Inter-annual variability of Net Ecosystem Productivity for a temperate mixed forest: A predominance of carry-over effects?

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ABSTRACT

This study presents twenty years of Net Ecosystem Productivity estimations obtained using eddy covariance in a mixed forest, dominated by beech with sparse conifers, at the Vielsalm station, in the Belgian Ardennes.

First the quality and reliability of the data set is discussed. An uncertainty analysis showed that if, on one hand, the site heterogeneity and set-up changes may strongly affect yearly NEP estimates, questioning thus the total carbon budget relevance, on the other hand, robust inter-annual anomalies may be obtained as long as a site dedicated data treatment is carefully applied. A validation of the anomalies by comparison with a growth index derived from tree ring measurements is given. The resulting anomalies (range: $[-206; +123]$ g C m^{-2} yr^{-1}, standard deviation: 93 g C m^{-2} yr^{-1}) being larger than their own uncertainty (~ 30 g C m^{-2} yr^{-1}), an inter-annual variability analysis is possible.

This analysis shows that the sources of NEP inter-annual variability at the Vielsalm station are multiple but the most prominent causes are biotic processes driven by carry-over effects of preceding meteorological events. The lowest observed NEP, in 2000, resulted from a bark beetle attack probably prompted by an early frost event in 1998. Besides, the robust lagged correlation between NEP anomalies and mean vapor pressure deficit during the preceding vegetation season also suggests a carry-over effect of water limitation during the previous year on the beech NEP. Mechanisms driving this carry-over effect are supposedly linked to tree physiology, which is confirmed by a dependency of canopy photosynthetic capacity to previous year water limitation. Some hypotheses, involving biomass allocation and bud formation, are proposed to explain its lagged impact on canopy photosynthetic capacity.

Other causes of NEP inter-annual variability are the radiation during the current vegetation season and the temperature at the end of the winter but the latter variable rather indicates an effect on the conifers interspersed in the plot. Overall, the photosynthetic capacity combined with these two factors explained about 75% of NEP inter-annual variability.

1. Introduction

Terrestrial ecosystems play an important role in climate change mitigation as they reabsorb about one third of the carbon emitted by anthropogenic activity (Le Quéré et al., 2018). However, the captured quantity varies greatly from year to year and the mechanisms underlying this reabsorption remain poorly understood. It is thus difficult to predict how this component of the global carbon budget will evolve in the future. A better understanding of the mechanisms controlling the inter-annual variability of carbon sequestration by ecosystems is needed and long-term carbon exchange follow-ups could help to

comprehend them. Since the end of the 1990s, several networks have been established around the world with this objective, e.g., Euroflux (Valentini et al., 2000); Asiaflux (Yamamoto et al., 2005); CarboEurope (Schulze et al., 2010); Ameriflux (Ameriflux, 2018); Ozflux (van Gorsel et al., 2018), Fluxnet (Baldocchi et al., 2001), ICOS (ICOS, 2018) and all of these used the eddy covariance method (Aubinet et al., 2012).

Measuring and analyzing long-term CO_2 exchanges between ecosystems and the atmosphere with the eddy covariance method is challenging, not only because of the difficulties in performing measurements and maintaining apparatus over a long-term perspective, but also in view of the long-term evolution that both the ecosystem and the

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measurement system undergo during the experiment (Hurdebise et al., 2017). In addition, further difficulties occur at sites characterized by heterogeneous canopies, as is the case for many forested sites. These evolutions may blur the inter-annual variability signal and need careful data treatment to unravel real source/sink variability and artificial variations. One of the aims of this paper is to establish a data treatment that, as far as possible, disentangles the artificial from the natural causes of carbon sequestration inter-annual variability.

At present several long-term studies (over ten years) are available and allow analysis of inter-annual variation of Net Ecosystem Productivity (NEP) by ecosystems to be deepened. In particular, several studies focused on temperate deciduous forests (Saigusa et al., 2005; Urbanski et al., 2007; Granier et al., 2008; Pilegaard et al., 2011; Froelich et al., 2015; Wilkinson et al., 2012) and a synthesis for all ecosystem types has been proposed recently by Baldocchi et al. (2018). The causes of inter-annual NEP variability in forests have been found to be multiple and to vary according to the climate and forest type but also, for given climate and forest type, from site to site. Most often identified causes include the variability of meteorological conditions (spring temperature, intensity or length of drought season, radiation), of the biotic response to the environmental forcing (Richardson et al., 2007); long-term trends (Pilegaard et al., 2011) and natural or anthropic disturbances (logging, fires, thinning, insect infestations). However, it is recognized that, even for a given site, it is generally not possible to explain NEP inter-annual variability with a single factor (Pilegaard et al., 2011). Until recently, only a few studies (Granier et al., 2008; Zielis et al., 2014) considered the impact on NEP variability of lagged or carry-over effects. The importance of these effects is however more and more often recognized by ecologists who highlight impacts on wood increment (Rohner et al., 2016), masting (Vacchiano et al., 2017), net primary productivity (Campioli et al., 2011; Babst et al., 2014) or carbon dynamics (Starr et al., 2016). Carry-over effects of drought stress in the prior season on growth have also been highlighted by Bréda et al. (2006) and Granier et al. (2008) while Desai (2014) also reported that moisture stresses in the preceding season may inhibit photosynthesis.

The present study is based on twenty years of measurements performed at the Vielsalm station (VS) in the Ardennes, Belgium. The site is a mixed forest composed of deciduous and coniferous species and the set-up has been modified after twelve years of measurements, therefore a long-term analysis required a specific methodology that took site heterogeneity and data harmonization into account. This paper thus aims to answer two main questions:

- Is it possible to obtain robust long-term budgets and inter-annual variability estimates in a heterogeneous forest and, if yes, which methodology can be followed in order to avoid biases due to heterogeneity and set-up changes?
- What are the main causes of inter-annual variability at VS? This question will be addressed by specifically focusing on direct but also on carry-over effects of antecedent weather conditions on canopy photosynthetic capacity and NEP.

2. Materials and methods

2.1. Site description

The Vielsalm station is located in a mature mixed forest in the Ardennes region in eastern Belgium (50°18'18" N, 5°59'53"E) at an altitude of about 470 m a.s.l. The winds blow mainly from the South West (SW) and the North East (NE). The vegetation in the vicinity of the measurement tower is a mixture of coniferous species, mainly Douglas fir (*Pseudotsuga menziesii* [Mirb.] Franco), Norway spruce (*Picea abies* [L.] Karst.), silver fir (*Abies alba* Miller), western hemlock (*Tsuga heterophylla* [Raf.] Sarg.) and deciduous species, mainly European beech (*Fagus sylvatica* L.). The species distribution around the tower is heterogeneous, the SW sector being covered mainly by beech (28–29 m height) with some conifers interspersed (30–35 m height), while the other sectors are mostly covered by conifers. Douglas firs (35–41 m height) are mainly concentrated in the NE sector. The Douglas firs were planted in 1935 and 1937 and the beeches in 1908. A more complete description of the vegetation has been given by Soubie et al. (2016). More complete descriptions of forest history have been given by Aubinet et al. (2001) for the period before 1996 and by Hurdebise et al. (2017) for the measurement period. Thinning was performed at the beginning of 2001, in mid-2003 and at the end of 2004. The soil at the site is 50–100 cm deep and is classified as a dystric cambisol. The soil surface is slightly sloping (3%) in the NW direction. The climate is temperate maritime with an annual mean temperature around 8.4 °C and an annual precipitation of 1000 mm without a dry season. The site provides a fetch of 1500 m in the SW direction and 500 m in the NE direction.

2.2. Site instrumentation

Eddy covariance measurements began at VS in August 1996 and are still running. Presently, VS is a candidate ICOS station. The present analysis focuses on the twenty years taken from 1 Jan 1997 to 31 Dec 2016. The eddy covariance set-up (infrared gas analyzer LI-6262, LI-COR Inc., Lincoln, NE, USA; 3D sonic anemometer SOLENT 1012R2, Gill Instruments, Lymington, UK) was installed at 36 m a.g.l. in August 1996 and moved to 40 m a.g.l. in March 1997. In May 2009, it was raised to 52 m a.g.l and, in 2014, it was updated in order to comply with ICOS recommendations (infrared gas analyzer LI-7200, LI-COR Inc., Lincoln, NE, USA; 3D sonic anemometer SOLENT HS50, Gill Instruments, Lymington, UK) and placed at 51 m a.g.l. The impact of measurement height on the flux estimates has been discussed in detail by Hurdebise et al. (2017).

Complementary measurements included above and within canopy air temperature and humidity, global, net and photosynthetically active radiation (PAR), soil temperature and moisture profiles, rainfall, mean atmospheric pressure, soil heat fluxes and CO_2 concentration profiles below the measurement point. All these measurements are taken bi-hourly. Sensor type, number and position varied during the 20 year period. More complete descriptions of the meteorological set-up are given by Aubinet et al. (2001) for the original system and by Vincke et al. (2016) for the current system.

2.3. Flux data treatment

The Eddysoft software package (Kolle and Rebmann, 2007) was used to perform data acquisition and flux computation for all the years. Computation and correction followed the recommended standard procedures (Rebmann et al., 2012). The double rotation method was used for coordinate rotation. The first steps of classical quality control were applied to the raw data (spike detection and stationarity test) and only those data meeting the quality criteria were retained (Aubinet et al., 2000). The spectral correction was based on the comparison between CO_2 and sensible heat cospectra (Foken et al., 2012), following a procedure described by De Ligne (2016): transfer functions and their cut off frequencies were obtained as the ratio of CO_2 and sensible heat cospectra, computed on each high quality half hour (stationarity criterion met; sensible heat > 20 Wm^{-2}). These functions were combined with a reference non attenuated local cospectrum (sensible heat cospectrum) in order to determine the correction factors. Look up tables grouping correction factors by wind velocity classes were built for 8 different periods (between each apparatus change), two wind sectors and two stability classes (stability threshold: z/L = 0.003).

Finally, data that did not meet the stationarity criteria (threshold 30%) were removed (Foken and Wichura, 1996). After these operations, 82% of the total data was available for analysis (Table SM I).

2.3.1. Data selection

As in many forested sites, the surrounding forest is heterogeneous. This implies that, before an analysis of flux inter-annual variability can be performed, it is necessary to disentangle the real variability of source and sink intensities from artefacts due to heterogeneity. This is especially critical at VS where the two most frequent wind directions (SW and NE) correspond not only to contrasting weather conditions but also to contrasting vegetation stands (Aubinet et al., 2005). As is usual in Western Europe, SW winds are associated with a weather disturbance regime corresponding generally to mild temperatures and a larger occurrence of cloudy and rainy periods and NE winds with an anticyclonic regime corresponding to periods with more sunny and dry days, with higher temperatures in summer and lower temperatures in winter (e.g., Malardel, 2005). In addition, at VS, the NE sector is covered by conifers and dominated by Douglas fir, while the SW sector is covered mainly by beech with some sparse conifers. We decided to focus on the SW sector (180°330°) for two reasons: first, anticyclonic conditions prevailed only 20% of the time and the NE data amounts were not sufficient to allow an inter-annual variability study to be performed. Secondly, as the Douglas firs were taller, the proximity of the measurement point to the canopy could induce biases (Hurdebise et al., 2017). As a result, 34% of data points were further removed from the initial set. However, this removal was biased because it mainly concerned fluxes measured during anticyclonic conditions. The data gap filling had thus to take this "meteorological bias" into account, as discussed in Section 2.3.3.

2.3.2. Low turbulence filtering

After adding a storage term to the selected turbulent CO_2 fluxes, the resulting half-hourly fluxes (NEP_h) were filtered in order to remove those collected during periods of low turbulence (u_* filtering; u_* threshold: $0.4\,m\,s^{-1}$). The computation of the storage term was based on half hourly profile measurements, following the procedure described by Aubinet et al. (2001). In order to avoid additional gaps due to the absence of profile measurements at certain times, a specific look-up table was generated to fill gaps in the storage flux data. To this end, available storage measurements for the 20 year period were sorted by period of the year (resolution: 1 month), hour of the day (resolution: one half hour) and u_* intensity (resolution: $0.1\,m\,s^{-1}$) into one look-up table that was then used to fill the gaps. This approach was preferred to a regression between storage estimates with a complete profile and with only the top CO_2 concentration measurements, as those regressions have been generally found poor at sites where decoupling is important (Nicolini et al., 2018). This procedure concerned 8% of the data in the studied wind sector (Table SM I) but, more importantly, it avoided a long-term data gap in 2009 and 2010 when the concentration profile was missing following a structural change to the tower (Table SM II). Finally, after these different operations, 31% (37% of day data; 24% of night data) of the data remained available (Table SM I). Thanks to the use of storage gap filling, this percentage was more or less the same for each year (Table SM II), corresponding to an amount of 4000–6000 available half hours each year.

2.3.3. Data gap filling and sum computation

In view of the large number of data gaps due to the wind direction screening and of the meteorological bias described above, a special attention should be brought to the data gap filling. We thus preferred to set-up our own approaches, better suited to the site specificities, rather than using turnkey programs (i.e. Reichstein et al., 2005). The NEP_h data gaps were filled using two different procedures, combining look-up tables and mean diurnal variations. A flow chart of the procedures is given in Fig. 1.

Six look-up tables (LUT, Fig. 1) were constituted, grouping selected data by ten-day periods, by temperature class (2 K resolution) for night fluxes ($PPFD < 5\,\mu mol\,m^{-2}\,s^{-1}$) and by PPFD class ($100\,\mu mol\,m^{-2}\,s^{-1}$ resolution) for day fluxes. In one day and one night look-up table ($LUT_{d,y}$ and $LUT_{n,y}$), the average NEP_h were computed separately for each year; in the others, they were averaged over longer periods. In order to take the 2009 measurement height change into account, two different periods were used: 1997–2008 and 2009–2016.

Mean diurnal variation (MDV) was also operated by building MDV tables that are similar to look-up tables but rely on different selection criteria. Here data selection and gathering was operated by ten-day periods and half-hour of the day. Three MDV tables were constituted, one computing NEP_h every year (MDV_y) and the others averaging NEP_h over the 1997–2008 and the 2009–2016 periods.

The advantage of using look-up tables based on PPFD and temperature classes is that they allow a correction of the meteorological bias (Section 2.3.1) to be made. Even if periods of high radiation and extreme temperatures are less frequent under the weather disturbance regime, they are sufficiently numerous to constitute specific classes and allow realistic gap filling. This was not the case with mean diurnal variation which depicts only average fluxes under the weather disturbance regime. Besides this, the advantage of using yearly values rather than long-term averages is that the former better takes inter-annual variability into account. The data gap filling procedure should thus preferentially use yearly look-up tables (Fig. 1). This was made, which allowed about 80% of the gaps to be filled. However, for the remaining gaps, a choice between yearly mean diurnal variation and long-term averaged look-up tables must be operated. Two procedures were then followed. Procedure 1 used yearly mean diurnal variations in order to better reflect the amplitude of inter–annual variability and it was used to compute yearly anomalies. Procedure 2 used averaged look up tables and was applied to provide the long-term carbon budgets as it better took the meteorological bias into account. Finally the last remaining gaps were filled with long-term averaged mean diurnal variation.

Although the difference between procedures affects only 11% of the total data, their impact on the mean annual sequestration is substantial, amounting to about $34\,g\,C\,m^{-2}\,yr^{-1}$ (Fig. 2a). An approach based on MDV only (not shown) would have differed from our NEP_y estimates by $75\,g\,C\,m^{-2}\,yr^{-1}$, which is much larger than the differences between gap filling methods predicted by Moffat et al. (2007). This is probably because of the larger size of the data gaps. However, as the MDV approach has been clearly identified as skewed due to meteorological bias, we did not consider this difference as an uncertainty source.

Besides this, procedure 1 better took inter–annual variability into account as 93% of the data were measured or estimated on the basis of data of the current year, while in procedure 2 this percentage was limited to 80%.

The impact of the storage correction was especially important on years during which storage measurements were not available (mainly 2009 and 2010). For these years the classical procedure would had automatically skipped some data, while turbulent measurements were of good quality and this could be avoided by applying the storage data gap procedure.

Daily (NEP_d) and yearly (NEP_y) net ecosystem productivities were finally obtained by NEP_h summation.

2.4. Derived variables for inter–annual variability computation

2.4.1. Anomaly computation

The anomalies were computed on a daily basis as the difference between the daily NEP (NEP_d) of the considered day and those of the same DOY averaged over an extended period. Two averaging periods, before and after the tower change (in April–May 2009), were considered in order to remove the impact of measurement height change on inter–annual variability. All anomaly computations were based on procedure 1 because it better captures inter-annual variability. Anomalies at a larger time scale (year, period) were computed by summation of the daily anomalies.
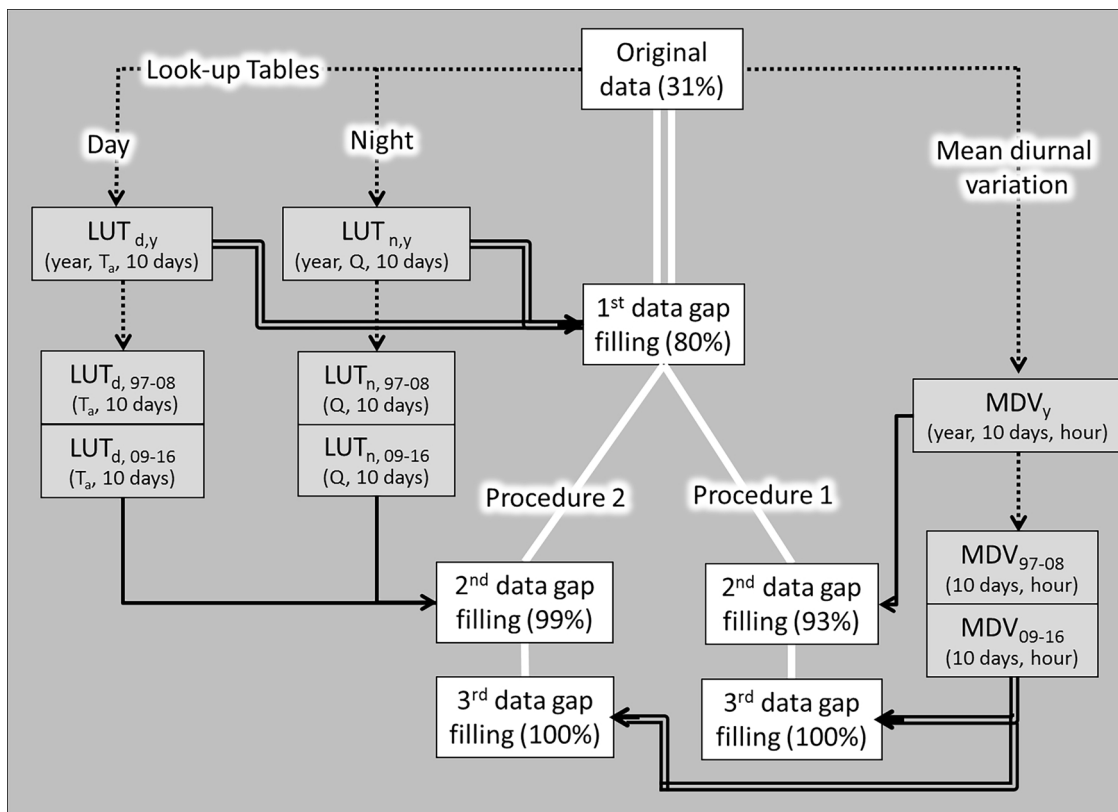
Fig. 1. Organigram of the data gap filling procedure. LUT: Look Up table; MDV : Mean diurnal variation.

2.4.2. Physiologic variables

In order to derive the characteristics of the canopy exchange capacity, independently of PAR, NEP_h to PAR (Q) responses were derived from direct measurements for every decade. We used an exponential curve (Mitscherlich equation, Aubinet et al., 2001) and derived assimilation at PAR saturation (A_{max}), quantum efficiency (α), dark respiration (R_d) and assimilation at 700 μmol m^{-2} s^{-1} (A_{700}), according to Eqs. (1) and (2). The last parameter was preferred to A_{max} and α as an estimate of canopy photosynthetic capacity.

$$NEP_h = A_{max}\left[1 - exp\left\{\frac{-\alpha\,Q}{A_{max}}\right\}\right] - R_d \tag{1}$$

$$A_{700} = A_{max}\left[1 - exp\left\{\frac{-\alpha\,700}{A_{max}}\right\}\right] \tag{2}$$

Anomalies of these parameters (AA) were computed similarly to those for NEP.

2.4.3. Uncertainty estimates

Uncertainties result from random errors or from an imperfect correction of systematic errors (JCGM, 2008). In eddy covariance, random errors include errors due to the stochastic nature of turbulence, to the instrument system and to changes in footprint while systematic errors result from unmet assumptions and methodological challenges, from instrumental calibration and design or from data processing (Richardson et al., 2012; Mauder et al., 2013).

To quantify the uncertainty on NEP_y at VS, we considered four sources: the total random error, including the three causes mentioned above, and three systematic errors. We focused on the night flux underestimation (unmet assumptions), the frequency correction (instrumentation design) and the gap filling (data processing). Calibration errors, instrumental errors or density effects were not taken into account, deeming that enough precautions had been taken to limit them.

In each case the uncertainty was not defined as the error itself but as resulting after the correction of the systematic error, due to an imperfect correction. Their estimation and the way they propagate in budgets were described below. Results are given in Table 1.

Uncertainties due to the total random error and to gap filling were both estimated at a half hourly scale. The first one was estimated for each measurement using the relation based on the daily difference approach proposed by Richardson et al. (2006) for forests. The second was estimated for each gap filled data as 1.96 times the flux standard deviation in the LUT or the MDV class used to fill the gap. They were summed quadratically together to get annual sums (Table 1, column C4).

We considered that the uncertainty associated to the night flux error resulted from an inadequate u_* threshold choice. It was estimated at an annual scale: NEP_y was computed several times, using each time a different (but constant) u_* threshold chosen in the range where normalized fluxes appear independent of u_* (namely, between 0.35 and 0.45 ms^{-1} at VS). For each year, a NEP_y distribution was thus obtained and the uncertainty was estimated as 1.96 times its standard deviation (Table 1, column C6).

The main source of uncertainty remaining after frequency correction is in the correction factor determination (Section 2.3). As the set up changes were operated at a frequency lower than once per year, it was considered as systematic at a yearly scale and computed for each year as the product of the flux and 1.96 times the average standard error of the correction factor (Table 1, column C8).

A global yearly uncertainty was obtained by summing quadratically the three preceding estimates. Global yearly uncertainties were averaged quadratically from 1997 to 2008 and from 2009 to 2016 (before and after the measurement height change) in order to obtain global multi-year uncertainties (Table 1, columns M4, M6 and M8). Finally, uncertainties on annual budget anomalies were obtained by summing quadratically global yearly and global multi-year uncertainties (Table 1, column C9).

2.4.4. Growth index computation

Twenty-four dominant beeches were cored at the end of 2011 at breast height with an increment borer (two perpendicular cores per tree). The individual ring widths from 1972 to 2011 were measured using the image analysis software WinDENDRO (Regent Instruments Canada Inc. (Guay et al., 1992)) and were then cross–dated by detecting regional pointer years, which were defined as those calendar years for which at least 75% of the cross dated trees presented a radial growth variation higher than 10% (Becker et al., 1994).

Tree ring indexes were computed by Soubie (2014) using a procedure proposed by Lebourgeois and Mérian (2012): low and intermediate frequencies were removed by dividing each individual series by a polynomial function adjusted on the forty year long series and by averaging these ratios by year. By this, a stationary time series with a mean of 1 and a homogeneous variance was obtained for each tree. The tree ring index was then computed by averaging these values on the 24 trees. Their uncertainty was estimated as 1.96 times the standard error of the mean. All computations were made using the R–software and the "dplR" package (Bunn, 2010; Mérian, 2013).

3. Results

3.1. Budget and inter–annual variability

Time series of NEP and principal weather variables are presented in the Supplementary Material, Fig. SM1. The average sequestration over twenty years (computed with procedure 2) was 411 g C m^{-2} yr^{-1} (Table 1, Fig. 2a) but this differed strongly (107 g C m^{-2} yr^{-1}) between the periods before and after measurement height change in 2009. This difference is much larger than the uncertainties associated with the eddy covariance method, which reached 7 and 11 g C m^{-2} yr^{-1} on the 1997–2009 and 2009–2016 long-term budgets respectively (Table 1, column C9). The impact of measurement height change on fluxes has been discussed by Hurdebise et al. (2017). They showed that, in some

sectors, the system was in the roughness sublayer, which could affect similarity conditions. However, they also showed that it was not the case in the SW sector studied here, so that the difference in the present case is more likely to be due to footprint changes.

However, as these errors are mainly systematic, they are expected to less affect year to year changes. For this reason, the following analysis will be mainly based on the anomalies computed, as described in Section 2.4.1. No further standardization is operated as the NEP$_y$ standard deviation was hardly affected by the measurement height change (91 and 95 g C m^{-2} yr^{-1} for 1997–2009 and 2009–2016 respectively). The uncertainties for anomalies, mainly associated with the eddy covariance method, are of the order of 30 g C m^{-2} yr^{-1} (Table 1).

For six years, the NEP$_y$ anomaly (NEPA$_y$) was comprised in the classes [−30; 30] m^{-2} yr^{-2} yr^{-1}, i.e., lower than their own uncertainty (1998, 2001, 2002, 2007, 2010 and 2013, Fig. 2b). Seven years (1999, 2003, 2006, 2008, 2009, 2014 and 2015) were characterized by a positive anomaly (larger than average sequestration) and seven years (1997, 2000, 2004, 2005, 2011, 2012 and 2016) by a negative anomaly (lower than average sequestration). Among these, 2000 appeared exceptional, the NEPA$_y$ reaching −200 g C m^{-2} yr^{-1}, more than twice the standard deviation. This year was found to be marked by a bark beetle attack that weakened and even killed some trees (La Spina et al., 2013) as discussed below.

3.2. Anomaly analysis

At a yearly scale, no significant correlation appeared between NEPA$_y$ and yearly averaged physiologic and weather variables (Table 2).

The following strategy was then followed: the year was divided in four periods corresponding to given vegetation development stages and we focused on the three periods that had the larger impact on yearly NEP (NEP$_y$). On these periods, direct correlations between periodical NEPA and weather (temperature, PAR, VPD, precipitation) or

Table 1
Yearly carbon sequestration and anomalies computed with the two procedures (g C m^{-2} yr^{-1}) and uncertainties. For details see text.

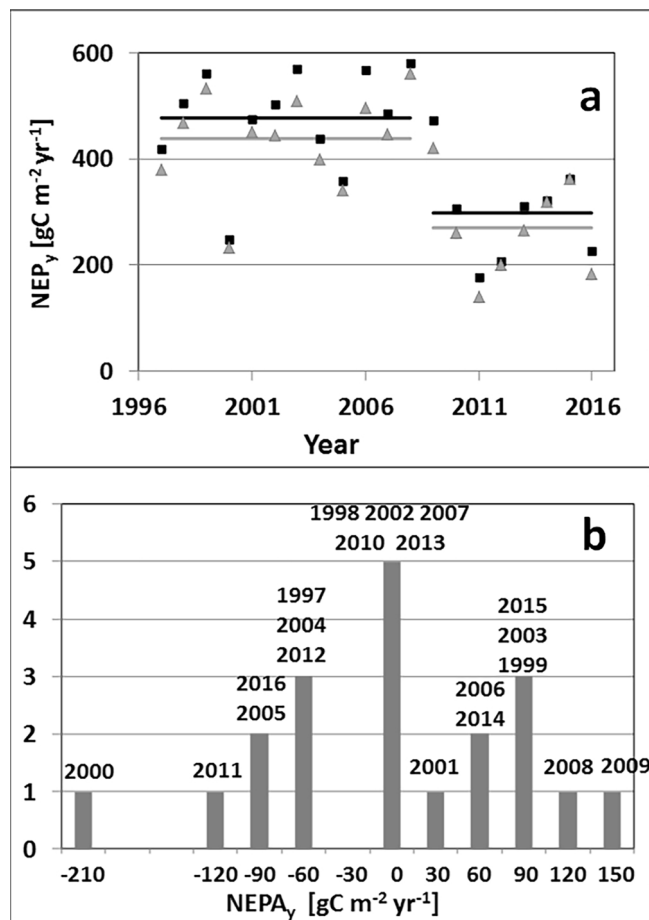| Year	NEP$_y$ (Procedure 2)	NEPA$_y$ (Procedure 1)	Random and Data gap filling uncertainty	u* correction uncertainty		Frequency correction uncertainty		Total Uncertainty
				Systematic (corrected)	Remaining	Systematic (corrected)	Remaining	on anomalies
C1	C2	C3	C4	C5	C6	C7	C8	C9 = (C4^2 + C6^2 + C8^2 + M4^2 + M6^2 + M8^2)$^{0.5}$
1997		−56	17	140	21	30	4	28
1998		8	17	50	23	37	5	30
1999		99	17	79	26	43	2	32
2000		−200	16	97	13	19	1	22
2001		18	16	51	15	36	1	22
2002		8	16	105	8	35	1	19
2003		83	16	107	17	41	2	24
2004		−55	16	95	13	32	1	22
2005		−87	16	87	10	27	1	20
2006		48	17	55	16	40	2	24
2007		10	16	64	14	36	3	22
2008		123	16	84	14	45	3	23
2009		148	22	133	14	34	3	28
2010		−10	21	133	12	21	4	27
2011		−115	20	178	22	11	2	31
2012		−68	20	188	17	16	3	29
2013		−8	21	134	26	21	4	36
2014		48	21	168	36	25	0	43
2015		92	20	139	17	29	0	28
2016		−86	20	269	28	15	0	36
Averages			M4		M6		M8	on budget
1997–2009	−454		5		5		1	7
2009–2016	−347		7		8		1	11
20 Years	−411							

Fig. 2. a: Yearly NEP estimated using different data gap filling procedures: Black squares: Procedure 1, grey triangles: Procedure 2. For details, see Section 2.3.3. b: frequency distribution of NEPA_y.

Table 2
Correlation coefficients between NEPA_y and corresponding physiological and climatic variables at different time scales. Significant correlations ($p < 0.05$) are indicated in bold.

	Year	Spring	Veg. S.	Fall
T_a	0.02	**0.54**	0.37	0.26
V	0.22	**0.50**	0.18	0.17
Q	0.20	**0.53**	0.32	0.27
P	0.01	− 0.14	− 0.12	− 0.26
AA	0.32	0.37	**0.64**	0.22
R_d	0.39	0.01	− 0.08	0.30

physiological (photosynthetic capacity, dark respiration) variable anomalies on the same period were sought, using stepwise regression. Carry-over effects of weather conditions on NEPA or A_{700} anomalies (AA) were then sought by computing lagged correlation between these variables and weather variable anomalies. Finally, direct and lagged correlations were combined in order to find the best predictors of inter annual NEP_y variability.

3.2.1. Direct correlations

The three periods of the year that were considered were: Spring (DOY 30–150), before full leaf development is reached by the beech, Vegetation season (DOY 150–250), corresponding to full leaf development and Fall (DOY 250–330), corresponding to the leaf senescence period. The vegetation season was the period during which both NEP and NEPA were the most intense: NEP_vs reached 84% of NEP_y in

1997–2008 and 119% of NEP_y in 2009–2016 while NEP_vs variability explained 74% of NEP_y variability (Fig. 3a). Spring NEP (NEP_sp) contributed from 23% (1997–2008) to 30% (2009–2016) of annual NEP (NEP_y). The correlation between NEPA_sp and NEPA_y was poor (Fig. 3b) but appeared much more important after the relation with NEPA_vs had been removed (Fig. 3c). Finally, fall NEP (NEP_f) constituted a minor part of the yearly budget (5% of NEP_y in 1997–2008; –15% of NEP_y in 2009–2016) and their anomalies were not correlated with NEPA_y (Fig. 3d–e).

Some direct correlations with physiologic and weather variables appeared (Table 2): NEPA was correlated with photosynthetic capacity anomalies (AA) in the vegetation season, while correlations with weather variables anomalies (air temperature, PAR, VPD) appeared only in spring. No significant correlation was found for NEPA_f.

As some correlations could be hidden by others, stepwise regressions were developed in order to investigate direct correlations more deeply. Stepwise regression steps between NEPA_vs and main driving variables were presented (Table 3, Fig. 4a–c). As expected from Table 2, a significant correlation with the photosynthetic capacity (AA _vs,) appears at step 1 (Fig. 4a). At step 2, significant correlations were obtained between the residuals of this relation and Q and T_a anomalies. The former was retained as the most significant (Fig. 4b). At step 3, no significant relations remained and the correlation with T_a anomaly disappeared. The two- variable regression was thus the best and explained about 58% of the NEPA_vs (Fig. 4c).

An almost similar pattern was found for NEPA_sp (Fig. 4d–f) with the difference that the correlation with Q anomaly was larger than those with AA at the first step. At the end the main direct driving variables were the same for the two periods and explain about 50% of the variability.

3.2.2. Lagged correlations

For each of the three periods, significant lagged correlations appeared between NEPA and some weather variable anomalies characterizing preceding year's vegetation season (between DOY 150 and 250 (y-1), Fig. 5a–c, dashed ellipses). These correlations were more or less important according to the variable and the season considered; they were not all significant but obey to a similar pattern: correlations with PAR, air temperature and VPD anomalies were negative and those with precipitation anomalies were positive and at least one of these variables had a significant correlation with NEPA.

A correlation of NEPA_sp with the previous winter temperature anomaly (around DOY 1) is also clearly apparent, in addition to the direct correlation with all weather variables (DOY 50 and beyond), as discussed in Section 3.2 (Fig. 5a, dotted ellipse).

Finally, significant positive correlations between NEPA_sp and temperature anomaly around DOY 155 of the preceding year (Fig. 5a) and between NEPA_f and weather conditions of the current year's vegetation season (DOY 160–200, Fig. 5c) also appear.

Carry-over effects of preceding year weather conditions on NEPA operated through mechanisms which, supposedly, involve tree physiology. Considering that AA could be a tracer for these mechanisms, we also analyzed lagged correlations between weather variables and this variable (Fig. 5d–f). For this analysis, years 1997 and 2000 were excluded, the first due to the absence of meteorological data before August 1996, the second because the strong AA observed for this year was clearly due to another cause (the bark beetle attack) that was independent of the weather conditions discussed here.

Although the correlations were less important, a similar coherent scheme appeared: lagged correlations with weather variable anomalies during the preceding vegetation season (DOY 150 (y – 1)) were significant for AA_vs and AA_f (Fig. 5e and f, dashed ellipses) but not for AA_sp (Fig. 5d). The two first correlations confirm that carry-over effects could affect photosynthetic capacity. The absence of correlation in spring is not surprising: first this period covers the leaf initiation and growth and thus also depends on leaf unfolding dynamics; secondly, AA
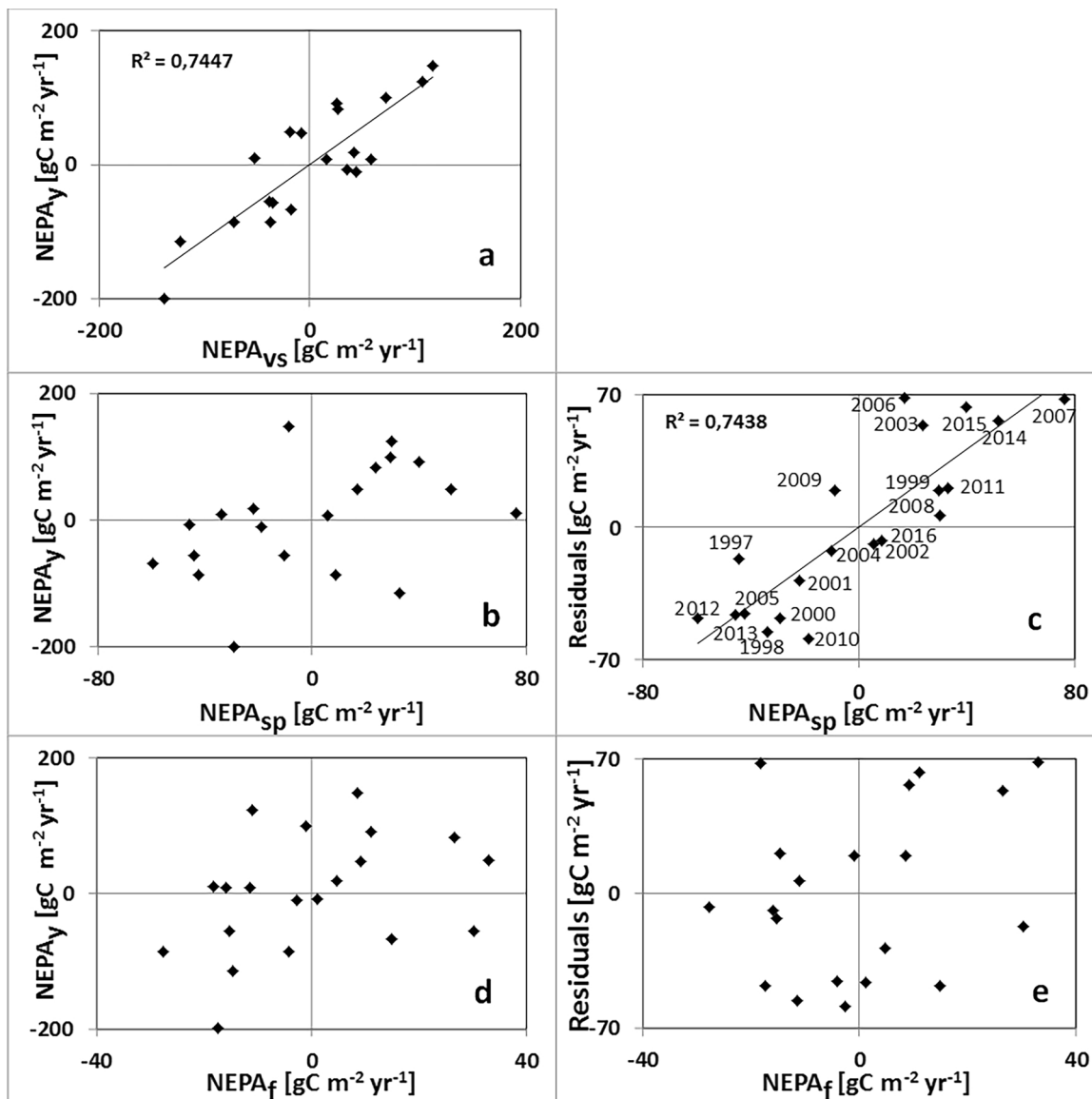
Fig. 3. Relations between NEP anomalies computed on the whole year (NEPA$_y$) and on limited periods: Fig. 3a: Vegetation season (vs, DOY 150–250); Fig. 3b: Spring (sp, DOY 150–330); Fig. 3d: Fall (f, DOY 250–330). Fig. 3c and e: relations between the NEPA$_y$ – NEPA$_{vs}$ relation residuals and NEPA$_{sp}$ (Fig. 3c) or NEPA$_f$ (Fig. 3e) anomalies.

estimates during this period are strongly influenced by the conifers present in the sub-plot. Both contribute to blur a signal that could result from carry-over effects. Besides this, the positive correlation with winter temperature anomaly (around DOY 1) observed for NEP$_{sp}$ (Fig. 5d, dotted ellipse) could attest the impact of temperature on assimilation starting dates in the stand.

Finally a positive correlation between AA$_{vs}$ and precipitation (main peak in DOY 60–70, Fig. 5e, dotted ellipses) also appears.

A stepwise regression was also developed in order to quantify the impact of lagged effects on AA$_{vs}$ and AA$_f$. However, it was limited to the first step as no significant relation remained at the second step. The best correlations at step 1 were obtained for both variables with previous vegetation season saturation deficit (p = 0.016 and 0.034 for vegetation season and fall, respectively) (Fig. 6a and c). In addition, AA$_{vs}$ correlation with spring precipitation anomalies was presented on (Fig. 6b).

3.2.3. Synthesis: main sequestration inter-annual variability drivers

In order to synthesize the impact of direct and carry-over effects on NEP$_y$ inter-annual variability, a stepwise regression of NEPA$_y$ with all

direct and lagged driving variables of seasonal NEPA was developed in order to find the best predictors of NEP$_y$ inter-annual variability. Step 1 and 2 showed that the most important driving variables were the photosynthetic capacity and the PAR during vegetation season as already suggested by the impact of these variables on NEPA$_{vs}$ (Fig. 4a, b). At step 3 (Fig. 7a), three variables were tested: T$_{0–60}$, V$_{y-1}$ and V$_{60–90}$. The best correlation improvement was obtained by adding early year temperature (T$_{0–60}$, Fig. 5d). Inclusion of carry-over effects through the introduction of V$_{y-1}$ did not improve the correlation so well, probably because its effect was already taken into account, through the A$_{700vs}$ parameter. Finally, the correlation improvement brought at step 4 by introducing V$_{60-90}$ as a fourth variable was very small. The three-variable regression (AA$_{vs}$, Q$_{vs}$ and T$_{0–60}$) explained about 75% of the inter-annual variability and the difference between simulated and observed anomalies was lower than anomaly uncertainty (30 g C m^{-2} yr^{-1}) for 15 years (Fig. 7).

Finally, a significant relation was found between NEPA$_y$ and tree ring index based on beech wood increment (Fig. 8).

Table 3
Stepwise regression: correlations between vegetation season and spring NEP anomalies and selected climate and physiological variables at each step of the regression. Significant correlations (p < 0.05) are indicated in bold. Table 3a: Vegetation season; Table 3b: Spring.

a	Pr	T_a	R_d	Q	AA	Model quality
NEPA$_{vs}$						
Rsq	n.s.	**0.22**	n.s.	n.s.	**0.44**	**0.44**
p		**0.04**			**0.002**	**0.002**
Residuals Step 1						
Rsq	n.s.	**0.26**	n.s.	**0.33**		**0.64**
p		**0.02**		**0.01**		**0.001**
Residuals Step 2						
Rsq	n.s.	n.s.	n.s.			
p						

b	Pr	T_a	R_d	A_{700}	Q	Model quality
NEPA$_{sp}$						
Rsq	n.s.	**0.29**	n.s.	**0.29**	**0.36**	**0.36**
p		**0.01**		**0.01**	**0.01**	**0.01**
Residuals Step 1						
Rsq	n.s.	n.s.	n.s.	**0.26**		**0.50**
p				**0.02**		**0.01**
Residuals Step 2						
Rsq	n.s.	n.s.	n.s.			
p						

4. Discussion

4.1. Significance of budgets and anomalies

The average NEP$_y$ at VS (411 g C m^{-2} yr^{-1}) was at the upper limit of the range found generally for temperate deciduous forests (between 160 and 390 g C m^{-2} yr^{-1}; Saigusa et al., 2005; Granier et al., 2008; Pilegaard et al., 2011; Froelich et al., 2015; Baldocchi et al. (2018). The value is probably not representative of a pure beech stand, as it was enhanced by the presence of conifers in the sub plot that assimilated carbon in winter and early spring, before leaf onset in the beech. Their impact could be roughly estimated by supposing that no assimilation should take place in the beech stand before leaf onset (early May) and thus the NEP during these days should be similar to those observed in January and February, when no assimilation takes place in the conifer. A rough estimate based on this assumption suggests an amplification of the uptake in the order of 80–130 g C m^{-2} yr^{-1} compared to a pure beech stand. Finally, the large NEP difference before and after 2009 (107 g C m^{-2} yr^{-1}) is probably because the measurement height change modified the relative contributions of coniferous and deciduous species in the footprint.

This suggests that, despite the caution taken during data selection and treatment, the absolute NEP$_y$ values obtained at the Vielsalm site can be considered to be very sensitive to stand heterogeneity and hardly representative of a pure beech stand. The main sources of uncertainty are not linked with the eddy covariance method itself, but rather result from site heterogeneity. Such problems are probably shared by many sites as heterogeneity is a common feature of both natural and managed forests. Nevertheless, as these uncertainties are mainly systematic, anomalies are expected to be less affected by them and could be much more robust as long as the data treatment has taken these problems into account. In our case, the selection of a wind sector, the preferential use of look-up tables for data gap filling and the computation of anomalies by treating fluxes separately before and after the tower-raising constitute features essential for obtaining robust anomalies. The uncertainty on anomalies is in the order of 30 g C m^{-2} yr^{-1}. Even if not all uncertainty sources have been considered in our analysis, this estimate appears reasonable. The robustness of the anomaly data is corroborated

further by their consistent relationships with weather and physiologic driving variables and their significant correlation with growth index (Fig. 8). Despite the relation between tree ring index and NEPA being not direct, as the former is also dependent on tree respiration and carbon allocation between the different tree organs, significant relations between these two variables can be expected, as shown by several authors (Babst et al., 2014; Teets et al., 2018).

4.2. Lagged effects on photosynthetic capacity

One of the most important results of this analysis is the highlighted carry-over effects on both NEPA and AA as attested by the lagged correlations between these variables and weather variables (Fig. 5). One effect is illustrated by the correlation between preceding vegetation VPD and NEPA$_{vs}$ (Fig. 5b), AA$_{vs}$ (Fig. 5e) and NEPA$_f$ (Fig. 5c); the other by the correlations between early spring precipitation or VPD and AA$_{vs}$ (Fig. 5e).

4.2.1. Impact of previous year weather

Analyses of the impacts of previous year weather conditions on NEP remain scarce (Desai, 2014; Zielis et al., 2014; Shen et al., 2016) and report very different results: as Desai (2014) suggested that moisture stress in the prior season could inhibit photosynthesis in a temperate deciduous forest, Shen et al (2016) suggested that increased precipitation on the previous year could decrease NEP of the current year in an arid savanna and Zielis et al. (2014) rather highlighted the role of minimum air temperature during the previous year spring in a subalpine forest dominated by conifers. This suggests the potential for multiple processes and different effects according to the ecosystem type.

Our observation of a negative correlation with preceding year VPD is in line with the observation by Desai (2014). It also corroborates different studies that highlight negative impacts of preceding year drought on NPP or tree growth (Granier et al., 2008; Müller-Haubold et al., 2013; Babst et al., 2014; Latte et al., 2016).

The mechanisms responsible of such delayed effects may be diverse. Bréda et al (2006) suggested that severe droughts could induce damages to tree structures due to cavitation and affect xylem plasticity (decrease of sapwood area) that could alter tree functioning for several years. In addition to these structural changes, several authors (Bréda et al., 2006; Meier and Leuschner, 2008; Müller-Haubold et al., 2013) suggest that precipitation intensity could also influence the patterns of biomass allocation to wood, leaf and fruit production in beech, low precipitations favoring storage in reproductive rather than in vegetative organs. In addition, Hertel et al (2013) suggested that, under water stress condition, beech trees could alter substantially their above-below ground carbon partitioning, favoring fine root development.

At VS, the occurrences of severe droughts are quite limited: even during the 2003 heat wave, the site was much lesser affected by drought than most of the other European sites (Ciais et al., 2005; Bréda et al., 2006; Granier et al., 2007). Even if the hypothesis of structural changes cannot be discarded, this suggests that the hypothesis of biomass allocation dependency on water conditions is more likely to act regularly: during drier years, characterized by larger VPD and lower precipitation, the biomass allocation to leaf buds would be restrained. Meier and Leuschner (2008) suggested that the water limitation is stronger in summer when leaf buds are forming so that it leads to a reduction of the bud number and thus of next season leaf number. This would explain the negative impact on NEPA of vegetation season VPD (V_{y-1}). No direct measurements of LAI or of leaf number were available at VS to confirm this hypothesis but it is corroborated by our observations of photosynthetic capacity (Fig. 6a and b). The present analysis also cannot determine if the biomass was allocated preferentially to root or fruits. No direct measurements of root development were available and the sole available information relative to fruit production was given at a regional scale: most intense masting years in
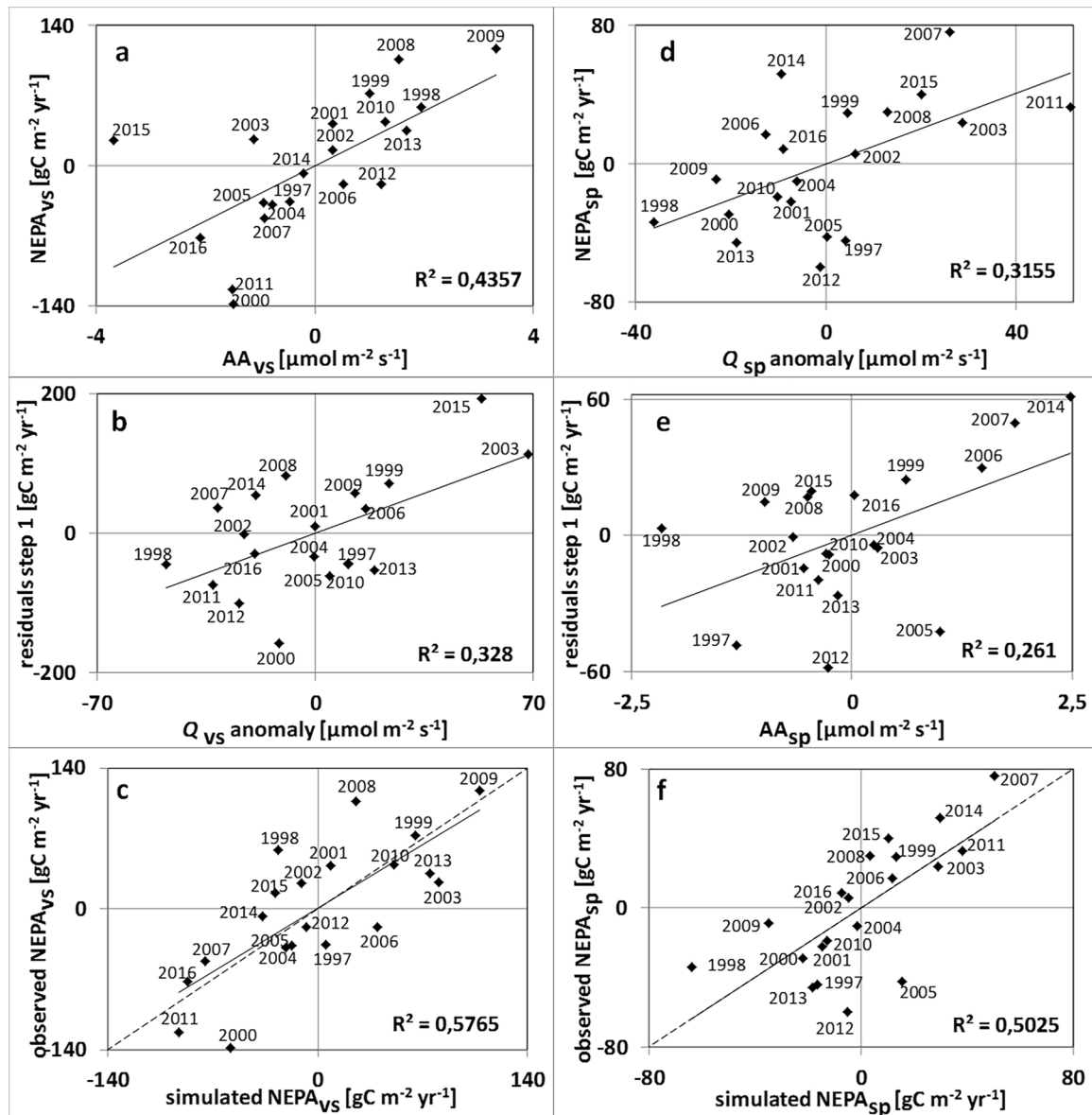
Fig. 4. Stepwise regression. Dependent variable NEP anomaly (NEPA). Left column: vegetation season (NEPA$_{vs}$); right column: spring (NEPA$_{sp}$). Fig. 4a and d: relation with best correlated variable at the first step. Fig. 4b and e: relation between residuals of the first regression and best correlated variable at step 2. Fig. 4c and f: relation between NEPA observations and estimations with the two-variable regression. The dotted line is the 1:1 line.

Wallonia (Comptoir forestier Wallon, personal communication) were found to coincide with the lowest NEP$_y$ (2000, 2011) and highest NEP$_y$ with absence of masting (1999, 2008). Similar observations have been made in beech forests by Pilegaard et al. (2011) in Denmark and Herbst et al. (2015) in Germany.

4.2.2. Impact of spring drought

A significant impact of spring drought on photosynthetic capacity was also observed (Figs. 5e and 6b). However, the correlation appears to be mainly driven by two years, one with dry spring (2015) and one with wet spring (2009). Impacts of spring drought on assimilation were found by some researchers: Latte et al. (2016) detected an impact of spring drought on tree ring growth on centennial beeches from Ardennes; Desai (2014) suggested that moisture stress at the beginning of the vegetation season inhibits photosynthesis; Müller-Haubold et al. (2013) found a positive influence of current year early summer precipitation on Net Primary Productivity and Meier and Leuschner (2008) suggested that spring water limitation could hinder leaf development. Wolf et al. (2016) explained the impact of spring drought, during the

2012 North American drought, by the early depletion of soil water resources during the warm spring that exacerbated water limitations during summer. However this explanation holds for climates characterized by a dry summer, which is not the case at VS where precipitations are present all the year. Anyway, the signal observed here is not clear enough to conclude definitely about this process.

4.3. Drivers of NEP$_y$ inter-annual variability

Contrary to many sites, no significant trend (Urbanski et al., 2007; Pilegaard et al., 2011; Froelich et al., 2015) or lagged autocorrelation (Baldocchi et al., 2018) in NEP$_y$ was found and the inter-annual NEP$_y$ standard deviation (91–95 g C m^{-2} yr^{-1}) is in the range of observations for temperate deciduous forests (100 g C m^{-2} yr^{-1}, (Baldocchi et al., 2018)).

As suggested by Desai (2014), the NEP$_y$ inter-annual variability, especially at VS, cannot be attributed to a unique cause, which explains the poor quality of single variable regression with NEP$_y$. Biotic influences, often driven by lagged weather effects, may contribute to inter-
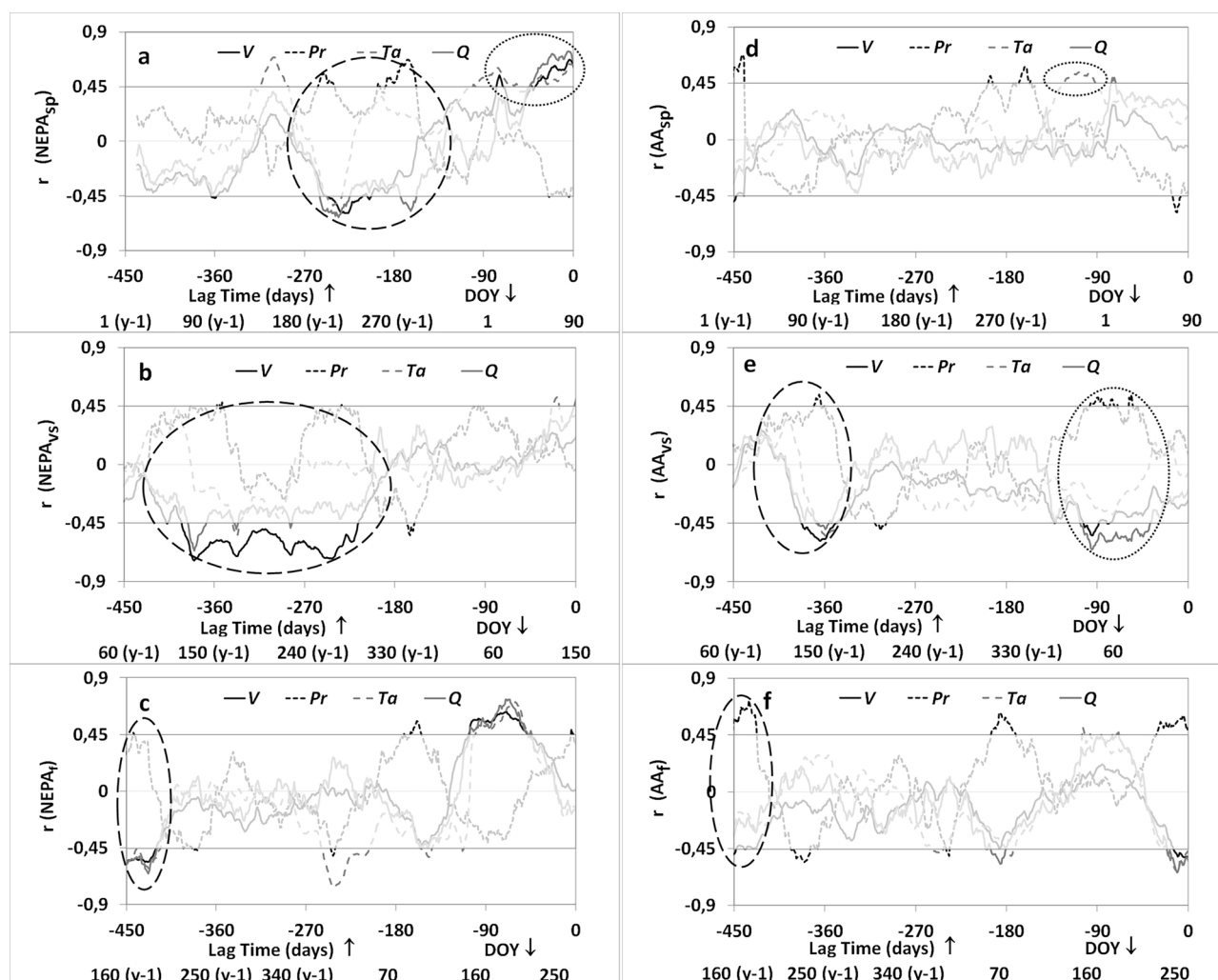
Fig. 5. Lagged correlation between periodical NEPA or photosynthetic capacity anomaly (*AA*) and weather variables averaged over a two month moving window (the lag time represents the lag between the beginning of the considered period and the moving window; DOY represents the real date of the beginning of the moving window). Left column: NEPA during spring (Fig. 5a), vegetation season (Fig. 5b) and fall (Fig. 5c). Right column: *AA* during spring (Fig. 5d), vegetation season (Fig. 5e) and fall (Fig. 5f). The semi-transparent frame covers non-significant correlations. V : Vapour pressure deficits; Pr : Precipitation; Ta : air temperature; Q : PAR.

annual changes.

The most intense $NEPA_y$, in 2000 ($-200\,g\,m^{-2}\,yr^{-1}$), resulted from the bark beetle attack that reduced the leaf surface and even led to tree destruction. A comparable attack with a comparable impact on NEP_y had been observed in 1998 in a Danish beech forest by Pilegaard et al. (2011). This is clearly a biotic effect but La Spina et al.(2013) also showed that such attacks are favoured by early frost events for which the trees are physiologically unprepared and which makes them more vulnerable. Such an exceptional early frost event had indeed been observed at VS in November 1998 (between DOY 321 and 343) and never reiterated during the 20 year period. This suggests that the biotic effect was in fact induced by a lagged meteorological effect. At VS, the insect attack was partly captured by our measurements and expressed by A_{700vs} and A_{700f} reductions (Fig. 4a). This reduction however was not strong enough to fully explain the $NEPA_y$ (Fig. 7). Interestingly, the effects of the insect attack did not propagate to the following years as both NEP_y and A_{700vs} appeared unaffected in 2001 and later (Figs. 4a and 7), supposedly due to the subsequent leaf development in the remaining trees.

Vegetation season photosynthetic capacity (A_{700vs}) and PAR appeared to be the most important driving variables of NEP inter-annual variability at both vegetation season and whole year scales. They both explain 58% of NEP_{vs} (Fig. 4c) and 42% of NEP_y variability. In particular, photosynthetic capacity variations mainly explained the larger NEP_{vs} and NEP_y in 1999, 2008 and 2009, despite average PAR conditions for the two latter years and the lower NEP_y in 2005, 2011 and 2016 (Fig. 4a). Here again, a biotic effect, illustrated by the A_{700} variability, appears mainly driven by preceding year water conditions (Section 4.2) suggesting that the carry-over effect of preceding year water shortages would be a key driver of NEP_y inter-annual variability.

Photosynthetically active radiation also impacts NEP_{vs} and NEP_{sp}, although the former correlation is hindered by correlation with A_{700} and only appears at stepwise regression step 2. It is, however, remarkable that extreme NEP_y and NEP_{vs} corresponded more to extreme photosynthetic capacities than to extreme PAR. Especially, the sunniest years (2003, 2015) are not associated to the largest NEP_y, despite exceptional high sunlight for these years (Fig. 4b). This is due to an important A_{700} reduction (Fig. 4a), possibly driven by the carry-over effects but also by drought conditions during the current vegetation season that could have induced partial stomatal closure, as observed previously (Aubinet et al., 2001). Conversely, the NEP_y of the cloudiest year (1998, Fig. 4b) was not as low as expected but rather closer to the average, which could also be explained (at least partly) by the high A_{700vs} for this year (Fig. 4a).
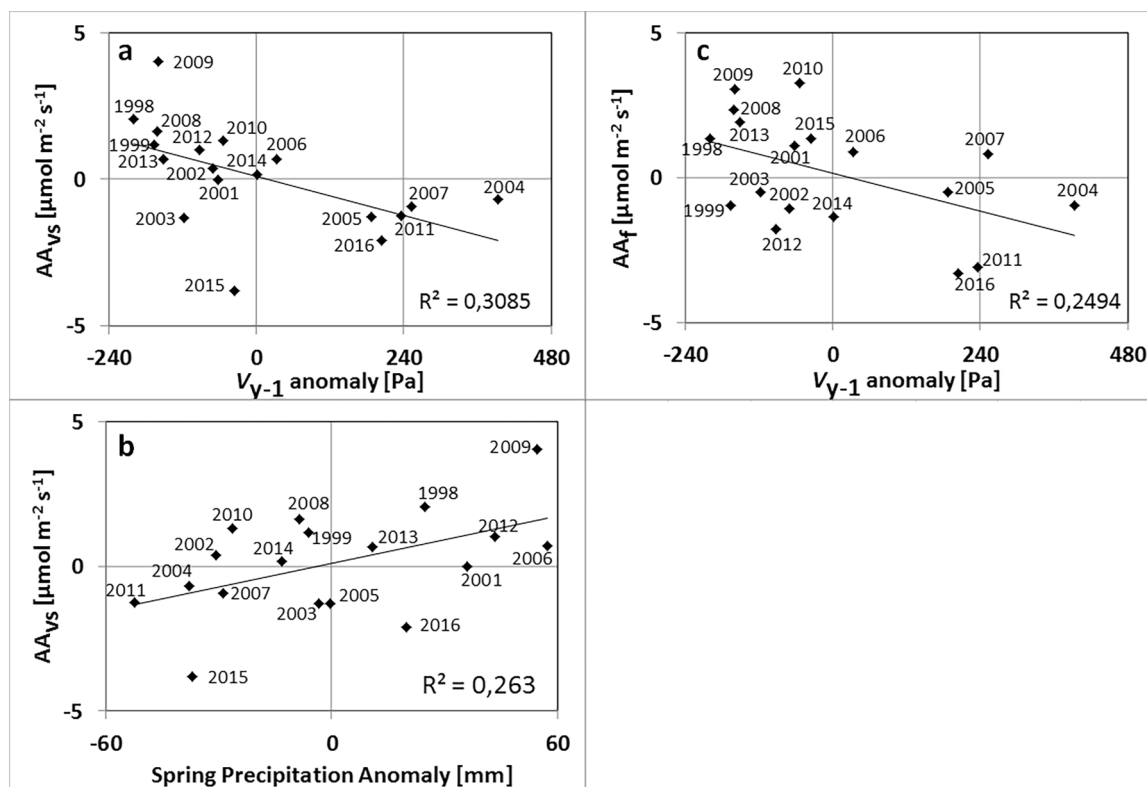
Fig. 6. Lagged weather impacts on canopy photosynthetic capacity anomalies. Relations with preceding vegetation season's vapor pressure deficit anomalies (V_{y-1}, Figs. 6 a) and spring precipitation anomaly (Fig. 6b), Fig. 6c : Relation between spring AA and preceding vegetation season's vapor pressure deficit anomalies.

An impact of PAR on temperate deciduous forests NEP_y inter-annual variability is not a common feature (Baldocchi et al., 2018). Although PAR appeared to be the main NEP driving factor at daily and seasonal scales, it is often not influential at the inter-annual scale. The correlation observed here may be because the VS is situated in a region where light is the most important net primary productivity limiting factor (Churkina and Running, 1998). This is corroborated by the fact that the two other deciduous forest sites where Baldocchi et al (2017) reported an impact of PAR on assimilation (i.e., Borden in Southern Ontario, Froelich et al. (2015) and Alice Holt Research Station in South Eastern England, Wilkinson et al. (2012)) are also situated in regions with similar constraints (Churkina and Running, 1998).

Winter air temperature also has a significant impact on NEP_y through its impact on NEP_{sp} (Figs. 5a and 7a and b), high winter and early spring temperatures favoring precocious assimilation. This was especially the case in 2007, 2008 and 2014 when very mild winter conditions prevailed (temperature anomalies for Jan–Mar: 2.7 °C, 1.9 °C and 2.8 °C, respectively) while in 1997, 2005, 2012 and 2013 colder temperatures (temperature anomalies for Jan–Apr: –1.2 °C, –1.4 °C, –0.5 °C and –1.4 °C, respectively) resulted in lower NEP precocity. In particular, it is interesting to note that as 2007 appears on the whole to be a normal year with a small NEP_y anomaly, it was one of the most atypical years of the 20 year period; characterized on one hand by an exceptionally mild winter and spring, which favoured early assimilation and on the other hand by the third cloudiest vegetation season. Consequently, the small NEP_y anomaly results from the compensation of two strong opposite (and independent) anomalies: positive in winter and early spring and negative during the vegetation season.

A dependence of NEP_y on NEP_{sp} (or, indirectly, on season length) was also observed at most deciduous sites (Saigusa et al., 2005; Urbanski et al., 2007; Granier et al., 2008; Pilegaard et al., 2011). Let note however that, at VS, spring assimilation operates before leaf onset in the beech and is thus more likely due to assimilation by the conifers spread in the beech sub-plot than to a precocious leaf out in the beech.

No clear impact of current year vapor pressure deficit and of dark respiration has been found, which could appear surprising. This would suggest that water stress affects carbon sequestration rather through indirect processes involving bud leaf formation than through direct processes involving stomatal closure. The absence of correlation between dark respiration and NEP_y (Table 3) suggests, as does the whole present study, that the NEP_y inter-annual variability was much more driven by assimilation than by respiration, in line with Baldocchi et al. (2018).

It is probable that, in view of the complexity of the mechanisms underlying NEP_y inter-annual variability, not all causes have been identified. In particular, over five years, the residuals of the relation between NEP_y and driving variable anomalies remained larger than their uncertainty (Fig. 7). Among the different possible causes of discrepancy, we identified a possible impact of fall NEP (2000, 2006, 2015), uncertainties in the A_{700} estimate due to insufficient data (2013), or the difficulty of statistical regressions to account for the exceptional character of an event (the insect attack in 2000). No plausible explanation was found for the fifth year (1998).

Finally, the study did not address the question of management. The forest underwent several thinning and tree cut events during the observation period. However, no information about the exact dates, location and thinning intensity were available, making this analysis impossible at VS. It is thus possible that some of the unexplained anomalies are due to management, although Granier et al. (2008), who studied another beech forest, showed that the thinning impact was limited.

5. Conclusions

This study suggests that uncertainties affecting carbon budgets at heterogeneous sites may be large and do not directly result from the eddy covariance method but from the heterogeneity itself. Uncertainties linked to the eddy covariance method (random
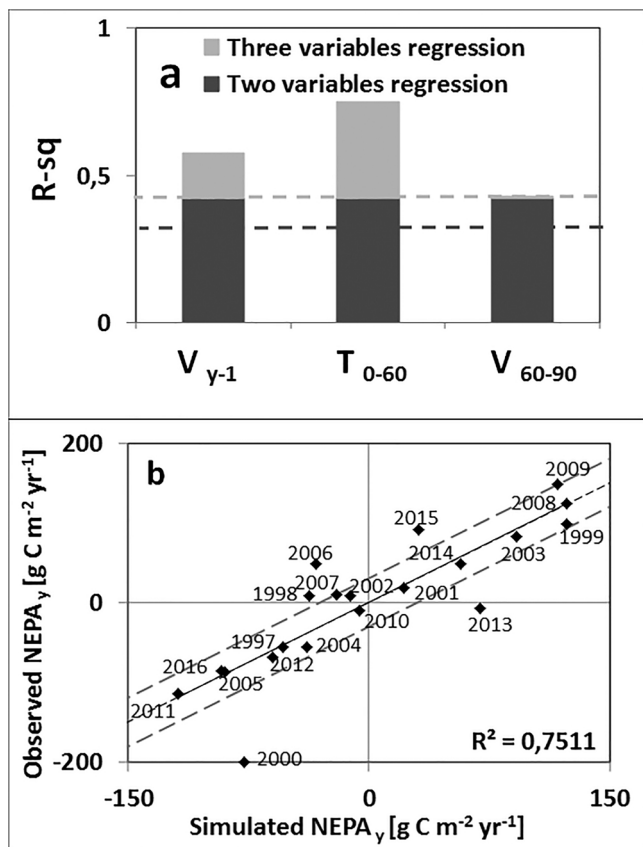
Fig. 7. Main sequestration inter-annual variability drivers. Fig. 7a : correlation coefficients of two variables (AA_{vs}, Q_{vs}) and three variables regressions (the third variable is either V_{y-1}, $T_{0–60}$ or V_{60-90}, respectively). The dotted lines indicate the significance threshold ($p = 0.05$) for each regression. Fig. 7b: Best three variable regression: relation between $NEPA_y$ observations and simulations based on AA_{vs}, Q_{vs} and T 0–60. The black dotted line is the 1:1 line. The grey dotted lines represent the ± 30 g C m^{-2} yr^{-1} range, corresponding to the average uncertainty affecting anomalies.
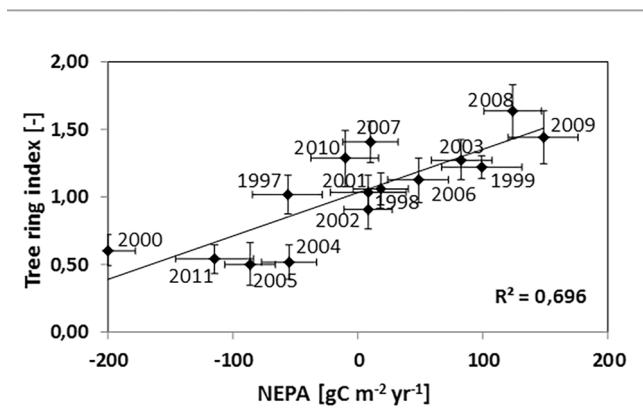

Fig. 8. Relation between $NEPA_y$ and tree ring index computed on the basis of wood increment. Vertical error bars represent the standard error of the tree index ring mean and the horizontal bar, the uncertainty computed in Table 1.

variability, u_* correction, frequency correction, data gap filling) only amounted to 7–11 g C m^{-2} yr^{-1} for the long-term budgets, while uncertainty linked to heterogeneity may be up to several hundreds of g C m^{-2} yr^{-1}. The tower height increase at VS, from 40 to 52 m in 2009, induced a 100 g C m^{-2} yr^{-1} difference in the NEP_y and the presence of isolated conifers in the beech subplot induced a bias for NEP_y, estimated to about 80–130 g C m^{-2} yr^{-1} compared to a pure beech stand.

If this questions the accuracy of heterogeneous forest annual budgets, this is not the case with yearly anomalies that are much more robust, provided a careful treatment is developed. In the present case, the treatment included the selection of a wind sector focusing on the target species (beech sub plot), the use of a data gap filling procedure centered on look up tables in order to avoid a biased selection of meteorological conditions and the computation of yearly anomalies considering measurement height changes during the experiment. As a result, uncertainties for anomalies (mainly resulting from eddy flux measurement and computation) are estimated to amount to about 30 g C m^{-2} yr^{-1}. Even if we cannot guarantee that all impacts of stand heterogeneity were removed from anomaly estimates (specifically, the NEP_{sp} inter-annual variability is still suspected to be linked to conifer activity), a sufficiently robust data set was obtained in order to highlight causes of NEP_y inter-annual variability.

The causes of NEP_y inter-annual variability were found to be multiple, but the main causes were carry-over effects. The effects of water limitations during the preceding vegetation season were especially apparent in 2004, 2005, 2007, 2011 and 2016 while the effect due to the early frost, in November 1998 was the 2000 bark beetle attack that provoked the largest NEP deficit of the 20 year period. Both effects significantly affected the photosynthetic capacity and NEP_y. To our knowledge, such legacy effects have not been reported in long-term eddy covariance studies and it would be interesting to test their impact at other sites.

Other causes of inter-annual variability were PAR during the vegetation season and winter temperature.

Acknowledgements

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agrformet.2018.07.024.

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