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## Precision requirements for space-based $X_{CO_2}$ data

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[1] Precision requirements are determined for space-based column-averaged CO<sub>2</sub> dry air mole fraction ( $X_{CO_2}$ ) data. These requirements result from an assessment of spatial and temporal gradients in  $X_{CO_2}$ , the relationship between  $X_{CO_2}$  precision and surface CO<sub>2</sub> flux uncertainties inferred from inversions of the  $X_{CO_2}$  data, and the effects of  $X_{CO_2}$  biases on the fidelity of CO<sub>2</sub> flux inversions. Observational system simulation experiments and synthesis inversion modeling demonstrate that the Orbiting Carbon Observatory mission design and sampling strategy provide the means to achieve these  $X_{CO_2}$  data precision requirements.

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### 1. Introduction

[2] Carbon dioxide (CO<sub>2</sub>) is a natural component of the Earth's atmosphere and a strong greenhouse forcing agent. Concentrations of atmospheric CO<sub>2</sub> fluctuated between 185 and 300 parts per million (ppm) over the last 500,000 years [*Intergovernmental Panel on Climate Change (IPCC)*, 2001]. However, since the dawn of the industrial era 150 years ago, human activity (fossil fuel combustion, land use change, etc.) has driven atmospheric CO<sub>2</sub> concentrations from 280 ppm to greater than 380 ppm. Such a dramatic short-term increase in atmospheric CO<sub>2</sub> is unprecedented in the recent geologic record, prompting Crutzen to label the current era as the Anthropocene [*Crutzen*, 2002]. Better carbon cycle monitoring capabilities and insight on the underlying dynamics controlling atmosphere exchange with the land and ocean reservoirs are needed as society begins to discuss active management of the global carbon system [*Dilling et al.*, 2003].

[3] Data from the existing network of surface in situ CO<sub>2</sub> measurement stations [*GLOBALVIEW-CO2*, 2005] indicate that the terrestrial biosphere and oceans have absorbed almost half of the anthropogenic CO<sub>2</sub> emitted during the past 40 years. The nature, geographic distribution, and temporal variability of these CO<sub>2</sub> sinks are not adequately understood, precluding accurate predictions of their responses to future climate change [*Friedlingstein et al.*, 2006; *Cox et al.*, 2000; *Fung et al.*, 2005]. Inverse modeling of the surface in situ CO<sub>2</sub> data [*GLOBALVIEW-CO2*, 2005] provide compelling evidence for a Northern Hemisphere terrestrial carbon sink, but the network is too sparse to quantify the distribution of the sink over the North American and Eurasian biospheres or to estimate fluxes over the Southern Ocean [*Gurney et al.*, 2002, 2003, 2004, 2005; *Law et al.*, 2003; *Baker et al.*, 2006a]. Existing models and measurements also have difficulty explaining why the

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atmospheric  $\text{CO}_2$  accumulation varies from 1 to 7 gigatons of carbon (GtC) per year in response to steadily increasing emission rates.

[4] Space-based remote sensing of atmospheric  $\text{CO}_2$  has the potential to deliver the data needed to resolve many of the uncertainties in the spatial and temporal variability of carbon sources and sinks. Several sensitivity studies have evaluated the improvement in carbon flux inversions that would be provided by precise, global space-based column  $\text{CO}_2$  data [Dufour and Breon, 2003; Houweling et al., 2004; Mao and Kawa, 2004; O'Brien and Rayner, 2002; Rayner et al., 2002; Rayner and O'Brien, 2001; Baker et al., 2006b]. The consensus of these studies is that satellite measurements yielding the column-averaged  $\text{CO}_2$  dry air mole fraction,  $X_{\text{CO}_2}$ , with bias-free precisions in the range of 1–10 ppm (0.3–3.0%) will reduce uncertainties in  $\text{CO}_2$  sources and sinks due to uniform and dense global sampling. As Houweling et al. [2004] demonstrated, the precision requirements for space-based  $X_{\text{CO}_2}$  data vary depending on the spatial and temporal resolution of the data and the spatiotemporal scale of the surface flux inversion. Clearly, the highest precision  $X_{\text{CO}_2}$  data (for example, 1 ppm or better) would best address the largest number of carbon cycle science questions. However, this requirement must be balanced against the significant technical challenges of delivering a satellite measurement/retrieval/validation system that can produce bias-free, sub-1% precision  $X_{\text{CO}_2}$  data. The space-based  $X_{\text{CO}_2}$  data must also be accurately calibrated to the WMO reference scale for atmospheric  $\text{CO}_2$  measurements so that they can be ingested simultaneously with suborbital data in synthesis inversion or data assimilation schemes without producing spurious fluxes.

[5] The Orbiting Carbon Observatory (OCO) was selected by NASA's Earth System Science Pathfinder (ESSP) program in July 2002 to deliver space-based  $X_{\text{CO}_2}$  data products with the precision, temporal and spatial resolution, and coverage needed to characterize the variability of  $\text{CO}_2$  sources and sinks on regional spatial scales and seasonal to interannual timescales [Crisp et al., 2004]. The mission is designed for a 2-year operational period with launch scheduled for 2008, the first year of the Kyoto Protocol commitment period. OCO will join the EOS Afternoon Constellation (A-Train), flying in a sun-synchronous polar orbit with a constant 1:26 p.m. local solar time (1326 LST) flyover, a 16-day (233 orbit) repeat cycle and near global sampling.

[6] The OCO science team analyzed a broad range of measurement and modeling data to define the science requirements for space-based  $X_{\text{CO}_2}$  data precision. The products of this investigation address two fundamental questions:

[7] 1. What precision does the OCO  $X_{\text{CO}_2}$  data product need to improve our understanding of  $\text{CO}_2$  surface fluxes (sources and sinks) significantly?

[8] 2. Does the measurement/retrieval/validation approach adopted in the OCO mission design provide the needed  $X_{\text{CO}_2}$  data precision?

[9] This paper analyzes atmospheric  $\text{CO}_2$  observations and modeling studies of  $\text{CO}_2$  sources and sinks to derive the science requirements for space-based  $X_{\text{CO}_2}$  data precision (question 1). Analyses of space-based and suborbital measurements, as well as the development and validation of retrieval algorithms demonstrating the potential of the OCO mission design to achieve the required  $X_{\text{CO}_2}$  precision (ques-

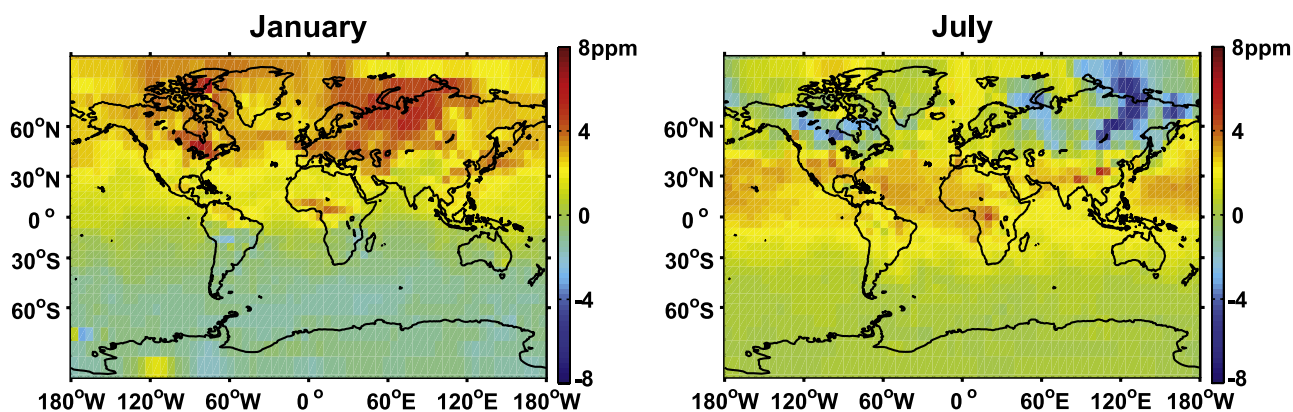
tion 2) are the subjects of recent [Kuang et al., 2002; Boesch et al., Space-based near-infrared  $\text{CO}_2$  retrievals: Testing the OCO retrieval and validation concept using SCIAMACHY measurements over Park Falls, Wisconsin, submitted to *Journal of Geophysical Research*, 2007, hereinafter referred to as Boesch et al., submitted manuscript, 2007; Washenfelder et al., Carbon dioxide column abundances at the Wisconsin tall tower site, submitted to *Journal of Geophysical Research*, 2007, herein referred to as Washenfelder et al., submitted manuscript, 2007] and ongoing studies.

## 2. $X_{\text{CO}_2}$ Precision Requirements

[10] Two community-wide undertakings define the current state of knowledge for the atmospheric  $\text{CO}_2$  budget: the GLOBALVIEW- $\text{CO}_2$  in situ measurement network [GLOBALVIEW- $\text{CO}_2$ , 2005] and the TransCom 3 transport/flux estimation experiment [Gurney et al., 2002, 2003, 2004, 2005; Law et al., 2003; Baker et al., 2006a]. The GLOBALVIEW- $\text{CO}_2$  network's emphasis on acquiring accurate measurements through rigorous experimental methods, constant calibration using procedures and materials traceable to WMO standards, and continual vigilance against biases has created the recognized reference standard data set for atmospheric  $\text{CO}_2$  observations. The network collects surface in situ  $\text{CO}_2$  measurements at approximately 120 stations worldwide, spanning latitudes from the South Pole to 82.4°N (Alert, Canada). Typical measurement uncertainties are on the order of 0.1 ppm (0.03%).

[11] The TransCom 3 project reported estimates of carbon sources and sinks from variations in the GLOBALVIEW- $\text{CO}_2$  data via inverse modeling with multiple atmospheric transport models. This assessment confirmed that carbon fluxes integrated over latitudinal zones are strongly constrained by observations in the middle to high latitudes. Flux uncertainties were also constrained by inadequacies in the transport models and the lack of observations in tropical forests. The latter result is not surprising since the GLOBALVIEW- $\text{CO}_2$  network strategy was originally designed specifically to avoid measurement contamination from air locally influenced by large  $\text{CO}_2$  sources or sinks. The inversions also exhibited significant uncertainties when trying to distinguish meridional contributions to the fluxes.

[12] Rayner and O'Brien [2001] showed that space-based  $X_{\text{CO}_2}$  data could dramatically improve our understanding of  $\text{CO}_2$  sources and sinks if these measurements provided adequate precision and spatial coverage. This study used a synthesis inversion model to estimate the surface-atmosphere  $\text{CO}_2$  flux uncertainties in 26 continent/ocean basin scale regions. The baseline was established by using measurements from 56 stations in the ground-based GLOBALVIEW- $\text{CO}_2$  network. The results were compared to simulations that used spatially resolved, global  $X_{\text{CO}_2}$  data. Rayner and O'Brien found that global, space-based  $X_{\text{CO}_2}$  data with 2.5-ppm precisions (and no biases) on  $8^\circ \times 10^\circ$  scales would be needed to match the performance of the existing ground based network at monthly or annual timescales. Space-based  $X_{\text{CO}_2}$  data with 1-ppm precisions were predicted to reduce inferred  $\text{CO}_2$  flux uncertainties of annual mean fluxes from greater than 1.2 GtC region<sup>-1</sup> year<sup>-1</sup> to less than 0.5 GtC region<sup>-1</sup> year<sup>-1</sup> when averaged over the annual cycle. Additionally,



**Figure 1.** Modeled column-averaged  $\text{CO}_2$  dry air mole fraction ( $X_{\text{CO}_2}$ ) simulated for the year 2000 using the CASA/MATCH model [Olsen and Randerson, 2004]. Values for 1300 LST on 15 January and 15 July are plotted relative to the annual average  $X_{\text{CO}_2}$  south of  $60^\circ\text{S}$ .

the uncertainties in all regions were more uniform for inversions using the space-based  $X_{\text{CO}_2}$  data.

[13] While these simulations clearly illustrate the advantages of precise space-based  $X_{\text{CO}_2}$  data, they do not explicitly quantify the data precision required for OCO because they do not simulate the spatial and temporal sampling strategy proposed for the OCO mission nor do they adequately characterize the sensitivity of source-sink inversions to  $X_{\text{CO}_2}$  data precision. To address these concerns, we combined simulated atmospheric  $\text{CO}_2$  data and transport models to estimate  $X_{\text{CO}_2}$  spatial gradients as well as global and regional scale  $X_{\text{CO}_2}$  variability. A series of observational system simulation experiments (OSSEs) sampled the synthetic  $\text{CO}_2$  fields using strategies simulating the GLOBALVIEW- $\text{CO}_2$  surface network [GLOBALVIEW- $\text{CO}_2$ , 2005] as well as the OCO satellite. Inverse modeling of these data characterized the relationship between the inferred surface flux uncertainties and uncertainties in the space-based  $X_{\text{CO}_2}$  data. We also investigated the use of inversions to detect bias in the  $X_{\text{CO}_2}$  data and what level of sensitivity such analyses would provide.

## 2.1. $X_{\text{CO}_2}$ Spatial and Temporal Gradients

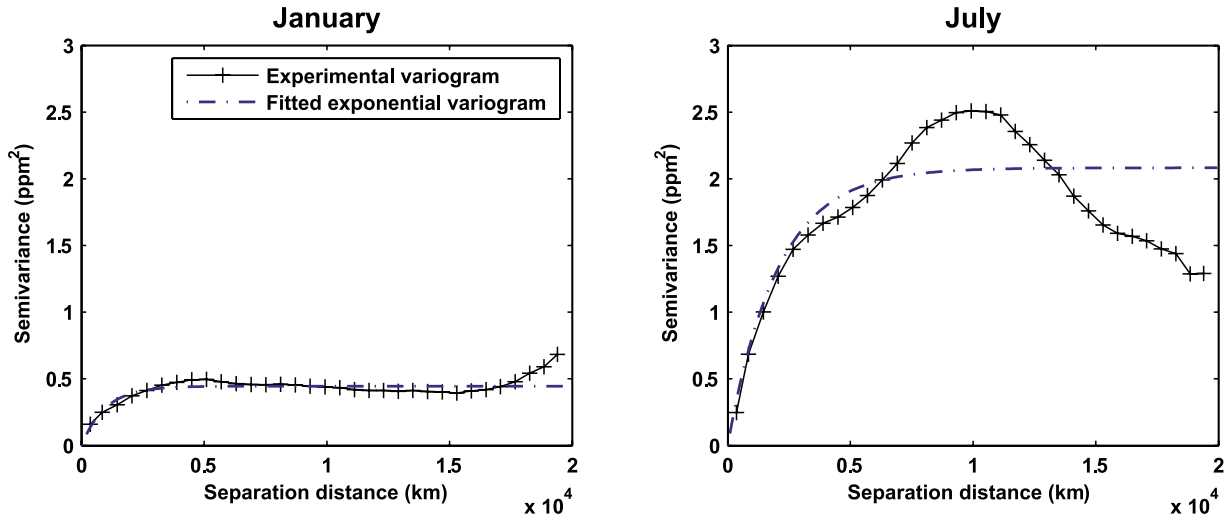
[14] Distributions of atmospheric  $\text{CO}_2$  were simulated with the Model of Atmospheric Transport and Chemistry (MATCH) three-dimensional atmospheric transport model [Olsen and Randerson, 2004]. MATCH represents advective transport using a combination of horizontal and vertical winds and has parameterizations of wet and dry convection and boundary layer turbulent mixing [Rasch et al., 1994]. MATCH operates off-line using archived meteorological fields which for this study were derived from the NCAR Community Climate Model version 3 with T21 horizontal resolution (approximately  $5.5^\circ \times 5.5^\circ$ ) and 26 vertical levels from the surface up to 0.2 hPa (about 60 km) on hybrid sigma pressure levels. The top of the first model level is approximately 110 m. The meteorological fields represent a climatologically “average” year rather than any specific year. This meteorological data was archived every 3 model hours and was interpolated to the 30-min MATCH time step. In this configuration MATCH has an interhemispheric transport time of approximately 0.74 years, about in the middle of the 0.55 to 1.05 year range of the models that participated in the TransCom 2 experiment [Denning et al.,

1999]. A single year of dynamical inputs was recycled for the multiyear runs used in this study.

[15] Constraints on  $\text{CO}_2$  sources and sinks incorporated fossil fuel emissions as estimated by Andres et al. [1996], atmosphere-oceanic exchange as estimated from sea-surface  $\text{pCO}_2$  measurement by Takahashi et al. [2002], and biospheric fluxes modeled using the Carnegie-Ames-Stanford Approach (CASA) model [Randerson et al., 1997], including a diurnal cycle of photosynthesis and respiration. Simulated  $X_{\text{CO}_2}$  data were obtained from the model output by integrating vertically according to the OCO averaging kernel at the T21 horizontal resolution. In these simulations terrestrial ecosystem exchange was annually balanced; in other words, we omitted a “missing” carbon sink necessary to balance fossil carbon sources with the atmospheric  $\text{CO}_2$  growth rate [Gurney et al., 2002; Tans et al., 1990].

[16] The 15th of each month was taken as a sample representative day for each month. Data were extracted for 1300 local time globally, as a preliminary approximation of  $X_{\text{CO}_2}$  as would be observed by OCO. The resulting data are presented for January and July 2000 in Figure 1. These data differ slightly from the monthly mean  $X_{\text{CO}_2}$  maps presented in Figure 9 of Olsen and Randerson [2004], capturing more of the instantaneous  $X_{\text{CO}_2}$  seasonal variability. All model values are reported relative to the annual mean surface mixing ratio south of  $60^\circ$  south. Figure 1 shows that the Northern Hemisphere  $X_{\text{CO}_2}$  variability is typically about 6 ppm. This is only 50% of the amplitude of the seasonal cycle in the near-surface concentrations of  $\text{CO}_2$  [see Olsen and Randerson 2004; Figure 5]. Somewhat larger high frequency variations, associated with passing weather systems and strong source regions, are also common. The monthly peak-to-peak amplitude of Southern Hemisphere  $X_{\text{CO}_2}$  is typically 2–3 ppm while the annual peak-to-peak amplitude varies from 6–7 ppm over tropical forests to less than 3 ppm over the Southern Ocean.

[17] These results indicate that space-based  $X_{\text{CO}_2}$  data with precisions better than 2 ppm are needed to resolve the peak-to-peak amplitudes in monthly and annual  $X_{\text{CO}_2}$ . This precision is also sufficient to resolve regional scale meridional variations over the Northern Hemisphere boreal forests or the Southern Ocean. The OCO sampling strategy (section 4) is specifically designed to return space-based



**Figure 2.** Global experimental and fitted theoretical variograms for CASA/MATCH modeled column-averaged  $\text{CO}_2$  dry air mole fraction ( $X_{\text{CO}_2}$ ) presented in Figure 1 (1300 LST for 15 January and 15 July 2000).

measurements with the high sensitivity and dense sampling in space and time required to attain this precision even when cloud and aerosol interference prevents observations of the complete atmospheric column in the majority of the observed scenes.

## 2.2. Global and Regional $X_{\text{CO}_2}$ Variability

[18] Global  $X_{\text{CO}_2}$  spatial variability was quantified by analyzing the CASA/MATCH  $X_{\text{CO}_2}$  data calculated for 2000. Raw and experimental variograms were calculated to quantify the global variability of  $X_{\text{CO}_2}$ . The raw variogram is defined for any two measurements as [Cressie, 1991]

$$\gamma(h) = \frac{1}{2} (z(x) - z(x'))^2 \quad (1)$$

where  $\gamma(h)$  is the raw variogram,  $z(x)$  is a measurement value at location  $x$ ,  $z(x')$  is a measurement value at location  $x'$ , and  $h$  is the separation distance between  $x$  and  $x'$ . The distance was calculated using the great circle distance between points on the surface of the earth [e.g., Michalak et al., 2004]:

$$h(\mathbf{x}_i, \mathbf{x}_j) = r \cos^{-1} (\sin \phi_i \sin \phi_j + \cos \phi_i \cos \phi_j \cos(\vartheta_i - \vartheta_j)) \quad (2)$$

where the coordinates  $\mathbf{x}_i = (\phi_i, \vartheta_i)$  are the latitude and longitude, respectively, of the sample locations, and  $r$  is the mean radius of the earth. The raw variogram values are averaged for different ranges of separation distance to obtain the experimental variogram. Because the variogram is designed to represent the portion of the  $X_{\text{CO}_2}$  distribution that cannot be represented by a deterministic trend, the consistent North-South  $X_{\text{CO}_2}$  gradient was accounted for by detrending the data with respect to latitude, using the simulated latitudinal gradient for 1300 LST each month. In this way, the variograms represent the stochastic, spatially

correlated, portion of the  $X_{\text{CO}_2}$  distribution, which is the portion that will need to be estimated to obtain a continuous  $X_{\text{CO}_2}$  distribution based on the point measurements taken by OCO. The resulting variograms are presented in Figure 2.

[19] The experimental variogram for each month was fitted using an exponential theoretical variogram model [Cressie, 1991; Michalak et al., 2004]

$$\gamma(h) = \sigma^2 \left( 1 - \exp\left(-\frac{h}{L}\right) \right) \quad (3)$$

where  $\sigma^2$  is the semivariance and  $L$  is the length parameter. The theoretical variogram describes the decay in spatial correlation between pairs of  $X_{\text{CO}_2}$  measurements as a function of physical separation distance between these samples. The overall variance at large separation distances is  $2\sigma^2$  and the practical correlation range is approximately  $3L$ . The  $\sigma^2$  and  $L$  parameters were estimated using a least squares fit to the raw variogram. The fitted variograms are presented in Figure 2, and the global variance and correlation range for each month are summarized in Table 1. The correlation length represents the distance at which the expected covariance between  $z(x)$  and  $z(x')$  approaches zero, and the measurement  $z(x')$  no longer provides useful information about the  $X_{\text{CO}_2}$  value  $z(x)$ . The variance indicates the maximum uncertainty at unsampled locations, in the absence of nearby measurements, assuming the overall mean or trend is known.

[20] This analysis shows that the CASA/MATCH  $X_{\text{CO}_2}$  field exhibits significant spatial correlation and that the degree of spatial correlation varies throughout the year. The variance is higher during the Northern Hemisphere summer and lower in winter. The seasonality of the global correlation length is less pronounced, but follows a similar pattern to that of the variance. These two factors have opposite effects on the required sampling intensity (i.e., a higher variance leads to a larger number of required sampling locations whereas a longer correlation length reduces the number of required

**Table 1.** Global  $X_{\text{CO}_2}$  Variability at 1:00 PM Local Time for a Representative Day in Each Month of the Year 2000 From CASA/MATCH Model Runs

Month	Correlation Length ( $3L$ ), km	Variance ( $2\sigma^2$ ), ppm <sup>2</sup>
January	2900	0.89
February	5100	1.08
March	5400	1.16
April	4900	1.45
May	5500	1.06
June	4300	1.24
July	6100	4.16
August	8300	3.71
September	7500	2.06
October	2800	1.08
November	700	0.98
December	2700	0.67
Annual Mean	4700	1.63

samples). Overall, because of the stronger seasonality of the variance of the  $X_{\text{CO}_2}$  distribution, it is expected that a larger fraction of samples will need to be processed in summer months in order to achieve a specified level of uncertainty in the interpolated  $X_{\text{CO}_2}$  field.

[21] On the basis of this global analysis, an average sampling interval of approximately 1500 km will be required globally to achieve an interpolated  $X_{\text{CO}_2}$  uncertainty with a standard deviation below 1 ppm. This represents the average sampling interval over the entire year, although individual months will require either sparser or denser measurements depending on the statistical characteristics of the  $X_{\text{CO}_2}$  variability in each month. This estimate is based on:

$$h_0 = -L \ln\left(1 - \frac{V_{\max}}{2\sigma^2}\right) \quad (4)$$

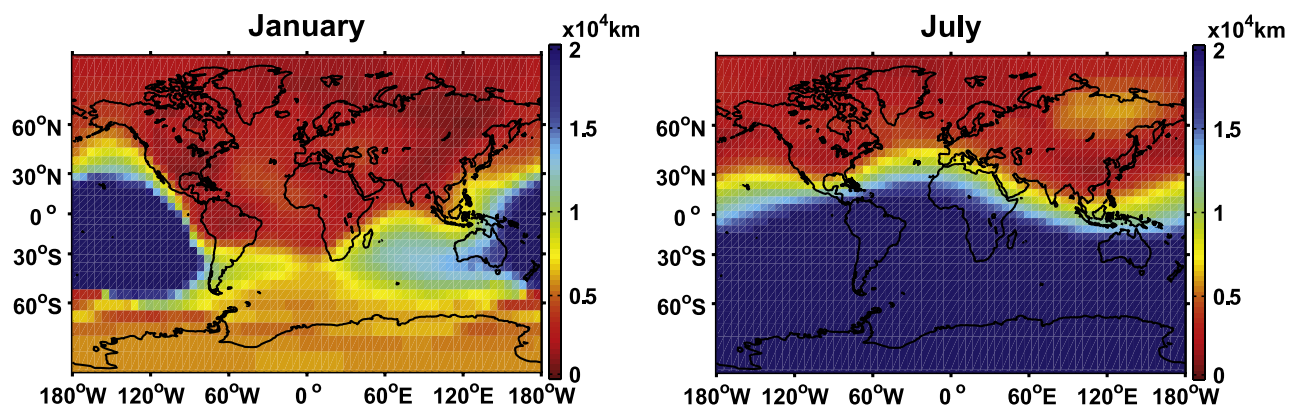
where  $L$  and  $\sigma^2$  are taken from the theoretical variogram and  $V_{\max}$  is the maximum allowable uncertainty, expressed as a variance. In the above calculation, we used the annual mean parameters and  $V_{\max} = 1 \text{ ppm}^2$ . Note that this analysis assumes that either (1) the value sampled by OCO is representative of the average  $X_{\text{CO}_2}$  on the scale modeled by CASA/MATCH, or that (2) the covariance structure as estimated at the CASA/MATCH model grid scale is valid at the smaller OCO measurement scale. In reality, OCO will

measure at a significantly smaller scale than the CASA/MATCH model resolution, and data at smaller scales tend to exhibit more variability relative to measurements that represent averages at larger scales. For these reasons, we expect the sampling interval required to achieve a maximum  $V_{\max} = 1 \text{ ppm}^2$  uncertainty in the interpolated  $X_{\text{CO}_2}$  product to be smaller for the OCO sampling scale relative to the CASA/MATCH data. Note also that we have not considered measurement errors in this calculation, which would again increase the amount of sampling required to constrain the interpolated error to a given uncertainty threshold.

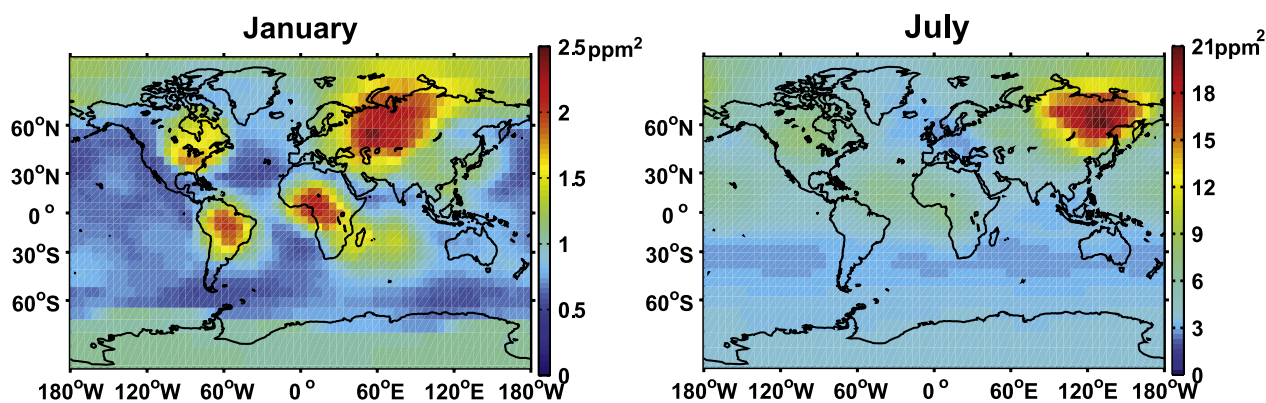
[22] To assess the regional variability of  $X_{\text{CO}_2}$ , a separate variogram was constructed for each grid cell of the  $5.5^\circ \times 5.5^\circ$  model output (2048 cells globally), centered at that grid cell. In calculating the raw variogram for each grid cell, only pairs of data points with at least one member within a 2000-km radius of the grid cell were considered. Therefore the raw variogram consisted of data pairs where either (1) both measurements were within 2000 km of the central grid cell, or (2) one measurement was within 2000 km of the central grid cell and the other was not. In essence, this approach quantifies the variability between measurements in the vicinity of a grid cell and the global distribution.

[23] The regional-scale raw variograms were fitted using weighted least squares and an exponential variogram, giving greater weight to pairs of points at shorter separation distances and constraining the correlation length to less than 20,000 km. The resulting correlation lengths and variances of the fitted theoretical variograms are presented in Figures 3 and 4, respectively. These global maps of parameters describe the regional correlation structure of the CASA/MATCH  $X_{\text{CO}_2}$ . The correlation structure exhibits temporal variability, as was seen in Figure 2, as well as strong spatial variability. This can be observed both in the variance and correlation lengths of the  $X_{\text{CO}_2}$  distributions. For example,  $X_{\text{CO}_2}$  in the Northern Hemisphere is correlated over shorter distances than the global average (Figure 3). The variability exhibited by the  $X_{\text{CO}_2}$  distribution is caused both by the scales and degree of variability of the underlying fluxes, as well as the variability induced by atmospheric transport.

[24] The results of the regional  $X_{\text{CO}_2}$  variability analysis are qualitatively consistent with the results of *Lin et al.* [2004], who also found longer correlation lengths over the Pacific



**Figure 3.** Locally estimated correlation lengths for CASA/MATCH modeled column-averaged  $\text{CO}_2$  dry air mole fraction ( $X_{\text{CO}_2}$ ) presented in Figure 1 (1300 LST for 15 January and 15 July 2000). In general, more  $X_{\text{CO}_2}$  retrievals will be required to characterize regions with shorter (red) correlation lengths.



**Figure 4.** Locally estimated variance for CASA/MATCH modeled column-averaged  $\text{CO}_2$  dry air mole fraction ( $X_{\text{CO}_2}$ ) presented in Figure 1 (1300 LST for 15 January and 15 July 2000). In general, more  $X_{\text{CO}_2}$  retrievals will be required to characterize regions with larger (red) variances.

relative to continental North America in their analysis of aircraft-derived partial- $X_{\text{CO}_2}$  fields. A quantitative comparison is difficult to establish because *Lin et al.* [2004] used a nonstationary power variogram to represent  $\text{CO}_2$  variability. Such a variogram does not have a finite maximum variance (i.e., sill) or correlation length to compare to those presented in Figures 3 and 4. One quantitative comparison that can be made is a calculation of the separation distance at which the expected difference in  $X_{\text{CO}_2}$  at two sampling locations is expected to reach a specified variance. Based on the variogram used in *Lin et al.* [2004], the separation distance at which the squared difference between vertically integrated  $\text{CO}_2$  concentrations ( $<9$  km) is expected to reach  $1 \text{ ppm}^2$  is 57 km over the North American continent in June 2003, and 727 km over the Pacific Ocean. Data over the Pacific Ocean were a composite of multiple years of springtime (February to April) and fall (August to October) data. For the CASA/MATCH data, the separation distance is 460 km over the North American continent for June 2000, and 13,600 km (March 2000) and 5200 km (September 2000) over the Pacific Ocean. The two sets of results are consistent in showing greater spatial variability over the continental regions, but *Lin et al.* [2004] shows more overall variability at smaller scales. The higher variability inferred by *Lin et al.* [2004] is most likely largely due to the scale at which the aircraft measurements were taken relative to the scale of the CASA/MATCH modeled data, and the limited vertical extent of the aircraft profiles. As was previously discussed, data at finer scales typically exhibit more variability relative to coarser data. This will need to be considered further in interpreting global model data in the context of fine scale OCO measurements. Regional scale  $X_{\text{CO}_2}$  variability will also be driven by local conditions and meteorology [*Nicholls et al.*, 2004]. Spatial and temporal heterogeneity of the  $X_{\text{CO}_2}$  covariance structure must therefore be taken into account in the design of a sampling strategy and retrievals.

### 3. $\text{CO}_2$ Fluxes from $X_{\text{CO}_2}$ Inversions

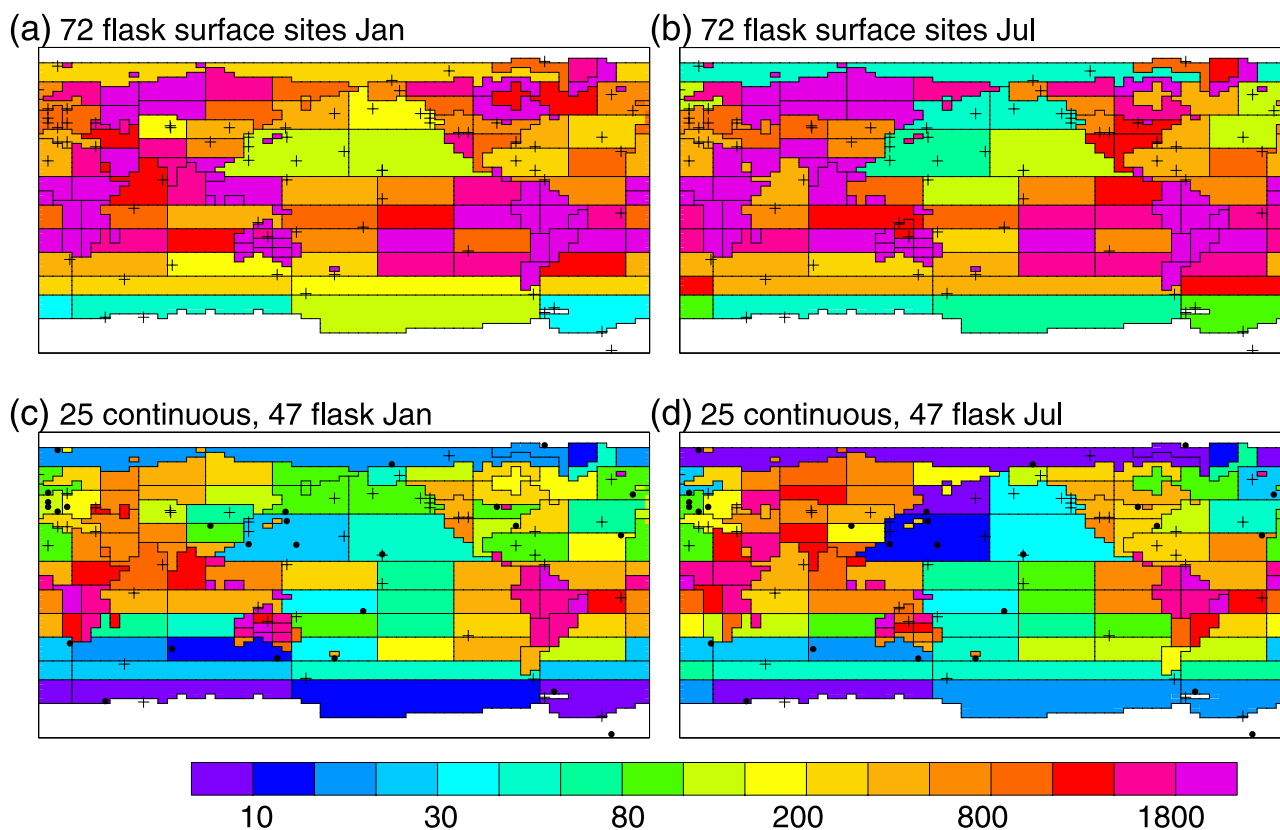
#### 3.1. Relationship Between OCO $X_{\text{CO}_2}$ Precision and Surface $\text{CO}_2$ Flux Uncertainties

[25] The synthesis inversion methods of *Rayner and O'Brien* [*O'Brien and Rayner*, 2002; *Rayner et al.*, 2002;

*Rayner and O'Brien*, 2001] were used to evaluate the impact of particular OCO mission design choices and the resultant regional scale  $X_{\text{CO}_2}$  data precisions on the surface  $\text{CO}_2$  flux uncertainties. That study used a higher resolution than *Rayner and O'Brien* [2001] (116 source regions versus 26) and used an orbit simulator to sample the model in accordance with satellite orbit and viewing geometry. This is more stringent than the uniform monthly mean sampling assumed by *Rayner and O'Brien* [2001]. The new study still retrieves monthly mean fluxes. We note that *Chevallier et al.* (*Chevallier et al.*, The contribution of the Orbiting Carbon Observatory to the estimation of  $\text{CO}_2$  sources and sinks: Theoretical study in a variational data assimilation framework, submitted to *Journal of Geophysical Research*, 2007, hereinafter referred to as *Chevallier et al.*, submitted manuscript, 2007) has increased both spatial and temporal resolution of the retrieved sources and still shows considerable potential for OCO measurements.

[26] *Rayner et al.* [2002] also studied the ability to retrieve actual fluxes from a set of synthetic or pseudodata sampled to mimic various in situ or remotely sensed products. They used fluxes representing fossil fuel combustion, the ocean air-sea gas exchange and the seasonal flux from the terrestrial biosphere. We follow that setup here.

[27] Following *Rayner and O'Brien* [2001], a baseline for comparisons with the simulated space-based  $X_{\text{CO}_2}$  data was established by performing synthesis inversion experiments to estimate the  $\text{CO}_2$  flux uncertainties for the GLOBALVIEW- $\text{CO}_2$  surface  $\text{CO}_2$  monitoring network over the seasonal cycle. These flux errors are expressed in grams of carbon per square meter per year, ( $\text{gC m}^{-2} \text{ yr}^{-1}$ ). The prior uncertainty for all regions was assumed to be  $2000 \text{ gC m}^{-2} \text{ yr}^{-1}$  for monthly fluxes. This is a very weak prior estimate so as not to artificially inflate the performance of the inversion system. Monthly mean  $\text{CO}_2$  flask data were simulated with an uncertainty that assumed that the monthly mean had been constructed from four samples (i.e., one per week) from each of the 72 surface stations. Results are shown for January (Jan) and July (Jul) in Figures 5a–5b. For this baseline case most regions have flux uncertainties in excess of  $1000 \text{ gC m}^{-2} \text{ yr}^{-1}$  with uncertainties greater than  $1500 \text{ gC m}^{-2} \text{ yr}^{-1}$  typical for most land regions.



**Figure 5.** (a and b) Surface CO<sub>2</sub> flux uncertainties ( $\text{gC m}^{-2} \text{yr}^{-1}$ ) for (a) January and (b) July from the baseline synthesis inversion case where the simulated CO<sub>2</sub> data are obtained from a surface network similar to the current network, which provides highly precise CO<sub>2</sub> pseudodata from 72 flask sites at weekly intervals. Small uncertainties are shaded in blue, large uncertainties in red/pink. Note that the scale is nonlinear. The flux uncertainties over the continents have not improved significantly over the a priori uncertainty of  $2000 \text{ gC m}^{-2} \text{yr}^{-1}$ . (c and d) CO<sub>2</sub> flux uncertainties for a simulated surface network that uses continuous surface pseudodata from 25 sites plus weekly flask pseudodata from the remaining 47 sites. See text for details.

[28] Figures 5c–5d show the flux uncertainties inferred by inverting a simulated network containing 25 continuous CO<sub>2</sub> monitoring sites plus 47 sites reporting weekly CO<sub>2</sub> flask measurements. The continuous monitoring sites were located based on current in situ measurements. Continuous surface measurements produce their greatest benefits in the vicinity of measurement stations that are located well away from strong sources and sinks. Even with the addition of the continuous CO<sub>2</sub> measurements, flux uncertainties remain greater than  $1000 \text{ gC m}^{-2} \text{yr}^{-1}$  in most continental regions near strong surface fluxes because of the limited spatial coverage offered by the continuous monitoring stations. The largest uncertainties are seen in South America, central Africa, and southern Asia.

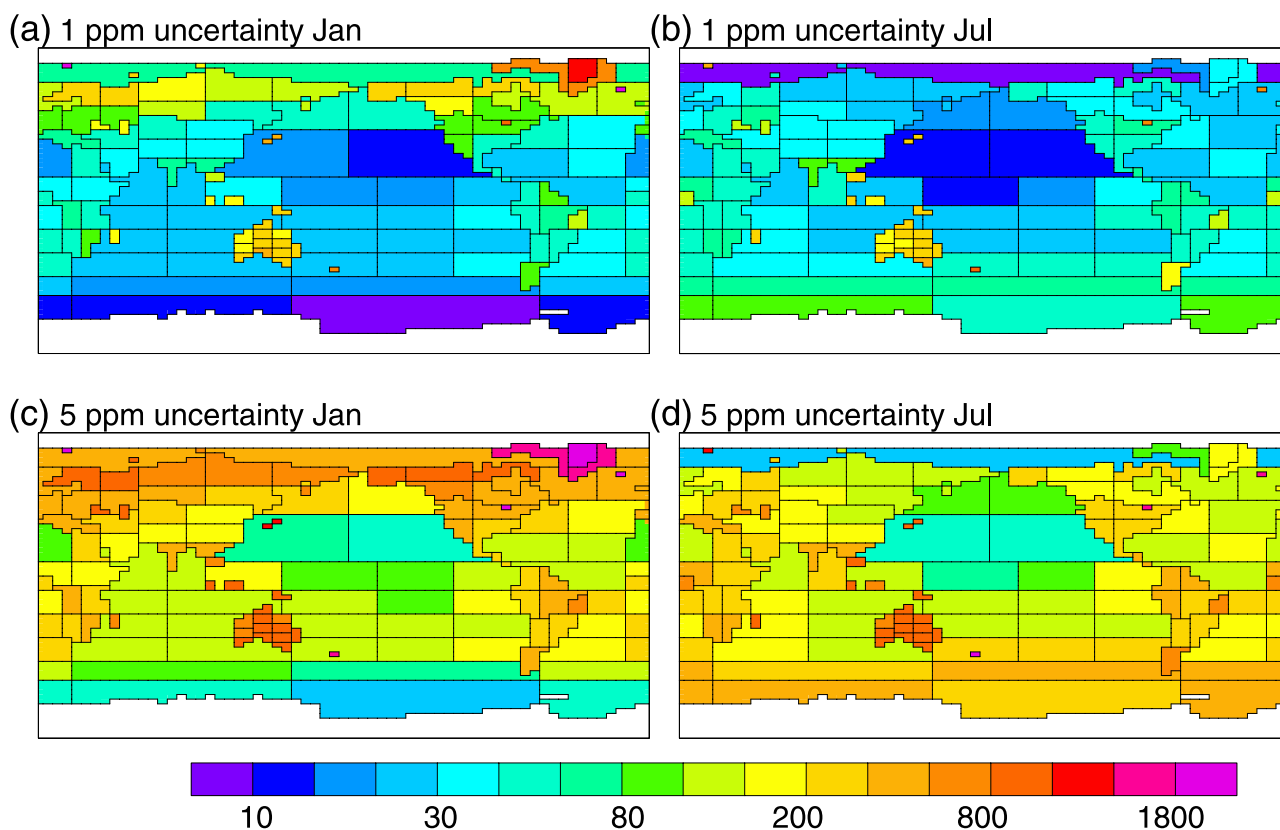
[29] Figure 6 shows January (Jan) and July (Jul) CO<sub>2</sub> flux uncertainties from synthesis inversion simulations assuming  $X_{\text{CO}_2}$  data sampled along the OCO orbit track with 1 ppm (0.3%, Figures 6a–6b) and 5 ppm (1.5%, Figures 6c–6d) precisions for monthly averages on  $4^\circ$  latitude  $\times$   $5^\circ$  longitude scales. For well-constrained regions in which the prior estimate has little impact, the flux uncertainty is proportional to the data uncertainty. The relationship breaks down for small regions (such as the subdivision of Australia in Figures 5 and 6) and at high latitudes where the measure-

ment frequency is lower. Such problems can be reduced by calculating fluxes over larger spatial scales after performing the inversion.

[30] The Northern Hemisphere terrestrial carbon sink is thought to absorb about  $1 \text{ GtC yr}^{-1}$  from the atmosphere [Gurney *et al.*, 2002]. The results presented in Figure 6 indicate that space-based  $X_{\text{CO}_2}$  data with monthly averaged precision of 1–2 ppm (0.3 to 0.5%) will yield flux uncertainties no greater than  $\sim 100 \text{ gC m}^{-2} \text{yr}^{-1}$  or  $0.1 \text{ GtC (10}^6 \text{ km}^2)^{-1} \text{yr}^{-1}$  (with the exception of Greenland). Inversions using such space-based  $X_{\text{CO}_2}$  data should be able to detect the  $1 \text{ GtC yr}^{-1}$  carbon sink if it is confined to an area or areas smaller than a few  $1000 \times 1000 \text{ km}$  regions, for example, Northeastern North America. We anticipate even greater sensitivity to detecting such a sink if space-based  $X_{\text{CO}_2}$  and in situ surface CO<sub>2</sub> data are combined in the inversion.

[31] Comparisons of the flux uncertainties inferred from the 5-ppm precision  $X_{\text{CO}_2}$  data (Figures 6c–6d) with results from the baseline inversion (Figures 5a–5b) show that, even at this degraded precision, the satellite data still provide a better constraint on surface fluxes for most regions. Augmenting the surface network with continuous monitoring stations (Figures 5c–5d) improves the surface flux constraints for





**Figure 6.** Surface  $\text{CO}_2$  flux uncertainties ( $\text{gC m}^{-2} \text{yr}^{-1}$ ) for January and July from simulations that used satellite pseudodata of  $X_{\text{CO}_2}$  with precision of (a and b) 1 ppm and (c and d) 5 ppm. Compare to Figure 5.

regions around one of these continuous monitoring sites, but still provides inadequate constraints in other regions, particularly tropical forests. Because of uniform spatial sampling over land and ocean and sheer data volume, space-based  $X_{\text{CO}_2}$  data will make a substantial impact on reducing continental scale flux uncertainties even at 5-ppm precision.

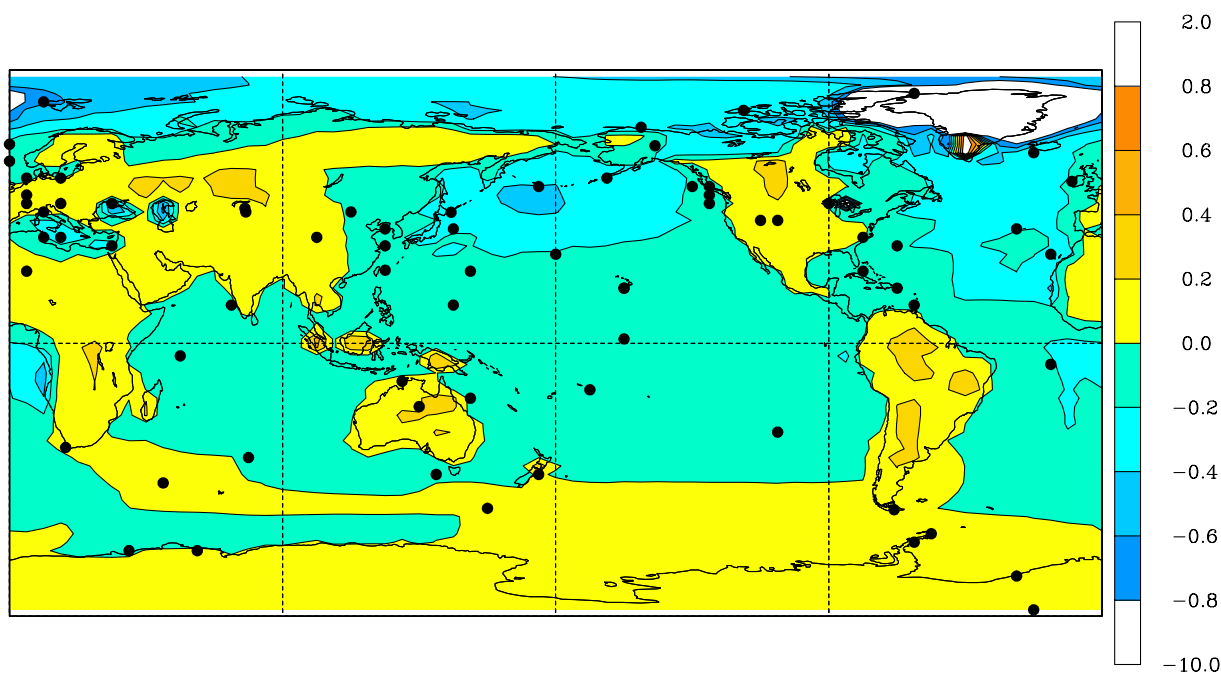
### 3.2. Effects of Systematic $X_{\text{CO}_2}$ Bias on $\text{CO}_2$ Flux Inversions

[32] The precision requirements space-based  $X_{\text{CO}_2}$  data presented in section 2 assumed random errors with no significant spatially or temporally coherent biases. This section addresses the potential impact of systematic biases in the space-based  $X_{\text{CO}_2}$  data on inferred  $\text{CO}_2$  flux uncertainties. Systematic biases might result from such measurement considerations as signal-to-noise ratio, viewing geometry, whether the observations were made over land or ocean, spatial variations in clouds or aerosols, topographic variations, diurnal effects on the vertical  $\text{CO}_2$  profile, etc. The effects of such biases on flux uncertainties depend on their spatial and temporal scale since  $\text{CO}_2$  sources and sinks are inferred from  $X_{\text{CO}_2}$  gradients. Constant global biases do not compromise  $X_{\text{CO}_2}$ -only flux inversions because they introduce no spurious gradients in the  $X_{\text{CO}_2}$  fields that could be misinterpreted as sources or sinks. However, a constant bias in space-based  $X_{\text{CO}_2}$  data would complicate inversions or assimilations that also included suborbital data or data from other satellite platforms. Biases occurring on spatial scales smaller than  $\sim 30$  km are not a major concern because they will be indistinguishable from random noise contributions

like scene-dependent  $X_{\text{CO}_2}$  variability. Coherent biases on 100–5000 km horizontal scales pose the greatest threat to the integrity of space-based  $X_{\text{CO}_2}$  data and must be corrected below detectable levels. Temporal biases occurring on seasonal time-scales will also complicate  $\text{CO}_2$  flux inversion and assimilation studies.

[33] Different biases were considered to define requirements for the OCO calibration and validation programs. For example, CASA/MATCH simulations indicate that a  $1 \text{ GtC yr}^{-1}$  Northern Hemisphere carbon sink superimposed on a background emissions source of  $6 \text{ GtC yr}^{-1}$  coming from the northern hemisphere would create an additional  $0.4 \text{ ppm } X_{\text{CO}_2}$  gradient between  $45^\circ\text{N}$  and  $45^\circ\text{S}$  (i.e., it would contribute about 1/6 of the  $X_{\text{CO}_2}$  gradient shown in Figure 1). If the space-based  $X_{\text{CO}_2}$  data were systematically biased by  $+0.2 \text{ ppm}$  in the Northern Hemisphere and  $-0.2 \text{ ppm}$  in the Southern Hemisphere, inversion modeling would fail to detect the sink. If they were systematically biased by  $-0.2 \text{ ppm}$  in the Northern Hemisphere and  $+0.2 \text{ ppm}$  in the Southern Hemisphere, inversion modeling would infer a Northern Hemisphere sink of  $2 \text{ GtC yr}^{-1}$  rather than  $1 \text{ GtC yr}^{-1}$ . In either of these hypothetical cases, the large discrepancy between the inferred fluxes and prior estimates would signal potential problems.

[34] The model described in section 3.1 was used to assess the impact of a small, spatially coherent land-ocean  $X_{\text{CO}_2}$  bias on surface flux inversions, and to determine whether such a bias could be detected. We performed two separate forward simulations. The control case was derived assuming a 1400 LST orbit while test case used  $X_{\text{CO}_2}$  data



**Figure 7.** Surface  $\text{CO}_2$  concentration annual mean differences (ppm) associated with a +0.1 ppm bias in the  $X_{\text{CO}_2}$  observations acquired over land. The locations of the surface  $\text{CO}_2$  monitoring network stations are shown as black circles.

biased by +0.1 ppm over land. The two resulting flux fields were input to the CRC-MATCH transport models and subsampled at 4-hour intervals at 72 stations. The (bias–control) near-surface  $\text{CO}_2$  concentration differences for the annual mean are shown in Figure 7. One might expect  $X_{\text{CO}_2}$  biases to reflect much larger errors near the surface, since spatial variations in  $\text{CO}_2$  (and many sources of bias) are largest there. In this test, the near-surface  $\text{CO}_2$  concentration differences are generally less than  $\pm 0.2$  ppm. However, the results are spatially coherent with positive differences inferred over land and negative differences inferred over the oceans. Thus, the comparison of surface  $\text{CO}_2$  concentration data and  $X_{\text{CO}_2}$  data flux inversions clearly reveals a land-ocean bias in the  $X_{\text{CO}_2}$  retrievals, even when the bias is only 0.1 ppm.

[35] We corrected the artificially biased  $X_{\text{CO}_2}$  retrievals by inverting the time series of (bias–control) differences simulated at each of the 72 surface sites with a 4-hour sampling frequency. The fluxes produced from this inversion were added to the fluxes from the test (biased) inversion. Figure 8 depicts the difference between these corrected fluxes and the original flux estimates from the unbiased  $X_{\text{CO}_2}$  data. Most regions show differences smaller than  $\pm 10 \text{ gC m}^{-2} \text{ yr}^{-1}$ . More importantly, the differences are no longer spatially coherent. Larger differences occur for land regions in the tropics where the surface network (black circles shown in Figure 7) is sparse. The annual mean land-ocean partition is corrected by the inversion of the surface data (shifting  $1.6 \text{ GtC yr}^{-1}$  from land to ocean).

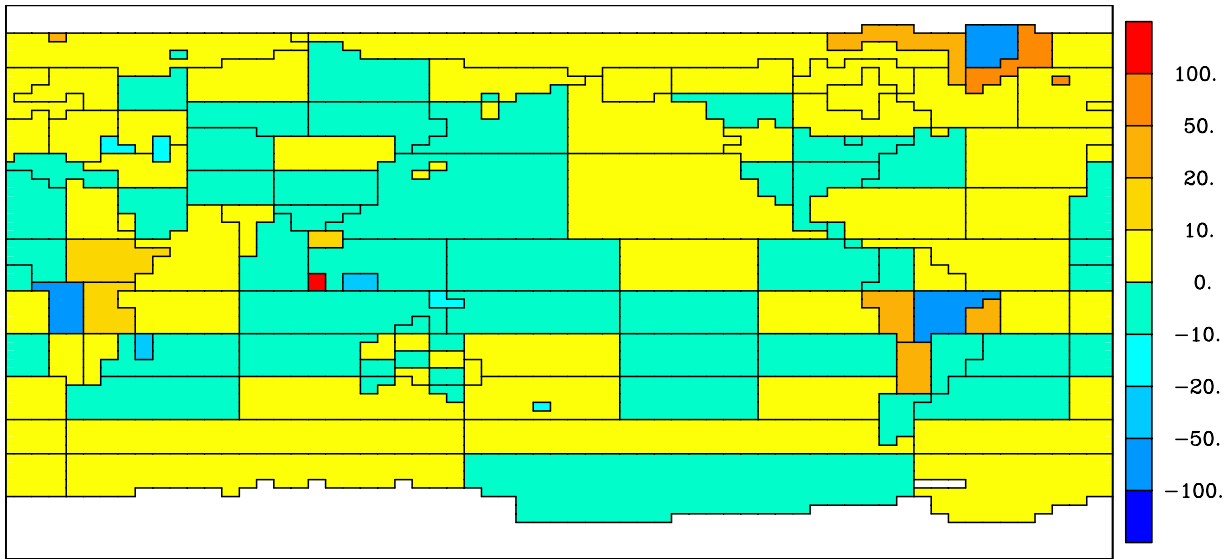
[36] These tests increase our confidence in the ability to validate space-based  $X_{\text{CO}_2}$  data to a precision of 1 ppm because, while biases on the order of 0.1 ppm will be difficult to detect directly, they can be detected and corrected by combining the space-based measurements with observations

from a reasonable number of surface stations. Fewer than 72 stations currently monitor  $\text{CO}_2$  continuously but for both practical and scientific reasons [e.g., Law *et al.*, 2002] there is a trend toward more continuous monitoring. We note that the procedure employed here is demanding on transport models. These tests also show the importance of  $\text{CO}_2$  sources-sink inversions (level 4 data products) in validating the  $X_{\text{CO}_2}$  retrievals (level 2 data products).

### 3.3. $\text{CO}_2$ Flux Constraints on Regional and National Spatial Scales

[37] Another OSSE was performed to assess the precision requirement for  $X_{\text{CO}_2}$  data to constrain  $\text{CO}_2$  fluxes on regional and national scales. We examined  $\text{CO}_2$  fluxes in Asia in spring. Studies by Suntharalingam *et al.* [2004] and Palmer *et al.* [2006] previously showed that high-density aircraft observations from the March to April 2001 TRACE-P aircraft campaign in Asian outflow over the NW Pacific [Jacob *et al.*, 2003] provide valuable constraints on the  $\text{CO}_2$  flux from different countries in Asia. We evaluate here the extent to which OCO-like  $X_{\text{CO}_2}$  data can disaggregate the  $\text{CO}_2$  fluxes from China, India, Japan, Korea, and Southeast Asia (Figure 9).

[38] Pseudoobservations for March to April 2001 were generated using the GEOS-CHEM global three-dimensional chemistry transport model. Details of the GEOS-CHEM model and the  $\text{CO}_2$  simulation may be found in the work of Suntharalingam *et al.* [2004]. We used version 4.21 of GEOS-CHEM driven by GEOS-3 assimilated meteorological fields for 2000 and 2001, at a horizontal resolution of  $2^\circ$  latitude  $\times$   $2.5^\circ$  longitude. GEOS-CHEM was also employed as the forward model in the inversion analysis. The seasonal  $\text{CO}_2$  surface flux in the model, aggregated over the regions considered here, is listed in Table 2.

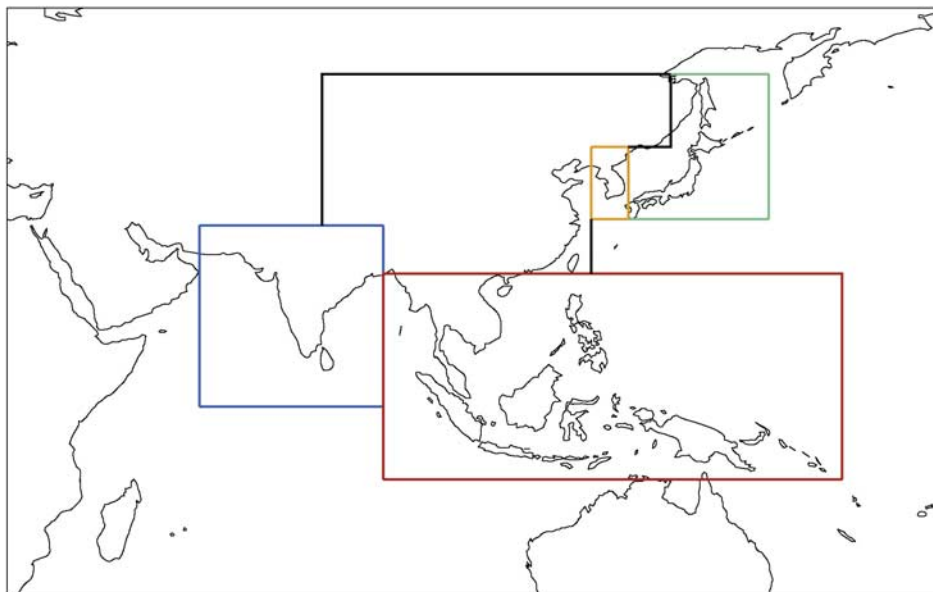


**Figure 8.** Surface  $\text{CO}_2$  flux errors ( $\text{gC m}^{-2} \text{yr}^{-1}$ ) inferred from an inversion of  $X_{\text{CO}_2}$  data biased by  $+0.1$  ppm over land that have been corrected using an inversion of the the  $X_{\text{CO}_2}$  differences given in Figure 7. Most regions show differences smaller than  $\pm 10 \text{ gC m}^{-2} \text{yr}^{-1}$  and the differences are no longer spatially coherent.

These flux estimates are based on the source inventories used by *Suntharalingam et al.* [2004]. These fluxes were adopted as the true surface fluxes of  $\text{CO}_2$  in our inversion analysis. The inversion was conducted using an a priori estimate of the fluxes obtained by perturbing the “true” fluxes within the a priori errors.

[39] The GEOS-CHEM simulation was conducted from 1 January 2000 to 30 April 2001, starting from observed  $\text{CO}_2$  latitudinal gradients. The first 13 months (to 31 January 2001) were used for initialization of the model

$\text{CO}_2$  background. Starting on 1 February 2001,  $\text{CO}_2$  surface fluxes for the different regions of Figure 9 were transported as separate tracers in the model; the background concentration as of 31 January was carried forward as an additional tracer with no further sources and sinks. We generated retrievals for OCO in March to April 2001 by sampling this pseudoatmosphere along the satellite orbit, transforming the modeled profiles with the OCO column averaging kernel, and adding noise. The retrieved pseudodata were limited to the region between the equator



**Figure 9.** Asian geographical regions used in the inversion analysis.  $\text{CO}_2$  surface fluxes from each region are given in Table 2.

**Table 2.** GEOS-CHEM  $\text{CO}_2$  Fluxes for March to April, 2001

Region	Symbol	C Flux <sup>a</sup> ( $\text{mg C m}^{-2} \text{d}^{-1}$ )	Area <sup>b</sup> ( $10^{10} \text{m}^2$ )
China	CHINA	596	1,421
Japan	JAPAN	1452	92
Korea	KOREA	3993	29
India	INDIA	744	336
Southeast Asia	SEASIA	533	456
Rest of the World <sup>c</sup>	ROTW	32	48,389

<sup>a</sup>Values are net fluxes and include contributions from fossil fuel and biofuel combustion, biomass burning, and exchange with the biosphere. The GEOS-CHEM model fluxes are taken as the “true” fluxes for purpose of the OSSE.

<sup>b</sup>Land area for flux regions defined in Figure 9.

<sup>c</sup>Includes the  $\text{CO}_2$  flux associated with the atmosphere-ocean exchange.

and  $64^\circ\text{N}$  and from  $2.5^\circ$  to  $167.5^\circ\text{E}$  for the purposes of this test. Model output was provided with 3-hour temporal resolution and we used the modeled  $\text{CO}_2$  profile closest to the 1326 LST OCO sampling time. Contributions from the different model tracers to the simulated  $\text{CO}_2$  concentrations were used to construct the Jacobian of the forward model for purpose of the inversion.

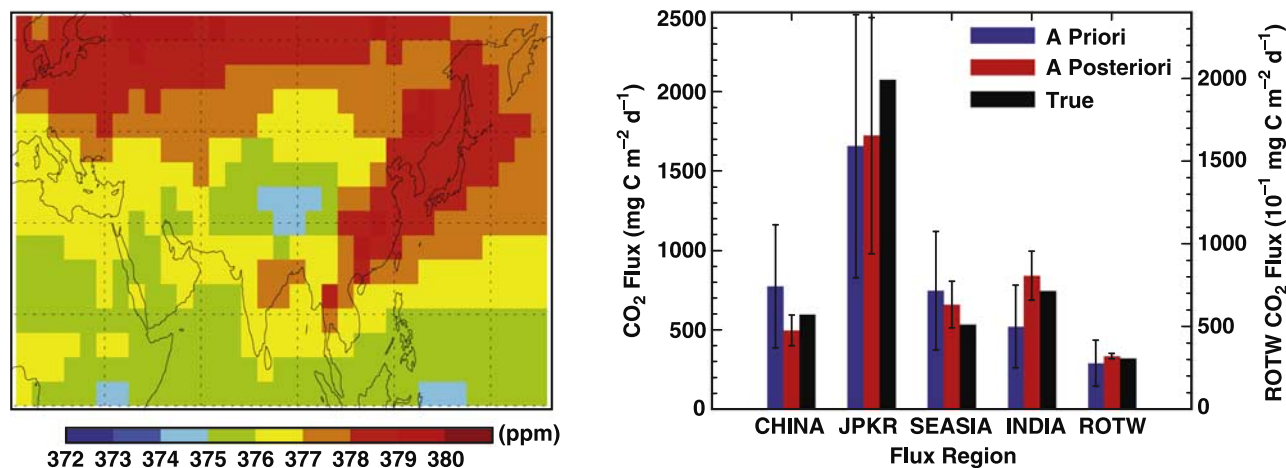
[40] To assess the precision requirements for  $X_{\text{CO}_2}$  in terms of monthly mean data with  $4^\circ \times 5^\circ$  resolution, the pseudoretrievals were correspondingly averaged and the results for March 2001 are shown in Figure 10a. In generating these observations we neglected the loss of data from cloud cover. Such data loss is inconsequential because of the large number of observations, as long as there are no correlations between  $\text{CO}_2$  column and cloud cover [Rayner *et al.*, 2002].

[41] We assumed that the  $\text{CO}_2$  flux errors from the different regions in Table 2 were uncorrelated, with a uniform a priori uncertainty of 50%. The actual uncertainties will vary with the relative contributions of different sectors to the regional  $\text{CO}_2$  sources. Emissions from fossil fuel use in the industrial and vehicular sectors are known to within about 10% [Streets *et al.*, 2003]. Emissions from the domestic fuel use sector (residential coal and biofuels), a major source in east Asia, may have uncertainties of about 50% on national scales [Palmer *et al.*, 2003; Suntharalingam *et al.*, 2004]. Emissions

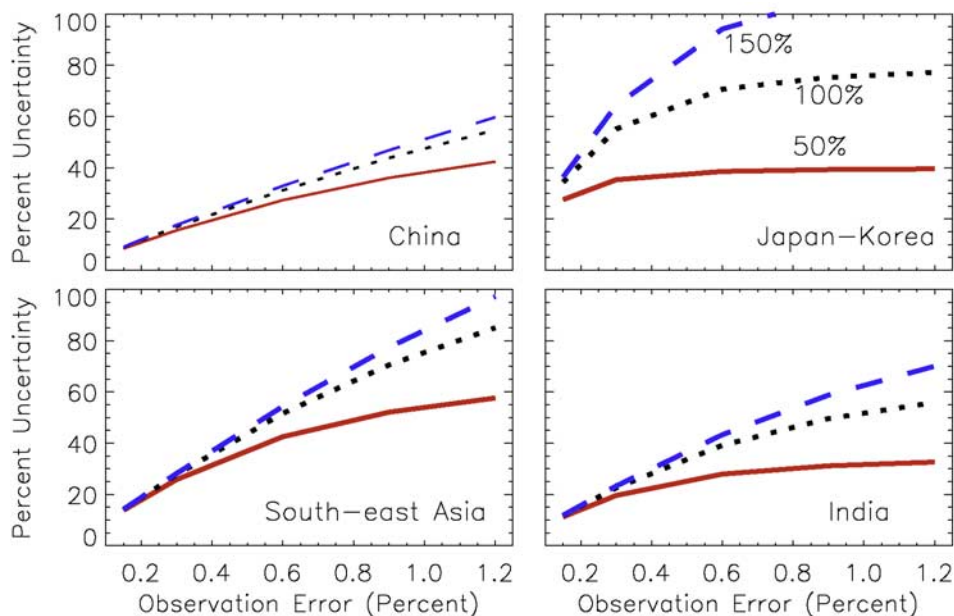
from biomass burning are uncertain by at least a factor of 2 [Palmer *et al.*, 2003]. Net fluxes from the terrestrial biosphere in East Asia are uncertain by  $\sim 100\%$  [Gurney *et al.*, 2002]. We also assumed no error covariance between individual OCO observations.

[42] Modeled  $X_{\text{CO}_2}$  values for March 2001, shown in Figure 10a, were convolved with 0.3% Gaussian measurement noise to generate the pseudoobservations. The a posteriori  $\text{CO}_2$  surface fluxes determined from the inversion are compared with the a priori and true fluxes in Figure 10b. We aggregated the fluxes from Japan and Korea because the  $4^\circ \times 5^\circ$  monthly mean  $X_{\text{CO}_2}$  pseudodata prohibited discriminating between emissions from these regions. The inverse model accurately updated the  $\text{CO}_2$  fluxes for the resulting four Asian regions. The flux uncertainty was significantly reduced for all regions, with the exception of the combined Japanese and Korean region (JPKR). The a posteriori errors for China, India, and south-east Asia improved to 16, 20, and 27%, respectively, from the a priori uncertainty of 50%.

[43] The result of the inversion analysis depends strongly on the observation error and on the a priori uncertainties assumed for the regional  $\text{CO}_2$  sources. Figure 11 shows the relative uncertainties of the a posteriori sources as a function of the observation error for three values of the a priori source uncertainty (50, 100, and 150%). The observations constrain the inferred  $\text{CO}_2$  fluxes from the Asian regions, with the exception of JPKR, when  $X_{\text{CO}_2}$  errors are 0.3% or less. With larger observation errors, it becomes more difficult for the inversion to resolve the contributions from individual regions, and the curves associated with the different a priori assumptions diverge. For example, with an observation uncertainty of 0.6% the a posteriori estimate for India is sensitive to the assumed a priori error and the estimates for both the Indian and Southeast Asian regions become strongly correlated with those from China (not shown). As expected, the error estimates for JPKR are most sensitive to the assumed a priori error, since this is the least well-constrained region in the inversion. These results demonstrate the potential for OCO observations to accurately disaggregate  $\text{CO}_2$  surface fluxes from India and China. This is important since these two regions are



**Figure 10.** (a) Modeled  $X_{\text{CO}_2}$  values for March 2001. (b) Comparison of a posteriori flux estimates (calculated with an observation error of 0.3%) with true and a priori fluxes. Red bars, a posteriori fluxes; blue bars, a priori fluxes; and black bars, true fluxes. Error bars show an uncertainty of  $1\sigma$ .



**Figure 11.** A posteriori uncertainty (relative to “true” flux estimates) as a function of observation error. Red solid line denotes a posteriori estimates starting from an a priori uncertainty of 50%, black dotted line corresponds to the case with a priori uncertainty of 100%, and blue dashed line is for an a priori error of 150%.

rapidly industrializing and experiencing significant land use changes.

#### 4. The OCO Sampling Approach

[44] The modeling studies of spatial and temporal  $X_{\text{CO}_2}$  variability and surface  $\text{CO}_2$  flux inversions define the science measurement requirements for space-based  $X_{\text{CO}_2}$  data. The OCO sampling strategy is designed to return observations that maximize precision and minimize bias in the space-based  $X_{\text{CO}_2}$  data so as to obtain the most accurate possible constraints on regional scale surface  $\text{CO}_2$  fluxes [Crisp *et al.*, 2004]. In situ measurements from tower [Bakwin *et al.*, 1998; Haszpra *et al.*, 2005] and aircraft [Anderson *et al.*, 1996; Andrews *et al.*, 1999; Andrews *et al.*, 2001a; Andrews *et al.*, 2001b; Bakwin *et al.*, 2003; Machida *et al.*, 2003; Matsueda *et al.*, 2002; Ramonet *et al.*, 2002; Sawa *et al.*, 2004; Vay *et al.*, 2003] have shown that vertical concentrations of  $\text{CO}_2$  can vary significantly, especially in the boundary layer. Therefore space-based measurements that sample the full atmospheric column are required. Space-based  $X_{\text{CO}_2}$  data must also capture variations in  $X_{\text{CO}_2}$  on seasonal to interannual timescales globally without diurnal biases. Measurements made from a polar, sun-synchronous orbit address these requirements. Scattering of solar radiation by clouds and optically thick aerosols prevents measurements that sample all the way to the surface. Spatial inhomogeneities within individual soundings (variations in topography, surface albedo, etc.) can compromise the accuracy of  $X_{\text{CO}_2}$  retrievals. A small sampling footprint mitigates both of these issues. The space-based  $X_{\text{CO}_2}$  data must be precise and unbiased over land and ocean (section 3.2), despite low surface albedos or other effects that may limit signal-to-noise levels. OCO includes both nadir

and glint observing modes to mitigate concerns about signal-to-noise issues and a point-and-stare (target) mode for routine validation of  $X_{\text{CO}_2}$  retrievals over a range of latitudes, viewing angles, and geophysical conditions. We also address whether space-based  $X_{\text{CO}_2}$  data acquired via the OCO sampling strategy is representative of the regional scale  $X_{\text{CO}_2}$  fields it samples.

##### 4.1. Space-Based Sampling Strategy

[45] The observatory will fly at the head of the earth observing system (EOS) Afternoon Constellation (A-Train), a polar, sun-synchronous orbit that follows the World Reference System 2 (WRS-2) ground track, providing global sampling with a 16-day repeat cycle and 1326 LST observations. This local time of day is ideal for spectroscopic observations of  $\text{CO}_2$  in reflected sunlight because the sun is high, maximizing the measurement signal-to-noise ratio, and because  $X_{\text{CO}_2}$  is near its diurnally averaged value at this time of day. This orbit also facilitates direct comparisons of OCO observations with complementary data products from Aqua (for example, AIRS temperature, humidity, and  $\text{CO}_2$  retrievals; Moderate Resolution Imaging Spectroradiometer (MODIS), Cloudsat, and Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) clouds and aerosols; MODIS surface type), Aura (TES  $\text{CH}_4$  and  $\text{CO}$ ), and other A-Train instruments. The 16-day repeat cycle enables tracking global  $X_{\text{CO}_2}$  variations twice per month, with nearby revisits ( $\sim 100$  km horizontal separation) occurring at least once every 6 days.

[46] Each OCO sounding includes bore-sighted spectra of solar radiation reflected from the Earth’s surface in the  $0.76 \mu\text{m}$   $\text{O}_2$  A-band and the  $\text{CO}_2$  bands at  $1.61$  and  $2.06 \mu\text{m}$ .  $X_{\text{CO}_2}$  is retrieved from the  $\text{CO}_2/\text{O}_2$  ratio. The OCO instrument and observing strategy were designed to obtain a sufficient

number of useful soundings to characterize the  $X_{\text{CO}_2}$  distribution accurately on regional scales, even in the presence of patchy clouds. The OCO instrument records up to eight soundings along a 10-km wide (nadir) cross-track swath at 3.0 Hz, yielding up to 24 soundings per second. As the spacecraft moves along its ground track at 6.78 km/s, each sounding will have a surface footprint with dimensions of  $1.25 \times 2.26$  km at nadir, yielding up to 390 soundings over each  $1^\circ$  latitude increment along the orbit track.

[47] OCO will collect science observations in nadir, glint, and target modes. The same sampling rate is used in all three modes. In nadir mode, the spacecraft points the instrument boresight to the local nadir, so that data can be collected along the ground track directly below the spacecraft. Science observations will be collected at all latitudes where the solar zenith angle is less than  $85^\circ$ . This mode provides the highest spatial resolution on the surface and is expected to return more useable soundings in regions that are partially cloudy or have significant surface topography.

[48] Glint mode was designed to provide superior signal-to-noise (SNR) performance at high latitudes and over dark ocean, where nadir mode observations might have difficulty meeting the  $X_{\text{CO}_2}$  precision requirements. In glint mode the spacecraft points the instrument boresight toward the bright “glint” spot, where solar radiation is specularly reflected from the surface. Glint measurements will provide 10–100 times higher signal over the ocean than nadir measurements [Kleidman et al., 2000; Cox and Munk, 1954]. Glint soundings will be collected at all latitudes where the local solar zenith angle is less than  $75^\circ$ . The nominal OCO mission operations plan is to switch between nadir and glint modes on alternate 16-day repeat cycles such that the entire Earth is sampled in each mode on monthly timescales. Operating in both nadir and glint modes each month is an ideal way to detect global bias in the  $X_{\text{CO}_2}$  product since the retrieved  $X_{\text{CO}_2}$  data and inferred carbon fluxes should be independent of the observation technique.

[49] Target mode will acquire “point and stare” validation observations of specific stationary surface targets as the observatory flies overhead. Simultaneous acquisition of solar-viewing Fourier transform spectrometer (FTS) data from a targeted OCO validation site provides a means to transfer calibration of the space-based  $X_{\text{CO}_2}$  data to the WMO standard for atmospheric  $\text{CO}_2$  [Washenfelder et al., 2007; Boesch et al., 2007]. Target passes will last up to 8 min, providing up to 10,000 soundings over a given site at local observing angles between  $0^\circ$  and  $\pm 85^\circ$ . Target mode enables the OCO team to assess the impact of viewing geometry on  $X_{\text{CO}_2}$  retrievals. Furthermore, the FTS validation sites have been distributed from pole-to-pole to identify and remove any biases that might arise as a function of latitude or region. Target passes will be conducted over each of the OCO validation sites 1–2 times per month. The Observatory will also regularly acquire target data over homogeneous Earth scenes such as the Sahara desert [Cosnefroy et al., 1996; Dingirard and Slater, 1999] and Railroad Valley, CA [Abdou et al., 2002] for vicarious radiometric calibration.

[50] The OCO observing strategy provides thousands of samples on regional scales for each 16-day orbit track repeat cycle. The observatory will collect up to 3400 soundings every time it flies over each  $1000 \times 1000$  km region. There

are at least five overflights of each region every 16 days, resulting in up to 17,000 regional soundings per repeat cycle. Analysis of high spatial resolution MODIS cloud data aggregated to the  $3 \text{ km}^2$  size of the OCO footprint indicates that on average only about 24% of these soundings will be sufficiently clear for accurate  $X_{\text{CO}_2}$  retrieval. Breon et al. [2005] recently analyzed GLAS data and determined that the global fraction of clear sky scenes ( $\tau < 0.01$ ) is  $\sim 15\%$  with an additional  $\sim 20\%$  of scenes having total cloud and aerosol optical depth  $\tau < 0.2$ , the approximate threshold for which precise  $X_{\text{CO}_2}$  retrievals are possible [Crisp et al., 2004; Kuang et al., 2002]. Thus, the OCO sampling strategy should yield between 2600 and 6000 soundings per region per 16-day repeat cycle as candidates for  $X_{\text{CO}_2}$  retrievals. Multiple passes through each region also provide constraints on subregional spatial and temporal  $X_{\text{CO}_2}$  variations that are associated with local topography, passing weather systems or other phenomena, and provide the data needed to identify systematic biases that could compromise the data, even in persistently cloudy regions. The large number of mostly clear scenes provides sufficient sampling statistics to support the OCO baseline plan of alternating between nadir and glint observations on alternating 16-day repeat cycles.

[51] If all errors in the space-based  $X_{\text{CO}_2}$  retrievals were purely random and individual soundings had uncertainties of 16 ppm, then one would need to perform retrievals on only 256 out of the 2600–6000 candidate soundings to achieve  $X_{\text{CO}_2}$  estimates with precisions of 1 ppm on 16-day intervals. The OCO team has adopted a more stringent 6 ppm worst case single sounding  $X_{\text{CO}_2}$  data precision requirement to ensure that useful data can be collected even in persistently cloudy regions (i.e., the Pacific Northwest coast of North America or Northern Europe in the winter), where typical data yields are anticipated to be much less than 10% of the total number of soundings. Sensitivity analyses indicate that a 6-ppm single sounding precision requirement also provides adequate precision to identify and characterize systematic biases within individual  $1000 \times 1000 \text{ km}^2$  regions.

## 4.2. Orbit Sampling Time of Day and Latitude Range

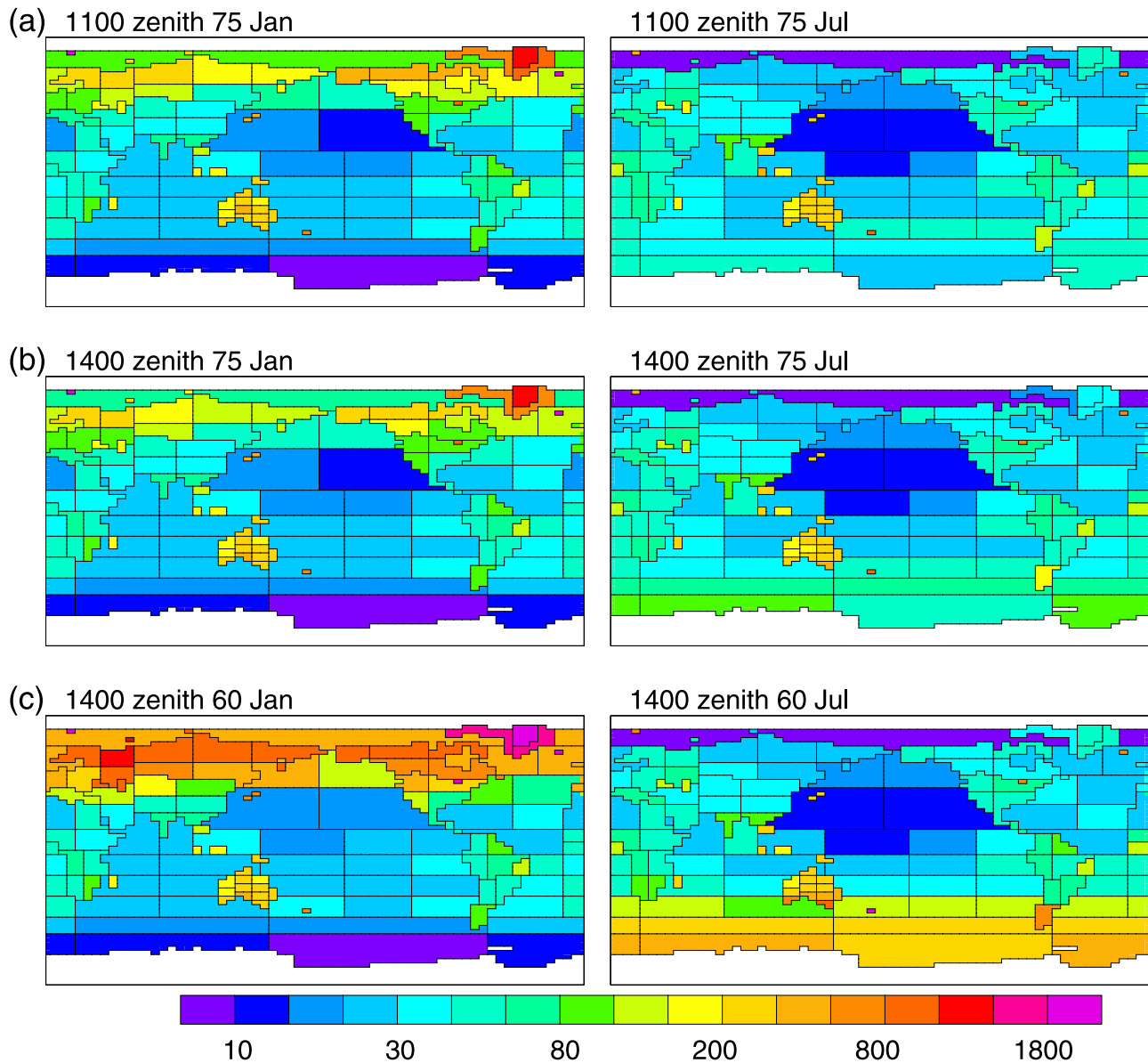
[52] As noted above, OCO will fly in a sun synchronous, polar orbit with an ascending 1326 LST equator crossing time. A series of synthesis inversion calculations, using the set-up of Rayner et al. [2002] previously described, were performed to ensure that space-based  $X_{\text{CO}_2}$  data acquired at this time of day yield the precision needed to characterize regional scale  $\text{CO}_2$  sources and sinks. These OSSEs also allowed us to assess the sensitivity of flux inversions to the range of solar zenith angles (SZA) sampled by the  $X_{\text{CO}_2}$  data. Three orbit choices were tested using the full data set, (i.e., no cloud obscuration):

[53] 1. 1100 orbit, with a solar zenith angle cut-off  $< 75^\circ$  (399,171 data points).

[54] 2. 1400 orbit, with a solar zenith angle cut-off  $< 75^\circ$  (391,796 data points).

[55] 3. 1400 orbit, with a solar zenith angle cut-off  $< 60^\circ$  (258,143 data points).

[56] All times are local solar times (LST) and refer to ascending equatorial crossing. Note that with the 1-hour time step in CRC-MATCH, 1400 LST seemed the best



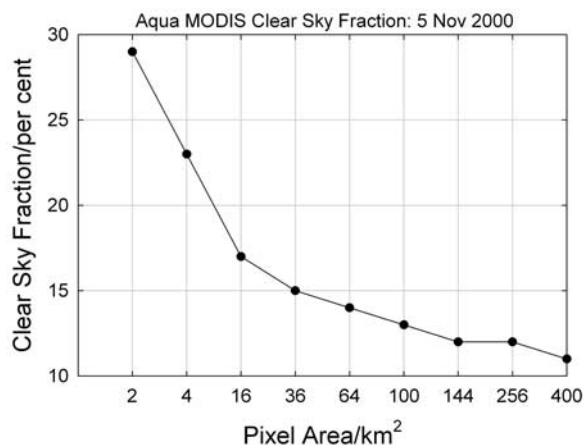
**Figure 12.** Flux uncertainties ( $\text{gC m}^{-2} \text{yr}^{-1}$ ) for January and July are shown for orbits with sampling times of 1100 and 1400 LST for cases with (a, b)  $\text{SZA} < 75^\circ$  and with a sampling time of 1400 LST for (c)  $\text{SZA} < 60^\circ$ . Small uncertainties are shaded in blue, large uncertainties in red/pink. Note that the scale is nonlinear. Compare to Figures 6a–6b.

match to the OCO equatorial crossing time of 1326 LST. All inversions assumed an OCO  $X_{\text{CO}_2}$  data precision of 1 ppm.

[57] Figure 12 shows January and July  $\text{CO}_2$  flux uncertainties, in  $\text{gC m}^{-2} \text{yr}^{-1}$ , for each of the three orbit/SZA cases. The prior uncertainty for all regions was  $2000 \text{ gC m}^{-2} \text{yr}^{-1}$ . In general, larger uncertainties are seen in smaller regions because the smaller regions are sampled less frequently than larger ones. The results for the 1100 and 1400 orbits that sample the globe at  $\text{SZA} < 75^\circ$  are very similar. There are large uncertainties at high latitudes in the winter hemisphere where the SZAs are largest. This is more noticeable in the Northern Hemisphere in January than in the Southern Hemisphere in July because the average region size is smaller in the northern high latitudes than

the southern high latitudes. As expected, the  $\text{SZA} < 60^\circ$  case gives larger uncertainties in winter at midlatitude to high latitude than the  $\text{SZA} < 75^\circ$  cases. It is noticeable that the loss of information impacts regions closer to the equator (to  $30^\circ$ ) in the  $\text{SZA} < 60^\circ$  case relative to the  $\text{SZA} < 75^\circ$  cases. We would expect a  $\text{SZA} < 60^\circ$  case to produce similar effects on the 1100 orbit.

[58] These simulations verify that space-based measurements from the OCO orbit are sufficient to meet the mission sampling requirements as well as providing explicit constraints on the range of SZAs over which measurements must be recorded. The OCO Science Requirements now specify that the observatory shall be capable of acquiring



**Figure 13.** Global clear-sky frequency versus spatial resolution computed using the MODIS 1-km cloud product.

data at solar zenith angles as large as  $75^\circ$  in glint mode, and at solar zenith angles as large as  $85^\circ$  in nadir mode.

#### 4.3. Diurnal Sampling Bias

[59] In addition to providing  $X_{\text{CO}_2}$  data with adequate precision to resolve key spatial and temporal  $X_{\text{CO}_2}$  gradients, the OCO mission design also minimizes sensitivity to diurnal variations in the  $X_{\text{CO}_2}$  data. For example, *Haszpra* [1999] found that only measurements obtained in the early afternoon can be considered as regionally representative of the  $\text{CO}_2$  mixing ratio in the planetary boundary layer based on measurements made at two monitoring sites located 220 km apart in the Hungarian plain. The 1326 LST sun synchronous polar orbit selected in the OCO mission design minimizes diurnal sampling bias, since the near-surface  $\text{CO}_2$  concentrations are close to their diurnally averaged values near this time of day [Olsen and Randerson, 2004]. Additionally, the largest diurnal variations in  $\text{CO}_2$  occur near the surface, and the amplitude of these variations decreases rapidly with height.  $X_{\text{CO}_2}$  data are therefore inherently much less sensitive to diurnal variations. CASA/MATCH simulations show that the residual uncertainty after correcting  $X_{\text{CO}_2}$  retrieved from 1326 LST observations to a 24-hour-averaged value will be  $<0.1$  ppm, and that existing models can correct for OCO diurnal sampling bias.

[60] To assess the impact of the 1326 LST sampling bias on the inferred surface  $\text{CO}_2$  flux inversions, benchmark surface fluxes were estimated from orbits sampling twice a day at 0600/1800 and 1100/2300, respectively. These orbits are used only to define sampling times for the  $\text{CO}_2$  fields for comparison: for example, it would be impossible to measure reflected sunlight at 2300 globally. These fluxes are compared to the flux estimates generated from the 1400 orbit with  $\text{SZA} < 75^\circ$ . We find that the differences between the monthly mean source estimates associated with diurnal sampling bias are usually smaller than the uncertainties on the 1400 orbit source estimates (for example, Figure 12b). Where larger differences do occur, it is not always possible to attribute these solely to diurnal biases. For example, sampling biases at high latitudes in the winter hemisphere due to the lack of sunlight are likely to swamp any diurnal effect there. This suggests that diurnal sampling biases

alone are not a serious problem in estimating  $\text{CO}_2$  sources and sinks at monthly intervals.

#### 4.4. Impact of Clouds on OCO Sampling

[61] We analyzed 1-km resolution MODIS cloud data to assess the science impact of cloud interference on the OCO sampling strategy. We adopted the Aqua MODIS products as the most representative of the cloud fields that OCO will encounter because OCO will fly in formation with the Aqua platform. See Figures 1 and 2 and Table 1 of *Breon et al.* [2005] for global distributions of clear sky and almost clear sky frequency.

[62] To determine the relationship between clear-sky frequency and spatial resolution, we used MODIS cloud mask results for nonpolar daytime surfaces on 5 November 2000. The pixel size for the MODIS Aqua product is  $1 \times 1$  km. For the present analysis, the MODIS pixels were aggregated into progressively larger square arrays ( $2 \times 2$ ,  $3 \times 3$ ,  $4 \times 4$  km<sup>2</sup>, etc.) with the array labeled clear if at least 95% of the 1-km pixels were “confident clear” in the MODIS cloud mask process. Globally averaged results for this analysis are presented in Figure 13.

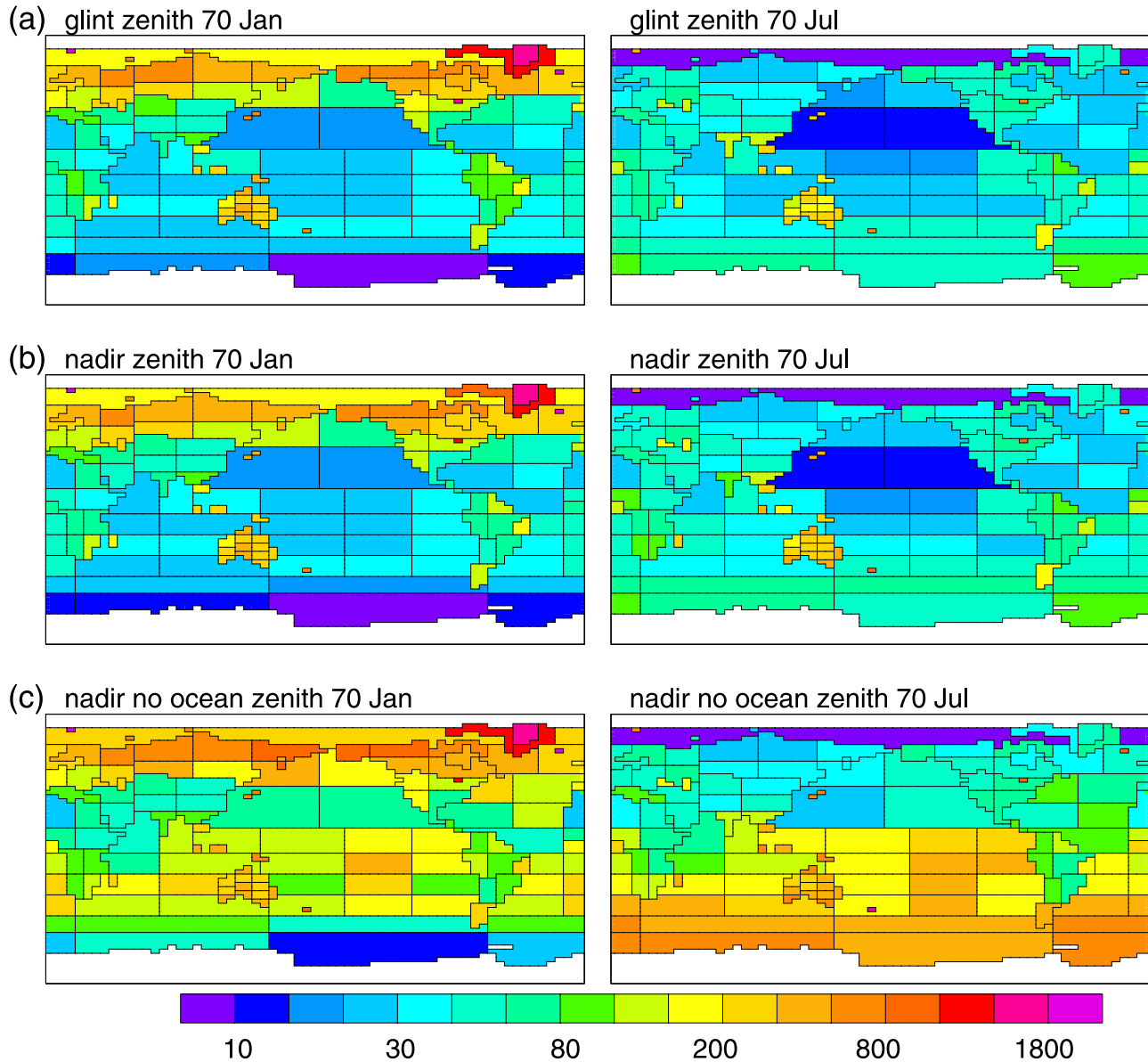
[63] The clear-sky frequency decreases rapidly with increasing field of view (FOV) area up to about 36 km<sup>2</sup> ( $6 \times 6$  km). For FOVs larger than 36 km<sup>2</sup>, the clear-sky frequency continues to decrease with increasing area, asymptotically approaching the 10% clear sky fraction commonly quoted for global averages, but the dependence on FOV area is significantly weaker. Figure 13 suggests that the clear-sky fraction for the 3 km<sup>2</sup> OCO FOV is approximately 24%, a value more than two times larger than the 10% clear-sky fraction assumed in early OCO mission design calculations. This analysis thus increases confidence that the OCO small footprint sampling strategy will provide a sufficient number of clear soundings for accurate  $X_{\text{CO}_2}$  retrievals. The potential impact of a clear sky bias on the  $\text{CO}_2$  fluxes inferred from OCO  $X_{\text{CO}_2}$  data is a question that requires further investigation.

#### 4.5. Flux Errors for Nadir and Glint Modes

[64] OCO science observations will alternate between nadir and glint observing modes on subsequent 16-day repeat cycles. In nadir mode, the spacecraft will collect data along the spacecraft ground track. This mode will provide the highest spatial resolution, and is expected to yield the most reliable data over continents, in regions occupied by patchy clouds, where spatial inhomogeneities could introduce systematic errors in the  $X_{\text{CO}_2}$  product. The primary shortcoming of this mode is that it is expected to yield lower measurement signal-to-noise ratios (SNR) over dark ocean surfaces. Glint mode addresses this issue by pointing the instrument boresight at the point on the surface where sunlight is specularly reflected toward the spacecraft. This mode is expected to yield measurements with a much higher SNR over the ocean, especially at high latitudes.

[65] Using the setup of *Rayner et al.* [2002], we performed three simulations to compare the uncertainties in the fluxes returned from observations made in nadir and glint modes. The comparison is not perfect since the glint calculations were explicitly screened for cloud as the ground track was calculated while the nadir calculations





**Figure 14.** Monthly  $\text{CO}_2$  flux uncertainty ( $\text{gC m}^{-2} \text{yr}^{-1}$ ) for January (left) and July (right) for (a) glint mode  $\text{SZA} < 70^\circ$ , (b) nadir mode  $\text{SZA} < 70^\circ$ , and (c) nadir mode  $\text{SZA} < 70^\circ$  excluding ocean measurements. All observations at 1400 LST. Compare for Figures 6a–6b.

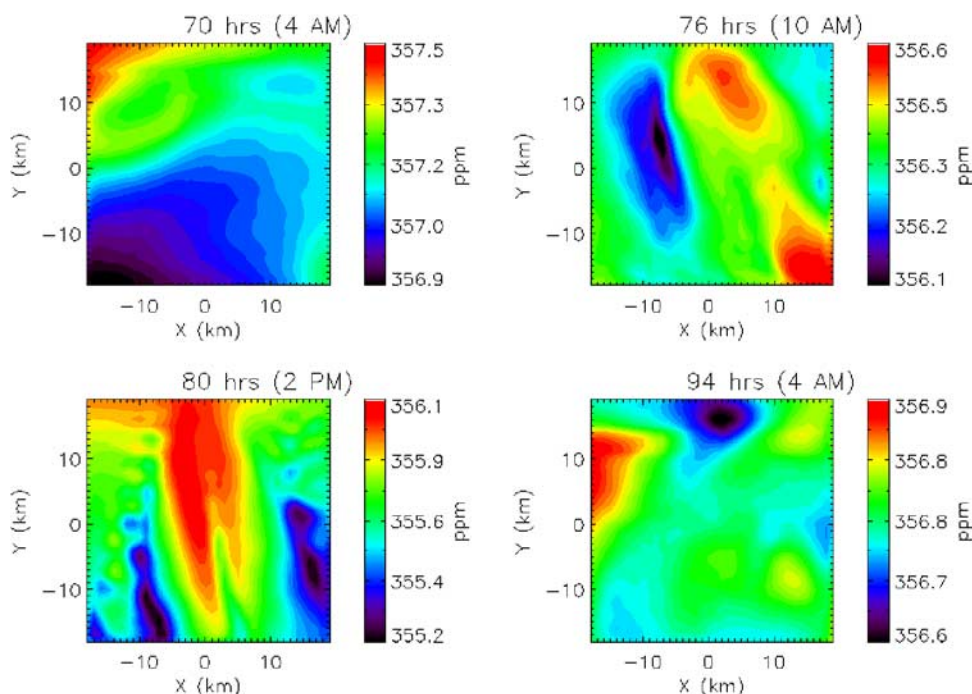
were not. To accommodate these differences, we normalized the data uncertainty to mimic equal sampling density in nadir and glint modes. The principal remaining difference between the two inversions is the coverage, which depends primarily on the choice of SZA cut-off. To focus exclusively on differences associated with the viewing geometry, we chose a  $\text{SZA} < 70^\circ$  for both inversions. This is somewhat pessimistic choice, since the nominal mission will acquire data at SZA as large as  $\theta_o = 75^\circ$  in glint mode and as large as  $\theta_o = 85^\circ$  in nadir mode. An additional nadir mode inversion was performed in which all soundings over oceans were omitted. This mimics a worst case scenario, where low albedos preclude reliable  $X_{\text{CO}_2}$  retrievals from nadir observations over ocean.

[66] Flux errors from these three inversion experiments are compared in Figure 14. The inversions show little

difference in the surface flux uncertainties for the nominal glint and nadir cases. This is not surprising since both modes provide similar coverage and were constrained to provide  $X_{\text{CO}_2}$  data with the same precision. The reduced spatial coverage degrades high latitude winter performance relative to the baseline case (Figure 6a). It is also interesting to note that even if nadir observations over ocean are omitted (Figure 14c), the dense spatial coverage provided over continents by the space-based  $X_{\text{CO}_2}$  measurements still offers an advantage over land regions compared to the existing flask and augmented continuous monitoring networks (Figure 5).

#### 4.6. Regional Scale $X_{\text{CO}_2}$ Representativeness Errors

[67] Accurate surface flux inversions do not require space-based  $X_{\text{CO}_2}$  data with contiguous spatial sampling



**Figure 15.** Spatial variations of simulated column mean  $\text{CO}_2$  mixing ratios (ppm) for four different times during 28 July 1997 on the 1-km grid centered at the WLEF tower.

due to atmospheric transport (Chevallier et al., submitted manuscript, 2007) and representativeness scale lengths [Gerbig et al., 2003; Lin et al., 2004]. OCO uses  $3\text{-km}^2$  footprints and a 10-km cross track swath to minimize potential biases associated with clouds and other sources of heterogeneity in the atmosphere and surface. It samples the atmosphere and surface rather than mapping them. Inferring surface  $\text{CO}_2$  fluxes from OCO  $X_{\text{CO}_2}$  data requires careful consideration, since inversion models typically use grids significantly larger (100–1000 km) than the OCO cross track swath (10 km). It is important that models aggregate OCO data to accurately represent spatial and temporal averages at the inversion model resolution. If this is not the case, the representativeness errors could be substantially increased.

[68] To address the question of short-term mesoscale representativeness errors in surface  $\text{CO}_2$  fluxes inferred from OCO  $X_{\text{CO}_2}$  data, we performed a 5-day simulation of surface fluxes and atmospheric  $\text{CO}_2$  concentration using the Regional Atmospheric Modeling System (RAMS) coupled to the Simple Biosphere Model (SiB2) on a nested set of four grids centered on the WLEF tall tower site in Park Falls Wisconsin for 26–30 July, 1997. Overall results and comparison to the tower observations are reported by Nicholls et al. [2004]. Here we report an analysis of potential representativeness error of north-south swaths of  $X_{\text{CO}_2}$  in the central part of the domain, formed by a  $38 \times 38$  grid with a  $1 \times 1$  km grid spacing. There are 45 vertical levels in this simulation, extending to 7.2 km.

[69] Several small lakes in the vicinity of the tower produced anomalous surface fluxes and, more importantly, anomalous circulations on some afternoons, leading to

variations of  $\text{CO}_2$  of as much as 6 ppm in the planetary boundary layer. These variations are apparent, although much weaker, in the column mean. Figure 15 shows the spatial variations in simulated  $X_{\text{CO}_2}$  for four times during a 24-hour period extending over 28–29 July 1997.

[70] We evaluated possible representativeness errors associated with mesoscale variations by comparing the mean of 1-km-wide N-S swaths of simulated column mean  $\text{CO}_2$  with the “true” domain-averaged column mean mixing ratio over the  $38 \times 38$  km grid at 1400 LST on each of the five days. The range of column mean mixing ratio at 1400 LST over the 5 days was 0.98 ppm. Spatial autocorrelation of swath means was quite high among swaths within 5 km of the target swath, so we used 19 degrees of freedom (38 swaths per day times 5 days divided by 10 autocorrelated neighboring swaths) in a  $t$  test. Under these conditions, we found that 95% of the swaths represented had mean mixing ratios within 0.18 ppm of the true domain-averaged mixing ratio.

[71] We also performed a similar calculation on a regional domain of  $600 \times 600$  km with 16-km grid spacing. Substantial spatial variability is imposed on the regional scale by the presence of the Great Lakes on the eastside of the domain. The range of column mean mixing ratio at 1400 LST was larger than on the mesoscale domain, with variations of 3.4 ppm over 5 days. Nevertheless, 95% of the N-S swaths captured the domain average within 0.17 ppm. These simulations provide confidence that the baseline OCO sampling strategy will deliver precise space-based  $X_{\text{CO}_2}$  data even in the presence of representativeness errors associated with realistic spatial variations in  $X_{\text{CO}_2}$ , since typical representativeness errors are much smaller than

1 ppm. These results also provide additional confidence in our ability to validate OCO space-based  $X_{\text{CO}_2}$  retrievals against ground-based solar-viewing FTS spectra obtained at Park Falls [Boesch et al., 2007; Washenfelder et al., 2007].

## 5. Conclusions

[72] Precision requirements for space-based  $X_{\text{CO}_2}$  data have been assessed for the Orbiting Carbon Observatory mission from the results of observational system simulation experiments and synthesis inversion models. The  $X_{\text{CO}_2}$  precision requirements were determined by evaluating the variability of spatial and temporal gradients in  $X_{\text{CO}_2}$ , the relationship between  $X_{\text{CO}_2}$  data precision and inferred surface  $\text{CO}_2$  flux uncertainties, and the OCO sampling strategy. The OCO measurement concept was tested using OSSEs and synthesis inversion models to infer regional scale  $\text{CO}_2$  sources and sinks from global and regional  $X_{\text{CO}_2}$  data.

[73] Simulated OCO  $X_{\text{CO}_2}$  data was ingested into synthesis inversion models to quantify the relationship between the  $X_{\text{CO}_2}$  precision and inferred surface-atmosphere  $\text{CO}_2$  flux uncertainties. On a global scale, uniform spatial sampling and the sheer number of space-based  $X_{\text{CO}_2}$  retrievals will still reduce the uncertainties in inferred surface-atmosphere  $\text{CO}_2$  fluxes compared to the fluxes inferred from the GLOBALVIEW- $\text{CO}_2$  network even if the space-based  $X_{\text{CO}_2}$  data had precisions as poor as 5 ppm on regional scales.  $X_{\text{CO}_2}$  precisions of 1–2 ppm are needed on regional scales to improve our knowledge of carbon cycle phenomena. Simulated sampling of  $\text{CO}_2$  data fields demonstrated the ability of the OCO measurement concept to constrain regional fluxes of  $\text{CO}_2$  and quantified the relationship between  $X_{\text{CO}_2}$  data precision and the ability to distinguish regional  $\text{CO}_2$  fluxes from China and India.

[74] The impact of systematic  $X_{\text{CO}_2}$  biases on  $\text{CO}_2$  flux uncertainties depends on the spatial and temporal extent of a bias since  $\text{CO}_2$  sources and sinks are inferred from regional-scale  $X_{\text{CO}_2}$  gradients. Source-sink inversion modeling demonstrated that a land/ocean systematic bias as small as 0.1 ppm could be identified and removed from the  $X_{\text{CO}_2}$  data product. Biases on spatial scales smaller than  $\sim 10^4 \text{ km}^2$  may be discounted since they will appear the same as random noise. Constant global scale  $X_{\text{CO}_2}$  biases do not affect the  $\text{CO}_2$  flux uncertainties since they introduce no error into the  $X_{\text{CO}_2}$  gradients. Persistent geographic biases at the regional to continental scale will have the largest impact on the inferred  $\text{CO}_2$  surface fluxes. Therefore the OCO validation program must identify and correct regional to continental scale  $X_{\text{CO}_2}$  biases.

## 6. Note Added in Proof

[75] Since the completion of the work reported here, Chevallier et al. (Chevallier et al., submitted manuscript, 2007) performed inversion experiments which demonstrate that OCO  $X_{\text{CO}_2}$  data reduce inferred surface  $\text{CO}_2$  flux uncertainties even more than anticipated in the analyses presented above.

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## References

- Abdou, W. A., C. J. Bruegge, M. C. Helmlinger, J. E. Conel, S. H. Pilonz, W. Ledebner, B. J. Gaitley, and K. J. Thome (2002), Vicarious calibration experiment in support of the multi-angle imaging spectroradiometer, *IEEE Trans. Geosci. Remote Sens.*, *40*, 1500–1511.
- Anderson, B. E., G. L. Gregory, J. E. Collins, G. W. Sachse, T. J. Conway, and G. P. Whiting (1996), Airborne observations of spatial and temporal variability of tropospheric carbon dioxide, *J. Geophys. Res.*, *101*(D1), 1985–1997.
- Andres, R. J., G. Marland, I. Fung, and E. Matthews (1996), A  $1^\circ \times 1^\circ$  distribution of carbon dioxide emissions from fossil fuel consumption and cement manufacture, 1950–1990, *Glob. Biogeochem. Cycles*, *10*, 419–429.
- Andrews, A. E., K. A. Boering, B. C. Daube, S. C. Wofsy, E. J. Hintsa, E. M. Weinstock, and T. P. Bui (1999), Empirical age spectra for the lower tropical stratosphere from in situ observations of  $\text{CO}_2$ : Implications for stratospheric transport, *J. Geophys. Res.*, *104*, 26,581–26,595.
- Andrews, A. E., et al. (2001), Mean ages of stratospheric air derived from in situ observations of  $\text{CO}_2$ ,  $\text{CH}_4$ , and  $\text{N}_2\text{O}$ , *J. Geophys. Res.*, *106*, 32,295–32,314.
- Andrews, A. E., K. A. Boering, S. C. Wofsy, B. C. Daube, D. B. Jones, S. Alex, M. Loewenstein, J. R. Podolske, and S. E. Strahan (2001), Empirical age spectra for the midlatitude lower stratosphere from in situ observations of  $\text{CO}_2$ : Quantitative evidence for a subtropical “barrier” to horizontal transport, *J. Geophys. Res.*, *106*, 10,257–10,274.
- Baker, D. F., et al. (2006a), TransCom 3 inversion intercomparison: Impact of transport model errors on the interannual variability of regional  $\text{CO}_2$  fluxes, 1988–2003, *Global Biogeochem. Cycles*, *20*, GB1002, doi:10.1029/2004GB002439.
- Baker, D. F., A. S. Doney, and D. S. Schimel (2006b), Variational data assimilation for atmospheric  $\text{CO}_2$ , *Tellus*, *58B*, 359–365.
- Bakwin, P. S., P. P. Tans, D. F. Hurst, and C. L. Zhao (1998), Measurements of carbon dioxide on very tall towers: Results of the NOAA/CMDL program, *Tellus*, *50B*, 401–415.
- Bakwin, P. S., P. P. Tans, B. B. Stephens, S. C. Wofsy, C. Gerbig, and A. Grainger (2003), Strategies for measurement of atmospheric column means of carbon dioxide from aircraft using discrete sampling, *J. Geophys. Res.*, *108*(D16), 4514, doi:10.1029/2002JD003306.
- Breon, F. M., D. M. O'Brien, and J. D. Spinhirne (2005), Scattering layer statistics from space borne GLAS observations, *Geophys. Res. Lett.*, *32*, L22802, doi:10.1029/2005GL023825.
- Cosnefroy, H., M. Leroy, and X. Briottet (1996), Selection and characterization of Saharan and Arabian desert sites for the calibration of optical satellite sensors, *Remote Sens. Environ.*, *58*, 101–114.
- Cox, C., and W. Munk (1954), Measurement of the roughness of the sea surface from photographs of the Sun's glitter, *J. Opt. Soc. Am.*, *44*, 838.
- Cox, P. M., R. A. Betts, C. D. Jones, S. A. Spall, and I. J. Totterdell (2000), Acceleration of global warming due to carbon cycle feedbacks in a coupled climate model, *Nature*, *408*, 184–187.
- Cressie, N. A. C. (1991), *Statistics for Spatial Data*, 900 p, Wiley, New York.
- Crisp, D., et al. (2004), The orbiting carbon observatory (OCO) mission, *Adv. Space Sci.*, *34*, 700–709.
- Crutzen, P. J. (2002), Geology of mankind, *Nature*, *415*, 23.
- Denning, A. S., et al. (1999), Three-dimensional transport and concentration of SF6—A model intercomparison study (TransCom 2), *Tellus*, *51B*, 266–297.
- Dilling, L., S. C. Doney, J. Edmonds, K. R. Gurney, R. Harriss, D. Schimel, B. Stephens, and G. Stokes (2003), The role of carbon cycle observations and knowledge in carbon management, *Ann. Rev. Environ. Resour.*, *28*, 521–558, doi:10.1146/annurev.energy.28.011503.163443.
- Dingirard, M., and P. N. Slater (1999), Calibration of space-multispectral imaging sensors: A review, *Remote Sens. Environ.*, *68*, 194–205.
- Dufour, E., and F.-M. Breon (2003), Spaceborne estimate of atmospheric  $\text{CO}_2$  column by use of the differential absorption method: Error analysis, *Appl. Opt.*, *42*, 3595–3609.
- Friedlingstein, P., et al. (2006), Climate-carbon cycle feedback analysis, results from the C4MIP model intercomparison, *J. Clim.*, *19*, 3337–3353.
- Fung, I., S. C. Doney, K. Lindsay, and J. John (2005), Evolution of carbon sinks in a changing climate, *Proc. Natl. Acad. Sci. U. S. A.*, *102*, 11,201–11,206, doi:10.1073/pnas.0504949102.
- Gerbig, C., J. C. Lin, S. C. Wofsy, B. C. Daube, A. E. Andrews, B. B. Stephens, P. S. Bakwin, and C. A. Grainger (2003), Toward constraining regional-scale fluxes of  $\text{CO}_2$  with atmospheric observations over a continent: 1. Observed spatial variability from airborne platforms, *J. Geophys. Res.*, *108*(D24), 4756, doi:10.1029/2002JD003018.

- GLOBALVIEW-CO2 (2005), Cooperative Atmospheric Data Integration Project - Carbon Dioxide. CD-ROM, NOAA CMDL, Boulder, Colorado [Also available on Internet via anonymous FTP to ftp.cmdl.noaa.gov, Path: ccg/co2/GLOBALVIEW].
- Gurney, K. R., et al. (2002), Towards robust regional estimates of CO<sub>2</sub> sources and sinks using atmospheric transport models, *Nature*, *415*, 626–630.
- Gurney, K. R., et al. (2003), TransCom 3 CO<sub>2</sub> inversion intercomparison: 1. Annual mean control results and sensitivity to transport and prior flux information, *Tellus*, *55B*, 555–579.
- Gurney, K. R., et al. (2004), TransCom 3 inversion intercomparison: Model mean results for the estimation of seasonal carbon sources and sinks, *Global Biogeochem. Cycles*, *18*, GB1010, doi:10.1029/2003GB002111.
- Gurney, K. R., Y. H. Chen, T. Maki, S. R. Kawa, A. Andrews, and Z. X. Zhu (2005), Sensitivity of atmospheric CO<sub>2</sub> inversions to seasonal and interannual variations in fossil fuel emissions, *J. Geophys. Res.*, *110*, D10308, doi:10.1029/2004JD005373.
- Haszpra, L. (1999), On the representativeness of carbon dioxide measurements, *J. Geophys. Res.*, *104*, 26,953–26,960.
- Haszpra, L., Z. Barcza, K. J. Davis, and K. Tarczay (2005), Long-term tall tower carbon dioxide flux monitoring over an area of mixed vegetation, *Agric. For. Meteorol.*, *132*, 58–77.
- Houweling, S., F. M. Breon, I. Aben, C. Rodenbeck, M. Gloor, M. Heimann, and P. Ciais (2004), Inverse modeling of CO<sub>2</sub> sources and sinks using satellite data: A synthetic inter-comparison of measurement techniques and their performance as a function of space and time, *Atmos. Chem. Phys.*, *4*, 523–538.
- Intergovernmental Panel on Climate Change IPCC (2001), Climate Change 2001: Synthesis Report. A Contribution of Working Groups I, II, and III to the Third Assessment Report of the Intergovernmental Panel on Climate Change, 398 pp., Cambridge Univ. Press, New York.
- Jacob, D. J., J. H. Crawford, M. M. Kleb, V. S. Connors, R. J. Bendura, J. L. Raper, G. W. Sachse, J. C. Gille, L. Emmons, and C. L. Heald (2003), The Transport and Chemical Evolution over the Pacific (TRACE-P) Aircraft mission: design, execution, and first results, *J. Geophys. Res.*, *108*(D20), 9000, doi:10.1029/2002JD003276.
- Kleidman, R. G., Y. J. Kaufman, B. C. Gao, L. A. Remer, V. G. Brackett, R. A. Ferrare, E. V. Browell, and S. Ismail (2000), Remote sensing of total precipitable water vapor in the near-IR over ocean glint, *Geophys. Res. Lett.*, *27*, 2657–2660.
- Kuang, Z., J. Margolis, G. Toon, D. Crisp, and Y. Yung (2002), Spaceborne measurements of atmospheric CO<sub>2</sub> by high-resolution NIR spectrometry of reflected sunlight: An introductory study, *Geophys. Res. Lett.*, *29*(15), 1716, doi:10.1029/2001GL014298.
- Law, R. M., D. J. Rayner, L. P. Steele, and I. G. Enting (2002), Using high temporal frequency data for CO<sub>2</sub> inversions, *Global Biogeochem. Cycles*, *16*(4), 1053, doi:10.1029/2001GB001593.
- Law, R. M., Y. H. Chen, K. R. Gurney, and the TransCom 3 modellers (2003), TransCom 3 CO<sub>2</sub> inversion intercomparison: 2. Sensitivity of annual mean results to data choices, *Tellus*, *55B*(2), 580–595.
- Lin, J. C., C. Gerbig, B. C. Daube, S. C. Wofsy, A. E. Andrews, S. A. Vay, and B. E. Anderson (2004), An empirical analysis of the spatial variability of atmospheric CO<sub>2</sub>: Implications for inverse analyses and space-borne sensors, *Geophys. Res. Lett.*, *31*, L23104, doi:10.1029/2004GL020957.
- Machida, T., K. Kita, Y. Kondo, D. Blake, S. Kawakami, G. Inoue, and T. Ogawa (2003), Vertical and meridional distributions of the atmospheric CO<sub>2</sub> mixing ratio between northern midlatitudes and southern subtropics, *J. Geophys. Res.*, *108*(D3), 8401, doi:10.1029/2001JD000910.
- Mao, J. P., and S. R. Kawa (2004), Sensitivity studies for space-based measurement of atmospheric total column carbon dioxide by reflected sunlight, *Appl. Opt.*, *43*, 914–927.
- Matsueda, H., H. Y. Inoue, and M. Ishii (2002), Aircraft observation of carbon dioxide at 8–13 km altitude over the western Pacific from 1993 to 1999, *Tellus*, *54B*, 1–21.
- Michalak, A. M., L. Bruhwiler, and P. P. Tans (2004), A geostatistical approach to surface flux estimation of atmospheric trace gases, *J. Geophys. Res.*, *109*, D14109, doi:10.1029/2003JD004422.
- Nicholls, M. E., A. S. Denning, L. Prihodko, P. L. Vidale, I. Baker, K. Davis, and P. Bakwin (2004), A multiple-scale simulation of variations in atmospheric carbon dioxide using a coupled biosphere-atmospheric model, *J. Geophys. Res.*, *109*, D18117, doi:10.1029/2003JD004482.
- O'Brien, D. M., and P. J. Rayner (2002), Global observations of the carbon budget: 2. CO<sub>2</sub> column from differential absorption of reflected sunlight in the 1.61 μm band of CO<sub>2</sub>, *J. Geophys. Res.*, *107*(D18), 4354, doi:10.1029/2001JD000617.
- Olsen, S. C., and J. T. Randerson (2004), Differences between surface and column atmospheric CO<sub>2</sub> and implications for carbon cycle research, *J. Geophys. Res.*, *109*, D02301, doi:10.1029/2003JD003968.
- Palmer, P. I., D. J. Jacob, D. B. A. Jones, C. L. Heald, R. M. Yantosca, J. A. Logan, G. W. Sachse, and D. G. Streets (2003), Inverting for emissions of carbon monoxide from Asia using aircraft observations over the western Pacific, *J. Geophys. Res.*, *108*(D21), 8828, doi:10.1029/2003JD003397.
- Palmer, P. I., P. Suntharalingam, D. B. A. Jones, D. J. Jacob, D. G. Streets, Q. Fu, S. A. Vay, and G. W. Sachse (2006), Using CO<sub>2</sub>:CO correlations to improve inverse analyses of carbon fluxes, *J. Geophys. Res.*, *111*, D12318, doi:10.1029/2005JD006697.
- Ramonet, M., et al. (2002), Three years of aircraft-based trace gas measurements over the Fyodorovskoye southern taiga forest, 300 km north-west of Moscow, *Tellus*, *54B*, 713–734.
- Randerson, J. T., M. V. Thompson, T. J. Conway, I. Y. Fung, and C. B. Field (1997), The contribution of terrestrial sources and sinks to trends in the seasonal cycle of atmospheric carbon dioxide, *Glob. Biogeochem. Cycles*, *11*, 535–560.
- Rasch, P. J., X. X. Tie, B. A. Boville, and D. L. Williamson (1994), A 3-dimensional transport model for the middle atmosphere, *J. Geophys. Res.*, *99*, 999–1017.
- Rayner, P. J., and D. M. O'Brien (2001), The utility of remotely sensed CO<sub>2</sub> concentration data in surface source inversions, *Geophys. Res. Lett.*, *28*, 175–178.
- Rayner, P. J., R. M. Law, D. M. O'Brien, T. M. Butler, and A. C. Dilley (2002), Global observations of the carbon budget: 3. Initial assessment of the impact of satellite orbit, scan geometry, and cloud on measuring CO<sub>2</sub> from space, *J. Geophys. Res.*, *107*(D21), 4557, doi:10.1029/2001JD000618.
- Sawa, Y., H. Matsueda, Y. Makino, H. Y. Inoue, S. Murayama, M. Hirota, Y. Tsutsumi, Y. Zaizen, M. Ikegami, and K. Okada (2004), Aircraft observation of CO<sub>2</sub>, CO, O<sub>3</sub> and H<sub>2</sub> over the North Pacific during the PACE-7 campaign, *Tellus*, *56B*, 2–20.
- Streets, D. G., et al. (2003), An inventory of gaseous and primary aerosol emissions in Asia in the year 2000, *J. Geophys. Res.*, *108*(D21), 8809, doi:10.1029/2002JD003093.
- Suntharalingam, P., D. J. Jacob, P. I. Palmer, J. A. Logan, R. M. Yantosca, Y. Xiao, M. J. Evans, D. G. Streets, S. L. Vay, and G. W. Sachse (2004), Improved quantification of Chinese carbon fluxes using CO<sub>2</sub>/CO correlations in Asian outflow, *J. Geophys. Res.*, *109*, D18S18, doi:10.1029/2003JD004362.
- Takahashi, T., et al. (2002), Global sea-air CO<sub>2</sub> flux based on climatological surface ocean pCO<sub>2</sub>, and seasonal biological and temperature effects, *Deep-Sea Res., Part 2, Top. Stud. Oceanogr.*, *49*(9–10), 1601–1622.
- Tans, P. P., I. Y. Fung, and T. Takahashi (1990), Observational constraints on the global atmospheric CO<sub>2</sub> budget, *Science*, *247*, 1431–1438.
- Vay, S. A., et al. (2003), Influence of regional-scale anthropogenic emissions on CO<sub>2</sub> distributions over the western North Pacific, *J. Geophys. Res.*, *108*(D20), 8801, doi:10.1029/2002JD003094.

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