Intercept)	-72.43	23.14	0	0	-3.13	0.00797	**
deltacdioxide	1.89	0.60	0.7193353	0.2282934	3.151	0.00766	**
total.biomass	0.00	0.00	0.643359	0.2207964	2.914	0.01208	*

	R^2 (PMVD)		
		R^2	0.49
deltacdioxide	0.27	R^2adj	0.42
total.biomass	0.23		

Re

	Estimate	SE	Beta	SE	*t*	Pr(>|t|)	
(Intercept)	8.29	11.17	0	0	0.742	0.473774	
total.biomass	0.00	0.00	1.1987591	0.2602084	4.607	0.000756	***
mat	-2.83	0.95	-0.6827285	0.2282482	-2.991	0.012272	*
s.wet.t	-40.44	14.10	-0.678389	0.2365233	-2.8680	0.0153	*
cor_age	-44.46	15.46	-0.744115	0.2588259	-2.8750	0.0151	*

	R^2 (PMVD)		
		R^2	0.68
total.biomass	0.326	R^2adj	0.57
mat	0.128		
s.wet.t	0.106		
cor_age	0.122		

NEP

	Estimate	SE	Beta	SE	*t*	Pr(>|t|)	
(Intercept)	-17.27	9.52	0	0	-1.814	0.084	(*)
deltacdioxide	0.95	0.32	0.5630301	0.1879885	2.995	0.0069	**
			R^2	0.30	R^2adj	0.27	

2. Relationships between C fluxes and predictor annual values using model averaging of generalized mixed models (only models with ΔAICc <4)

2.1 – Models using data from the 23 forests

Response variable ~ maximum lai anomalies + (mean S deposition + S anomalies + CO_2)^2 + (mean N deposition + N anomalies + CO_2)^2 + (MATc + MAT anomalies + CO_2)^2 + (MAPc + SPEI + CO_2)^2 + mean S deposition * mean N deposition + MATc * MAPc, where ^2 indicates a second-order interaction of the variables within the brackets. SE, standard error; Rel. Imp, relative importance. Significance levels: $^{(*)}$, $P < 0.1$; *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$.

List of acronyms

cdioxide.an: CO_2 concentration anomalies

lai.max.an: Maximum LAI anomalies

ndep: Mean N deposition

sdep: Mean S deposition

n.wet.an: N deposition anomalies

s.wet.an: S deposition anomalies

mat: climatic mean annual temperature

map: climatic mean annual precipitation

tmean.an: mean annual temperature anomalies

spei: Standardized Precipitation Evapotranspiration Index

2.1.1 NEP (92-11)

	Estimate	SE	Adjusted SE	Rel. Imp	z	Pr(>|z|)	
(Intercept)	6.039	19.799	19.885	1.00	0.30	0.76	
cdioxide.an	5.048	1.364	1.369	1.00	3.69	0.00	***
cdioxide.an:s.wet.an	0.961	0.451	0.452	0.98	2.13	0.03	*
s.wet.an	5.616	8.319	8.340	0.98	0.67	0.50	
tmean.an	-7.788	10.075	10.098	0.55	0.77	0.44	
n.wet.an	-2.490	6.281	6.293	0.38	0.40	0.69	
sdep	0.138	1.286	1.365	0.30	0.10	0.92	
ndep	0.051	1.151	1.223	0.27	0.04	0.97	
cdioxide.an:ndep	0.099	0.244	0.244	0.18	0.41	0.69	
lai.max.an	-2.053	8.066	8.091	0.17	0.25	0.80	
cdioxide.an:sdep	-0.096	0.254	0.254	0.16	0.38	0.71	
spei	-0.891	6.748	6.775	0.13	0.13	0.90	
cdioxide.an:n.wet.an	-0.096	0.340	0.341	0.13	0.28	0.78	
map	0.002	0.017	0.018	0.11	0.09	0.93	
mat	0.077	0.777	0.820	0.10	0.09	0.93	
cdioxide.an:tmean.an	-0.032	0.290	0.291	0.07	0.11	0.91	
s.wet.an:sdep	0.062	0.358	0.358	0.06	0.17	0.86	
ndep:sdep	0.001	0.031	0.033	0.01	0.04	0.97	
n.wet.an:ndep	-0.026	0.265	0.266	0.01	0.10	0.92	

97 models ΔAICc <4

2.1.2 GPP (92-11)

	Estimate	SE	Adjusted SE	Rel. Imp	z	Pr(>|z|)	
(Intercept)	-5.828	28.361	28.476	1.00	0.205	0.838	
cdioxide.an	5.293	2.507	2.514	1.00	2.11	0.035	*
s.wet.an	-19.629	11.082	11.117	0.93	1.77	0.077	(*)
tmean.an	22.734	20.754	20.820	0.87	1.09	0.275	
n.wet.an	14.917	9.909	9.948	0.65	1.50	0.134	
spei	43.668	34.964	35.080	0.61	1.25	0.213	
cdioxide.an:s.wet.an	-0.807	0.539	0.541	0.49	1.49	0.136	
mat	2.171	3.248	3.445	0.40	0.63	0.529	
cdioxide.an:mat	-0.693	0.439	0.441	0.22	1.57	0.116	
cdioxide.an:tmean.an	1.381	1.458	1.465	0.19	0.94	0.346	
cdioxide.an:n.wet.an	-0.623	0.665	0.668	0.16	0.93	0.352	
sdep	-0.168	2.322	2.458	0.14	0.07	0.945	
mat:tmean.an	5.444	4.344	4.363	0.12	1.25	0.212	
ndep	-0.862	2.205	2.335	0.12	0.37	0.712	
lai.max.an	10.438	23.878	23.984	0.09	0.44	0.663	
map	-0.014	0.069	0.073	0.09	0.19	0.848	
cdioxide.an:spei	-1.553	2.628	2.640	0.07	0.59	0.556	
cdioxide.an:sdep	0.464	0.300	0.301	0.06	1.54	0.124	
cdioxide.an:ndep	0.238	0.248	0.249	0.01	0.96	0.339	
n.wet.an:ndep	-1.150	1.066	1.071	0.01	1.07	0.283	
map:spei	-0.153	0.131	0.132	0.01	1.16	0.246	
s.wet.an:sdep	-0.527	1.037	1.042	0.00	0.51	0.613	

308 models ΔAICc <4

2.1.3 Re (92-11)

	Estimate	SE	Adjusted SE	Rel. Imp	z	Pr(>|z|)	
(Intercept)	-8.685	32.851	32.996	1.00	0.263	0.79	
cdioxide.an	2.350	3.421	3.435	1.00	0.684	0.49	
cdioxide.an:mat	-1.397	0.420	0.422	1.00	3.31	0.00	***
cdioxide.an:s.wet.an	-1.706	0.595	0.597	1.00	2.86	0.00	**
mat	0.739	2.987	3.184	1.00	0.23	0.82	
n.wet.an	27.860	9.811	9.852	1.00	2.83	0.00	**
s.wet.an	-34.042	11.286	11.337	1.00	3.00	0.00	**
tmean.an	24.452	27.341	27.418	1.00	0.89	0.37	
cdioxide.an:sdep	1.139	0.487	0.488	0.99	2.33	0.02	*
sdep	0.455	3.350	3.563	0.99	0.13	0.90	
ndep	-1.603	3.277	3.500	0.70	0.46	0.65	
lai.max.an	38.867	21.993	22.094	0.68	1.76	0.08	(*)
cdioxide.an:ndep	-0.742	0.333	0.335	0.66	2.22	0.03	*
spei	36.969	34.103	34.219	0.56	1.08	0.28	
mat:tmean.an	5.645	4.008	4.026	0.47	1.40	0.16	
cdioxide.an:tmean.an	1.583	1.364	1.370	0.29	1.16	0.25	
cdioxide.an:n.wet.an	0.721	0.931	0.935	0.17	0.77	0.44	
cdioxide.an:spei	-2.825	2.594	2.606	0.15	1.08	0.28	
map	-0.033	0.071	0.076	0.12	0.44	0.66	
s.wet.an:sdep	-0.280	1.030	1.035	0.10	0.27	0.79	
n.wet.an:ndep	-0.626	0.989	0.994	0.09	0.63	0.53	
ndep:sdep	-0.112	0.306	0.328	0.07	0.34	0.73	
map:spei	-0.137	0.125	0.126	0.01	1.09	0.28	

173 models ΔAICc <4

2.1.4 LAI (92-11)

	Estimate	SE	Adjusted	Rel. Imp	z	Pr(>|z|)	
(Intercept)	1.515	0.715	0.718	1.00	2.110	0.03490	*
cdioxide.an	0.013	0.013	0.013	1.00	0.980	0.32710	
map	0.003	0.001	0.001	1.00	2.782	0.00540	**
mat	-0.076	0.066	0.069	1.00	1.093	0.27420	
sdep	0.079	0.040	0.042	1.00	1.864	0.06240	(*)
cdioxide.an:mat	0.003	0.001	0.001	0.99	2.352	0.01870	*
cdioxide.an:sdep	-0.002	0.001	0.001	0.92	2.254	0.02420	*
s.wet.an	-0.029	0.032	0.032	0.50	0.906	0.36500	
tmean.an	-0.046	0.049	0.050	0.44	0.929	0.35300	
cdioxide.an:s.wet.an	-0.003	0.001	0.001	0.36	1.798	0.07220	(*)
n.wet.an	-0.023	0.017	0.017	0.36	1.308	0.19070	
spei	0.286	0.316	0.317	0.28	0.905	0.36550	
cdioxide.an:map	0.000	0.000	0.000	0.24	1.046	0.29560	
map:spei	-0.001	0.000	0.000	0.18	1.712	0.08680	(*)
cdioxide.an:tmean.an	-0.005	0.003	0.003	0.17	1.369	0.17110	
cdioxide.an:n.wet.an	-0.002	0.002	0.002	0.15	1.391	0.16430	
map:mat	0.000	0.000	0.000	0.11	0.634	0.52600	
ndep	0.015	0.035	0.038	0.09	0.396	0.69200	
s.wet.an:sdep	0.002	0.003	0.003	0.09	0.863	0.38820	
map:sdep	0.000	0.000	0.000	0.07	0.269	0.78790	
mat:tmean.an	0.010	0.011	0.011	0.07	0.911	0.36230	
cdioxide.an:spei	0.008	0.007	0.007	0.07	1.192	0.23330	
cdioxide.an:ndep	0.001	0.001	0.001	0.00	0.631	0.52800	

204 models ΔAICc <4

2.2 – Regional model NEP (EU + USA)

variable	Estimate	SE	Adjusted SE	Rel. Imp	z	Pr(>|z|)	
(Intercept)	687.4000	264.9000	265.0000	1.00	2.59	0.0095	**
cdioxide	-1.5390	0.7030	0.7030	1.00	2.19	0.0286	*
cdioxide:n.wet.an	-0.4264	0.1311	0.1311	1.00	3.25	0.0011	**
cdioxide:ndep	1.0140	0.0922	0.0922	1.00	11.00	< 2e-16	***
cdioxide:sdep	-0.8905	0.1088	0.1089	1.00	8.18	< 2e-16	***
cdioxide:spei	-1.5300	0.3536	0.3537	1.00	4.33	0.0000	***
mat	-15.3000	13.8800	13.9000	1.00	1.10	0.2710	
mat:tmean.an	0.8379	0.3018	0.3019	1.00	2.78	0.0055	**
n.wet.an	168.8000	49.1600	49.1700	1.00	3.43	0.0006	***
n.wet.an:ndep	-0.9037	0.3027	0.3027	1.00	2.99	0.0028	**
ndep	-386.5000	34.7000	34.8100	1.00	11.10	< 2e-16	***
ndep:sdep	1.0070	0.2110	0.2117	1.00	4.76	0.0000	***
s.wet.an	-1.9660	29.7300	29.7400	1.00	0.07	0.9473	
s.wet.an:sdep	0.7524	0.2444	0.2444	1.00	3.08	0.0021	**
sdep	331.0000	41.1200	41.2300	1.00	8.03	< 2e-16	***
spei	575.8000	133.2000	133.2000	1.00	4.32	0.0000	***
tmean.an	-84.8500	79.1600	79.1700	1.00	1.07	0.2838	
map	-0.2179	0.2418	0.2422	0.95	0.90	0.3682	
cdioxide:tmean.an	0.3233	0.1830	0.1831	0.69	1.77	0.0774	(*)
map:spei	-0.0154	0.0086	0.0086	0.68	1.79	0.0730	(*)
cdioxide:map	0.0009	0.0006	0.0006	0.57	1.61	0.1071	
cdioxide:mat	0.0532	0.0348	0.0348	0.54	1.53	0.1266	
map:sdep	-0.0042	0.0031	0.0031	0.43	1.34	0.1811	
map:mat	-0.0009	0.0016	0.0016	0.21	0.52	0.6002	
cdioxide:s.wet.an	0.0647	0.1698	0.1698	0.20	0.38	0.7033	

72 models ΔAICc <4

2.3. Results from the saturated models (model summaries and temporal contributions) using temperature and SPEI for the warm half of the year (April – September) for the 23 forests.

2.3.1 – NEP

	Estimate	Std. Error	Df	z value	Pr(>|z|)
(Intercept)	20.554	108.339	254	0.19	0.8497
lai.max.an	-24.745	16.931	254	-1.46	0.1451
sdep	-1.869	9.653	15	-0.19	0.8491
s.wet.an	-11.379	19.527	254	-0.58	0.5606
cdioxide.an	4.870	4.791	254	1.02	0.3104
ndep	-0.027	5.353	15	-0.01	0.9961
n.wet.an	10.620	17.327	254	0.61	0.5405
mat	1.906	15.530	15	0.12	0.9039
tmean.an	-7.744	18.963	254	-0.41	0.6834
map	-0.028	0.188	15	-0.15	0.8816
spei.hot	14.591	66.859	254	0.22	0.8274
sdep:s.wet.an	1.548	1.193	254	1.30	0.1957
sdep:cdioxide.an	-0.644	0.369	254	-1.74	0.0823
s.wet.an:cdioxide.an	1.596	0.682	254	2.34	0.0202
ndep:n.wet.an	-1.561	1.159	254	-1.35	0.1790
cdioxide.an:ndep	0.679	0.286	254	2.37	0.0184
cdioxide.an:n.wet.an	-1.137	0.738	254	-1.54	0.1246
mat:tmean.an	-1.662	2.284	254	-0.73	0.4675
cdioxide.an:mat	0.527	0.341	254	1.55	0.1229
cdioxide.an:tmean.an	-0.065	1.090	254	-0.06	0.9523
map:spei.mars.hot	-0.016	0.080	254	-0.20	0.8420
cdioxide.an:map	-0.005	0.007	254	-0.79	0.4291
cdioxide.an:spei.hot	2.310	1.689	254	1.37	0.1726
sdep:ndep	0.052	0.482	15	0.11	0.9157
sdep:map	0.001	0.013	15	0.08	0.9382
mat:map	0.0001	0.020	15	0.005	0.9964

Temporal contributions

	mean y^{-1}	SE	t	pval
Data trend	7.599	2.099	3.62001	0.00040
cdioxide	10.130	1.576	6.4286	0.00000
n.wet.an	3.739	1.938	1.9294	0.03159
s.wet.an	-3.337	2.246	-1.4858	0.07388
tmean.an	-0.745	2.214	-0.3365	0.36942
spei	0.408	2.255	0.1811	0.42875
LAI	0.046	1.844	0.0251	0.49007
Unknown	-2.643	5.392	-0.49	0.31385

2.3.2 – GPP

	Estimate	Std. Error	Df	z value	Pr(>|z|)
(Intercept)	46.118	153.439	254	0.30	0.7640
lai.max.an	-0.954	24.981	254	-0.04	0.9696
sdep	2.463	13.671	15	0.18	0.8595
s.wet.an	-46.436	28.650	254	-1.62	0.1063
cdioxide.an	6.139	6.887	254	0.89	0.3735
ndep	1.986	7.589	15	0.26	0.7972
n.wet.an	44.522	25.507	254	1.75	0.0821
mat	-7.676	21.996	15	-0.35	0.7320
temp.mars.hot.an	55.680	28.190	254	1.98	0.0493
map	-0.118	0.266	15	-0.44	0.6641
spei.mars.hot	207.028	99.193	254	2.09	0.0379
sdep:s.wet.an	1.704	1.748	254	0.98	0.3304
sdep:cdioxide.an	0.786	0.532	254	1.48	0.1409
s.wet.an:cdioxide.an	-0.595	1.001	254	-0.59	0.5530
ndep:n.wet.an	-2.075	1.704	254	-1.22	0.2244
cdioxide.an:ndep	-0.029	0.412	254	-0.07	0.9436
cdioxide.an:n.wet.an	-0.372	1.084	254	-0.34	0.7317
mat:temp.mars.hot.an	-5.843	3.406	254	-1.72	0.0875
cdioxide.an:mat	-0.875	0.490	254	-1.78	0.0755
cdioxide.an:temp.mars.hot.an	0.526	1.620	254	0.32	0.7457
map:spei.mars.hot	-0.202	0.118	254	-1.71	0.0877
cdioxide.an:map	-0.005	0.010	254	-0.53	0.6000
cdioxide.an:spei.mars.hot	-0.288	2.500	254	-0.12	0.9085
sdep:ndep	-0.211	0.683	15	-0.31	0.7612
sdep:map	0.050	0.019	15	0.00	0.9980
mat:map	0.014	0.029	15	0.47	0.6428

Temporal contributions

	mean y-1	SE	t	pval
Data trend	10.385	2.853	4.2637	0.00009
cdioxide	7.011	1.590	4.4095	0.00006
n.wet.an	-1.678	2.430	-0.6903	0.24766
s.wet.an	6.585	2.026	3.2503	0.00142
tmean.an	0.419	2.039	0.2054	0.41932
spei	0.146	2.152	0.0680	0.47312
LAI	-1.167	1.836	-0.6356	0.26493
Unknown	-0.931	5.730	-0.1625	0.43698

2.3.3 – Re

	Estimate	Std. Error	Df	z value	Pr(>|z|)
(Intercept)	25.225	136.630	254	0.18	0.8537
lai.max.an	25.745	22.808	254	1.13	0.2600
sdep	4.548	12.174	15	0.37	0.7139
s.wet.an	-34.849	26.065	254	-1.34	0.1824
cdioxide.an	1.073	6.188	254	0.17	0.8625
ndep	2.097	6.763	15	0.31	0.7608
n.wet.an	32.642	23.254	254	1.40	0.1616
mat	-10.084	19.586	15	-0.51	0.6142
temp.mars.hot.an	63.783	25.864	254	2.47	0.0143
map	-0.090	0.237	15	-0.38	0.7110
spei.mars.hot	193.082	90.885	254	2.12	0.0346
sdep:s.wet.an	0.102	1.588	254	0.06	0.9486
sdep:cdioxide.an	1.428	0.479	254	2.98	0.0031
s.wet.an:cdioxide.an	-2.239	0.910	254	-2.46	0.0146
ndep:n.wet.an	-0.377	1.553	254	-0.24	0.8082
cdioxide.an:ndep	-0.703	0.370	254	-1.90	0.0587
cdioxide.an:n.wet.an	0.806	0.986	254	0.82	0.4146
mat:temp.mars.hot.an	-4.201	3.131	254	-1.34	0.1809
cdioxide.an:mat	-1.427	0.441	254	-3.24	0.0014
cdioxide.an:temp.mars.hot.an	0.557	1.486	254	0.37	0.7081
map:spei.mars.hot	-0.188	0.108	254	-1.73	0.0841
cdioxide.an:map	0.001	0.009	254	0.07	0.9476
cdioxide.an:spei.mars.hot	-2.758	2.288	254	-1.21	0.2291
sdep:ndep	-0.266	0.608	15	-0.44	0.6683
sdep:map	-0.001	0.017	15	-0.08	0.9407
mat:map	0.014	0.026	15	0.55	0.5898

Temporal contributions

	mean y-1	SE	t	pval
Data trend	2.792	2.818	0.9911	0.1648
cdioxide	-1.356	1.713	-0.7916	0.2174
n.wet.an	-2.615	3.165	-0.8262	0.2076
s.wet.an	10.937	2.390	4.5766	0.0000
tmean.an	1.446	2.116	0.6837	0.2497
spei	-0.008	2.230	-0.0034	0.4987
LAI	0.553	2.181	0.2534	0.4008
Unknown	-6.166	6.388	-0.9652	0.1711

Supplementary Material

Chapter 5

Spatial variability and controls over biomass stocks, carbon fluxes, and resource-use efficiencies across forest ecosystems

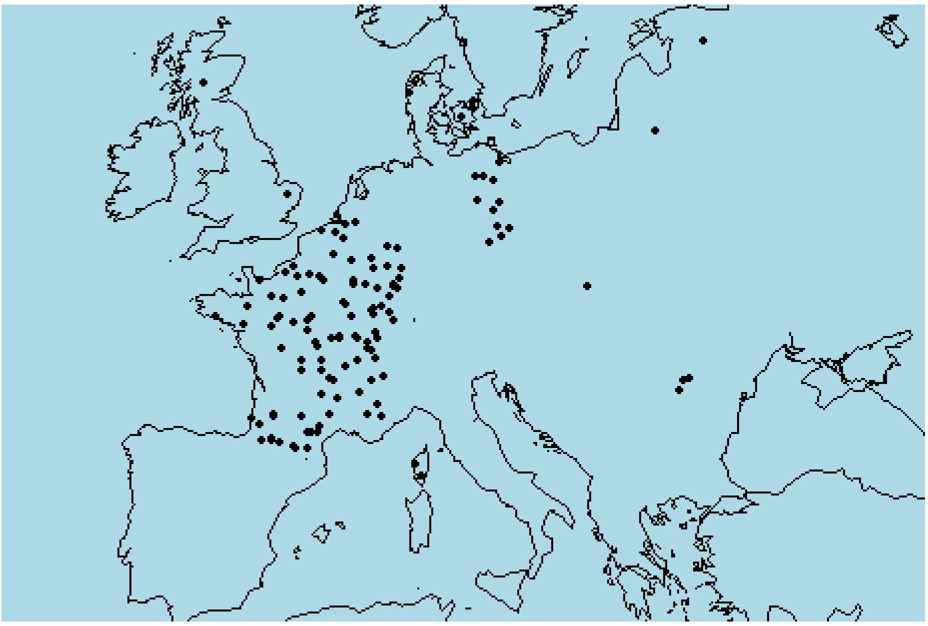

Figure S5.1: Map showing the location of the 126 forests monitored in this study.

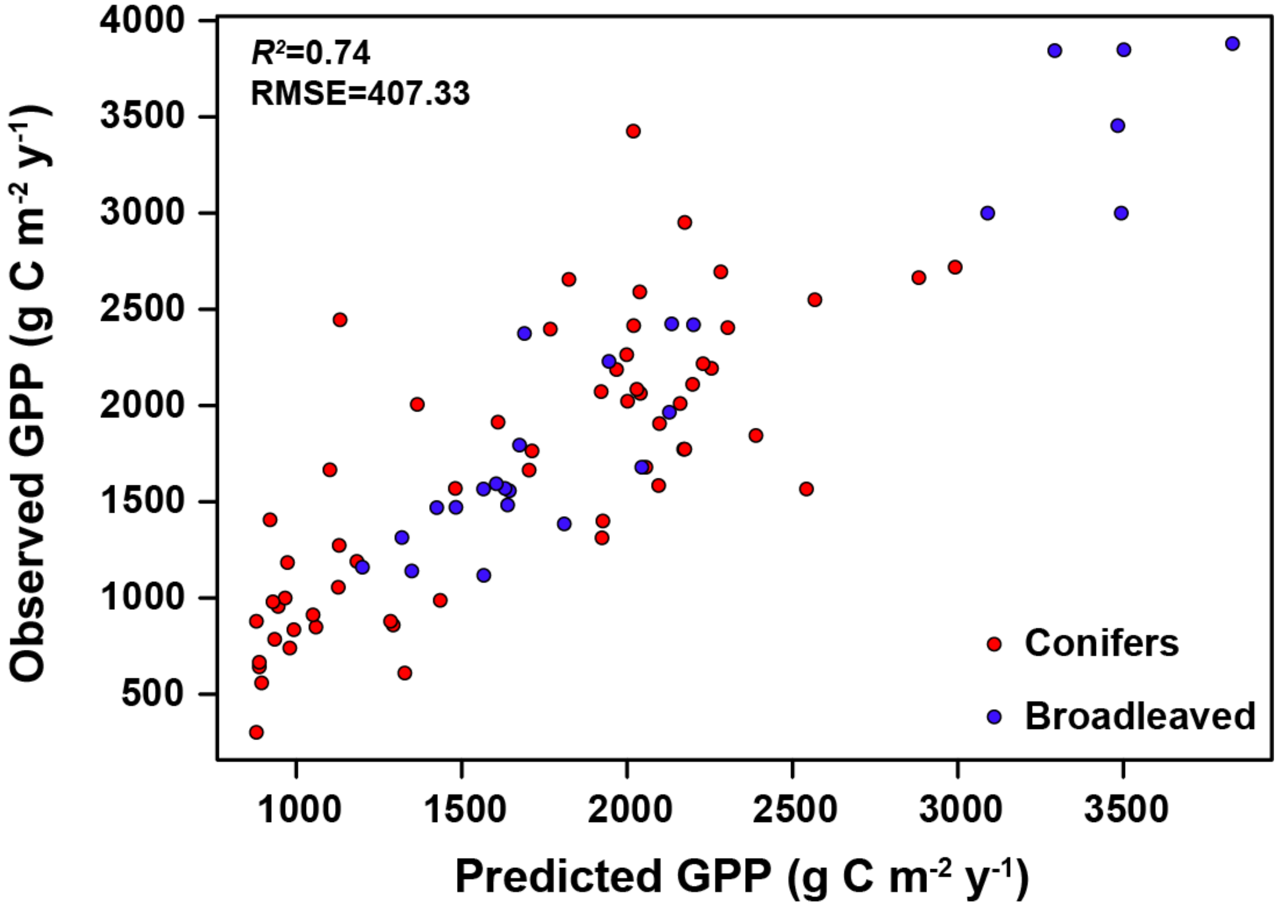

Figure S5.2: Observed versus predicted GPP values from the model used to estimate GPP for the study sites. See materials and methods and Section 1: Estimating GPP in the supplementary material for further information about model adjustment.

Table S5.1: Species (mean ± SE) fruit net primary production (NPP) (g C m^{-2} y^{-1}), allocation to fruit NPP (fruit NPP GPP^{-1} = %GPP), mean maximum fruit NPP (Max NPP), and coefficient of variation (CV), consecutive disparity (D), and first autocorrelation coefficient (AR1) of fruit NPP. AR1 P shows the significance of the AR1 coefficients from a *t*-test, and *n* indicates the number of plots per species. Different letters indicate significant differences (P < 0.05) amongst species (Tukey's HSD test for multiple comparisons).

	NPP		**%GPP**		**Max**		**CV**		**D**		**AR1**	**AR1 *P***		***n***
Abies alba	18.7 ± 3.3	abcd	1.4 ± 0.3	ab	43.1	a	0.83 ± 0.08	b	1.00 ± 0.11	cd	-0.15 ± 0.04	0.0717	ab	11
Fagus sylvatica	16.1 ± 2.5	abcd	1.2 ± 0.2	ab	49.0	a	1.42 ± 0.08	a	2.02 ± 0.15	a	-0.42 ± 0.04	<0.0001	b	26
Picea abies	25.0 ± 5.2	abcd	1.8 ± 0.4	ab	46.2	a	0.76 ± 0.09	b	0.89 ± 0.12	cd	-0.27 ± 0.08	0.0011	ab	19
Pinus nigra	40.6 ± 9.9	cd	2.9 ± 0.7	ab	66.6	a	0.52 ± 0.08	b	0.63 ± 0.12	d	-0.06 ± 0.02	0.7322	ab	3
Pinus pinaster	19.4 ± 2.6	abcd	1.1 ± 0.2	ab	42.2	a	0.78 ± 0.08	b	1.17 ± 0.19	bcd	-0.33 ± 0.12	0.0060	ab	5
Pinus sylvestris	26.8 ± 3.2	bd	2.1 ± 0.3	b	54.6	a	0.60 ± 0.05	b	0.77 ± 0.09	d	-0.09 ± 0.06	0.1538	ab	24
Pseudotsuga menziesii	6.1 ± 1.7	ab	0.5 ± 0.2	a	13.1	a	1.06 ± 0.32	ab	0.64 ± 0.10	d	0.07 ± 0.12	0.5249	a	6
Quercus petraea	12.3 ± 1.5	ac	0.9 ± 0.1	a	44.5	a	1.36 ± 0.08	a	1.71 ± 0.11	ab	-0.20 ± 0.06	0.0012	ab	20
Quercus robur	16.9 ± 4.6	abcd	1.3 ± 0.4	ab	49.6	a	1.35 ± 0.12	a	1.51 ± 0.16	abc	-0.10 ± 0.09	0.2431	ab	12

Table S5.2: Species (mean ± SE) foliar C, N, P, and K concentrations and stoichiometries (C:N, C:P, and N:P). Concentrations have units of mg g^{-1} except for C, which is per cent of dry weight. C:N, C:P, and N:P ratios are calculated on a mass basis. Different letters indicate significant differences (P < 0.05) amongst species (Tukey's HSD test for multiple comparisons), and *n* indicates the number of plots per species.

	C		N		P		K		C:N		C:P		N:P		*n*
Abies alba	52.42 ± 0.11	ab	12.94 ± 0.31	bc	1.16 ± 0.04	bc	5.61 ± 0.25	bc	40.02 ± 0.75	b	452.6 ± 15.8	b	11.32 ± 0.44	c	11
Fagus sylvatica	53.07 ± 0.43	a	24.23 ± 0.53	a	1.17 ± 0.05	bc	7.04 ± 0.32	abc	22.11 ± 0.53	c	479.9 ± 18.5	b	21.73 ± 1.02	a	26
Picea abies	51.35 ± 0.37	ab	13.61 ± 0.30	bc	1.34 ± 0.07	b	5.60 ± 0.25	bc	38.10 ± 0.74	b	397.0 ± 17.1	b	10.48 ± 0.41	c	19
Pinus nigra	53.50 ± NA	a	14.90 ± 3.62	bc	1.17 ± 0.11	bc	6.37 ± 0.49	abc	41.47 ± NA	b	428.0 ± NA	b	12.47 ± 2.17	c	3
Pinus pinaster	52.41 ± 0.26	ab	9.06 ± 0.55	c	0.70 ± 0.08	c	4.60 ± 0.81	c	60.34 ± 5.00	a	808.1 ± 97.3	a	13.59 ± 1.88	bc	5
Pinus sylvestris	52.51 ± 0.15	ab	15.87 ± 0.58	b	1.28 ± 0.04	b	5.43 ± 0.13	bc	34.41 ± 1.23	b	429.0 ± 15.7	b	12.67 ± 0.70	c	24
Pseudotsuga menziesii	53.02 ± 0.22	ab	16.30 ± 0.43	b	1.21 ± 0.06	b	7.44 ± 0.44	ab	32.63 ± 0.77	b	443.4 ± 23.3	b	13.65 ± 0.83	bc	6
Quercus petraea	52.38 ± 0.18	ab	23.66 ± 0.53	a	1.10 ± 0.05	bc	7.16 ± 0.27	abc	22.60 ± 0.47	c	502.1 ± 24.4	b	22.11 ± 0.86	a	20
Quercus robur	52.56 ± 0.71	ab	24.92 ± 1.47	a	1.33 ± 0.07	b	7.80 ± 0.76	a	22.35 ± 1.99	c	420.5 ± 34.8	b	19.99 ± 1.85	ab	12

Table S5.3: Species (mean ± SE) foliar S, Fe, Ca, Mg, Mn, Zn, and Cu concentrations. S, Ca, and Mg concentrations have units of mg g^{-1}, and Fe, Mn, Zn, and Cu have units of μg g^{-1}. Different letters indicate significant differences (P < 0.05) amongst species (Tukey's HSD test for multiple comparisons), and *n* indicates the number of plots per species.

	S		Fe		Ca		Mg		Mn		Zn		Cu	
Abies alba	0.95 ± 0.03	d	47.98 ± 3.09	b	8.33 ± 0.92	a	1.35 ± 0.10	abc	917.14 ± 305.36	b	29.42 ± 1.07	bc	4.01 ± 0.07	c
Fagus sylvatica	1.50 ± 0.04	ab	95.30 ± 3.45	ab	7.24 ± 0.69	ab	1.12 ± 0.11	abc	1390.59 ± 182.55	ab	23.91 ± 1.48	bcd	7.16 ± 0.20	a
Picea abies	0.91 ± 0.04	d	54.76 ± 3.62	b	5.14 ± 0.58	bcd	1.00 ± 0.07	abc	823.44 ± 146.23	b	22.54 ± 1.61	cd	2.98 ± 0.14	c
Pinus nigra	0.96 ± 0.19	d	89.07 ± 21.53	ab	2.79 ± 0.47	d	0.95 ± 0.18	abc	512.33 ± 150.54	b	37.15 ± 7.95	ab	4.50 ± 0.56	bc
Pinus pinaster	0.84 ± 0.04	d	53.20 ± 5.30	b	3.25 ± 0.42	d	1.48 ± 0.12	ab	182.33 ± 64.20	b	25.53 ± 3.19	bcd	3.01 ± 0.46	c
Pinus sylvestris	1.01 ± 0.04	d	59.98 ± 5.82	b	3.30 ± 0.20	d	0.83 ± 0.05	ac	621.43 ± 66.07	b	42.64 ± 1.86	a	4.18 ± 0.23	c
Pseudotsuga menziesii	1.11 ± 0.02	cd	66.14 ± 3.73	b	3.47 ± 0.33	cd	1.41 ± 0.08	abc	904.38 ± 109.14	b	22.83 ± 1.69	bcd	4.35 ± 0.28	bc
Quercus petraea	1.36 ± 0.03	bcd	89.69 ± 4.66	ab	6.40 ± 0.28	abc	1.60 ± 0.06	a	1920.72 ± 129.54	a	11.27 ± 0.59	e	6.84 ± 0.17	a
Quercus robur	1.64 ± 0.05	a	105.82 ± 7.96	a	6.84 ± 0.41	abc	1.76 ± 0.21	a	1129.10 ± 136.85	ab	14.70 ± 1.75	de	7.61 ± 0.34	a

1. Estimating GPP

Model summary

	Estimate	SE	β	SE	*t*	Pr(>|*t*|)	
(Intercept)	985.637	284.828	0.000	0.000	3.46	0.000883	***
Leaf type - conifers	-239.186	236.925	-0.138	0.136	-1.01	0.315877	
MAP	-0.422	0.271	-0.484	0.311	-1.556	0.123863	
MAT	-9.244	18.794	-0.068	0.137	-0.492	0.624226	
Foliar NPP	4.627	0.798	0.517	0.089	5.795	1.42E-07	***
Leaf type - conifers:map	0.378	0.186	0.453	0.223	2.032	0.045615	*
MAP:MAT	0.035	0.013	0.829	0.303	2.734	0.007762	**

	R^2		
Leaf type	0.029	R^2	0.7374
MAP	0.219	R^2_{adj}	0.7169
MAT	0.222	**RMSE**	407.33
Foliar NPP	0.241	**Error%**	9.15%
Leaf type:MAP	0.009	**df**	77
MAP:MAT	0.016	P	<0.0001

Model crossvalidation (75% data as training test - 25% validation data)

	2.50%	50%	97.50%	Mean	SE
R^2	0.636	0.707	0.767	0.706	0.033
R^2_{adj}	0.616	0.691	0.754	0.690	0.034
RMSE on crossvalidation	268.765	396.577	526.764	396.700	67.726
% error on crossvalidation	7.38%	11.52%	17.08%	11.40%	2.63%

2. Data exploration

2.1 Redundancy Analysis (RDA)

Variable significance (10 000 permutations)

	Df	Variance	*F*	Pr(>*F*)	
Foliar S	1	0.0018424	10.7599	0.0006999	***
GPP	1	0.0029443	17.1944	1.00E-04	***
Foliar Zn	1	0.0018485	10.7949	0.0011999	**
MAP	1	0.001212	7.0782	0.0057994	**
Foliar C	1	0.0009082	5.3038	0.0193981	*
Foliar P	1	0.0006911	4.0362	0.0393961	*
Residual	86	0.0147261			

Axis significance (10000 permutations)

	Df	Variance	*F*	Pr(>*F*)	
RDA1	1	0.0157633	93.1281	1.00E-04	***
RDA2	1	0.0003503	2.0694	0.1379	
RDA3	1	0.0000337	0.1993	0.7981	
RDA4	1	0.0000109	0.0646	0.954	
RDA5	1	0.0000008	0.0045	0.9996	
Residual	87	0.0147261			

2.2. PERMANOVA (10000 permutations)

Type I ANOVA	Df	Sum of Sqs	Mean Sq	*F*	R^2	Pr(>*F*)	
Foliar S	1	0.19798	0.197985	55.101	0.28	3.60E-03	**
GPP	1	0.05338	0.053377	14.855	0.07	1.00E-04	***
Foliar Zn	1	0.07381	0.073808	20.541	0.10	0.0002	***
MAP	1	0.02811	0.028106	7.822	0.04	0.0029	**
Foliar C	1	0.0317	0.031701	8.823	0.04	0.040996	*
Foliar P	1	0.01864	0.018638	5.187	0.03	0.007099	**
Residuals	86	0.30901	0.003593		0.43		
Total	92	0.71262			1		

Type II ANOVA	Sum of Sqs	Mean Sq	Df	*F*	Pr(>*F*)	
Foliar S	0.0403	0.040303	1	11.2168	0.716	
GPP	0.08453	0.084527	1	23.5248	1.00E-04	***
Foliar Zn	0.04598	0.045984	1	12.7978	0.006999	**
MAP	0.02948	0.02948	1	8.2044	0.0015	**
Foliar C	0.0246	0.024596	1	6.8453	0.081492	.
Foliar P	0.01864	0.018638	1	5.1872	0.007599	**
Residuals	0.30901	0.003593	86			
Total	0.71262		92			

Supplementary Material

Chapter 7

Masting in oaks: disentangling the effect of flowering phenology, airborne pollen load and drought

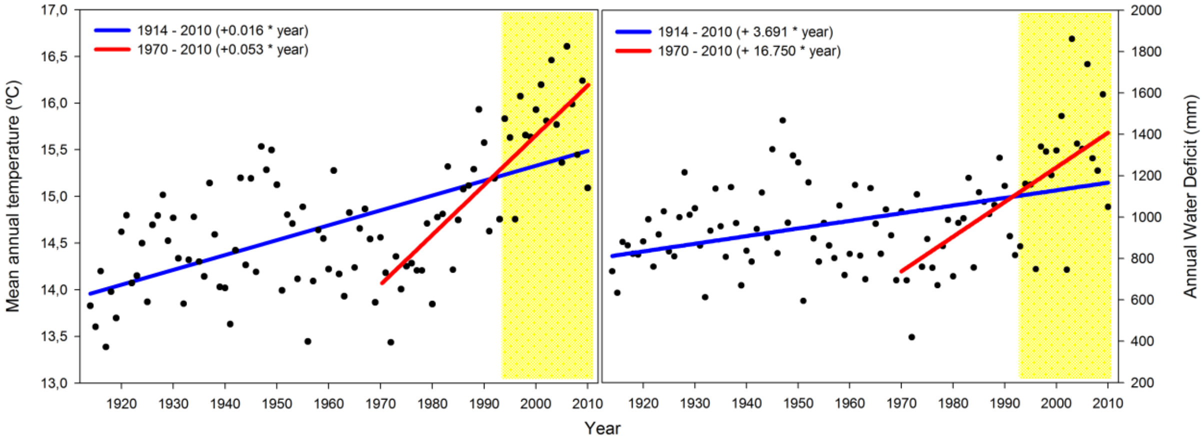

Figure S7.1: a) Mean annual temperature and b) water deficit evolution of the Fabra Observatory since 1914. Notice the stronger warming after 1970. It appears highlighted the study period 1994 – 2010. Temperature: $R^2_{1914-2010} = 0.38$, p-value < 0.0001; $R^2_{1970-2010} = 0.67$, p-value < 0.0001. Water deficit: $R^2_{1914-2010} = 0.17$, p-value < 0.0001; $R^2_{1970-2010} = 0.44$, p-value < 0.0001.

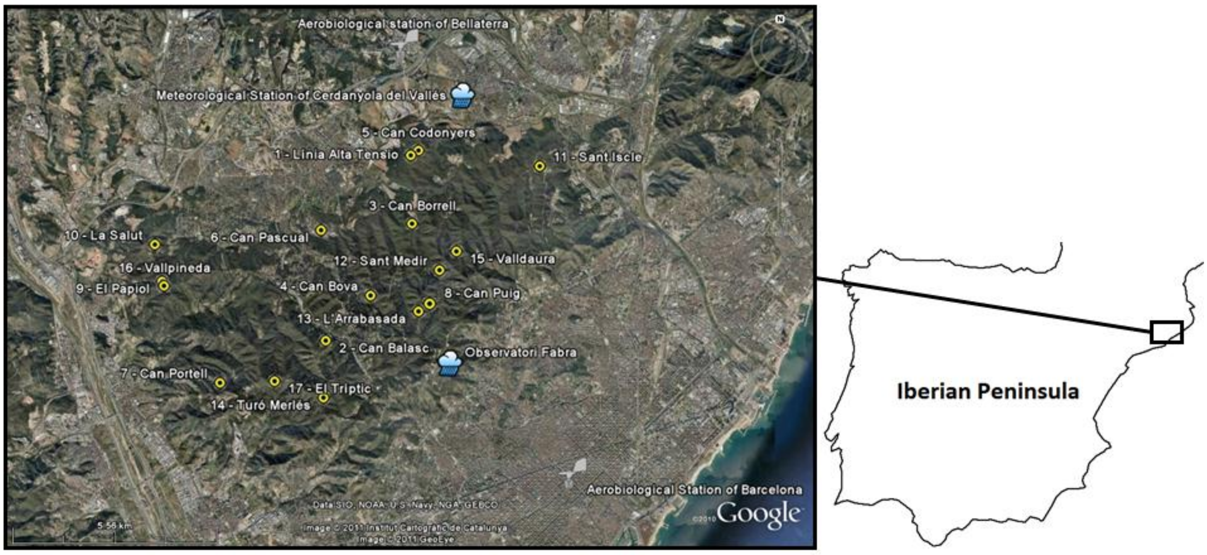

Figure S7.2: Orthophotomap of the study area showing meteorological and aerobiological stations and the plots located over the Collserola Massif.

Table S7.3: Accumulated *Growing Degree Day* (GDD) from 1st January to the start of the pollination period for a base temperature of 0º C (mean ± standard error). RMSE: Root Mean Square Error of the model predicting the date of the onset of flowering, BCN: Barcelona and BTT: Bellaterra.

		Accumulated GDD		Model Adjustment	
		Mean	**CV**	**RMSE**	**Std Err**
BCN	***Q. pubescens***	**817.1 ± 20.8**	**0.11**	**7.45**	**7.64**
	Q. ilex	**961.9 ± 27.5**	**0.12**	**8.64**	**8.90**
BTT	***Q. pubescens***	**779.7 ± 17.1**	**0.09**	**5.82**	**5.98**
	Q. ilex	**904.7 ± 42.2**	**0.19**	**13.02**	**13.39**

Acknowledgements

Vull agrair al meus directors Josep Peñuelas i Sara Vicca, a més de l'Ivan Janssens, per l'excel·lent tasca de direcció de la meva feina que han dut a terme durant aquests quatre anys, per l'amabilitat de les seves crítiques, pels coneixements traspassats i per deixar-me màniga ample a l'hora d'enfocar la meva recerca. Agraeixo també al Josep Maria Espelta per la seva ajuda durant els meus inicis al CREAF i a aquell bon dia en que vam coincidir en un curs d'ecologia al Montseny. Moltes gràcies també a tots aquells coautors que han col·laborat en l'elaboració dels treballs d'aquesta tesi. A tots vosaltres, i de tot cor, gràcies.

Però gràcies també a la Carlota Masvidal, que m'acompanya dolçament des de fa temps. Als pares, per portar-me a muntanya quan era una criatura i que van despertar en mi el saber apreciar la natura. Gràcies als companys del CREAF, per les bones estones i el safareig. I gràcies als companys de la Delegació de la Serralada Litoral Central, pels mostrejos de fonts dels caps de setmana, que fan que no se m'oblidi d'on surten les dades que analitzo. Així que gràcies també a l'R i al R core team, per la seva indiscutible contribució en aquesta tesi.

I en un àmbit, si es vol, més metafísic: gràcies al Montseny, al Montnegre, a Cèllecs i a Burriac, tots fonts d'inspiració i serenitat. Gràcies a les dones d'aigua, als gorgs negres, als serpents i als menadors de la feram boscana, per fer-me somiar despert. Gràcies a la funció caòtica determinista que governa la meva vida i que fa que, a dia d'avui, encara li ho pugui agrair. Gràcies als Portafardells, que aquest any *tornaran a ser a Mataró, per poder tocar el crostó a aquells que sense miraments ens omplen de patiments*. Gràcies a la poesia recitada sota la llosa d'un dolmen, als embotits de Ca la Petita, al pa de la fleca, als formatges de Can Gorgs i Can Pujol, al moscatell de Can Montserrat i a l'aigua fresca de la font de les Nàiades. Gràcies, Sòcrates, per ensenyar-me que no només no sabem gaire res sinó també a viure sense estar mai ni massa trist ni massa content. I a tots aquells éssers, eteris o corporis, no esmentats fins ara i que creieu que també mereixeu ser agraïts: de tot cor, moltes gràcies!