Atmospheric CO₂ inversions at the mesoscale using data driven prior uncertainties. Part2: the European terrestrial CO₂ fluxes

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1 **Abstract**

3 Optimized biogenic carbon fluxes for Europe were estimated from high resolution regional scale

4 inversions, utilizing atmospheric CO_2 measurements at 16 stations for the year 2007. Additional

5 sensitivity tests with different data-driven error structures were performed. As the atmospheric

6 network is rather sparse and consequently contains large spatial gaps, we use a priori biospheric

7 fluxes to further constrain the inversions. The biospheric fluxes were simulated by the

8 Vegetation Photosynthesis and Respiration Model (VPRM) at a resolution of 0.1° and optimized

9 against Eddy covariance data. Overall we estimate an a priori uncertainty of 0.54 GtC y^{-1} related

10 to the poor spatial representation between the biospheric model and the ecosystem sites. The sink

11 estimated from the atmospheric inversions for the area of Europe (as represented in the model

12 domain) ranges between 0.23 and 0.38 GtC y^{-1} (0.30 and 0.49 GtC y^{-1} up-scaled to geographical

13 Europe). This is within the range of posterior flux uncertainty estimates of previous studies using

14 ground based observations.

1 Introduction

Global and regional atmospheric inversions have been applied using atmospheric CO_2 measurements made by a global network since two decades to infer terrestrial carbon fluxes using surface in situ or flask measurements of CO_2 dry mole fractions. The optimization of CO_2 biospheric fluxes for the European domain has been the focus of interest in previous studies either using pseudo or real data (Gurney et al., 2004; Peters et al., 2010; Carouge et al., 2010a; Carouge et al., 2010b; Rivier et al., 2010; Broquet et al., 2011; Broquet et al., 2013; Peylin et al., 2013). Retrieved fluxes from most of the inversions are obtained from global systems at coarse resolution which makes difficult to retrieve the spatial and temporal flux variability at finer scales. Large uncertainties in the flux retrievals are introduced due to the coarse resolution of the transport models used and due to the network sparseness (Peters et al., 2010). For example the prevailing westerly winds and the fact that all atmospheric sites are mainly located in central Europe, introduce large flux uncertainties at eastern European regions.

Apart from ground based observations, satellite measurements have also been recently used in atmospheric inversions to infer terrestrial fluxes (Basu et al., 2013; Deng et al., 2014; Chevallier et al., 2014). The advantage of using space-borne measurements lies on the high density of the observations providing the opportunity to constrain regions which the ground network does not see. However satellite based inversions significantly differ from ground based inversions, reporting a larger annual uptake for Europe. A characteristic example is the estimated European uptake in the study by Reuter et al. (2014). They calculated an uptake of 1.02 GtCy^{-1} which triggered an ongoing debate on whether those estimates are data driven or they lack robustness due to deficiencies in the satellite observations and in the inverse modeling (Feng et al., 2016).

One of the largest sources of uncertainty in inversions is the atmospheric transport uncertainty. Modeled tracer dry mole fractions are biased particularly due to uncertainties of vertical mixing near the surface (Gurney et al., 2003; Gerbig et al., 2008; Houweling et al., 2010). As a consequence, posterior flux estimates are also biased because biases in concentrations are translated into biases in fluxes through the optimization procedure. Propagation of uncertainties in winds (Lin and Gerbig, 2005) and in mixing heights (Gerbig et al., 2008) for summer months

1 with active vegetation resulted in uncertainties in simulated dry air mole fractions of 5.9 ppm and

2 3.5 ppm respectively.

3 The current study is a continuation of the Kountouris et al. (2016) study (hereafter referred to as

4 Ko16) in which the inversion system and its set-up were assessed based on pseudo data. As a

5 next step we apply the modeling framework to real CO_2 atmospheric observations. Our main

6 objectives in the second part of this work are to investigate the potential to infer flux estimates

7 for Europe with reduced uncertainties, and to estimate biospheric fluxes at high spatial resolution

8 and for a full year. We use a spatial flux resolution of 0.25^o x 0.25^o, and the state space allows

9 optimizing 3-hourly NEE corrections to the prior NEE fluxes at a nominal spatial resolution of

10 0.5^o x 0.5^o. A data driven error structure is implemented consistent with model-data flux

11 mismatches (Kountouris et al., 2015) as tested in part 1 (Ko16) of this study. Further, different

12 error structures are used and assessed including also a spatial error structure with a hyperbolic

13 correlation shape as suggested by Chevallier et al. (2012). Since spatial autocorrelations have

14 been found to be very short, the annual aggregated uncertainty over the European domain is

15 smaller than traditionally assumed (see also Ko16). The error inflation necessity and

16 implementation was addressed in Ko16 either by inflating the error covariance or, more

17 formally, by introducing a bias term. However the hyperbolic correlation shape suggested by

18 Chevallier et al. (2012) has a stronger impact from larger distances compared to the exponential

19 shape, leading to an aggregated uncertainty which does not require to be inflated. We perform

20 also a number of sensitivity tests to account for misrepresentation of the fossil fuel signal and

21 also for transport uncertainties due to vertical mixing.

22 This paper is structured as follows: Section 2 describes the inversion system, the network and

23 station data which are used and details the assumed error structure. Section 3 shows the results of

24 the goodness of fit, and the retrieved fluxes. The data fitting and the reliability of the posterior

25 fluxes are extensively discussed in section 4.

1   **2 Methods**

2   **2.1 Two-step inversion**

4   Real-data inversions require a nested inversion scheme, since observations contain also

5   contributions from regions outside of the Domain of Interest (DoI). As in part 1 of this study

6   (Ko16), the Jena Inversion System (Rödenbeck 2005) including the two-step nesting scheme

7   (Rödenbeck et al., 2009; Trusilova et al., 2010) was used. This scheme allows for combining

8   regional and global inversions within a consistent system. Here we only provide a brief

9   description as details are given in Rödenbeck et al. (2009) and Trusilova et al. (2010). The

10   atmospheric transport models TM3 (step 1) (Heimann and Körner, 2003) and STILT (step 2)

11   (Lin et al., 2003) were used for transport at the global and regional domain, respectively. For the

12   global runs, TM3 was used at a spatial resolution of 4° latitude x 5° longitude, driven by

13   meteorological fields from the ERA-Interim reanalysis produced by ECMWF (Dee et al., 2011).

14   The transport matrix for the regional inversions was identical to the one used for the synthetic

15   data study in part 1.

16   In the first step, a global inversion is performed using the global transport model. The outcome is

17   an optimized flux field, at coarser scale for the full period (FP) and the global domain. Then two

18   forward runs are performed. The first run uses the global transport model over the FP, computing

19   the modeled mixing ratios Δc_{mod1}. The second run initializes again the global transport model but

20   only within the regional DoI. This can be regarded as a regional simulation, but with coarse

21   resolution, yielding modeled mixing ratios Δc_{mod2}. Then the "remaining mixing ratio" is

22   calculated for all the observing sites inside the DoI:

23   $$\Delta c_{remain} = c_{meas} - (\Delta c_{mod\,1} - \Delta c_{mod\,2} + c_{ini})$$ (1)

24   were c_{ini} the initial condition which corresponds to a well mixed atmosphere with a given initial

25   tracer mixing ratio.

26   In step two, the high-resolution transport model is used for the regional inversion within the DoI,

27   where all fluxes are represented at fine resolution. For this inversion the vector containing the

1   measured mixing ratios c_{meas} are replaced by the "remaining mixing ratios" Δc_{remain}. The

2   optimized fluxes from this step are the high-resolution fluxes of interest.

4   **2.2 Atmospheric network and data**

6   For step 1 we used the same station network as in version s04_v3.6 of the Jena Carboscope CO_2

7   inversion (http://www.bgc-jena.mpg.de/CarboScope/?ID=s04_v3.6), with 64 stations globally. For

8   step 2 (regional inversion) continuous and flask measurements from 16 stations within Europe

9   were used as described in Ko16 (see also Table 1). Of those 16 stations 7 are already included in

10 the step 1 inversion. All provided valid values were used, except those paired flask

11 measurements that differ more than 0.34 ppm which were omitted. Measurements from the

12 continuous stations were aggregated to hourly values where needed, and neighboring values

13 differing by more than 1 ppm were omitted. Night and day time observations were selected

14 depending on the type of station (Ko16). As all institutions report mixing ratio values traceable

15 to WMO (World Meteorological Organization) calibration scale, we expect compatibility

16 between the different datasets (also see Rödenbeck et al., 2006).

17 In this study we use the site HEI (Heidelberg) which is traditionally not used for European CO_2

18 flux inversions as being considered too local (Broquet et al., 2013; Rödenbeck et al., 2009;

19 Rivier et al., 2010). The Heidelberg region is considered to be one of the most polluted regions in

20 Germany (Fiedler et al. 2005) and therefore could bias the flux estimates. Moreover the WES

21 (Westerland) site contains long periods with no data. This could potentially affect posterior flux

22 estimates since extended data gaps can lead to jumps in the presence of biases. Thus we evaluate

23 the performance and the sensitivity of the European flux estimates to the network configuration,

24 by performing also an inversion (referred to as S2, see Table 2) excluding HEI and WES.

2.3 A-priori information and uncertainties

A set of inversion cases differing in the prior information, the error structure and the station configuration was realized (see overview in Table 2). Prior information derived from both biosphere models (VPRM and GBIOME-BGCv1) is used to investigate the impact of the prior fields to the posterior flux estimates. Furthermore an ensemble of inversions using different error structures is used to investigate the impact on the posterior flux estimates and uncertainties.

Similarly to the synthetic inversion (Ko16) we use the base case B1 which inflates the prior uncertainty by up-scaling the error covariance matrix, and case S1 which includes a bias term. In the base case the VPRM model provides the prior flux field, and exponentially decaying correlations are assumed. The bias component in the S1 scenario will always have a correction with the same sign for all grid-cells as it just scales a predefined flux field. In the S1 case it follows the shape of the annually averaged respiration flux, in the S1a case that of the a priori net biogenic flux, and in the S1b case again that of the annually averaged respiration flux, but with monthly temporal resolution of the bias term to allow for some temporal flexibility. The B2 inversion refers to the scenario where GBIOME-BGCv1 was used as a priori information instead of VPRM, and the error structure does not contain a bias term. With this case we can evaluate how sensitive the posterior flux estimates are with respect to the prior information which has been used. We also examine a spatial error structure based on a hyperbolic (instead of an exponential) spatial correlation shape as suggested in Chevallier et al. (2012) which we will refer to as S3 scenario.

Note that in most of the inversions performed, VPRM fluxes were used as prior information. Those fluxes are already optimized using EC measurements, therefore evaluation of the posterior flux estimates against EC data at the local scale could result in posterior fluxes that are limited or even not further constrained (since they are already optimized). In contrast, posterior fluxes produced with BIOME-BGC used as prior are expected to show significantly larger corrections compared to the prior estimations, and are therefore used for evaluation against EC data. Nevertheless in most cases we use VPRM as prior in order to keep our estimates as data-driven

1   as possible through the overall optimization procedure; at local scale by using EC data, and at

2   regional scale using the atmospheric dry mole fractions.

3   As in the synthetic experiment (Ko16) the temporal decorrelation time was set to 31 days. In

4   Kountouris et al. (2015), model-data comparisons representative at site scale (around 1 km)

5   showed spatial correlation lengths of 40 km whilst model-model comparisons representative at

6   50 km resolution identified a correlation scale of 370 km. Considering also that the state space

7   has a resolution of 50 km, the spatial decorrelation length was chosen to be approximately 100

8   km (66 km in meridional, and 130 km in zonal direction). In the prior error covariance, diagonal

9   elements of 2.27 $\mu mol m^{-2} s^{-1}$ were assumed, consistent with the model-data flux mismatches as

10   calculated in Kountouris et al. (2015). Propagating this spatiotemporal error structure yields a

11   domain-integrated uncertainty (E_{st}) of 0.15 GtC y^{-1}. Note that this is substantially smaller than

12   for the synthetic experiment due to the much shorter spatial correlation length scales. A total

13   annual, domain integrated uncertainty E_{tot} of 0.3 GtC y^{-1} was assumed, which corresponds to

14   twice the standard deviation of annual terrestrial flux estimates for 2007 between terrestrial

15   biosphere models taken from the global carbon atlas (http://www.globalcarbonatlas.org). This is

16   also consistent with the prior uncertainty (for Europe) assumed for the global inversions

17   performed by the Jena inversion system. For those inversions in which the additional bias term

18   was considered (S1, S1a, and S1b scenarios), its error E_{BT} was calculated using

19   $$E_{tot}^2 = E_{ST}^2 + E_{BT}^2 \qquad\qquad (2)$$

20   For the S3 scenario using hyperbolic correlations similar to Chevallier et al. (2012) ($\frac{1}{1+d}$), a

21   characteristic value d (lag distance) was used such that the correlation drops after around 60 km

22   to 1/e of its initial value, consistent with the hyperbolic fit to the model-data flux residual

23   autocorrelation in Kountouris et al. (2015). For this case no additional bias term was needed, as

24   the spatially and temporally aggregated uncertainty was found to be 0.32 GtC y^{-1}, which is very

25   close to the uncertainty assumed for the inversions (0.3 GtC y^{-1}).

26   Furthermore, we include ocean fluxes from Mikaloff-Fletcher et al. (2007), and anthropogenic

27   emissions from the EDGAR v4.1 inventory scaled at national level for individual years

28   according to the BP (British Petroleum) statistical review of world energy (BP, 2012) following

1 Steinbach et al. (2011). Anthropogenic emissions are considered to be perfectly known (with no

2 prior uncertainty), as one typically assumes that there is more a-priori knowledge regarding the

3 anthropogenic emissions as compared to biogenic fluxes. As the inversion cannot distinguish

4 between biogenic and anthropogenic signals, any errors in the a-priori anthropogenic emissions

5 will be included as corrections to the NEE flux.

7 **2.4 Diagnostics and aggregation of fluxes**

9 Similar to Ko16 we use the χ_c^2 metric to evaluate the goodness of fit for each station (Eq. 3)

$$\chi_c^2 = \frac{\sum_t \frac{(\Delta c_t)^2}{\sigma_t^2}}{n} \qquad (3)$$

11 where Δc_t is the model-data mismatch in dry mole fractions for a given observation time t, n the

12 number of observations and σ_t the assumed uncertainty. Further we make use also of the reduced

13 χ_r^2 (Eq. 4) where J_{min} is the cost function at its minimum

$$\chi_r^2 = 2\frac{J_{min}}{n} \qquad (4)$$

15 For more details about the chi-square metric the reader is referred to Ko16 study.

16 The optimized fluxes are derived at 0.25º spatial and daily temporal resolution from the inversion

17 system. We post-process the fluxes by aggregating them spatially at country/domain-wide scales

18 and temporally at monthly/annual scales.

19 Flux comparisons with other studies require that both fluxes refer to the same geographical

20 region. Typically studies refer to TransCom regions with a European domain that expands more

21 into the Eurasian region. To scale our results to the TransCom EU region, we calculated the flux

22 ratio between the TransCom EU region and our European domain from the first step of the two-

23 step inversion (global inversion), and used this ratio (about 1.3) to scale our posterior estimates

24 and the corresponding uncertainties (presented in Fig. 7).

1   **3 Results**

3   **3.1 Simulated CO_2 and goodness of fit**

5   Figure 1 presents a comparison of observed and modeled daily averages of the nighttime (hours

6   23, 00, 1, 2, 3, 4 UTC) CO_2 dry air mole fractions for the Schauinsland station (SCH), a

7   mountain station, for the year 2007. The prior estimates (gray line) as derived from a forward

8   model run using VPRM flux fields are systematically lower than the observations (black line)

9   with the most divergent values occurring during the growing season. A similar pattern was found

10   for the other atmospheric stations. Posterior CO_2 timeseries from all the inversions are in much

11   closer agreement with the observations.

12   Table 3 summarizes the statistics between the modeled and the observed CO_2 dry mole fractions

13   for all stations based on daily averages using the respective sampling times for mountain and

14   other stations. Of note is that the real data inversions include errors due to the modeling of

15   transport, which is not the case in the synthetic experiment in Ko16 as the same transport model

16   was used for forward and inversion runs. Standard deviations of the posterior residuals (observed

17   – modeled) show an average decrease for all inversion setups and for all stations of 59%

18   compared to the prior residuals. Correlations between prior and observed as well as posterior and

19   observed mole fractions (also Table 3) were likewise increased on average from 0.48 to 0.93. Of

20   note is that B1 and B2, which use an inflated prior error covariance for the spatiotemporal

21   component, show larger improvement relative to the prior in RMSD and some limited

22   improvement in correlation coefficient, compared to those inversions where a bias component

23   was included (S1, S1a, S1b). Figure 2 visually summarizes the goodness of fit in a Taylor

24   diagram for cases B1 and S1, presenting prior and posterior estimates of the correlation and the

25   normalized standard deviation between modeled and observed CO_2 dry mole fraction time-series.

26   It is obvious that the additional flexibility of B1 in the spatiotemporal flux distribution results in

27   a better reproduction of the concentration variability. The same picture emerges when comparing

28   the B1 and B2 inversions to S3 (see Table 3). Although all these cases assume no explicit bias

29   term in the error structure, the larger correlations from areas farther away for the S3 case with a

30   hyperbolic correlation causes a reduced number of effective degrees of freedom, which results in

1 larger residuals in posterior-observed mole fractions (Table 3) comparable to those of the S1

2 case.

3 Calculating the goodness of fit using the station-specific χ_c^2 values from Eq. (3), most of the sites

4 (Table 3) show values around 1, indicating that the misfits are inside the uncertainty range. For

5 the CBW, HEI, JFJ, KAS sites, values above 1 regardless the error structure were found, with the

6 most extreme value of 5.17 for the HEI site in the S3 inversion. This could suggest that for a

7 polluted site as HEI larger uncertainties should be considered.

8 The reduced χ_r^2 values regarding the overall model performance (Eq. 4) for all inversion set ups

9 is found to be close to 1 with χ^2 values of 1.08 (B1), 1.16 (B2), 1.17 (S1), 1.17 (S1a), 1.19 (S1b),

10 0.89 (S2) and 1.25 (S3), suggesting that the assumed prior uncertainty describes well the actual

11 uncertainties.

13 **3.2 Posterior flux estimates at different scales**

15 The annually integrated spatial flux distribution is presented in Fig. 3 for all the different

16 inversion settings. Differences between the results based on the two general error structures (with

17 and without the bias term) were observed mainly in central and Western Europe (longitudes less

18 than 20º E), where the network provides a strong constraint. This difference is characterized by

19 stronger spatial flux variability for the general B1 case, with multiple transitions between carbon

20 sources and sinks at regional scales. The same picture emerges for the western part of Europe. In

21 contrast, all the inversions including a bias component (S1, S1a, S1b) yield a more homogeneous

22 flux distribution with somewhat finer structure in the flux retrievals (e.g France and north-east

23 part of Europe). Comparisons between S1, S1a, S1b flux distributions do not show any

24 significant difference. Almost the same picture emerges when comparing B1 and S2 cases,

25 indicating that excluding the 2 stations does not have a very strong influence on our annual flux

26 estimates. However spatial differences were observed for the areas close to the two sites. The

27 most important one applies for the area near the HEI station where we observed a transition from

28 source to net carbon sink when excluding the corresponding site. The choice of the prior does

29 only have a small impact on the mean flux as can be seen by comparing posterior fluxes from B1

1   and B2 despite the significant differences in the flux innovations (Fig. 3). All innovations show

2   that positive fluxes were added mainly in central Europe and more intensively for the cases were

3   no bias term was used. Overall the results suggest that the general error structure matters, i.e.

4   whether or not to include a bias term, but how the bias is implemented is of less importance for

5   the retrieved flux patterns. One would expect that the flux distribution from the S3 case would

6   follow the general flux structure from the inversions without the bias term. Interestingly the

7   distribution is similar to the one obtained from the inversions with the bias term (cases S1, S1a,

8   and S1b). This shows that inversions assuming correlations with a strong contribution from the

9   far field have similar characteristics as inversions that assume a flat bias term.

10 Figure 4 shows the spatially aggregated posterior flux estimates for the full domain with the

11 corresponding uncertainties integrated at monthly and at annual temporal scales. The same prior

12 uncertainty was used for cases B1 and B2 although they differ in prior flux field. Posterior

13 estimates from B1 (blue line/shading) and B2 (green line/shading) inversions do not show any

14 significant difference at monthly and annual scales despite the large difference in prior fluxes.

15 We observe that the maximum uptake occurs slightly earlier for the B2 case. Monthly fluxes

16 from the S3 inversion also show the same temporal evolution. We do not observe any significant

17 difference in monthly fluxes for the S1 (red line/shading) and S1a (violet line/shading)

18 inversions. Both cases are comparable to the B1 and B2 cases at monthly and annual scales. A

19 slightly different picture emerges from the S1b inversion, where the bias term allowed for more

20 degrees of freedom for monthly corrections. The resulting seasonal cycle is somewhat smaller,

21 with reduced summer carbon uptake. Inversions that included the bias term yielded smaller

22 posterior uncertainties at both temporal scales, which is expected as the spatiotemporal

23 component of the uncertainty was not inflated as was the case for the B1 scenario. Flux retrievals

24 from the reduced network (sensitivity case S2) show a slightly deeper sink, but the differences to

25 the base case B1 are insignificant (i.e. clearly within the posterior uncertainties).

26 All of the inversions suggest Europe to be a carbon sink, with a range of -0.23 ± 0.13 GtC y^{-1} to -

27 0.38 ± 0.17 GtC y^{-1} for the S1b and B1 inversions respectively. The mean annual posterior flux

28 estimate for Europe averaged over different inversions amounts to - 0.32 GtC y^{-1}.

29 Posterior monthly flux estimates at smaller spatial scales (country level) are shown in Fig. 5.

30 Areas that are not well constrained by the current network show some divergence in the posterior

1   flux estimates although not significant considering the uncertainty range. For example Germany,

2   which is better constraint, shows a limited spread of the posterior fluxes with an annually

3   averaged standard deviation between the different posterior flux estimates being 0.0009 GtC y^{-1},

4   while United Kingdom (which is less well constrained) shows a slightly larger spread of the

5   posterior estimates with an annually averaged standard deviation of 0.002 GtC y^{-1}. Note that the

6   posterior uncertainties are smaller by about 36% for the S1 case, which is related to the smaller

7   prior uncertainties at monthly time scales (see also section 3.2 in Ko16).

9   **3.3 Validation against eddy covariance measurements**

11   As shown in Ko16, eddy covariance measurements in principle have the potential for

12   quantitative evaluation of the retrieved fluxes from the inversions. Here we used posterior flux

13   estimates from the B2 inversion for evaluation against eddy covariance measurements, as the

14   prior flux fields in B2 (GBIOME-BGCv1) were not optimized using eddy covariance

15   measurements. Gap-filled data were downloaded from the European Fluxes Database Cluster

16   (http://www.europe-fluxdata.eu). A modified flux-site network compared to the one reported in

17   Kountouris et al. (2015) was used. Specifically we omitted sites that they have not been used for

18   the VPRM optimization (*CH-Fru, CH-Lae, CH-Oe1, ES-LMa, FR-Avi, FR-Mau, IT-Cas, IT-*

19   *LMa, IT-Ro2, NL-Dij, NL-Lut, SE-Sk1, SK-Tat*) as well as sites that were not available as gap-

20   filled data (*CH-Dav, ES-Agu, FR-Aur*). Further some more sites were added both for the VPRM

21   optimization and for the flux comparisons (*CZ-wet, DK-Sor, HU-Bug, IT-Non, NL-Ca1, PL-wet,*

22   *RU-Fyo, UK-PL3*). Monthly averaged fluxes were extracted, with weights for each vegetation

23   class that compensate for the asymmetry between number of flux towers per vegetation type and

24   the fraction of land area covered by the specific vegetation type, similar to Ko16.

25   The analysis of the monthly prior biospheric fluxes in Fig. 6 reveals significant differences

26   between observed and prior fluxes from the inversion. The GBIOME-BGCv1 model

27   systematically overestimates the observed fluxes throughout the year. The retrieved fluxes from

28   the inversion (dark green line) are closer to the observed fluxes, with a stronger uptake compared

29   to the prior during spring and summer time. The timing of the peak uptake is shifted to one

1   month earlier in comparison to the observations. The mean absolute bias (averaged absolute

2   differences between prior/posterior and observed fluxes) is significantly reduced by 52% from

3   0.84 to 0.40 $gCm^{-2}day^{-1}$. The standard deviation of the residuals is reduced by around 24%, from

4   0.68 for the prior to 0.40 $gCm^{-2}day^{-1}$ for the posterior residuals. Splitting the sites into two main

5   categories, the first only with crops, and the second with non crop sites, revealed differences on

6   how well those sites can be represented. Clearly best matches were found for the non crop sites

7   with a reduction in the mean absolute bias of 51% whilst for the crop sites it is limited to 38%.

9   **4 Discussion**

11   We performed a series of atmospheric CO_2 inversions based on atmospheric data taken from 16

12   European stations for 2007. Different data-driven error structures in the prior error covariance

13   were assessed, and optimized biospheric fluxes were retrieved and post-processed at various

14   temporal and spatial scales for further evaluation. In this part we discuss the fitting performance

15   of the inversion system, and we detail the comparisons between our flux estimates at grid,

16   national and continental scales against eddy covariance data and reported flux estimates from

17   previous studies. Finally we discuss how sensitive flux retrievals are in the presence of erroneous

18   representation of the fossil fuel fluxes, and the site selection.

20   **4.1 Goodness of fit**

22   Site-specific misfits show a reasonable fit to the atmospheric data. Nevertheless in 4 cases

23   (CBW, HEI, JFJ, and KAS) site-specific χ_c^2 values were found to be larger than 1 (see also Table

24   3), indicating that either the model-data mismatch errors were chosen too small, or the

25   spatiotemporal resolution of the flux model is too coarse compared to the biosphere fluxes and

26   therefore small scale variations are not resolved (Rödenbeck et al., 2003). In fact this seems to be

27   the case for the JFJ and KAS sites as those are high altitude sites with steep cliffs. In such a

28   complex terrain the atmospheric circulation is hard to be simulated from the transport models.

1   Regarding CBW and in particular HEI, those are polluted sites and it would be reasonable to

2   assume larger model-data mismatch uncertainty since the model is too coarse to resolve the fossil

3   fuel emission patterns. One could argue that using higher spatial resolution to couple fossil fuel

4   fluxes with transport models might reduce the model-data mismatch uncertainties, and hence

5   improve posterior fluxes. To investigate that, we performed a forward run at coarser (0.25º) and

6   higher (1/12º lat. X 1/8º lon.) spatial resolution using only the fossil fuel emissions. As we use a

7   Lagrangian transport model, fluxes at higher resolution than that of the meteorological fields can

8   be used such that the simulated fossil fuel signals contain more spatially detailed information

9   (Lin et al., 2003). The derived concentration signal was subtracted from the observations and

10 subsequently an atmospheric inversion was performed. We report no significant differences

11 between the retrieved fluxes indicating that simply increasing the spatial resolution to about 10

12 km is not enough to correctly represent the fossil fuel distribution.

13 The reduced χ_r^2 values in our study (between 1.08 and 1.25) are larger than those found by Tolk

14 et al. (2011) where values between 0.34 and 0.78 were found for their pixel based inversion,

15 indicating a more conservative choice for their model-data mismatch errors. Even lower values

16 were reported in the study by Peylin et al. (2005) with values ranging from 0.01 up to 0.6

17 depending on the assumed correlations. χ^2 values from Zhang et al. (2015) were within a range of

18 1 to 4, but were modified by inflating the error covariances through an iterative procedure,

19 resulting in χ_r^2 values comparable to ours. Concluding, the χ_r^2 values give confidence that the

20 assumed prior uncertainties are well defined. We note though that examining the χ_r^2 values is not

21 always a sufficient metric to evaluate the defined uncertainties (Michalak et al., 2005; Chevallier,

22 2007).

24 **4.2 Validation against eddy flux measurements**

26 At the local scale the inversion shows ability to capture the observed flux variability at monthly

27 scale, as shown for the B2 case (see Fig. 6). The residuals between posterior model and eddy

28 covariance flux-data for monthly and site averaged fluxes show a range of misfits not exceeding

29 1.04 gCm^{-2}day^{-1} which is comparable with Broquet et al. (2013), where misfits up to

1   1.5 $gCm^{-2}day^{-1}$ were found using 6 years of data (2002-2007). Of note is that the estimated

2   carbon uptake agrees well with the estimated uptake for 2007 in Broquet et al. (2013) (within the

3   uncertainty range). However, in contrast to the synthetic inversion, the real data inversion

4   showed a larger monthly averaged posterior bias equal to 0.40 $gCm^{-2}day^{-1}$ compared to the -0.04

5   $gCm^{-2}day^{-1}$ for the synthetic case in Ko16. The poorer performance in terms of bias compared to

6   the synthetic case is presumably mainly caused by the representation error. In the synthetic

7   inversion we created a true flux field at the same spatial resolution as the posterior flux

8   estimates, and sampled this true flux distribution at the specific eddy covariance measurement

9   location. This does not include any spatial representation error of the EC measurements

10 (footprint about 1 km) with respect to the spatial resolution of 25 km at which the fluxes are used

11 within the inversion. A further cause for this poorer performance is related to the transport error,

12 as in the synthetic case the same transport was used to create the synthetic observations and to

13 perform the inversion, while in the real data inversions the observed atmospheric mole fraction

14 are a result of real transport which can only be approximated with the transport model used for

15 the inversion.

16 Differences between posterior flux retrievals and observed NEE fluxes at the eddy covariance

17 stations are clearly driven from the crop sites. The good agreement between posterior inverse

18 flux estimates and fluxes measured with the eddy covariance technique at non-crop sites can be

19 attributed to the relatively stable, within the year, land condition. Contrastingly, crop areas are

20 subject to human activities throughout the year. Soil enrichment with organic fertilizers,

21 irrigation and harvesting, can severely influence the carbon balance of the local ecosystem. Thus

22 the poor performance between inverse estimates and eddy covariance flux measurements at crop

23 sites can be linked to the extensive anthropogenic influence on those areas. Further it is worth to

24 mention that atmospheric concentrations implicitly contain more components than just the NEE

25 signal e.g. fire emissions. Such emissions are captured in the atmospheric observations

26 (representative scale of hundreds of km) but might not be captured from the eddy covariance flux

27 measurements which they have a very short representative scale of around 1 km.

4.3 Reliability of European flux estimates

4.3.1 Mismatch in bottom-up and top-down methods

Of note is the strong flux correction when using a-priori fluxes from VPRM with an uptake of 0.96 GtC y^{-1} compared to the 0.3 GtC y^{-1} after the inversion. The large correction of about 0.66 GtC y^{-1} corresponds to roughly twice the prior uncertainty. We note that VPRM is a diagnostic model which uses simple light use efficiency and respiration equations and MODIS indices, with parameters optimized to match hourly observations of NEE fluxes (Mahadevan et al., 2008). It does not account for land management and land use changes (i.e. crop harvest, deforestation), thus it will estimate a strong sink even for lands that have been harvested, with the respiration fluxes resulting from the use of the harvest (e.g. as food) not included. Those so-called lateral carbon fluxes, that are seen by the atmospheric inversion, account for approximately 0.165 GtC y^{-1}) of the prior-posterior flux difference (Ciais et al., 2008). The rest of the difference of about 0.5 GtC y^{-1} might be related to local characteristics of eddy covariance sites, which VPRM is not able to represent. Spatial variations of NEE from VPRM are driven by those of EVI, which is used at a spatial resolution of 1 km. For example, a crop field with typical dimensions of 100 m – 200 m surrounded by other fields with different crop rotation (and differing phenology) are hard to represent with 1 km resolution EVI (even with the highest possible resolution of 250 m for MODIS reflectances). To quantitatively assess the impact of this representation error in combination with the selection of sites used for the VPRM optimization, the annual domain wide C-budget from VPRM was recalculated after omitting one site per vegetation type at a time and optimizing the VPRM parameters (Jackknife delete-1 method). Detailed results are shown in Table 4. The derived Jackknife standard error amounted to 0.54 GtC y^{-1}, with a dominant contribution from the cropland vegetation class (0.50 GtC y^{-1}). This uncertainty can fully explain the mismatch between the a priori and the posterior fluxes, and it emphasizes the importance of site selection and site representativeness in up-scaling local eddy covariance measurements to larger regions.

The estimated uncertainty for VPRM fluxes based on jackknifing is larger than the prior uncertainties assumed for the atmospheric inversions. Hence, one could argue that the prior fluxes using VPRM (which indicate a too strong sink) combined with a too small prior

uncertainty in the inversion leads to erroneous posterior flux estimates. However the optimized biogenic fluxes from all inversions converge at the annual and domain-integrated scale. A particular example is that of the B2 inversion. Even though the GBIOME-BGCv1 fluxes differ greatly from those produced by VPRM, this inversion is fully in line with the results from the rest of the inversions, indicating that the optimized flux estimates are not biased by the a priori flux fields but instead are driven by the atmospheric data.

4.3.2 Sensitivity to anthropogenic emissions

Another source of biospheric flux misrepresentation is the fossil fuel inventories. As mentioned in section 2.3 we do not allow for corrections in anthropogenic emissions, as they are assumed to be better known than the terrestrial fluxes. An overestimation/underestimation in anthropogenic emissions will thus lead to a stronger/weaker biospheric sink in atmospheric inversions. The anthropogenic emissions we use are 0.32 GtCy^{-1} (27%) lower for the EU-12 countries compared to those used by Rivier et al. (2010) (1.2 GtCy^{-1}). Peylin et al. (2011) estimates the difference between national totals for the different emission inventories to be around 10%. In a study by Ciais et al. (2009) uncertainties of total fossil-fuel CO_2 emissions in the European Union 25 member states were estimated to 19%, based on four different emission inventories. For the EU-25 countries, EDGAR emissions were found to be 12% larger than the mean of the GAINS (Greenhouse Gas and Air Pollution Interactions and Synergies), UNFCC (United Nations Framework Convention on Climate Change) and CDIAC (Carbon Dioxide Information Analysis Center) inventories (Ciais et al. 2009, table 2). Sensitivity tests with increased prior fossil fuel emissions showed that the added fossil fuel increases the estimated uptake by almost 50% relative to the added anthropogenic emissions. Taking an extreme scenario where the fossil fuel emissions are increased by 17% or 0.3 GtC y^{-1} (resulting in 1.77 GtC y^{-1} compared to 1.47 GtC y^{-1} total emissions for EU-domain), we estimate a European carbon sink for the B1 set up of -0.51 ± 0.17 GtCy^{-1} compared to -0.38 ± 0.17 GtC y^{-1} for the standard B1 case. Thus the additional assumed fossil fuel emissions increased the estimated uptake by 0.13 GtCy^{-1}, which is about 44% of the added anthropogenic emissions. The fact that the resulting increase in the biospheric sink does not fully correspond to the increase in assumed emissions is likely a result

1 of the sparse network, where emissions from regions further away from the measurement sites

2 are not fully registered in the simulated mole fractions.

4 **4.3.3 Sensitivity to site selection**

6 Uncertainties in vertical mixing and especially in the nocturnal boundary layer (Gerbig et al.,

7 2008) should be carefully addressed as they might lead to erroneous estimations of the carbon

8 uptake. Typically in atmospheric inversions the model-data mismatch error (measurement error

9 covariance) accounts also for uncertainties due to the transport (i.e. wrong representation of the

10 nocturnal boundary layer). The set of network stations includes 6 mountain stations, for which

11 we use night-time observations (day-time for non mountain stations) as these measurements are

12 considered to be representative for the free troposphere. Errors can be introduced if the

13 measurement height assumed in the transport model is within the modeled nocturnal stable

14 boundary layer while in the real world it is not, which would lead to an overestimation in the

15 simulated CO_2 signals from respiration or vice versa. In the inversion this would be compensated

16 by introducing stronger uptake fluxes to match the observed CO_2 time series. In order to

17 investigate whether our results are influenced by the use of mountain stations, we performed an

18 additional inversion using the B1 error structure, but excluding all these stations. The resulting

19 sink in Europe was found to be -0.41 ± 0.17 GtCy^{-1} which is fully in line with B1 inversion using

20 all sites, suggesting that our estimates are not biased due to misrepresentation of the mountain

21 stations.

23 **4.3.4 Retrieved fluxes and comparison to previous inverse estimates**

25 The retrieved spatially resolved fluxes showed a sensitivity in their spatial patterns to the a priori

26 error structure, specifically to the inclusion of a bias component, as indicated by differences

27 between the B1 and S1 cases. Such differences were not identified in the synthetic experiment in

28 Ko16, however there a much larger spatial correlation length scale was assumed. In the synthetic

29 inversions the long correlation length (766 km at the zonal and 411 km at the meridional

1   direction) drastically reduces the effective number of degrees of freedom, forcing the fluxes to be

2   smoothly corrected, regardless of the use of the bias component. In the real data inversions the

3   shorter correlation length (around 100 km), combined with the required larger error inflation

4   (compared to the synthetic inversions) for the B1 and B2 cases, increases the effective number of

5   degrees of freedom. By using a bias component (S1, S1a, S1b cases) or by using the hyperbolic

6   correlation shape (S3) with stronger large-scale correlation, instead of inflating the

7   spatiotemporal error component, fluxes remain less flexible at gridscale.

8   Our knowledge regarding annual CO_2 flux estimates for Europe is still highly uncertain, in part

9   due to the limited number of regional inversions focusing on this domain. Flux estimates from

10   previous studies, mainly global inversions, show a wide range (Fig. 7). We estimated an annual

11   European carbon sink (ranging between -0.23 ± 0.13 and -0.38 ± 0.17 GtC y^{-1} for the different

12   inversion scenarios, Fig. 4 d)), which is however representative for a smaller European region

13   compared to the TransCom European region typically used in other studies. The up-scaled flux

14   estimates (see also section 2.4) for the TransCom EU region have a range of -0.30 to -0.49 GtC

15   y^{-1}. Ciais et al. (2000) estimated a European sink of -0.3 ± 0.8 GtC y^{-1} for the target period 1985-

16   1995, however in contrast to our study they used a global system and a gap filling algorithm

17   since 42% of the observational data were missing. A recent study from Peylin et al. (2013)

18   computed the mean European sink for the period 1998-2001 to be -0.44 ± 0.45 GtC y^{-1} by

19   utilizing eleven different global inversion systems. Gurney et al. (2004) performed also global

20   inversions and found the mean European annual fluxes for 1992 – 1996 period to be -0.98 ± 0.4

21   GtC y^{-1} which is larger compared to our estimations. Moreover, our results for the mean net

22   monthly fluxes over Europe agreed very well with Rivier et al. (2010) who estimated for the

23   1998-2001 time frame using five different transport models in their inversion that the maximum

24   seasonal uptake occurs in July and lies between -10 and -80 $gCm^{-2}month^{-1}$, while our results

25   show maximum uptake in June with a range of -33 to -37 $gCm^{-2}month^{-1}$ for the different

26   inversion cases. We note that the annual flux differences between our flux estimates and those

27   from other studies may be also caused due to the interannual flux variability. Nevertheless this

28   should not be expected to critically drive those differences since posterior uncertainties found to

29   be larger than interannual variations (Broquet et al., 2013) making the significance of the

30   variations questionable.

1   A recent study from Reuter et al. (2014) based on inversions using satellite observations
2   estimated the carbon budget for the TransCom European region. For the year 2007 the sink was
3   found to be -1.1 ± 0.30 GtC y^{-1}, much larger compared to most of other inversion estimates using
4   ground observations. However Feng et al. (2016) tried to investigate why atmospheric inversions
5   using satellite observations, show an elevated European uptake, through a series of sensitivity
6   tests. They linked the increased uptake when using satellite measurements to potential
7   observation biases and to the emission spatial patterns. Further Feng et al. (2016) highlighted that
8   the large European uptake is related up to 60-90 % from systematically higher modeled CO_2
9   fluxes transported into Europe from regions outside of the domain. As this looks to be a problem
10 related with column measurements this is not the case in our study since ground observations
11 were used. In addition we use the two step inversion scheme which limits the influence from the
12 far field as we calculate the concentration signal from outside the domain and subtract that from
13 the observations. Whilst the flux uncertainties outside the domain are not propagated, still they
14 can be expressed as uncertainties in the observation space. However if biases introduced from
15 the global inversion to the fluxes outside of the domain, then regional flux estimations may
16 differ.

17 At national scale we can compare our results to those obtained by Meesters et al. (2012) for the
18 Netherlands, who estimated the annual national carbon sink to about -0.017 ± 0.004 GtCy^{-1}. Our
19 estimations are very close, with a range of − 0.012 ± 0.004 GtCy^{-1} (S1 inversion) to − 0.014 ±
20 0.005 for the B2 inversion. Of note is that the carbon budget estimates for Netherlands agree
21 remarkably well despite the substantial differences between the two studies: Meesters et al.
22 (2012) used an inversion scheme that solves for scaling factors of the gross prior fluxes. Spatial
23 correlations of 100 km were assumed but only for photosynthetic fluxes within the same land use
24 class. In addition the domain of interest (Netherlands) has a stronger constraint as four stations
25 located within the domain were used, while our inversion only uses one station (CBW), with the
26 rest of the stations being at least 360 km away (WES). Both studies assume approximately the
27 same fossil fuel emissions (0.051 GtC y^{-1} vs. 0.053 GtC y^{-1} in Meesters et al. (2012)).

28 **5 Conclusions**

1   This study is a follow up work from Kountouris et al. (2016). In this second part, the inverse

2   modeling framework was deployed using real atmospheric data from 16 stations in Europe, to

3   infer biospheric carbon fluxes. Different prior error structures were assumed to investigate how

4   sensitive posterior fluxes are. The results are validated and compared at different temporal and

5   spatial scales. Satisfactory agreement was found when posterior inverse flux estimates were

6   compared against eddy covariance observations at local scale, as well as against previous studies

7   at national and continental scales, which gives us confidence for our carbon flux estimations. We

8   calculated a sink for the European continent which amounts of -0.23 ± 0.13 GtC y^{-1} to $-0.38 \pm$

9   0.17 GtC y^{-1} depending on the assumed prior error structure.

10   A special effort was also made to avoid potential biased flux estimations due to site selection (i.e.

11   heavily polluted sites, or sites that are within the nocturnal boundary layer) by performing

12   inversions using different network configurations. We did not observe any significant impact at

13   least for monthly and annual scales. Further we studied also how sensitive biospheric carbon

14   fluxes are, when wrong fossil fuel emissions are assumed. We found that due to the network

15   sparseness the fossil fuel emissions are not fully captured in the simulated mole fractions which

16   may bias the flux estimates.

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1 Table 1. Information on the stations used for the regional inversions. Same network applied for

2 the synthetic, and the real data inversions in Kountouris et al. (2016). In first column the term

3 "type" stands for continuous (C) or flask (F) data. Under "Data origin" WDCGG means "World

4 Data Centre for Greenhouse Gases".

Site Code / type	Name	Latitude (°)	Longitude (°)	Height (m.a.s.l.) (m)	Measurement height (above ground) (m)	Model height	Data provider	Data origin	Citation
BAL/ F	Baltic Sea, Poland	55.50	16.67	8	57	28	NOAA	Direct contact	Dlugokencky et al. 2015
BIK/C	Bialystok, Poland	53.23	23.03	183	90	90	MPI-BGC	Direct access	Popa et al. (2010)
CBW/ C	Cabauw, Netherlands	51.58	4.55	-2	200	200	ECN	Direct contact	Vermeulen et al. (2011)
CMN/ C	Monte Cimone, Italy	44.18	10.7	2165	12	670	IAFMS	WDCGG	Alemanno et al. (2014)
HEI/C	Heidelberg, Germany	49.42	8.67	116	30	30	University of Heidelberg	CarboEurope	Hammer et al. (2008)
HPB/ F	Hohenpeissenberg, Germany	47.80	11.01	934	50	10	NOAA	Direct contact	-
HUN/ C	Hegyhatsal, Hungary	46.95	16.65	248	115	96	HMS	WDCGG	Haszpra et al. (2001)
JFJ/C	Jungfraujoch, Switzerland	46.55	7.98	3572	10	720	University of Bern	CarboEurope	-
KAS/	Kasprowy	49.23	19.93	1987	5	480	UKRAK	CarboEurope	Necki et

C	Wierch						, AGH	ope	al. (2013)
LMU/ C	La Muela, Spain	41.36	-1.6	570	79	80	University of Barcelona	CarboEurope	-
MHD/ C	Mace Head, Ireland	53.33	-9.90	25	10	15	LSCE	WDCGG	Ramonet et al. (2010)
OXK/ C	Ochsenkopf, Germany	50.03	11.81	1022	163	163	MPI-BGC	CarboEurope	Thompson et al. (2009)
PRS/ C	Plateau Rosa, Italy	45.93	7.71	3480	-	500	RSE	WDCGG	Ferrarese et al. (2015)
PUY/ C	Puy De Dome, France	45.77	2.97	1465	10	400	LSCE	CarboEurope	Lopez et al. (2015)
SCH/ C	Schauinsland, Germany	47.92	7.92	1205	-	230	UBA	WDCGG	-
WES/ C	Westerland, Germany	54.93	8.32	12	-	15	UBA	WDCGG	-

1 Glossary for the data providers: AGH: University of science and Technology Polland, ECN: Energy research Centre

2 of the Netherlands, HMS: Hungarian Meteorological Service, IAFMS: Italian Air Force Meteorological Service,

3 LSCE: Le Laboratoire des Sciences du Climat et de l'Environnement, MPI-BGC: Max Planck Institute for

4 BioGeoChemistry, NOAA: National Oceanic and Atmospheric Administration, RSE: Ricerca sul Sistema

5 Energetico, UBA: Umweltbundesamt, UKRAK: Department of Environmental Physics Polland

Table 2. Overview of the inversion scenarios. "Shape" describes the internal structure of the bias component (proportional to respiration R or to Net Ecosystem Exchange NEE), and "Time vary" indicates whether the bias component also has temporal variations or not. The fifth column "Prior" represents the terrestrial model used as prior, and "Correlation shape" describes the functional form used for the spatial prior uncertainty correlation, either exponential (E) or hyperbolic (H). The last column indicates whether the full or the reduced station network was assumed.

Inversion code	Bias component	Shape	Time vary	Prior	Correlation shape	No. of Stations
B1	-	-	-	VPRM	E	16
B2	-	-	-	GBIOME	E	16
S1	Yes	R	Flat	VPRM	E	16
S1a	Yes	NEE	Flat	VPRM	E	16
S1b	Yes	R	Vary	VPRM	E	16
S2	-	-	-	VPRM	E	14
S3	-	-	-	VPRM	H	16

Table 3. RMSD (first column in ppm) and correlation coefficients (second column) between observations and prior/posterior CO_2 dry mole fractions for daily "daytime" or "nighttime" averaged values and for each station. The third column shows χ_c^2, the normalized dry mole fraction mismatch per degree of freedom for 7-day averaged residuals, as a measure of how well the data were fitted. The format for each station is as follows: RMSD $|$ r^2 $|$ χ^2.

	Prior	B1	B2	S1	S1a	S1b	S2	S3
BAL	7.12 | 0.20 | 69.35	1.48 | 0.97 | 0.89	1.53 | 0.97 | 0.93	2.26 | 0.93 | 2.04	2.26 | 0.93 | 2.03	2.25 | 0.93 | 2.02	1.41 | 0.97 | 0.83	2.37 | 0.92 | 2.07
BIK	8.20 | 0.52 | 60.10	2.93 | 0.93 | 0.88	3.17 | 0.92 | 0.99	3.52 | 0.90 | 1.51	3.52 | 0.90 | 1.53	3.51 | 0.90 | 1.53	2.93 | 0.93 | 0.88	3.78 | 0.88 | 1.70
CBW	8.71 | 0.23 | 83.98	3.43 | 0.88 | 2.05	3.49 | 0.88 | 2.18	4.09 | 0.83 | 2.47	4.09 | 0.83 | 2.48	4.09 | 0.83 | 2.49	3.42 | 0.88 | 1.99	4.33 | 0.81 | 2.61
CMN	4.20 | 0.40 | 31.73	1.26 | 0.96 | 0.16	1.35 | 0.95 | 0.19	1.45 | 0.94 | 0.19	1.44 | 0.95 | 0.19	1.46 | 0.94 | 0.21	1.25 | 0.92 | 0.15	1.57 | 0.94 | 0.26
HEI	14.04 | 0.37 | 31.28	6.93 | 0.84 | 3.05	7.07 | 0.83 | 3.07	7.92 | 0.79 | 4.22	7.91 | 0.79 | 4.23	7.92 | 0.79 | 4.23	-	8.34 | 0.77 | 5.17
HPB	5.06 | 0.43 | 15.61	1.41 | 0.91 | 0.34	1.70 | 0.94 | 0.50	2.00 | 0.96 | 0.65	2.01 | 0.91 | 0.66	2.00 | 0.91 | 0.65	1.41 | 0.96 | 0.33	2.03 | 0.91 | 0.67
HUN	7.44 | 0.55 | 66.36	2.58 | 0.94 | 0.84	2.74 | 0.93 | 0.88	3.07 | 0.92 | 1.32	3.08 | 0.92 | 1.34	3.08 | 0.92 | 1.33	2.58 | 0.94 | 0.87	3.43 | 0.90 | 1.98
JFJ	4.52 | 0.03 | 21.39	1.96 | 0.77 | 1.59	2.23 | 0.72 | 1.53	2.07 | 0.75 | 1.83	2.07 | 0.75 | 1.82	2.07 | 0.75 | 1.84	1.95 | 0.78 | 1.58	2.10 | 0.74 | 1.98
KAS	6.35 | 0.39 | 52.58	3.41 | 0.87 | 2.90	3.43 | 0.87 | 2.89	3.88 | 0.82 | 3.96	3.88 | 0.82 | 3.99	3.87 | 0.83 |3.93	3.29 | 0.77 | 2.77	4.01 | 0.81 | 4.67
LMU	6.01 | 0.05 | 29.00	1.45 | 0.94 | 0.29	1.51 | 0.94 | 0.28	1.74 | 0.92 | 0.59	1.74 | 0.92 | 0.58	1.76 | 0.92 | 0.60	1.44 | 0.95 | 0.29	1.84 | 0.91 | 0.68
MHD	4.50 | 0.21 | 22.24	1.23 | 0.94 | 0.24	1.20 | 0.94 | 0.21	1.29 | 0.92 | 0.31	1.74 | 0.93 | 0.31	1.76 | 0.94 | 0.31	1.23 | 0.94 |	1.26 | 0.94 | 0.27

							0.24	
OXK	5.39 | 0.28 | 38.95	2.45 | 0.85 | 0.79	2.52 | 0.84 | 0.85	2.78 | 0.81 | 1.19	2.78 | 0.81 | 1.20	2.79 | 0.81 | 1.20	2.41 | 0.86 | 0.70	2.98 | 0.78 | 1.59
PRS	2.98 | 0.07 | 20.75	1.06 | 0.89 | 0.46	1.10 | 0.88 | 0.49	1.16 | 0.87 | 0.52	1.16 | 0.87 | 0.52	1.17 | 0.87 | 0.52	1.07 | 0.89 | 0.45	1.22 | 0.86 | 0.53
PUY	4.86 | 0.29 | 39.48	2.05 | 0.87 | 0.67	2.16 | 0.86 | 0.75	2.40 | 0.82 | 0.97	2.40 | 0.82 | 0.97	2.40 | 0.82 | 0.95	2.02 | 0.88 | 0.71	2.48 | 0.81 | 1.27
SCH	5.18 | 0.24 | 41.77	1.90 | 0.89 | 0.27	2.00 | 0.88 | 0.28	2.23 | 0.85 | 0.51	2.23 | 0.85 | 0.51	2.23 | 0.85 | 0.51	1.84 | 0.90 | 0.24	2.38 | 0.84 | 0.70
WES	8.06 | 0.23 | 41.77	2.21 | 0.94 | 0.27	2.00 | 0.94 | 0.28	2.23 | 0.91 | 0.51	2.23 | 0.91 | 0.51	2.23 | 0.91 | 0.51	-	2.38 | 0.90 | 0.70

Table 4. Results from Jackknife delete-1 statistics for VPRM estimated domain-wide NEE for different vegetation classes and for all of the land area. The uncertainty in NEE from all land area was derived assuming independence in the vegetation class specific uncertainties. Note the strong asymmetry between the fraction of land area covered by the different vegetation classes and the number of eddy covariance sites used, indicating over/under representation: for example 8 crop sites represent 51% of the land area, while 15 grassland sites represent 5.6% of the land area of Europe.

	NEE [GtC/y]	NEE uncertainty [GtC/y]	Number of sites	Fraction of land area [%]
Evergreen forest	-0.165	0.039	16	16.5
Deciduous forest	-0.174	0.020	5	4.4
Mixed forest	-0.025	0.176	2	8.4
Open shrub[a]	-0.201	-	1	13.8
Savanna[a]	-0.012	-	0	0.3
Crop	-0.443	0.502	8	51.0
Grass	0.059	0.026	15	5.6
Total	0.960	0.536	47	100

[a]Uncertainties for open shrubland and savanna could not be derived due to the lack of representative eddy covariance sites
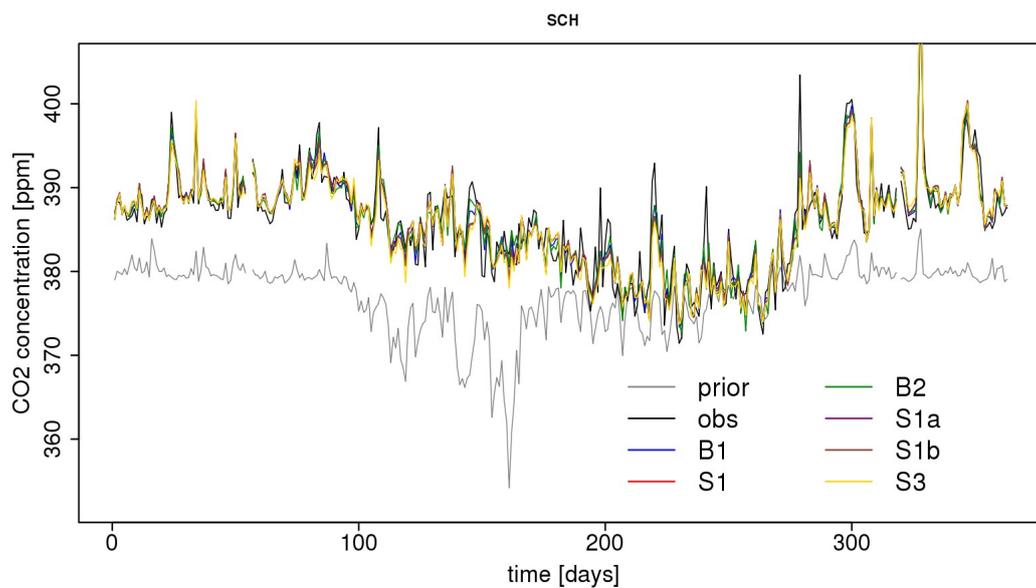
Figure 1. Daily nighttime (23:00-4:00 UTC) averages for prior, true, and posterior CO_2 dry mole fraction time series for the Schauinsland site for the real data inversion. Time starts at 1st January 2007.
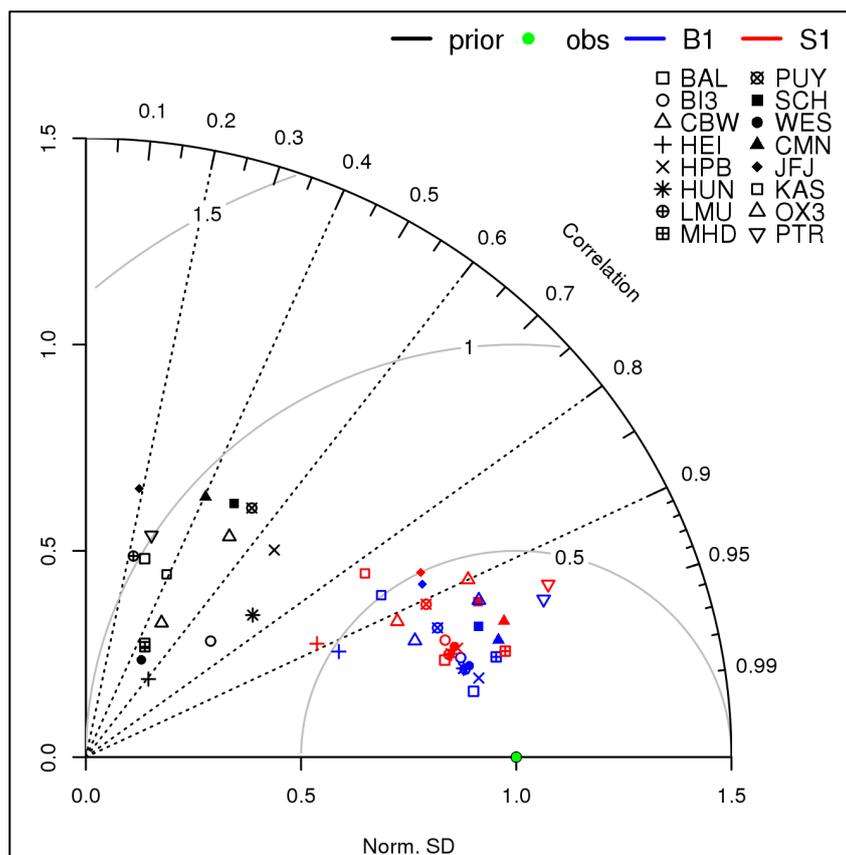
Figure 2 Taylor diagram for modeled and observed time-series of CO_2 dry mole fractions. Prior (black), observed (green, the perfect match of modeled and observed time-series) and the different inversion cases (B1 blue; S1 red) are displayed. Different symbols denote different atmospheric stations. The normalized SD was calculated as the ration of the SD of the modeled time-series to the SD of observations. Gray semi-circles show contours of the standard deviation of the model error.
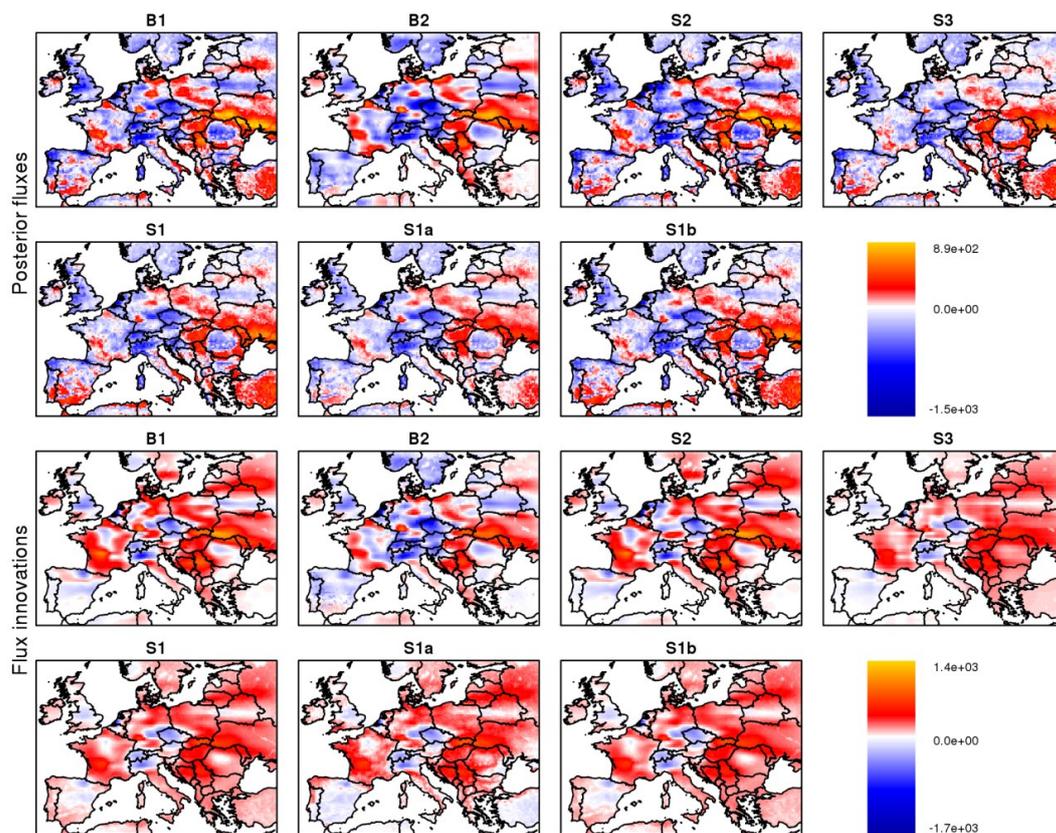
Figure 3. Annual biogenic flux spatial distribution (top two rows) and flux innovations (posterior - prior) (bottom two rows) as estimated from the different inversions for the real data case. Units are in $gCy^{-1}m^{-2}$.
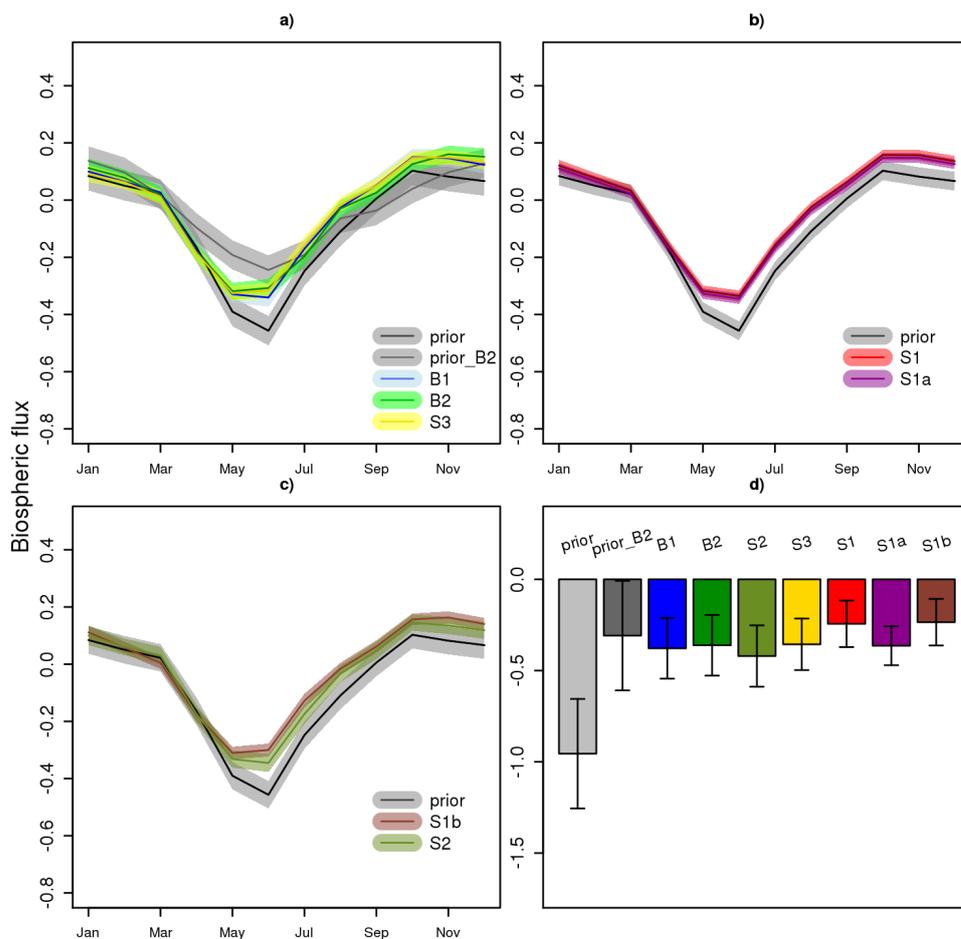
Figure 4. Monthly and annual (panel d) biosphere fluxes integrated over the domain. Panel a) shows B1, B2 and S3 cases, b) S1 and S1a and the c) panel shows S1b and S2 cases. Note that all inversions share the same annual prior uncertainty but monthly prior uncertainties differ. Units are in GtC month^{-1} and GtC y^{-1} for monthly and annual fluxes, respectively
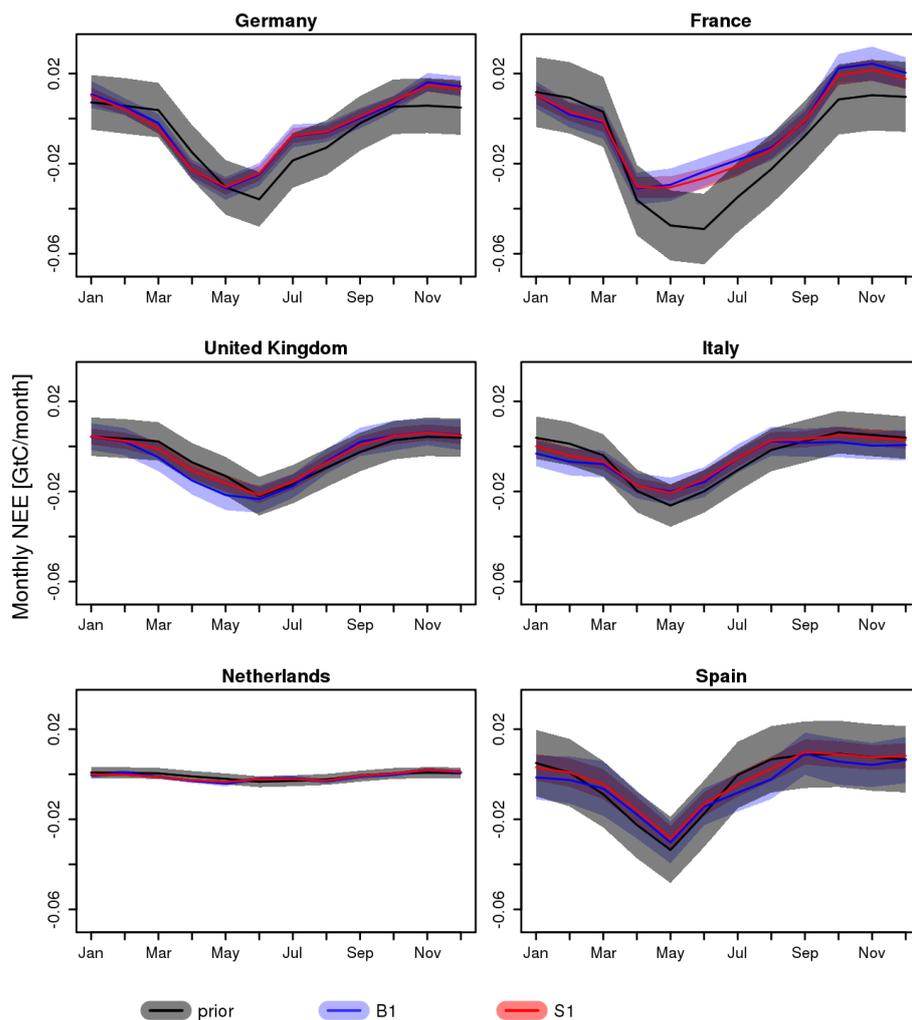
Figure 5. Temporal evolution of prior and posterior monthly NEE for selected European countries.
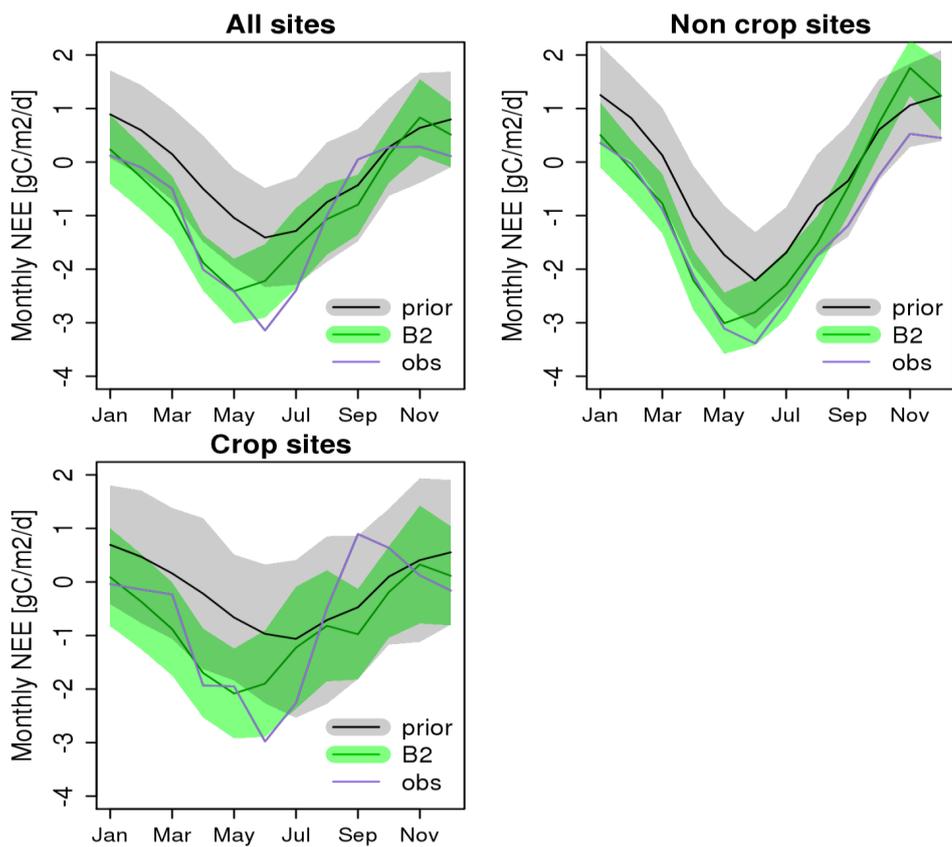
Figure 6. Temporal evolution of monthly NEE ($gCm^{-2}day^{-1}$) averaged over all EC sites (top left), excluding crop (top right), and using only crop sites (bottom). Uncertainties (error of the mean monthly NEE) are indicated by the shaded areas.
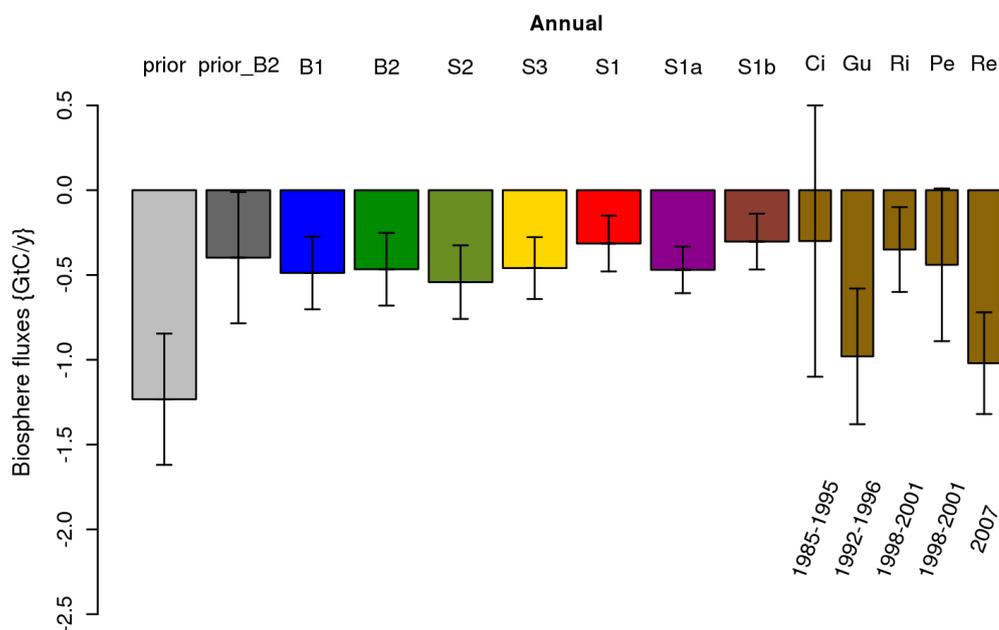
Figure 7. Annual European biogenic CO_2 fluxes in $GtCy^{-1}$ for the different inversions and comparison to previous studies. Fluxes are upscaled to the TransCom EU domain. Labels of the references are as follows: Ci : Ciais et al. (2000); Gu : Gurney et al. (2004); Ri : Rivier et al. (2010); Pe : Peylin et al. (2013); Re : Reuter et al. (2014). Periods for the inverted fluxes are given below the flux estimates.