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Estimating regional terrestrial carbon fluxes for the Australian continent using a multiple-constraint approach

II. The Atmospheric constraint

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ABSTRACT

Bayesian synthesis inversion was applied to in-situ hourly CO_2 concentrations measured at Cape Grim, Australia to refine the estimates of monthly mean gross photosynthesis, total ecosystem respiration and net ecosystem production by the CSIRO Biospheric Model (CBM) for eight regions in Australia for the period 1990–1998. It was found that in-situ measurements of hourly CO_2 concentrations at Cape Grim could provide significant information about the carbon fluxes from Tasmania, central-south and south-east Australia only. The process-based model, CBM, overestimates the ecosystem respiration during summer in south-east Australia, but underestimates ecosystem respiration in Tasmania and central-south Australia. It was concluded that the respiration submodel of CBM should be improved to account for the seasonal variation in the plant and soil respiration parameters in south-east Australia. For the whole period of 1990 to 1998, the mean net ecosystem productions of terrestrial ecosystems in Tasmania, central-south Australia and south-east Australia were estimated to be, respectively, 6 ± 10, 7 ± 27 and -64 ± 18 Mt C yr^{-1}. The yearly uptake rate (being negative) of the terrestrial ecosystems in south-east Australia was smallest (-42 ± 55 Mt C yr^{-1}) in 1998 and largest (-91 ± 52 Mt C yr^{-1}) in 1992.

1. Introduction

In a companion paper, Wang and Barrett (2003) estimated three key parameters in the CSIRO Biospheric Model (CBM) (Wang and Leuning, 1998; Wang et al., 2001) using 183 field measurements of net primary production (NPP), and estimates of monthly canopy green area index from remote sensing. Assuming a steady-state terrestrial biosphere everywhere in Australia, they used CBM and an error model to estimate the means of monthly gross photosynthesis, plant and soil respiration and their standard deviations (SDs) for eight regions between 1990 and 1998. They found that the seasonal NPP of the Australian continent is higher in the Austral spring and autumn than in the Austral summer or winter. Mean total NPP of the Australian continent varied between 0.8 and 1.1 Gt C yr^{-1} between 1990 and 1998, with a coefficient of variation, CV (defined as the ratio of SD and mean), between 0.24 and 0.34; the coefficient of variation of monthly mean NPP for the Australian continent varied from 0.43 to 1.28. Seasonal net ecosystem productivity (NEP) is lowest (or most negative) in the Austral winter and highest (most positive) in the Austral summer. The CV of annual NEP varies between 4 and 30 for the whole Australian continent. The confidence in the estimate of annual NEP is therefore low.

In this study, we include an atmospheric constraint for estimating the carbon fluxes from different regions in Australia. Measurements of atmospheric CO_2 concentrations can be used to infer surface carbon fluxes using an inverse technique. Among various inverse techniques that have been applied to infer global net carbon fluxes, Bayesian inversion may be currently the

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most common for global carbon cycle studies (Enting, 2002).

To estimate carbon fluxes from measurements of atmospheric CO_2 concentrations, Bayesian synthesis inversion requires the prior estimates of the mean and SD of the amount of CO_2 emissions, and the responses of atmospheric CO_2 concentration to the surface emissions from different land regions in Australia. The relative variations of all fluxes in space and time are not determined in the inversion, but are provided by the CBM modelling results as presented in the companion paper (Wang and Barrett, 2003); only the amount of emissions that are assumed to be constant over a region within a given period (a month in this study) are estimated by the inversion. An atmospheric model was used to calculate the response of atmospheric CO_2 concentration at a location to surface CO_2 flux from a region within the model domain.

Almost all previous atmospheric inversion studies used monthly mean surface CO_2 concentrations measured under "baseline" conditions. Under baseline conditions, the air samples are free from contamination by the recent local land air mass, and are considered as being representative of the large-scale background air mass. It is known that surface CO_2 concentrations under non-baseline conditions are more variable, and are related to the carbon fluxes from the local land surface. Using model-generated "data", Law et al. (2002) recently found that continuous 4-hourly measurements of surface CO_2 concentrations in Australia provided significantly more information about carbon fluxes from the Australian continent than using the weekly or monthly measurements of surface CO_2 concentrations under "baseline" conditions only.

In-situ, continuous measurements of atmospheric CO_2 have been made since 1976 at Cape Grim (40.68°S, 144.68°E), near the north-west tip of Tasmania (Beardsmore and Pearman, 1987). Because of the predominant westerly winds and being surrounded by a vast area of ocean, the temporal variation of in-situ CO_2 concentrations measured at Cape Grim on a time scale of less than a few days is little affected by the distant land areas of Africa and South America. In this study we shall apply Bayesian synthesis inversion to in-situ hourly surface CO_2 concentrations measured at Cape Grim from 1990 to 1998 to improve the estimates of gross photosynthesis, total ecosystem respiration by Wang and Barrett (2003) and fossil fuel CO_2 emissions from the Australian continent.

The paper is organised as follows. Section 2 describes the methods of estimating surface carbon fluxes from the Australian region, atmospheric transport modelling and Bayesian synthesis inversion; section 3 describes the data we used in the inversion; section 4 describes the major findings, and section 5 discusses the significance of those findings.

2. Methods

2.1. Estimation of surface CO_2 fluxes from the Australian region

The temporal changes in the surface CO_2 concentrations measured at Cape Grim are related to the net CO_2 fluxes in the region, so we must include all major sources and sinks in the inversion. Carbon fluxes from terrestrial ecosystems modelled by CBM are: gross photosynthesis, total ecosystem respiration and net ecosystem production. Other major sources are fossil fuel burning, biomass burning and ocean uptake, and are estimated as follows.

Using the national inventory methodology (National Greenhouse Gas Inventory Committee, 1999) and the yearly spatially explicit statistics (Australian Bureau of Statistics, 1998), we estimated the CO_2 emissions from fossil-fuel burning in Australia from 1990 to 1998. Fossil fuel emissions were divided into two categories: firstly the emissions from the energy industry, such as power plants and coal mines, and secondly the emissions from transport, manufacturing industries and construction, and some other sectors. Emissions from the energy industry were calculated as the amount of fuel consumed multiplied by an emission factor that depends on fuel type. The total emission from power plants or coal mines was allocated to the grid cell where the power plants or coal mines are located; four fuel types were considered: brown coal, black coal, natural gas and others. The total national CO_2 emissions from non-energy industries was spatially distributed proportional to the population. We used the spatially explicit population census data for 1997 in this study (Australian Bureau of Statistics, 1998). We then estimated the hourly CO_2 emissions by assuming that the emission rate is constant within a year.

Among all the CO_2 sources, biomass burning contributes only a small fraction of total CO_2 emissions in south or south-east Australia and Tasmania. In northern Australia or Queensland, CO_2 emission from biomass burning is very seasonal and is a significant fraction of the annual carbon budget in the region. In this study, we assumed that the biomass burning in northern Australia has little influence on surface CO_2 concentration at Cape Grim (<0.2 ppm), which is supported by the simulation results using an atmospheric transport model. Therefore we did not include CO_2 emissions from biomass burning in our inversion.

We also calculated the uptake of CO_2 by the surrounding oceans to assess its influences on the CO_2 concentration of baseline air. The CO_2 uptake by the ocean, F_o, was calculated as

$$F_o = \kappa \Delta p \tag{1}$$

where κ is the transfer velocity, and was calculated as a function of wind speed at 10 m above the ocean surface using the relation presented by Wanninkhof (1992), and Δp is the monthly mean partial pressure difference between the ocean surface water and ambient air, taken from Takahashi et al. (1997). The interannual variability of Δp was not considered in this study.

2.2. *Atmospheric transport modelling*

A limited area atmospheric model, DARLAM (McGregor and Walsh, 1994) that has been found to simulate the synoptic variation of radon-222 at Cape Grim satisfactorily (Kowalczyk and McGregor, 2000), was used in this study. DARLAM was used to calculate the influence of emission or uptake of CO_2 from a region within the model domain on the surface CO_2 concentration at Cape Grim. DARLAM has a horizontal resolution of 75 km and 18 vertical levels covering the area between 10 and 60°S and 80 and 180°E. The highest level is 10 hPa, and the lowest level is at approximately 40 m, which is comparable to the 70-m sampling inlet height at Cape Grim. Transport of CO_2 from each region was treated as a passive tracer in DARLAM, see Kowalczyk and McGregor (2000). DARLAM uses semi-Lagrangian advection in the horizontal (McGregor, 1993), and total variation diminishing advection in the vertical.

CO_2 fluxes from gross photosynthesis and total ecosystem respiration from each land region were treated as two independent tracers (16 in total). CO_2 emissions from fossil fuel burning from the whole Australian continent and CO_2 uptake by the surrounding ocean within the DARLAM domain were treated as another two independent tracers. Concentrations at the lowest model vertical level at Cape Grim were saved for each of the 18 tracers every model time step. In calculating the evolution of the three-dimensional concentration field of each tracer from a region, we set the initial concentration field to zero, and updated the emission or uptake from tracers every model time step. The concentration of any tracer was set to a constant value at the model boundaries (zero in this study); this is to assume that the concentration of the air entering the domain of the atmospheric transport model is the same as the concentration of baseline air observed at Cape Grim. The concentration of baseline air was subtracted from the observed CO_2 concentrations at Cape Grim before inversion. This is reasonable, since Cape Grim is remote from other land regions outside Australia in the southern hemisphere, and we estimated that the longitudinal gradient of CO_2 concentration between the south-west and south-east Australia coasts was less than 0.5 ppm (also see Monfray et al., 1996). We accounted for the influences of large-scale background air and CO_2 uptake by the surrounding oceans on the surface CO_2 concentration at Cape Grim by detrending the in-situ CO_2 concentrations using baseline CO_2 concentration.

2.3. *Bayesian synthesis inversion using a Kalman filter*

For a non-reactive trace gas in the atmosphere, such as CO_2, the concentration at location s (e.g. Cape Grim) is linearly related to the surface flux as:

$$c_t(s) = c_t^*(s) + \sum_n \int_{t_0}^{t} \int_{\Omega} f_i(t^*, s^*) g_i(t, t^*, s^*, s)\, \mathrm{d}s^*\, \mathrm{d}t^* \tag{2}$$

where $c_t(s)$ is the surface CO_2 concentration at time t and location s, $c_t^*(s)$ represents the surface CO_2 concentration at time t and location s when CO_2 fluxes from all land surfaces within the model domain are zero; t_0 is the beginning of the period for which the inversion is applied, $f_i(t^*,s^*)$ is the CO_2 emission rate from source i at time t^* and location s^*; g_i is the influence of unit emission from source i at time t^* and location s^* on the surface CO_2 concentration at time t and location s, and is calculated using the atmospheric transport model, DARLAM for emissions from each of eight land regions in the Australian continent separately (see section 2.2); Ω is the model domain and n is the number of sources. In this study we estimate $c_t^*(s)$ as follows:

$$c_t^*(s) = c_{bt}(s) + c_0 + \varepsilon_b \tag{3}$$

where $c_{bt}(t, s)$ is the surface CO_2 concentration measured at location s under "baseline" conditions at time t; c_0 represents any systematic difference in the mean between $c_t^*(s)$ and $c_{bt}(s)$, and ε_b is a random variable representing the error in the estimate of baseline CO_2 concentrations. $c_{bt}(s)$ was estimated from a spline fit to all the in-situ hourly CO_2 measurements under baseline conditions at Cape Grim (see the next section for more details).

The total amount of CO_2 emission from source i between time t_0 and t_1, F_i is given by

$$F_i = \int_{t_0}^{t_1} \int_{\Omega} f_i(t^*, s^*)\,\mathrm{d}s^*\,\mathrm{d}t^* \tag{4}$$

where t_1 is the end of the period. In this study, we wish to estimate the surface CO_2 flux F_i from in-situ hourly measurements of c_t at Cape Grim by inversion (we shall drop "s" from c_t and c_{bt} in the subsequent equations). In the synthesis inversion, the Australian continent is divided into eight regions based on boundaries of different states and territories and distribution of different vegetation types. The relative variation of surface carbon flux in space and time within each region, $f_{i,\mathrm{prior}}(t, s)$ is taken from the modelling results by CBM (Part I: Wang and Barrett, 2003). Only the total emissions from all sources are unknown, and are estimated from inversion. We assume that

$$f_i(t, s) = \alpha_i f_{i,\mathrm{prior}}(t, s) \tag{5}$$

$$F_{i,\mathrm{prior}} = \int_{t_0}^{t_1} \int_{\Omega} f_{i,\mathrm{prior}}(t^*, s^*)\,\mathrm{d}s^*\,\mathrm{d}t^* = \frac{F_i}{\alpha_i}. \tag{6}$$

A second error in the model calculation may arise from transport modelling, this error has been discussed in detail by many others and is a subject of a major international intercomparison (Law et al., 1996; Gurney et al., 2002). Here we assume that

$$g_i = g_i^* + \varepsilon_g \tag{7}$$

where $g_i^*$and ε_g represent the true value of g_i and the model error in atmospheric transport, respectively. Substituting eqs. (4)–(7) into (2), and integrating over time, we have

$$\begin{aligned} c_t - c_{bt} &= c_0 + \sum_n F_i \phi_{i,t} \\ &\quad + \sum_n F_i \int_{t_0}^{t} \int_{\Omega} \frac{f_{i,\mathrm{prior}}(t^*, s^*)}{F_{i,\mathrm{prior}}} \\ &\quad \times \varepsilon_g(t, t^*, s^*, s)\,\mathrm{d}s^*\,\mathrm{d}t^* + \varepsilon_b \end{aligned} \tag{8}$$

where

$$\phi_{i,t} = \int_{t_0}^{t} \int_{\Omega} \frac{f_{i,\mathrm{prior}}(t^*, s^*)}{F_{i,\mathrm{prior}}} g^*(t, t^*, s^*, s)\,\mathrm{d}s^*\,\mathrm{d}t^* \tag{9}$$

and is calculated using DARLAM.

The last two terms in eq. (8) represent the errors in the modelled surface CO_2 concentration due to errors in transport modelling and in estimating background baseline CO_2 concentrations, respectively. The magnitude of the sum of these two terms, denoted by δ_t, may vary with t.

As atmospheric transport is diffusive, the error in atmospheric transport modelling, δ_t, is autocorrelated (see Enting, 2002). We model δ_t, using a first-order autoregressive model; that is

$$\delta_t = \beta \delta_{t-\Delta t} + \varepsilon_0 \tag{10}$$

where β represents the dependence of δ_t on $\delta_{t-\Delta t}$, Δt is the model time step (3600 s in this study), and ε_0 is white noise. Therefore eq. (8) can be written as

$$c_t - c_{bt} = c_0 + \sum_n \alpha_i F_{i,\mathrm{prior}} \phi_{i,t} + \beta \delta_{t-\Delta t} + \varepsilon_0. \tag{11}$$

There are $n + 1$ unknowns (c_0, and α's) that are to be estimated from N hourly measurements of c_t in eq. (11). Equation (11) can be recast into state-space form, and solved using the Kalman filtering technique (Enting, 2000; Trudinger et al., 2002). The Kalman filter is a recursive algorithm that updates the estimates of the mean and covariance of the state of a system at time t based on the estimates of the state at the previous time step, $t - \Delta t$ and the noisy measurements at time t. Therefore the Kalman filter is Bayesian. The state space form of eq. (11) is as follows:

$$\boldsymbol{x}_t = \boldsymbol{\Phi}_{t-\Delta t} \boldsymbol{x}_{t-\Delta t} + \boldsymbol{w}_{t-\Delta t} \tag{12}$$

$$\boldsymbol{Z}_t = \mathbf{H}_t \boldsymbol{x}_t + \boldsymbol{v}_t, \tag{13}$$

where

$$x_t = (F_{1,t}, \ldots. F_{n,t}, c_{0,t}, \delta_{t,t})^T$$

$$\Phi_t = \begin{pmatrix} \boldsymbol{I}_{n+1} & 0_{n+1} \\ 0_{n+1} & \beta \end{pmatrix}$$

$$\boldsymbol{H}_t = (\phi_{1,t}, \phi_{2,t}, \ldots.. \phi_{n,t}, 1, 0),$$

where $\boldsymbol{x}_t$ represents the state vector at time t (t from t_0 to $t_0 + N\Delta t$). Every state variable (or flux in this study) is here treated as a stochastic variable; $\boldsymbol{w}_t$ represents the random forcing, assumed to be stochastic with zero mean and covariance $\boldsymbol{Q}$, $\boldsymbol{Z}_t$ is the measurement at time t; $\boldsymbol{H}_t$ is the projection matrix; $\boldsymbol{v}_t$ is the measurement error, and is assumed to be white noise with zero mean and covariance $\boldsymbol{R}$. The covariance matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$ have dimensions of $(n+2) \times (n+2)$ and 1×1, respectively. The initial values of the off-diagonal elements in $\boldsymbol{Q}$ are all zero, and the initial values of the diagonal elements are σ_1^2, $\sigma_2^2 \cdots$, σ_n^2, σ_o^2, σ_Q^2, where σ_i is the initial estimate of the SD of mean α_i, in the Kalman filter; σ_{Q} is the SD of the white noise term in eq. (12), and represents errors in the prior estimates of the spatial and temporal patterns of the surface fluxes; $\boldsymbol{R} = \sigma_{\mathrm{R}}^2$, where σ_{R} includes measurement error and the mismatch between modelled and observed surface CO_2 concentrations due to factors such as limited resolution in the atmospheric transport model, errors in meteorological forcings and so on.

Once the initial estimates of $\boldsymbol{Q}$, $\boldsymbol{R}$ and $\boldsymbol{x}$ are given, the Kalman filtering is applied in two steps: the forward pass and smoothing. In the forward pass, the Kalman filtering is used to estimate the state at time t using all measurements up to time t in the smoothing, the entire set of measurements is used to update the estimate of the state at every time step. Further details can be found elsewhere (Gelb, 1974; Trudinger et al., 2002; Wang and Bentley, 2002).

We applied the Bayesian synthesis inversion to the measurements of in-situ hourly surface CO_2 concentrations at Cape Grim to obtain the improved estimates of all F_i, and their SDs ($i = 1$ to 17). Note the tracer representing CO_2 uptake by the surrounding oceans was not used in the inversion but used to assess the magnitude of c_0 (see section 4.1). The mean and SD of monthly net ecosystem production for all eight land regions were calculated from the estimates of monthly gross photosynthesis and total ecosystem production for each of eight regions and the covariance matrix. Therefore estimates were obtained by inversion for three monthly carbon fluxes for each of the eight land regions: gross photosynthesis, total ecosystem respiration and net ecosystem production, and the fossil fuel emission from the whole Australian continent.

To assess the information contained in surface CO_2 concentration measurements about the terrestrial carbon fluxes in the Australian continent, we define a new variable, χ as

$$\chi = 1 - \frac{\sigma_{\mathrm{inverse}}}{\sigma_{\mathrm{prior}}}. \tag{14}$$

If in-situ surface CO_2 measurements at Cape Grim do not provide any information about the carbon fluxes from a region of the Australian continent, the SD of monthly mean carbon fluxes by the Kalman filtering will be equal to that of the prior estimate, and $\chi = 0$. The larger χ is, the more information in-situ atmospheric CO_2 measurements at Cape Grim can provide about that flux.

3. Data

In-situ, continuous measurements of atmospheric CO_2 have been made by non-dispersive infrared analysers since 1976 at Cape Grim (40.68ºS, 144.68ºE), near the northwest tip of Tasmania (Beardsmore and Pearman, 1987). In this study we use in-situ hourly CO_2 concentration data over the period 1990–98. We fitted a spline that acts like a low-pass filter and reduces the signal with a period shorter than 60 d by 50% (Enting, 1987) to all the surface CO_2 concentrations measured at Cape Grim under baseline conditions to give "baseline" CO_2 concentration at time t. Under baseline conditions, the air samples at Cape Grim are free from contamination by the local land air mass, and are considered as being representative of the large-scale background air mass. Baseline conditions were determined *a posteriori* from the hourly in-situ measurements of CO_2 concentration selected for consistency, wind speed and wind direction (Beardsmore and Pearman, 1987). Figure 1 shows the in-situ measurements of hourly CO_2 concentrations under

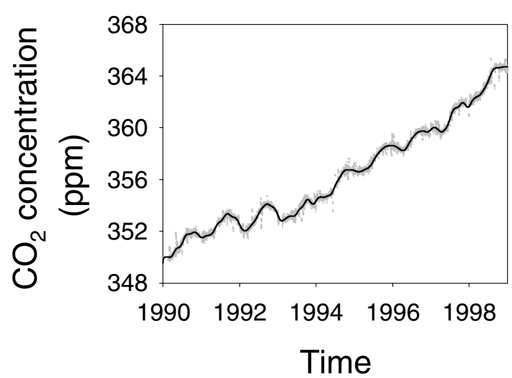

Fig. 1. In-situ measurements (symbol) of hourly CO_2 concentrations at Cape Grim, north-west Tasmania, Australia under baseline conditions for the period 1990–98. The curve is the spline fit to all the baseline data with 50% attenuation of shorter than 60 d.

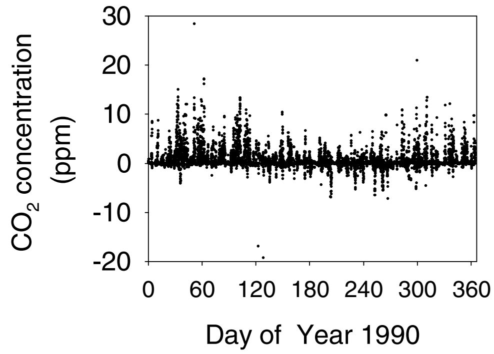

Fig. 2. Detrended in-situ hourly CO_2 concentrations that were calculated as the differences between in-situ hourly CO_2 concentration and the spline-interpolated CO_2 concentration for the baseline condition at Cape Grim.

baseline conditions and the spline fit to the data for the period 1990–98; c_b was estimated from the fitted spline, and was then used to detrend all in-situ hourly CO_2 concentration measurements at Cape Grim (see Fig. 2 as an example for all hours of 1990). All CO_2 concentration data referred to subsequently are detrended unless specified. The data in Fig. 2 show that the mean concentration is higher in the Austral summer than in the Austral winter, and the detrended CO_2 concentrations become negative quite frequently during the Austral winter, implying a carbon sink in the Australian region.

Bayesian synthesis inversion requires prior estimates of all F_i and c_0 and their SDs, and the response functions, $\phi_{i,t}$ for each CO_2 flux. These carbon fluxes include: CO_2 exchange between terrestrial ecosystems and atmosphere, and CO_2 emissions from fossil fuel burning.

The annual fossil fuel CO_2 emissions increased at a rate of 2.44% per year, or 2 Mt C yr^{-1} over the period 1990–98. Figure 3a shows the spatial distribution in 1990. Two cities, Melbourne and Sydney, have CO_2 emission rates above 3.5 g C m^{-2} d^{-1}. The CV of Australian total emissions from fossil fuel is assumed to be 20% (National Greenhouse Gas Inventory Committee, 1999).

In estimating the surface carbon fluxes from different parts of the Australian continent, the Australian continent is divided into eight regions (Fig. 3b). We used the mean and SD of the monthly gross photosynthesis ($P_{g,m}$) and total ecosystem respiration ($R_{t,m}$) estimated using CBM by Wang and Barrett (2003) for each of the eight land regions as our prior estimates for terrestrial ecosystems in the inversion (Fig. 4).

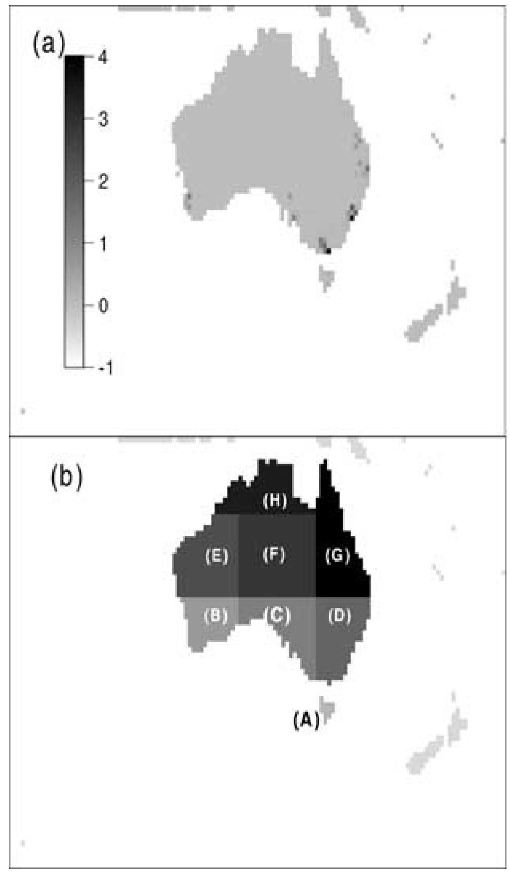

Fig. 3. (a) Spatial distribution of annual mean CO_2 emission from fossil fuel burning (g C m^{-2} d^{-1}) in Australia in 1990; (b) the boundary of eight land regions in Australian and the domain of the atmospheric model, DARLAM.

4. Results

4.1. Choices of the parameter values in Bayesian synthesis inversion

Results from Bayesian synthesis inversion depend on the prior estimates of all carbon fluxes (F_i, σ_i) and the parameters in eqs. (1), (12) and (13). The parameters are: c_0 (both mean and SD), β, σ_R, and σ_Q. The choice of a suitable value for each of those parameters is very important. For example, if the value of stochastic forcing, σ_Q is too small, the state variable,

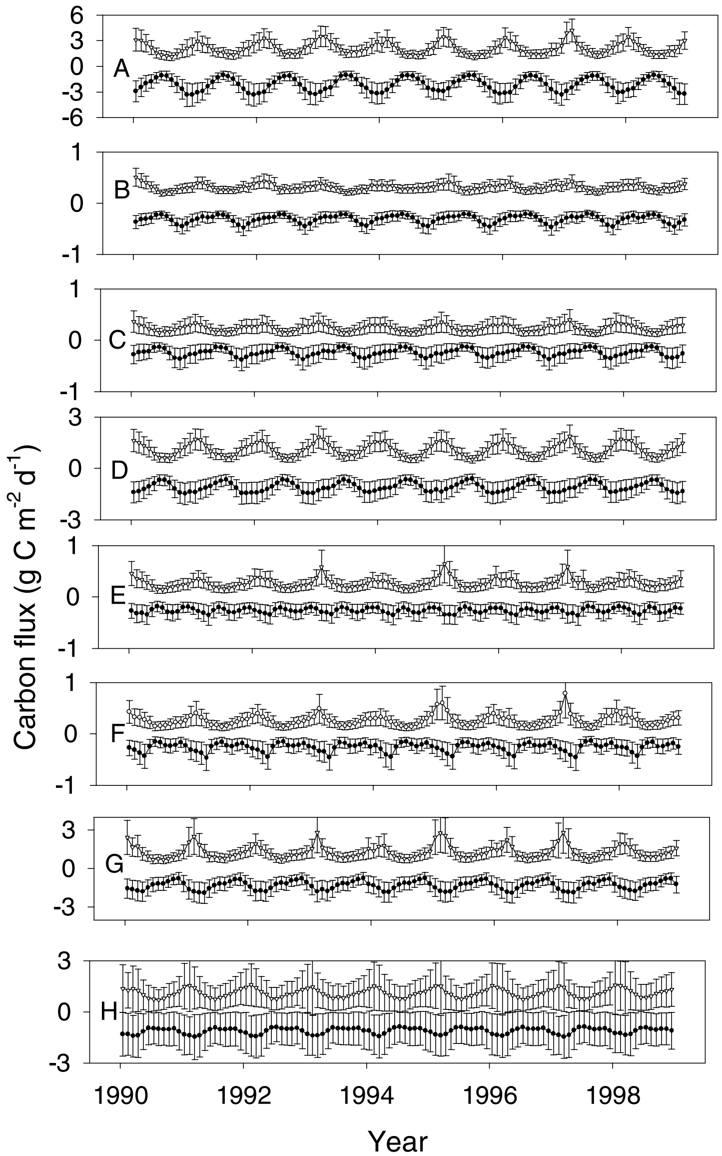

Fig. 4. Mean and one SD of monthly mean gross photosynthesis (solid symbol) and total ecosystem respiration (open symbol) as estimated by CBM for the period 1990–99 for regions A to H.

$\boldsymbol{x}_t$, cannot vary enough to fit the observed CO_2 concentration data, meaning that some useful information in observed CO_2 concentration data will not be adequately used to constrain the inversion results; if σ_Q is too large, the estimate of $\boldsymbol{x}_t$ may be too variable and the uncertainty will be too large. Similar responses of $\boldsymbol{x}_t$ to σ_R can also be demonstrated. The sum of σ_Q and σ_R needs to be significantly smaller than the variability in the observed surface CO_2 concentrations, otherwise we are too pessimistic. As pointed out by Trudinger et al. (2002), the inversion results are more sensitive to the σ_Q/σ_R than the values of σ_Q or σ_R individually.

The term c_0 in eq. (4) represents the systematic bias in estimating large-scale background CO_2

concentration, and depends on the influence of oceanic CO_2 uptake within the model domain. The CO_2 concentration of the "baseline" air entering the western coast of the Australian continent may be different from c_b, and that difference depends on the CO_2 uptake rate of the Indian and southern oceans, west of Cape Grim. DARLAM simulations show that the annual mean influences of CO_2 uptake by the surrounding oceans within the DARLAM domain upon the surface CO_2 concentrations at Cape Grim is about 0.3 ppm. Therefore the prior estimates of the mean and SD of c_0 are set to 0 ppm and 1 ppm, respectively.

One of the key assumptions in linear Kalman filtering is that the unexplained residues are normal-distributed (Gelb, 1974). In this study, we used the first-order autoregressive model [see eq. (10)] to account for the non-random variation in the residues that was not explained by errors in measurements and transport modelling. The key parameter in the first-order autoregressive model is β. To estimate β, eq. (11) was fitted to all the detrended hourly data for each month separately with $\beta = 0$, and the unexplained residual at time t was linearly regressed against that at time $t - \Delta t$. The value of β was calculated as $b/(1 - r^2)$, where b is the slope of regression and r is the correlation coefficient (Wang and Bentley, 2002). In this study an estimate of 0.67 for β was used for all the data from 1990 to 1998 for consistency. We refitted all the observed CO_2 concentrations with $\beta = 0.67$ in the first-order autoregressive model and found that there was no systematic bias in the unexplained residues (data not shown).

If the systematic variation in the unexplained residues is not adequately accounted for in the inversion, we can be too optimistic, or underestimate the uncertainty, σ_i. This can be a serious problem in inverting high-frequency (subdiurnal) CO_2 concentration data, because of the limited spatial resolution and inaccurate representation of subgrid mixing processes in the transport model, whereas global inversions so far have only used monthly concentrations representing baseline conditions, and the unexplained residues in the global inversions usually are quite small; systematic bias in the unexplained residue is a less serious problem than in regional inversion using high-frequency CO_2 concentration data (Enting, 2002), In this study we compared the estimates of gross photosynthesis and total ecosystem respiration for $\beta = 0.67$ with those for $\beta = 0$ by inversion for region D in 1990 (Fig. 5). The estimates of the mean gross photosynthetic or total ecosystem respiratory fluxes of different months by inversion using $\beta = 0$ are more variable (Fig. 5a), and the reductions in the prior estimates of SDs by inversion (χ) using $\beta = 0.67$ are on average about 10% less than those using $\beta = 0$ for gross photosynthesis and total ecosystem respiration (Fig. 5b). If we take $\beta = 0$ in the inversion, then we are too optimistic about the amount of information in the observed data, and consequently underestimate the SD of the mean. Because of the strong correlation between gross photosynthetic and total ecosystem respiratory fluxes, the estimates of the mean monthly mean net ecosystem production ($P_{e,m}$) by inversion are not significantly affected by β (data not shown), but the reduction in the prior estimate of SD of $P_{e,m}$ by inversion using $\beta = 0.67$ is about 15–20% less than that using $\beta = 0$ (data not shown here). Similar results have also been obtained for regions A and C.

The parameter σ_R represents errors in the CO_2 measurements and transport modelling, and variation of surface CO_2 concentration within the DARLAM grid box including Cape Grim. The weighting of each CO_2 concentration measurement in the inversion is inversely proportional to σ_R. The precision of in-situ CO_2 concentration measurements at Cape Grim is about 0.2 ppm. Considering other systematic differences in the calibration standards (Masarie et al., 2001), the more realistic error of in-situ CO_2 concentration measurements is probably about 0.5 ppm. However, no measurements are available for assessing the representativeness of the surface CO_2 measurements at Cape Grim for its 75 km by 75 km surrounding area. Modelled concentrations at a sea point nearest to Cape Grim were used in the inversion. Based on the results of Kowalczyk and McGregor (2000), we estimated that the difference in the surface CO_2 concentration between Cape Grim and the sea grid point in DARLAM should be less than 0.5 ppm. The error in transport modelling is much more uncertain, and is probably less than 1 ppm on average based on previous studies (Kowalczyk and McGregor 2000; Wang and Bentley, 2002).

The sensitivity of inversion estimates to σ_R showed that the estimates of mean and SD of monthly gross photosynthesis, total ecosystem respiration and net ecosystem production by inversion were rather insensitive to σ_R when σ_R varies between 1 and 3 ppm. The SD of the mean carbon flux decreases with an increase in σ_R, but the change is very small (data not shown). Therefore we chose a value of 2 ppm for σ_R. Choices of σ_R or σ_Q are also determining by examining χ^2 of the covariance in the innovation matrix in the Kalman

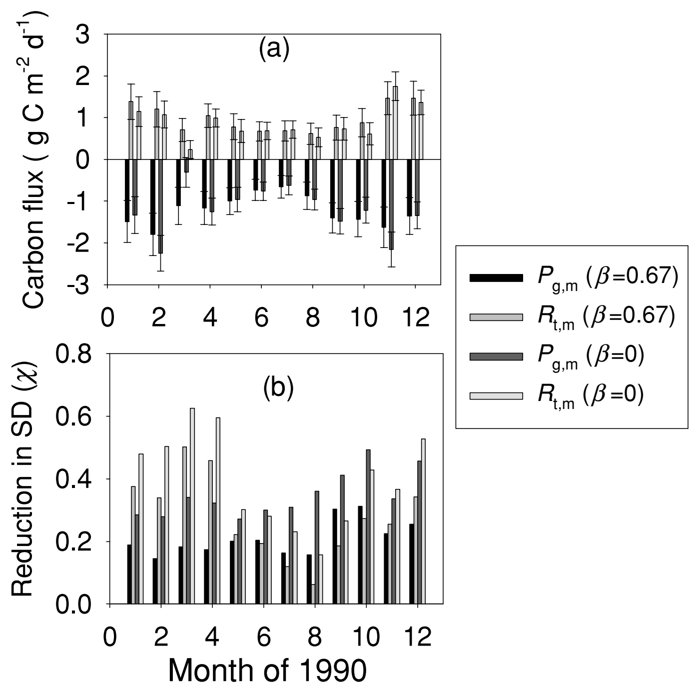

Fig. 5. (a) Estimated monthly mean gross photosynthesis ($P_{g,m}$) and monthly mean total ecosystem respiration ($R_{t,m}$) with $\beta = 0$ or $\beta = 0.67$ for region D in 1990; (b) reduction in SD, χ, of the estimated monthly mean gross photosynthesis and monthly mean total ecosystem respiration with $\beta = 0$ or $\beta = 0.67$.

filtering. Suitable values were chosen when χ^2 normalised by the number of observation is close to 1 (Trudinger et al., 2002).

The SD of stochastic forcing in Kalman filtering, σ_Q, is used to represent errors in the temporal and spatial patterns of surface CO_2 fluxes from different land regions in Australia, as discussed at the beginning of this section. To estimate σ_Q, we fitted eq. (11) to the detrended hourly CO_2 concentration data for each month for the period 1990–98 using the Kalman filter technique with $\sigma_Q = 0$, $\sigma_R = 2$ ppm, $\beta = 0$ and the prior estimates of all F_i and c_0. The maximum unexplained residual in the best-fitted regression for each month for the whole period 1990–98 gives the maximum value of σ_Q, which is 4 ppm.

We then studied the sensitivities of the estimates of the mean of the three carbon fluxes and the reduction of the prior estimates of SDs by inversion to σ_Q by fitting eq. (11) to the observed CO_2 concentration data at Cape Grim for 1990. For region D, the estimated monthly fluxes, gross photosynthesis ($P_{g,m}$) and total ecosystem respiration ($R_{t,m}$) by inversion are very similar between $\sigma_Q = 3$ ppm and $\sigma_Q = 4$ ppm, but quite different from those for $\sigma_Q = 2$ ppm for three months in 1990. The net flux, $P_{e,m}$, is rather insensitive to σ_Q. The reduction in SDs of mean $P_{g,m}$ and $R_{t,m}$ decrease by about 50% when σ_Q increases from 2 to 3 ppm, and decrease by less than 10% when σ_Q increases from 3 to 4 ppm. Therefore we took a value of 3 ppm for σ_Q in this study.

4.2. *Estimating carbon fluxes from the eight land regions of Australia*

Using the prior estimates of all carbon fluxes and their SDs and the estimates of parameters required by the Kalman filtering technique, we used Kalman filtering to fit the in-situ hourly CO_2 concentrations at Cape Grim for each month separately for the period 1990–1998, and obtained the estimates of the monthly means and SDs of three carbon fluxes for all eight regions. We found that the reduction in SDs by inversion was insignificant for the three carbon fluxes from central, western and northern parts of the Australian continent (region B, E, F, G or H). We concluded that in-situ measurements of surface CO_2 concentrations at Cape

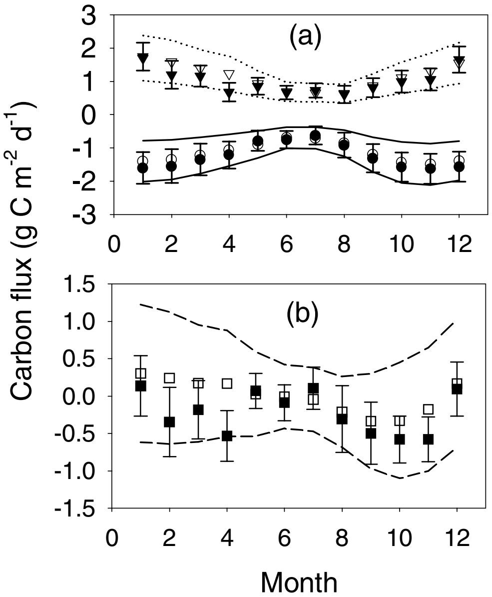

Fig. 6. (a) Prior estimates of monthly mean of gross photosynthesis (open circles) and total ecosystem respiration (open triangles) by the process-based model CBM for region D in 1990. The solid and dashed lines represent the mean ±1 SD of the prior estimates of monthly mean gross photosynthesis or monthly mean total ecosystem respiration, respectively. The inversion estimates of monthly mean gross photosynthesis (closed circles) and monthly mean total ecosystem respiration (closed triangles) and their SDs are also shown; and (b) estimate of the monthly mean NEP by CBM (open squares) and the mean ±1 SD (dashed lines) by CBM (dashed lines) for region D in 1990. The estimates of the mean and one SD of the monthly mean NEP by inversion are also shown (solid square).

Grim provided very little information about the three carbon fluxes from those five regions.

Figure 6 compares the mean and SD of three monthly carbon fluxes, $P_{g,m}$, $R_{t,m}$ and $P_{e,m}$, by inversion with those from the process-based model CBM for region D in 1990. The estimated monthly fluxes of $P_{g,m}$ and $P_{e,m}$ by inversion are more negative than those by CBM, and the estimated monthly fluxes of $R_{t,m}$ by inversion are less than those by CBM. As a result, the inversion estimated that the terrestrial ecosystem in region D was a carbon sink between February and April and between August and November, whereas CBM predicted that the terrestrial ecosystem in region D was a carbon sink between August and November, and a carbon source during other months in 1990 (Fig. 6b).

Because the prior estimate of the SD of mean total ecosystem respiration flux is greater than that of the mean gross photosynthetic flux, and gross photosynthesis is only active during the daytime, reduction in the SD of monthly mean ecosystem respiration flux is greater than that of the gross photosynthetic flux in 1990 (Fig. 6a). As atmospheric CO_2 concentration is proportional to the net surface carbon fluxes, and the measured CO_2 concentrations are unable to separate the contribution of $P_{g,m}$ to $P_{e,m}$ from that of $R_{t,m}$, the reduction in the SD of mean $P_{e,m}$, $\chi_{e,m}$ is greatest among all three carbon fluxes, varying from 5 to 68% (Fig. 6b). Variation in $\chi_{e,m}$ among different months is related to the atmospheric transport, and will be discussed later.

If we aggregate the monthly fluxes for different years for the period 1990–98, the SD of the monthly mean carbon fluxes is reduced because of an increase in sample size (Fig. 7). For Tasmania (region A), the estimate of monthly total gross photosynthesis by inversion is less negative, and the estimates of monthly net ecosystem respiration and net ecosystem production by inversion are higher (more positive) than those by CBM for the period from September to December. The differences in the estimates of the three carbon fluxes between inversion and CBM are very small for other months (January–August) in region A.

For central-south Australia (region C), CBM overestimates monthly gross photosynthesis and underestimates monthly total ecosystem respiration from January to May, and underestimates monthly gross photosynthesis from July to October, as compared with the estimates by inversion. As a result, the net ecosystem flux by CBM is lower (or a weaker source) from November to June and less negative (or a weaker sink) from July to October than those by inversion for region C.

For south-east Australia (region D), the estimates of monthly mean gross photosynthesis by inversion agree quite well with those by CBM, but the estimates of monthly mean total ecosystem respiration by inversion are significantly lower than those by CBM for the period October to April. The inversion estimates that the terrestrial ecosystem in region D was a carbon sink for all months except May and June. The inversion results suggest that the plant and soil respiration rate at 20 °C for the period October to April should be lower than that for the other months of the year. We modelled plant and soil respiration as functions of temperature or temperature and soil moisture, respectively, and did not consider the substrate limitation

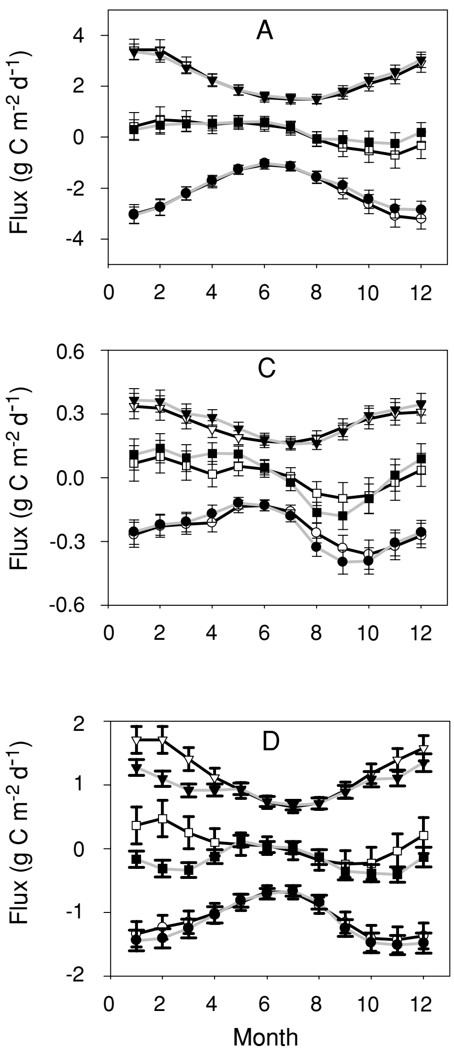

Fig. 7. Monthly mean and its one SD of gross photosynthesis (circle), total ecosystem respiration (inverted triangle) and NEP (square) for regions A, C and D averaged over the period 1990–98 by CBM (open symbol and black line) or by Bayesian synthesis inversion (filled symbol and grey line).

in CBM, and could overestimate the respiration rate. When soil was dry, it is likely that plant root respiration was reduced (Law et al., 2000; Silver and Miya, 2001), which was not taken into account in CBM. Several recent studies have found that soil and root respiration is often limited by the supply of substrate (Giardina and Ryan, 2000; Hogberg et al., 2001). During Austral winter, the air temperature is low, soil is relatively wet and the ground is commonly covered by green grass that can provide adequate supply of substrate for soil microbial through root exudation. Respiration is less limited by substrate and soil moisture in the winter than other times of the year. Therefore our respiration model, which does not consider substrate limitations on ecosystem respiration or water limitation on root respiration, can estimate the respiration in the winter quite well, but may significantly overestimate respiration during other times of the year.

We also compared the inversion estimates of monthly fossil fuel emissions from Australia with the inventory estimate, and found that the SD of the mean monthly fossil fuel emission was only reduced by less than 5%. The prior estimates of monthly mean fossil fuel CO_2 emission is constant throughout the year, but the estimate of monthly mean fossil fuel CO_2 emission by inversion shows higher emission rate in the winter or in the summer than that in the spring, which is consistent with the seasonal variation of electricity demand under Australian climatic conditions. However, in-situ measurements of CO_2 concentrations at Cape Grim do not provide significantly more information than the Australian national inventory about CO_2 emission from fossil fuel because that signal to noise ratio at Cape Grim of fossil fuel emissions from the Australian continent is much smaller than those of other terrestrial biospheric fluxes and consequently there is only a small reduction in the prior estimate of uncertainty ($<5\%$). The inversion results do not necessarily mean that the Australian national inventory of fossil fuel emission is accurate within $\pm 10\%$. The results about fossil fuel emissions from the inversion must be treated cautiously.

4.3. Sensitivity of inversion estimates to prior uncertainties of the carbon fluxes

To assess how much information the atmospheric concentration measurements can give about carbon fluxes in different regions of the Australian continent, we calculated the mean reduction of SD of all three monthly carbon fluxes ($\chi_{p,m}$, $\chi_{t,m}$ and $\chi_{e,m}$). The results for regions A, C and D are shown in Fig. 8. The SD reduction is not significantly different from zero for all other regions or for fossil fuel CO_2 emissions in Australia. For any of regions A, C and D, the reduction in SD for three different carbon fluxes is that $\chi_{e,m} > \chi_{t,m} > \chi_{p,m}$ (Fig. 8). Reduction in the SD of monthly mean carbon fluxes is also greatest in region D and smallest in region C among the three regions.

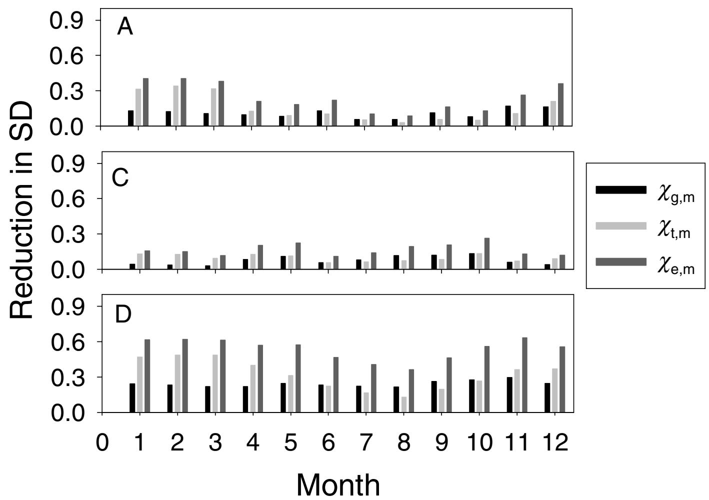

Fig. 8. Reduction in SD of three monthly mean fluxes: gross photosynthesis ($\chi_{g,m}$), total ecosystem respiration ($\chi_{t,m}$) and NEP ($\chi_{e,m}$) by inversion averaged over the period 1990–98 for three regions (A, C and D).

Because of the relatively long distance from region C to Cape Grim, the signal-to-noise ratio of a unit emission is smallest in region C among the three regions; therefore reduction in SD of the monthly mean carbon fluxes is also smallest. Studies of air parcel back trajectories also found that the variation in χ between different months for all three regions was closely related to the frequency of air parcel back trajectories passing over the regions in different months, and the distance between Cape Grim and the region. Region A, although being closest to Cape Grim, has lower χ than region D, because with the predominant westerlies, CO_2 emissions from a much larger area in region D than in region A are detected at Cape Grim. Among the three regions, A, C and D, region C has the lowest carbon fluxes and longest distance from Cape Grim, and therefore the lowest χ.

Whether in-situ measurements of surface CO_2 concentrations at Cape Grim contain any significant new information about the carbon fluxes from a region in Australia also depends on the prior estimate of the SD of the mean carbon flux. If we know the emission from a region very poorly, the prior estimate of SD of the mean emission is large and in-situ measurements of CO_2 concentrations at Cape Grim may provide some further information about the emission from that region, so that the estimate of SD by inversion will be significantly smaller than the prior estimate of SD; and vice versa. To study the sensitivity of our inversion results to prior estimate of SD for regions A, C and D, we varied the prior estimate of SD of each monthly mean carbon flux during 1990 to 1998 by multiplying the SD estimated by CBM (Wang and Barrett, 2003) by a constant factor (a), and applied the Kalman filter to in-situ hourly measurements of CO_2 concentrations at Cape Grim, and obtained the SD and mean of monthly mean carbon fluxes. Figure 9 shows that the estimates of monthly NEP by inversion are not very different from the prior estimates, and that the reduction in the SD of monthly NEP is less than 20% for regions A and C for $a = 0.5$. Therefore the atmospheric CO_2 measurements at Cape Grim do not provide significant additional information about terrestrial net carbon fluxes from those two regions when $a = 0.5$. For region D, the reduction in SD by inversion is greater than 20% and the estimates of monthly NEP by inversion are significantly less (more negative) than the prior estimates for all months except May, June, July and August (Fig. 9). The results in Fig. 9 also confirm that the prior estimates of monthly NEP in region D for the period October–April are high, because the process-based model, CBM overestimates the monthly total ecosystem respiration for those months (data not shown). The reduction in the SD of monthly NEP increases with a for all three regions. It is likely that the prior estimate of SD of monthly NEP are underestimated (Wang and Barrett, 2003), therefore in-situ measurements of CO_2 concentration at Cape Grim can

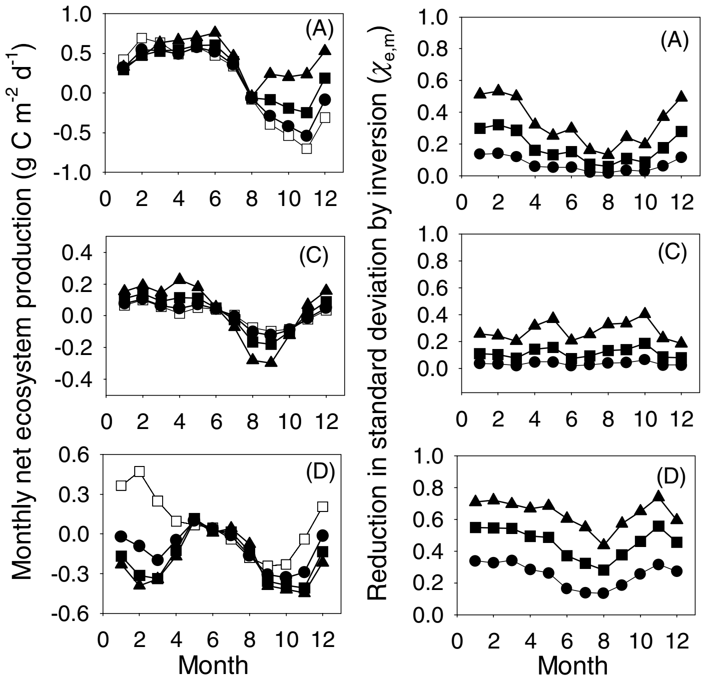

Fig. 9. Variation in estimates of monthly NEP (three plots on the left) or its SD (three plots on the right) by inversion for regions A, C and D with three different prior estimates of SD [filled circles: $a = 0.5$; filled square: $a = 1$; filled triangles: $a = 2$; a is the ratio of the SD of the prior estimate and the SD as estimated by Wang and Barrett (2003) using CBM]. The prior estimates of mean monthly NEP for the three regions are also shown (open squares). All inversion results were calculated as the means for the same month for the period 1990–98.

provide significant information about the net carbon fluxes in all three regions.

5. Discussion

In this study we constrained the estimates of carbon fluxes from different parts of the Australian continent using in-situ measurements of CO_2 concentrations at Cape Grim. We have found that measurements of atmospheric CO_2 concentrations at Cape Grim can provide significant information about the terrestrial carbon fluxes in the central-south (region C), south-east (region D) and Tasmania (region A). This is the first study applying an atmospheric constraint to reduce the uncertainties of the monthly mean terrestrial carbon fluxes estimated by a process-based model for Australia. This approach has been advocated by several groups over the last few years (Schimel, 1995; Tans et al., 1996; Canadell et al., 2000).

We developed a consistent framework for applying multiple constraints at different spatial and temporal scales for estimating carbon fluxes from the Australian continent. CBM was used to provide lower boundary conditions (Wang and Leuning, 1998; Wang et al., 2001) in DARLAM and predictions of the energy and carbon fluxes (Wang et al., 2001; Wang and Barrett, 2003). The latter were also used as prior estimates in the Bayesian synthesis inversion.

Terrestrial ecosystem models have been used to synthesize our knowledge at process-level and to make predictions where direct measurements may not be available. Verification of the predictions of carbon fluxes at regional to global scales has been difficult. Measurements of atmospheric CO_2 concentrations were previously used to identify some deficiencies in global terrestrial ecosystem models (Heimann et al., 1998; Nemry et al., 1999). Most of the global studies have so far only used flask data that were collected monthly under baseline conditions. Biological processes, photosynthesis and respiration, controlling the carbon exchange between terrestrial biosphere and atmosphere, can vary from hour to hour, and the atmospheric signature of those two carbon exchange processes is much smeared in the measurements of monthly atmospheric concentrations. In-situ high frequency measurements of atmospheric surface CO_2 concentrations can provide significant constraints on the estimate of regional carbon fluxes, as demonstrated in our study. Recent studies using model-generated "data" have also demonstrated that significant new information about Australian regional continental carbon fluxes can be obtained using the high-frequency (e.g., daily) data of CO_2 concentration measurements in Australia (Law et al., 2002; 2003).

At present, there are about 30 sites around the world where surface CO_2 concentrations are being measured continuously. If in-situ measurements of hourly or subdiurnal CO_2 concentrations can be used in global atmospheric inversion, the number of observations will be increased by at least two orders of magnitude. Some of the difficulties in applying synthesis inversion to these high-frequency data are: (1) the atmospheric transport models used in the inversion must be capable of representing the synoptic variation of atmospheric mixing reasonably, and (2) the surface flux over a land surface will be much more variable in space and time; the prior estimates of spatial and temporal pattern of surface fluxes over a short-time scale in synthesis inversion are therefore difficult to determine without using a process-based terrestrial ecosystem model. Some progress has been made. For example, Kaminski et al. (2002) applied atmospheric inversion to the observed global atmospheric CO_2 concentrations and obtained estimates of two key parameters in the ecological model.

Continuous measurements are being made at 70 sites around the world on surface CO_2, water and energy fluxes (Running et al., 1999), and more measurements have been made by plant biologists and remote sensing scientists. All these measurements, focusing on different aspects of the terrestrial ecosystems, are made at different temporal and spatial scales, and have their own limitations (Baldocchi et al., 2000; Schimel et al., 2001). Only by collecting all this information into a unified framework can we gain a deeper understanding of the metabolism of the terrestrial ecosystem at regional or global scale, at which direct measurements of surface fluxes are still very limited or not yet available. The multiple-constraint approach can make use of measurements at a range of spatial or temporal scales through a process-based model, and lead to the discovery of deficiencies in our present understanding, such as the modelling of ecosystem respiration in CBM.

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