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Atmospheric Measurement Techniques

# Towards space based verification of $CO_2$ emissions from strong localized sources: fossil fuel power plant emissions as seen by a CarbonSat constellation

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**Abstract.** Carbon dioxide ($CO_2$) is the most important man-made greenhouse gas (GHG) that cause global warming. With electricity generation through fossil-fuel power plants now being the economic sector with the largest source of $CO_2$, power plant emissions monitoring has become more important than ever in the fight against global warming. In a previous study done by Bovensmann et al. (2010), random and systematic errors of power plant $CO_2$ emissions have been quantified using a single overpass from a proposed CarbonSat instrument. In this study, we quantify errors of power plant annual emission estimates from a hypothetical CarbonSat and constellations of several CarbonSats while taking into account that power plant $CO_2$ emissions are time-dependent. Our focus is on estimating systematic errors arising from the sparse temporal sampling as well as random errors that are primarily dependent on wind speeds. We used hourly emissions data from the US Environmental Protection Agency (EPA) combined with assimilated and re-analyzed meteorological fields from the National Centers of Environmental Prediction (NCEP). CarbonSat orbits were simulated as a sun-synchronous low-earth orbiting satellite (LEO) with an 828-km orbit height, local time ascending node (LTAN) of 13:30 (01:30 p.m. LT) and achieves global coverage after 5 days. We show, that despite the variability of the power plant emissions and the limited satellite overpasses, one CarbonSat has the potential to verify reported US annual $CO_2$ emissions from large power plants ($\geq 5\,\mathrm{Mt\,CO_2\,yr^{-1}}$) with a systematic error of less than ∼4.9 % and a random error of less than ∼6.7 % for 50% of all the power plants. For 90 % of all the power plants, the systematic error was less than ∼12.4 % and the random error was less than ∼13 %. We additionally investigated two different satellite configurations using a combination of 5 CarbonSats. One achieves global coverage everyday but only samples the targets at fixed local times. The other configuration samples the targets five times at two-hour intervals approximately every 6th day but only achieves global coverage after 5 days. From the statistical analyses, we found, as expected, that the random errors improve by approximately a factor of two if 5 satellites are used. On the other hand, more satellites do not result in a large reduction of the systematic error. The systematic error is somewhat smaller for the CarbonSat constellation configuration achieving global coverage everyday. Therefore, we recommend the CarbonSat constellation configuration that achieves daily global coverage.

## 1 Introduction

Carbon dioxide ($CO_2$), a major greenhouse gas that contributes to global warming had been at values between 270 and 290 ppm for the past thousand years before industrialization (Forster et al., 2007, FAQ 2.1 Fig. 1). Since the industrial revolution (around 1750 AD), $CO_2$ has increased by 36 % (Forster et al., 2007). Global warming is now recognized as an impending threat to mankind and the ecosystem, driven mainly by the increase of man-made greenhouse gases (GHG). In order to curb the increase of greenhouse gases,

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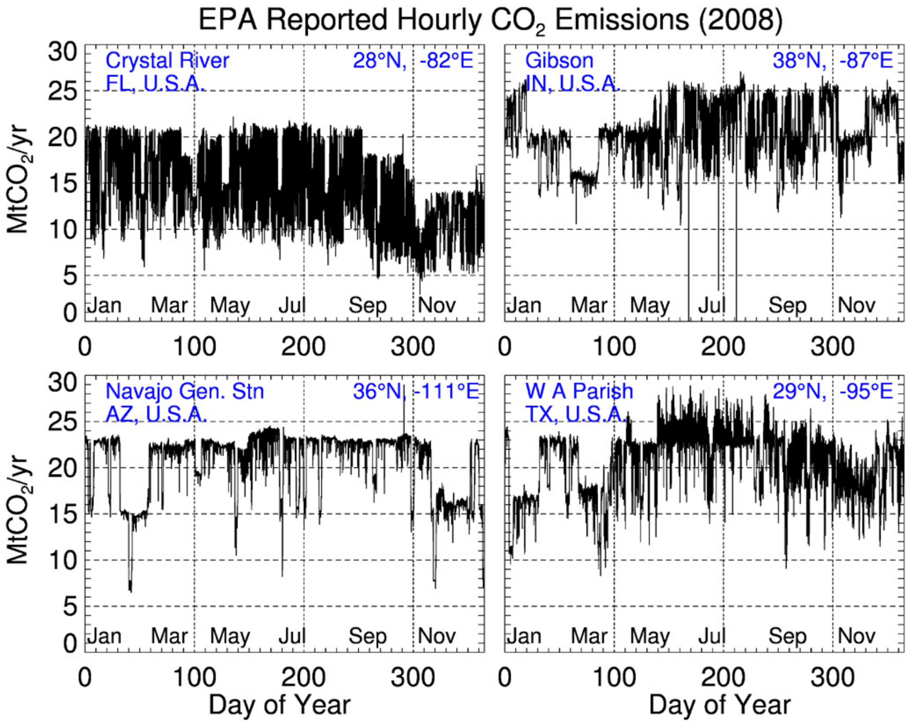


**Fig. 1.** Hourly $CO_2$ emissions from four selected power plants in the US as reported to the EPA. For consistency, the hourly $CO_2$ emissions (in tons $CO_2\ h^{-1}$) were converted to $Mt\ CO_2\ yr^{-1}$.

legally binding agreements to cut greenhouse gas emissions have been established under the Kyoto protocol. However, compliance, monitoring and verification of emissions is and will still remain a challenge.

Up to three quarters of the atmosperic $CO_2$ increase have been attributed to fossil fuel combustion (e.g. in power plants, steel plants), gas flaring (at refineries, oil platforms, etc.) and cement production (Forster et al., 2007). However, despite their importance, these $CO_2$ sources have not been well quantified. For example, the uncertainty in world's annual fossil fuel emissions is $\pm 6$ to $\pm 10\,\%$ (or 0.6 to $1.0\ Pg\ C\ yr^{-1}$) (Marland and Rotty, 1984, Marland, 2008). This uncertainty is 1.5 to 3.3 times larger than the uncertainty in the atmospheric $CO_2$ accumulation ($\pm 0.3$ to $\pm 0.4\ Pg\ C\ yr^{-1}$) (Marland, 2008). The uncertainty in fossil fuel emissions is also an important limitation in inversion calculations of global carbon mass balance because, as pointed out by Oda and Maksyutov (2011), most common inversion frameworks assume fossil fuel emissions as well known quantities, only biospheric and oceanic fluxes are corrected via optimization (e.g. Gurney et al., 2002). As a result, even small uncertainties in the budget and the distribution of fossil fuel emissions introduce substantial errors in the overall carbon budget derived from atmospheric inversions, when the resolution is increased from continental scales to regional, national or urban carbon budgets. As an example to highlight this, Gurney et al. (2005) did a sensitivity study of atmospheric inversions. They illustrated that the lack of seasonality on fossil fuel emissions produced biases of up to 50 % of the seasonal flux estimates during certain times of the year in the US. In another study, Corbin et al. (2010) used a high resolution fossil fuel inventory for the US and showed that regional near-surface $CO_2$ concentrations are altered by

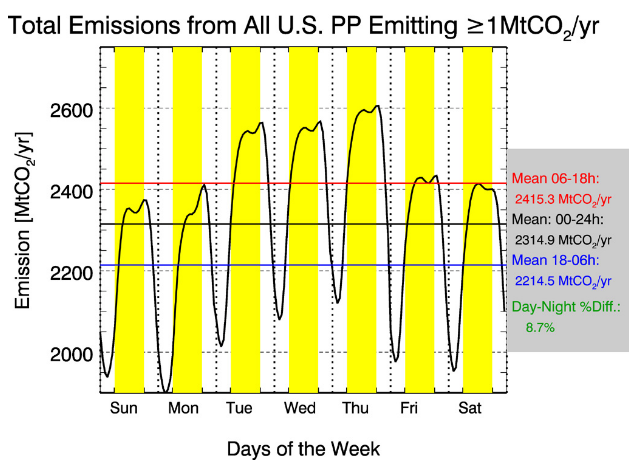


**Fig. 2.** Diurnal cycle of $CO_2$ emissions summed over all power plants (PP) in the US emitting more that $1.0\ Mt\ CO_2\ yr^{-1}$ for 2008. The hours between 06:00 a.m. to 06:00 p.m. (daytime) are highlighted in yellow.

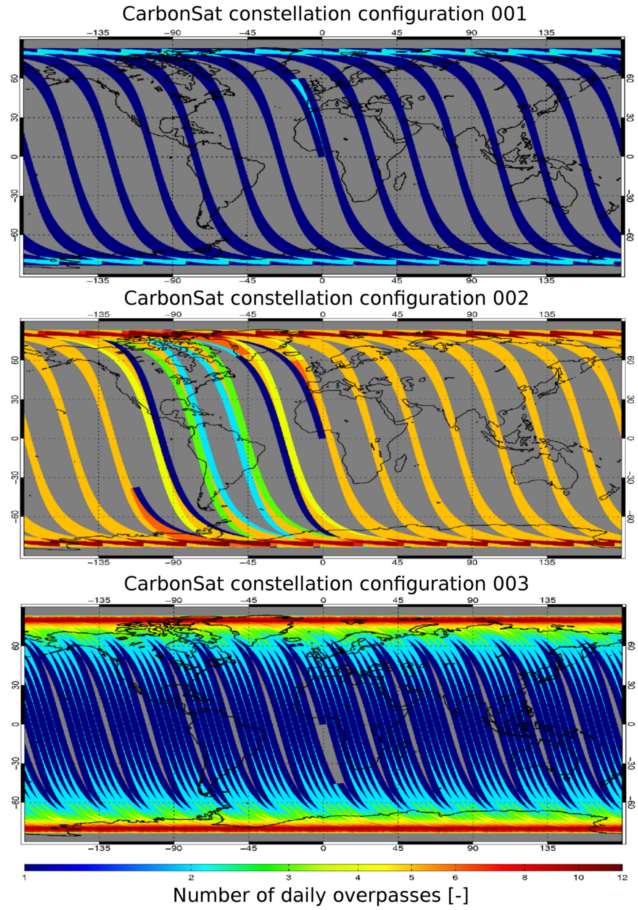


**Fig. 3.** Top panel: one-day coverage for one-CarbonSat (configuration 001). Middle panel: one-day coverage for a 5-satellite constellation with each satellite passing over the target on the same day every 2 h (configuration 002). Bottom panel: one-day coverage for a 5-satellite constellation all with a local time at ascending node of 13:30 and one day apart (configuration 003). The assumed swath width of CarbonSat is 500 km.

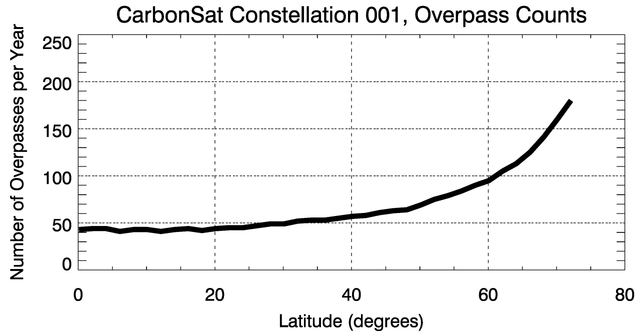


**Fig. 4.** Approximate number of overpasses per year over a target as a function of latitude. Power plants in the mid latitudes will have about 50 overpasses per year for a 1-CarbonSat scenario (configuration 001). Clear sky probability obtained from MODIS can be used to provide an approximation of the cloud free measurements over a target (see Fig. 5).

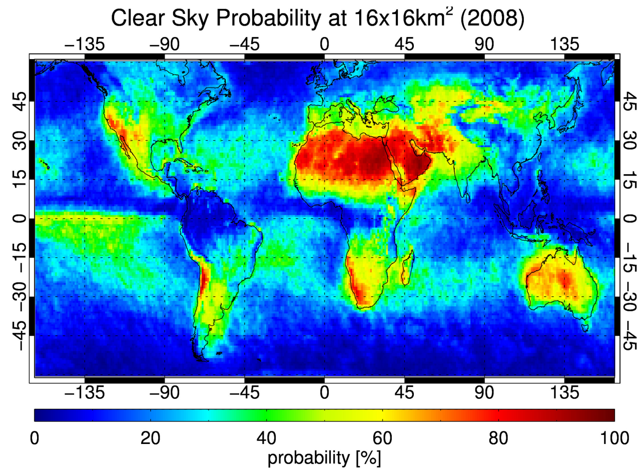


**Fig. 5.** Clear-sky probability from MODIS calculated at $16 \times 16\,km^2$.

more than 15 ppm when seasonal variablility of fossil fuel emissions was included in their model.

Power plants play a big role in the magnitude of fossil fuel emissions. For instance, in 2009, fossil-fuel power plants supplied about 69 % of the US electricity demand and is responsible for 41 % of the total anthropogenic $CO_2$ emissions in the US (US EPA: www.epa.gov/climatechange/emissions/co2_human.html), making it the economic sector with the largest source of $CO_2$ (Petron et al., 2008). Although the US has strict emissions reporting laws under the 1990 Clean Air Act, the maximum allowed error in hourly reported power plant $CO_2$ emissions using Continuous Emission Monitoring Systems (CEMS) are around 14 % (Peischl et al., 2010). In Europe, under the European Union Emissions Trading Scheme (EU ETS) (Ellerman and Buchner, 2007), large $CO_2$ emitters (>500 kt $CO_2$ $yr^{-1}$, accounting for ~40 % of EU $CO_2$ emissions) are required to report annual emissions and are entitled to emission allowances. Since 1 January 2005, $CO_2$ emission allowances can be bought or sold by more than 11 500 installations across Europe (Ellerman and Buchner, 2007). The value of the allowances distributed under the EU ETS (2005–2007) is about $41 billion (at about € 15/t $CO_2$, with € 1.00 = $ 1.25) (Ellerman and Buchner, 2007). The amount of money involved makes accurate $CO_2$ reporting valuable. However, Evans et al. (2009) examined the $CO_2$ calculation approach implemented in the EU ETS and mentioned that it contains a bias that can be up to 20 % against direct measurement. Power plant emissions monitoring is therefore becoming more and more important, not only because $CO_2$ means money under the existing cap and trade systems, but more importantly to improve our understanding of the carbon sources and sinks as needed for reliable climate prediction. To accomplish this globally, mechanisms that are not intrusive nor infringe upon sovereignty of countries are required, such as satellites.

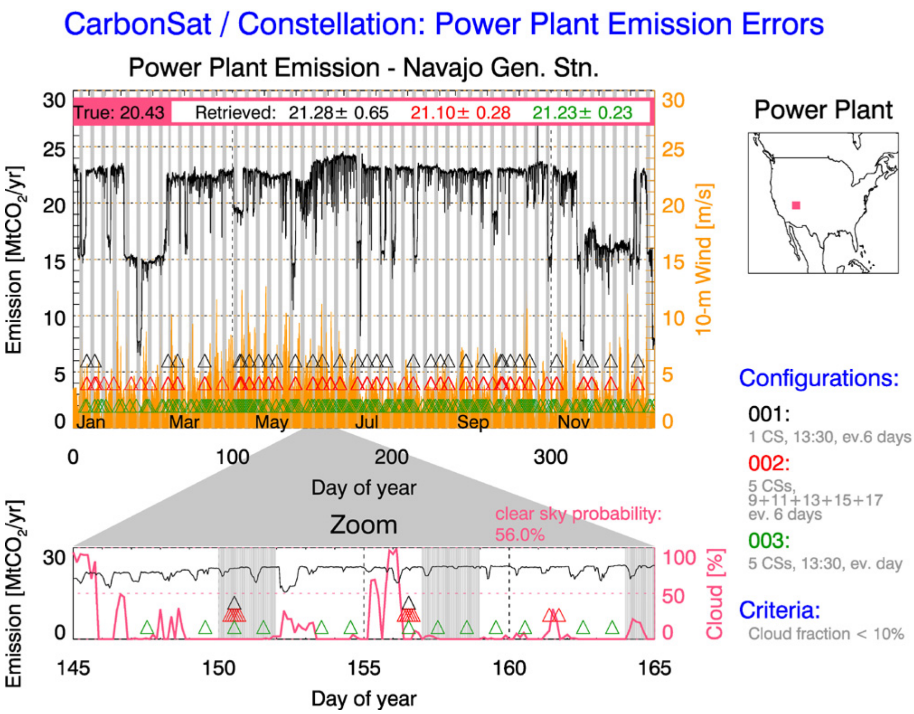


**Fig. 6.** Top panel: $CO_2$ emissions of a power plant in Arizona, USA (Navajo generating station) reported to the EPA for 2008 (black lines). The color-coded triangles represent simulated overpasses for three different CarbonSat configurations (001–003, see Table 1) during clear sky conditions (defined as less than 10 % cloud cover in a 32 × 32 km area near the position of the power plant and its surroundings). Weekends are indicated by the gray shaded areas. The second y-axis represent the wind speeds (yellow, superimposed). The "true" value of 20.43 (in Mt $CO_2$ $yr^{-1}$) is simply the sum of the reported $CO_2$ for this year. The "retrieved" values of 21.28, 21.10, 21.23 and the corresponding 1-$\sigma$ errors (in Mt $CO_2$ $yr^{-1}$) are the values that would have been retrieved for CarbonSat configurations 001, 002 and 003, respectively. For clarity, days 145 to 165 are zoomed in (lower panel) showing the cloud cover (in %, pink lines).

SCIAMACHY on ENVISAT (Burrows et al., 1995, Bovensmann et al., 1999) is the first satellite to perform Planetary Boundary Layer (PBL)-sensitive measurements of column-averaged $CO_2$ and $CH_4$ mixing ratios (i.e. $XCO_2$ and $XCH_4$) using the short-wave infrared and near infrared spectra (Buchwitz et al., 2007, Frankenberg et al., 2011, Schneising et al., 2011). There are also a number of satellite instruments that measure tropospheric $CO_2$ in nadir mode such as HIRS/TOVS (Chédin et al., 2002, 2003), AIRS (Engelen et al., 2004, Engelen and Stephens, 2004, Engelen and McNally, 2005), IASI (Crevoisier et al., 2009), and TES (Kulawik et al., 2010). These instruments measure in the thermal infrared (TIR) part of the electromagnetic spectrum, yielding high sensitivity in the middle and upper troposphere but have low sensitivity in the lower atmospheric layers, where the regional GHG source and sink signals are largest. This low sensitivity limits the information content with respect to regional $CO_2$ and $CH_4$ sources and sinks. And so, dedicated greenhouse gas satellite instruments have been built recently as a response to the urgency of quantifying $CO_2$ from space; the Orbiting Carbon Observatory (OCO) from the USA's side (Kuang et al., 2002; Crisp et al., 2004; Miller et al., 2007) and Japan's Greenhouse Gases Observing Satellite (GOSAT) (Hamazaki et al., 2004; Kuze et al., 2009). These instruments were designed to perform highly accurate and precise global $CO_2$ (and $CH_4$ for GOSAT) measurements from space down to the PBL. GOSAT was successfully launched in 2009, but unfortunately, OCO failed to reach orbit and was lost shortly after its launch on 24 February 2009 (Palmer and Rayner, 2009). However, because of the importance of remote verification of $CO_2$ emissions from space, the US government under the Obama administration has decided to build OCO-2 (Boesch et al., 2011), an exact copy of OCO, expected to be launch-ready by 2013. Active remote sensing of $CO_2$ using satellite-based laser systems are also under investigation (see Amedieck et al., 2009, Bréon and Ciais, 2009 and references given therein). In spite of the numerous remote sensing satellites and the improvements in $CO_2$ and $CH_4$ measurements, monitoring of strong localized sources such as power plants using satellite observations is still not possible now and in the near future. To achieve this, and to continue the time series of PBL-sensitive $CO_2$ and $CH_4$ observations from space, which started with SCIAMACHY on Envisat, CarbonSat (Bovensmann et al., 2010) was proposed. And just recently, the potential of remote sensing to determine power plant emission was successfully demonstrated using an airborne instrument

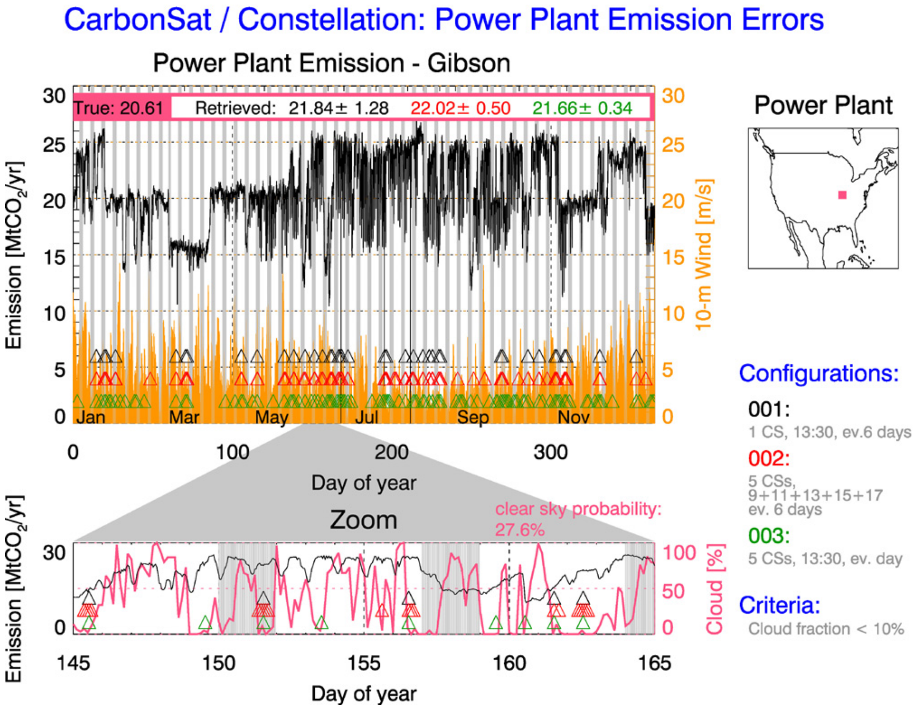


**Fig. 7.** Same as Fig. 6 for the power plant Gibson in Indiana.

applying the same methodology as proposed for CarbonSat (Krings et al., 2011).

CarbonSat has been selected by the European Space Agency (ESA) to be one of two candidates for the 8th Earth Explorer Opportunity Mission (EE-8) to be launched in 2019 at the earliest. CarbonSat's goal is to globally measure atmospheric $CO_2$ and $CH_4$ with the precision, accuracy, spatial resolution and coverage needed to provide crucial information on the sources and sinks of these greenhouse gases. Due to the wide coverage (goal: 500 km swath width) and high spatial resolution (2 km × 2 km) of CarbonSat, its measurements can be used for several applications. One of them is monitoring of greenhouse gas "hot spot" emission sources, such as power plants.

In this paper, we extend the work done by Bovensmann et al. (2010) by utilizing actual power plant emissions in the USA combined with high-resolution re-analyzed data of local meteorological conditions (winds and cloud cover). We present a characterization of systematic and random errors that would arise from power plant monitoring using hypothetical CarbonSat constellations. For the systematic errors, we focus on errors of annual emission estimates arising from sparse temporal coverage. The random error is due to instrument (detector) noise. The orbits and sampling characteristics were simulated for this purpose. We are able to quantify this type of systematic error because the power plant emissions are known in this study. In reality only the random error is known and the sampling error component has to be estimated e.g. from the results of the study at hand.

This manuscript is organized as follows: In the next section, we describe the power plant emission database and the meteorological fields that were used, together with the simulated satellite constellation overpasses. A concise description of the statistical analyses used to arrive at the error estimates are also presented. In Sect. 3, we show the results from the statistical analyses and provide discussions explaining the errors and the differences between the selected constellation configurations. We also attempt to investigate the year-to-year variablity in emissions of some power plants. Conclusions for this study and arguments for a preferred constellation are presented in Sect. 4.

## 2 Data and methods

This section describes the data we used for the statistical analyses, most of which are originally available online from United States government agencies. For this work we focus on power plants in the conterminous United States due to the exemplary strictness of the reporting requirements imposed on electric generation utility power plants in this country.

### 2.1 Environmental Protection Agency Clean Air Markets-Data and maps (EPA CAMD) emissions database

Electric Generation Utility (EGU) power plants in the US are required by law to report hourly averaged emissions of nitrogen oxides ($NO_x$), sulfur dioxide ($SO_2$) and carbon dioxide

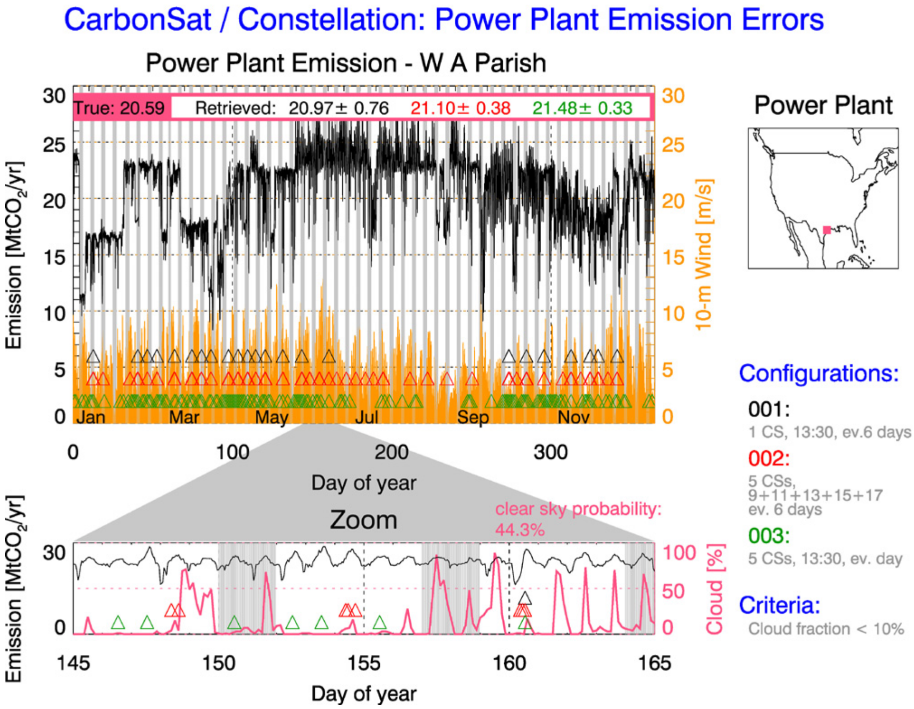


**Fig. 8.** Same as Fig. 6 for the power plant W. A. Parish in Texas.

($CO_2$) as indicated under Title 42 of the US code section 7561k (Peischl et al., 2010). The latest emission data from major power plants are delivered by Continuous Emission Monitoring Systems (CEMS), which determine mixing ratios of $NO_x$, $SO_2$ and $CO_2$ from the stack exhaust of each plant. Hourly emission fluxes are calculated by combining the information on the mixing ratios with stack flow rate measurements. These data are subject to quality control procedures and reported to the US Environmental Protection Agency (EPA) every quarter. The data are then posted and made available for download at the EPA website (http://camddataandmaps.epa.gov/gdm/index.cfm). Different contractors perform periodical assessments of the accuracy of the data through independent sampling of the stack gases and flow rates. In order for CEMS to be compliant with the US Code of Federal Regulations (C.F.R.), tests must agree to within ±10 % for $NO_x$, $SO_2$ and $CO_2$ concentrations (with CEMS showing no low bias compared to the tests) and within ±10 % for stack flow rates, as mentioned in Peischl et al. (2010). Assuming random errors are normally distributed, mass emission rates from EGUs equipped with CEMS should be accurate to better than ±14 % (after summing the concentration and flow uncertainties in quadrature) and enhancement ratios (e.g. $NO_x/CO_2$) should also be accurate to better than ±14 %, assuming the stack flow rate uncertainties are the same for each trace gas measurement (Peischl et al., 2010). Note that ±14 % is the maximum difference allowable for CEMS and the independent tests, however Evans et al. (2009) mentioned that measurements of $CO_2$ concentrations from certified CEMS have a typical uncertainty of <1 % and flow rates from certified gas flow CEMS have typical uncertainties of <5 %. So that the overall uncertainty of $CO_2$ flux measurements for any given hour is less than 5.1 %. Thus, the EPA CAMD data provide a unique, objective and detailed estimation of the $CO_2$ emissions from power plants (Petron et al., 2008). Petron et al. (2008) further established the robust nature of the CAMD data set by presenting cases of regional-scale emissions anomalies that are apparent in the data set and explaining these anomalies by known events in regional power generation and distribution.

Figure 1 shows the hourly $CO_2$ emissions from four selected power plants in the US. By making use of the CAMD data, the strong daily, weekly and seasonal cycles of $CO_2$ emissions from power plants can be taken into account in studying the associated errors arising from the sampling characteristics of CarbonSat. For our purpose, we only selected power plants with more than or equal to 1 Mt $CO_2$ $yr^{-1}$ emissions because 1) CarbonSat error limitations dictate that only power plants emitting above 0.8 Mt $CO_2 yr^{-1}$ could be measured (Bovensmann et al., 2010) and 2) Power plants emitting more than 1 Mt $CO_2$ $yr^{-1}$ are more likely to supply the electricity to the grid continuously.

Electrical consumption is not constant throughout the day, so power plants have to adjust their power output according to this demand. This is reflected on the power plant $CO_2$ emissions. Figure 2 shows the characteristic emissions of all power plants in the US summed over the days in a week (emissions are taken at the local times of the power plants).

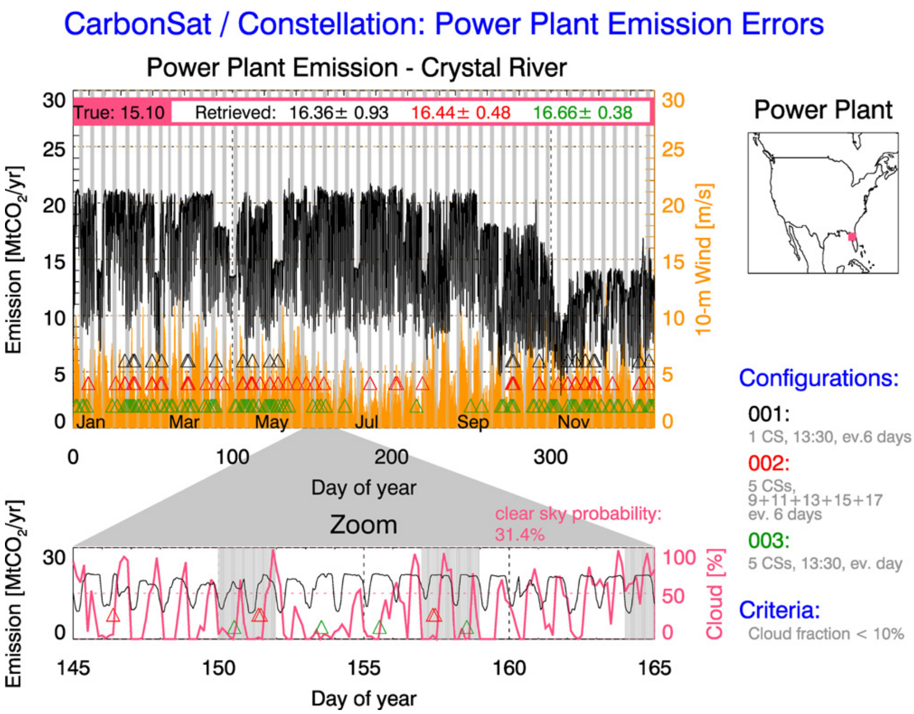


**Fig. 9.** Same as Fig. 6 for the power plant Crystal River in Florida.

An important feature is that the demand and therefore the emissions, have strong diurnal variations. The average day-night difference in emissions alone are around 9 % from all power plants. During the day, power demand varies strongly. The peak demand usually happens around mid-morning and around late afternoon. However, since power plants may also supply a city thousands of kilometers away (e.g. Navajo Generating Station supplying Los Angeles ~900 km away), the times of the peak demands may vary. There are also day-to-day variations in the emissions, i.e. weekends have usually lower emissions and peak emissions are usually observed in the middle of the week (see also Fig. 4 of Petron et al., 2008). This makes it even more important for an instrument to have short revisit times in order to monitor power plant emissions and capture its variablity from space.

### 2.2 NCEP-NARR wind vectors and cloud cover

National Centers for Environmental Prediction-North American Regional Reanalysis (NCEP-NARR) is an extension of the NCEP global reanalysis. It is run over the North American region. The NCEP-NARR model uses very high resolution NCEP Eta Model (32 km/45-layer) together with the Regional Data Assimilation System (RDAS). This system assimilates precipitation along with other variables. The improvements in the model/assimilation have resulted in a dataset with substantial improvements in the accuracy of temperature, winds and precipitation compared to the NCEP-DOE Global Reanalysis 2 (http://www.esrl.noaa.gov/psd/data/gridded/data.narr.monolevel.html). Outputs of surface (10 m above ground) wind vectors (u and v) and cloud cover are given in 3 h bins, which are then interpolated to the reported hourly emissions of each power plant. NCEP NARR wind and cloud cover data are given in a 32 km × 32 km grid. For our purpose, we selected the data points closest to the power plant targets.

### 2.3 CarbonSat constellation configurations

Studies have been performed on different satellite orbit configurations, while taking into account the reported $CO_2$ emissions and the NCEP meteorology. Our first approach was to simulate overpasses from a single CarbonSat satellite with the following characteristics: orbit height: 828 km, inclination: 98.7°, orbit period: 6087.6 s and a Local Time Ascending Node (LTAN) of 13:30 (01:30 p.m.). This orbit was simulated using Satellite Tool Kit (STK, http://www.agi.com/products/by-product-type/applications/stk/). We define this as configuration 001, where global coverage is achieved approximately every 5 days (see Fig. 3, top panel). Configuration 002 is an extension of configuration 001. It has 5 CarbonSat satellites that also have the same orbit characteristics but with LTANs that are two hours apart. Global coverage is also achieved in approximately 5 days (see Fig. 3, middle panel). Lastly, configuration 003 has also 5 CarbonSat satellites all having an LTAN of 13:30 and are one day apart, which means that global coverage will be achieved every day (Fig. 3, lowest panel). Table 1 summarizes the

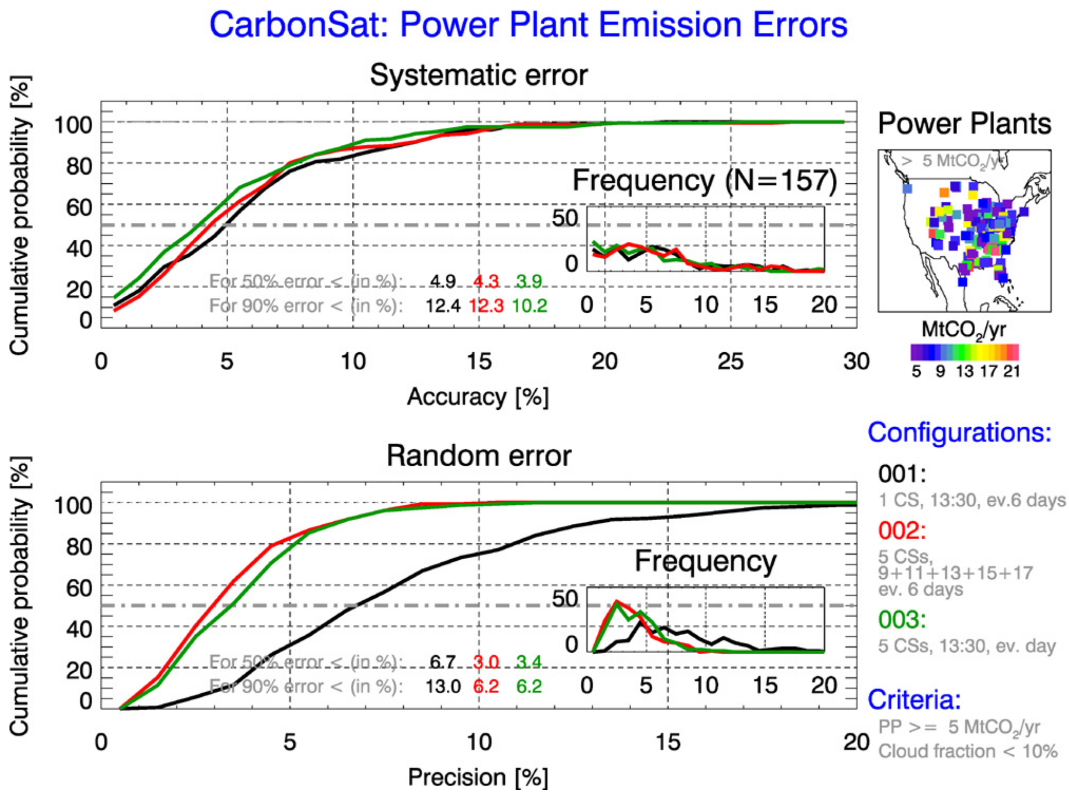


**Fig. 10.** Error analysis for different CarbonSat configurations, done for power plants with emissions of more than or equal to 5 Mt $CO_2$ $yr^{-1}$. The systematic errors for different configurations (color-coded) are shown in the top panel and random errors are shown in the bottom panel.

characteristics of the different CarbonSat configurations. For visual clarity, we also plotted the expected number of CarbonSat overpasses per year as a function of latitude in Fig. 4. Power plants in the mid-latitudes, where most industrialized nations are located, will have about 50 overpasses per year. The clear-sky probabilities obtained from MODIS can help to provide an approximation of the cloud-free measurements over a target (Fig. 5), so that from the number of theoretical overpasses (Fig. 4), one can deduce the expected cloud free measurements just by looking at the MODIS dataset. However, care must be taken in doing the interpretation because very thin cirrus clouds are sometimes hard to detect with passive satellite instruments (Reuter et al., 2009).

### 2.4 Estimation of errors

Bovensmann et al. (2010) analyzed and quantified several error sources arising from the retrieval of power plant $CO_2$ emissions. From a single CarbonSat overpass, they studied errors due to aerosols, instrument noise, advection and mixing. They found that the random error arising from instrument noise primarily depends on near-surface wind speed ($\sim$1 Mt $CO_2$ per 1 $ms^{-1}$) because with increasing wind speed, the amplitude of the $CO_2$ emission plume gets smaller so that instrument noise becomes more important. They also found that neglecting enhanced aerosol concentrations in the power plant plume may result in errors in the range of 0.2–2.5 Mt $CO_2$ $yr^{-1}$, depending on power plant aerosol emission.

In this study, we focus on systematic errors of inferred annual emissions arising from sparse sampling and on the wind speed dependent statistical (random) error, which can be interpreted as the $CO_2$ emission detection limit for power plants and other strong $CO_2$ point sources as mentioned in Bovensmann et al. (2010).

The total error of the derived annual power plant emissions is a combination of sampling error (systematic error) and random error (due to wind speed). Within this study, we are able to quantify both error components because the power plant emissions are assumed to be known. Whereas in reality, only the random error is known and the sampling error component would have to be estimated e.g. from the results of the study at hand.

First, we determine the systematic errors due to sparse sampling. We simulated satellite overpasses for each power plant location. For each overpass, we took the power plant's reported $CO_2$ emission (at 13:00 LT – local time) and assume that CarbonSat would measure the same amount of $CO_2$ without errors. Since the power plant load and the corresponding $CO_2$ emissions vary with time, this sparse sampling

**Table 1.** Different CarbonSat configurations.

| Configuration ID | Number of satellites | LTAN | Global coverage |
|---|---|---|---|
| 001 | 1 | 13:30 | after 5 days |
| 002 | 5 | 09:30, 11:30, 13:30, 15:30, 17:30 | after 5 days |
| 003 | 5 | 13:30 | after 1 day |

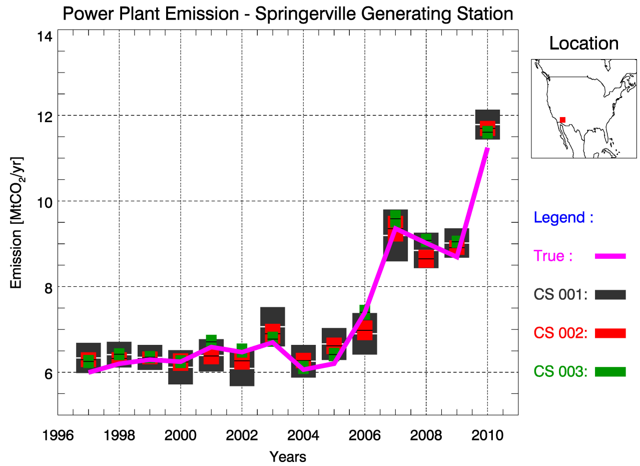


**Fig. 11.** Reported annual emissions from the Springerville generating station in Arizona, USA (1997–2010). The yearly (true) emissions are denoted by the magenta line. The simulated measurements from three different CarbonSat constellation configurations are represented by the bars (color-coded). The height of the bars represent the random errors for the annual emission estimate.

at fixed time intervals is expected to yield a bias in the $CO_2$ annual emission estimate. The sparse sampling will be further reduced depending on the cloud cover at the power plant location because we assume that CarbonSat will not be able to measure during scenarios with a cloud fraction of more than 10% in a $32 \times 32\,\mathrm{km}^2$ area (i.e. we require an essentially cloud-free scene around the power plant in order to observe most of the $CO_2$ emission plume. So simulated overpasses with cloud contamination of $>10\,\%$ are flagged and considered as "no measurement". The estimated annual $CO_2$ emission measured by CarbonSat ($\hat{E}$) over a certain power plant is then calculated as:

$$\hat{E} = \frac{1}{n} \sum_{j=0}^{n} E_j^t \, N. \tag{1}$$

$E_j^t$ is the "true" $CO_2$ emitted by a power plant at the overpass hour $j$, with values reported in tons $CO_2\,h^{-1}$. This is the value that CarbonSat would measure. We multiply this by $N$, the number of hours in a year so that $\hat{E}$ has the units of $\mathrm{Mt\,CO_2\,yr^{-1}}$, then divide by $n$, the actual number of overpass hours. The "true" power plant annual emission ($E^T$, in units of $\mathrm{Mt\,CO_2\,yr^{-1}}$) is the sum of all $E_i^t$, the reported $CO_2$ at hours $i$ for the whole year:

$$E^T = \sum_{i=0}^{N} E_i^t. \tag{2}$$

The bias is simply the difference between $\hat{E}$ (the annual emission as retrieved from CarbonSat) and $E^T$(the true annual $CO_2$ emission) (see results shown in Figs. 6–9 for different CarbonSat scenarios applied to selected power plants, as discussed in detail below).

As mentioned before, we assume that the error of each simulated measurement is only dependent on the wind speed at the time of the satellite pass over the power plant location, neglecting other possible error sources. In line with the findings of Bovensmann et al., 2010, we also assume that the measurement random errors are linear, i.e. we conservatively assigned a 1.0-$\mathrm{Mt\,CO_2\,yr^{-1}}$ error for every 1-$\mathrm{ms^{-1}}$ wind speed (Bovensmann et al., 2010 showed that the error is to a good approximation 0.8 $\mathrm{Mt\,CO_2\,yr^{-1}}$ per 1 $\mathrm{ms^{-1}}$ wind speed) .

We calculate the random error of $\hat{E}$ by consequently applying the laws of error propagation. With CarbonSat measurements $E_j^t$ expressed in $\mathrm{Mt\,CO_2\,yr^{-1}}$ we can write the Jocobian of $\hat{E}$ as:

$$\mathbf{K}_{\hat{E}} = \left[\frac{1}{n}, \ldots, \frac{1}{n}\right] \tag{3}$$

where $n$ is equal to the number of overpasses. The error covariance matrix $\mathbf{S}_{\hat{E}}$ is given by

$$\mathbf{S}_{\hat{E}} = \begin{bmatrix} \mathrm{Var}\,(E_1) & \cdots & \mathrm{Cov}\,(E_1,\, E_n) \\ \vdots & \ddots & \vdots \\ \mathrm{Cov}\,(E_n,\, E_1) & \cdots & \mathrm{Var}\,(E_n) \end{bmatrix}. \tag{4}$$

The diagonal terms of $\mathbf{S}_{\hat{E}}$ represent the errors (squared) derived from the wind speed at the time of the overpass at the power plant location. We assume that the data are independent so that the off diagonals of $\mathbf{S}_{\hat{E}}$ are zero. The variance of the estimate $\hat{E}$ is then calculated as:

$$\mathrm{Var}\left(\hat{E}\right) = \mathbf{K}_{\hat{E}}\, \mathbf{S}_{\hat{E}}\, \mathbf{K}_{\hat{E}}^T \tag{5}$$

which is equivalent to:

$$\mathrm{Var}\left(\hat{E}\right) = \frac{1}{n^2} \sum_{j=0}^{n} \mathrm{Var}\left(E_j\right). \tag{6}$$

Thinking of the application to real measurements where no true emission values are known, one could use the method proposed by Reuter et al. (2010) to estimate the total error of an averaged quantity as a combination of the measurement error and the sampling error without knowledge on the true average value of the distribution.

## 3 Results and discussion

Figure 6 shows typical hourly emissions of a power plant in Arizona, USA (Navajo Generating Station) for 2008. The top panel of Fig. 6 shows the systematic error calculations obtained from the different configurations. For each overpass, a measurement consists of two values, the estimated emission (assumed to be free of systematic errors) and its wind speed-dependent statistical uncertainty (random error). The estimated annual emission as inferred from the CarbonSat observations is the mean of the measured emissions of all overpasses, i.e. $\hat{E}$. The variance of $\hat{E}$ follows from Eq. (5). As can be seen for this example (see bar on top), the true emission is 20.43 Mt $CO_2$ $yr^{-1}$. For configuration 001 the estimated emission is $21.28 \pm 0.65$ Mt $CO_2$ $yr^{-1}$. For configuration 002, the retrieved value would be $21.10 \pm 0.28$ Mt $CO_2$ $yr^{-1}$ and for configuration 003: $21.23 \pm 0.23$ Mt $CO_2$ $yr^{-1}$. As expected, systematic errors occur due to the sparse sampling. As also expected, the estimated uncertainty (random error) is reduced by about a factor of two for a constellation of 5 satellites (square root dependence). The systematic error is somewhat smaller if 5 satellites are used but only marginally. This is because, in this example, the $CO_2$ emissions during day do not vary so much (therefore one sample per day is sufficient). Also, the day-to-day variations are small, even when comparing weekdays with weekends (grey shaded areas). The Navajo generating station partially supplies the city of Los Angeles (~900 km away) as well as the city of Las Vegas (www.srpnet.com/about/stations/navajo.aspx). These are two cities that have a huge electricity demand for air-conditioning, leading to a large day-night difference in power demand, especially in the summer months. Figures 7–9 show similar plots for three other power plants. These plants are only some of the highest $CO_2$-emitting power plants in the US. As can be seen, the characteristics of the hourly emissions are different for each power plant. For example, for the power plant Crystal River (Fig. 9), the day/night contrast is substantial. Since power consumption at night is usually lower than during the day, this leads to systematically higher retrieved values for all configurations. We have also compared the differences in emissions during cloudy and clear skies. Although there is a link between temperature and electrical consumption (Petron et al., 2008), we found that the difference in emissions during cloudy and clear days is very small (~3 %) when averaged over all the power plants we investigated.

The statistics for all power plants are shown in Fig. 10. It shows the results for power plants emitting more than or equal to 5 Mt $CO_2$ $yr^{-1}$ in the US (157 power plants). The results can be summarized as follows: The systematic error of the annual $CO_2$ emissions of all power plants in the US emitting more than or equal to 5 Mt $CO_2$ $yr^{-1}$ as obtained from one CarbonSat due to sparse time sampling is less than 4.9 % for 50 % of the power plants and less than 12.4 % for 90 % of all power plants. Using a combination of 5 CarbonSats essentially does not result in a large reduction of this error. However, the smallest systematic error is obtained with configuration 003. This is because the day-to-day variability is larger (e.g. differences between weekdays and weekends) compared to the variability during the day (i.e. from 09:00 a.m. to 05:00 p.m.) as can be seen in Fig. 1.

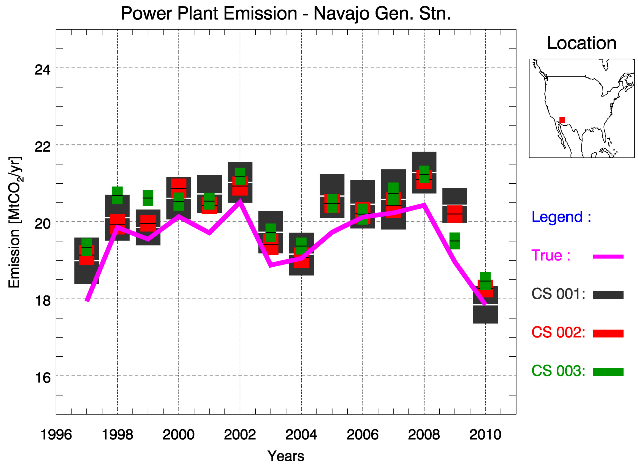


**Fig. 12.** Same as Fig. 11 for the Navajo generating station in Arizona, USA.

The statistical (or random) error of the estimated emissions using one CarbonSat is less than 6.7 % for 50 % of the power plants ($\geq$5 Mt $CO_2$ $yr^{-1}$) and less than 13.0 % for 90 % of all power plants ($\geq$5 Mt $CO_2$ $yr^{-1}$) . This improves by approximately a factor of two if 5 CarbonSats are used (configuration 002 and 003). Qualitatively, the same conclusions can be drawn if all power plants emitting more than 1 Mt $CO_2$ $yr^{-1}$ are used (see Table 2) or all those emitting more than 10 Mt $CO_2$ $yr^{-1}$.

By contrast, hourly mass emission rates reported by Electric Generation Utility (EGU) power plants in the US equipped with CEMS are reported to only require an accuracy of 14 % or better (Peischl et al., 2010), despite the fact that the $CO_2$ flux estimates from CEMS can have an uncertainty of <5.1 % (Evans et al., 2009). CEMS can also be used in the EU-ETS as long as the comparison with calculated data shows equal or less uncertainty. As however pointed out by Evans et al. (2009), "uncertainty as it is used here has nothing to do with accuracy (i.e. closeness to "truth" or lack of bias) ... only with the precision or repeatability of the data". Moreover, the $CO_2$ calculation approach used in the European Trading Scheme may have a bias of up to 20 % in annual $CO_2$ emissions compared to direct measurement according to Evans et al. (2009). The study was done on power

**Table 2.** Error estimates on annual power plant (PP) emissions from three different CarbonSat configurations.

| Power Plant (PP) emissions and associated errors from CarbonSat estimates (in %) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Error type | Power plant | $\geq$1 Mt $CO_2$ $yr^{-1}$ | | | $\geq$5 Mt $CO_2$ $yr^{-1}$ | | | $\geq$10 Mt $CO_2$ $yr^{-1}$ | | |
| | Sample size | Configuration ID | | | Configuration ID | | | Configuration ID | | |
| | | 001 | 002 | 003 | 001 | 002 | 003 | 001 | 002 | 003 |
| Systematic | 50 % of all PP | $\leq$6.1 | $\leq$5.7 | $\leq$5.6 | $\leq$4.9 | $\leq$4.3 | $\leq$3.9 | $\leq$4.1 | $\leq$4.5 | $\leq$3.8 |
| | 90 % of all PP | $\leq$17.4 | $\leq$16.6 | $\leq$17.6 | $\leq$12.4 | $\leq$12.3 | $\leq$10.2 | $\leq$10.9 | $\leq$8.9 | $\leq$9.6 |
| Random | 50 % of all PP | $\leq$11.4 | $\leq$9.0 | $\leq$9.5 | $\leq$6.7 | $\leq$3.0 | $\leq$3.4 | $\leq$4.3 | $\leq$1.8 | $\leq$2.0 |
| | 90 % of all PP | $\leq$24.3 | $\leq$23.9 | $\leq$23.3 | $\leq$13.0 | $\leq$6.2 | $\leq$6.2 | $\leq$7.0 | $\leq$3.2 | $\leq$3.3 |

plants with capacities of ~500 MW (i.e. power plants emitting approximately 5 Mt $CO_2$ $yr^{-1}$).

In another study, Ackerman and Sundquist (2008) investigated annual $CO_2$ emissions from 828 coal-fired power plants. They compared two databases – the EPA eGRID database containing directly measured $CO_2$ and the Department of Energy's Energy Information Administration (DOE/EIA) database of fuel data from individual power plants. Ackerman and Sundquist (2008) found that the average absolute difference between calculated and (within stack) measured annual $CO_2$ emissions was 17.1 % (Table 1 of Ackerman and Sundquist, 2008). Based on their analysis, Ackerman and Sundquist (2008), concluded that "it is important to recognize that the ongoing quantification of accuracy and uncertainties will always require the application of multiple estimation procedures." CarbonSat or a constellation of CarbonSats, while not outperforming CEMS based monitoring systems, will be able to independently provide an estimate on power plant emissions, especially for those areas of the world, where no CEMS or equivalent systems are available or accessible.

Regarding changes in annual $CO_2$ emissions, it is also important to know up to what extent CarbonSat would be able to detect reductions or increases in emissions of power plants. Therefore, we extend our method to 14 years of emissions data reported by three selected power plants. Figure 11 shows the annual variability of $CO_2$ emissions from the Springerville generating station as well as the estimated annual $CO_2$ emissions from three different CarbonSat constellation configurations (color-coded). It can be seen that CarbonSat captures the changes in emissions, for example, the huge increase in 2006 after the company has installed a third unit (418 MW). The decrease in emissions from 2008–2009, probably as a consequence of a fire at the station, is also detected. In December 2009, Unit 4 (400 MW) became operational, this explains the increased emissions in the following year, which is also captured by CarbonSat. For information on the power plant and its history, see also: www.tucsonelectric.com/Company/News/SGS3/index.

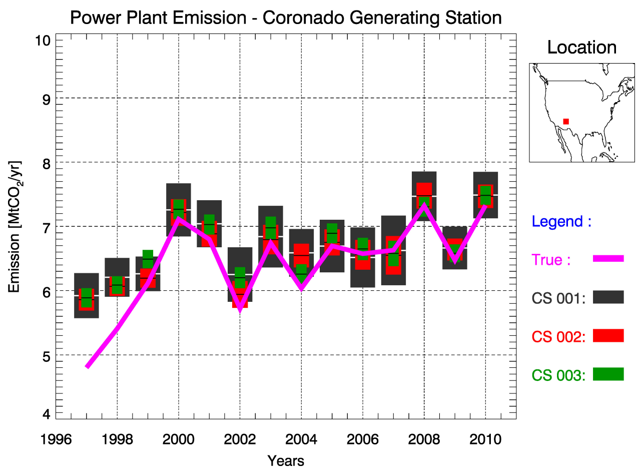


**Fig. 13.** Same as Fig. 11 for the Coronado generating station in Arizona, USA

asp and www.sourcewatch.org. Figure 12 shows the annual emissions of the Navajo generating station. There is a slight tendency for CarbonSat to over-estimate the annual emissions, but the variability could be well captured. The reduction in 2010 could also be noticed. A possible explanation to this reduction is the implementation of the renewable energy policy by the Los Angeles Department of Water and Power (LADWP). In 2010, LADWP has achieved its goal of reducing $CO_2$ emissions (~2.5 Mt $CO_2$ $yr^{-1}$) by sourcing up to 20 % of its power from green and renewable energy (www.ladwp.com/ladwp/cms/ladwp04197.jsp). Figure 13 shows an example of a somewhat steady annual $CO_2$ emission from a power plant (Coronado generating station in Arizona). The agreement between the reported $CO_2$ emissions and the simulated CarbonSat measurements are quite good, especially in the years after 1998. Figures 11–13 indicate that CarbonSat has the potential to be an important tool for monitoring power plant annual emission changes.

## 4 Summary and conclusions

From the orbit, swath and measurement characteristics of the proposed CarbonSat satellite instrument, we have characterized errors arising from power plant $CO_2$ emissions monitoring. We quantified two types of errors: (i) systematic error of annual emissions arising from sparse sampling of the power plant's emission and (ii) wind speed-dependent random errors caused by instrument detector noise (Bovensmann et al., 2010). We used a database containing hourly $CO_2$ emissions from US power plants and combined this with reanalyzed meteorological conditions (wind, cloud cover). Two CarbonSat constellations, both comprising of 5 CarbonSat satellites, were also studied. We have shown that, despite the variability of the power plant emissions and the limited satellite overpasses, one CarbonSat can independently verify reported annual $CO_2$ emissions from large power plants ($\geq$5 Mt $CO_2$ $yr^{-1}$) with a systematic (sampling) error of $\sim$4.9 % or better for 50 % of all the power plants and $\sim$12.4 % or better for 90 % of all the power plants. Using a combination of 5 CarbonSats improves the random errors by approximately a factor of two, but essentially does not result in a large reduction of the systematic error. The reason is that the systematic error caused by sparse time sampling is mainly determined by day/night emission characteristics (CarbonSat can only measure during daytime).

Two configurations of 5-CarbonSat constellations have been investigated. One achieves global coverage every day but only at fixed local times (configuration 003). The other performs measurements every 2 h but only achieved global coverage after 5 days (configuration 002). For the purpose of power plant emissions monitoring, both configurations are similar but configuration 003 achieves somewhat smaller systematic errors. Configuration 002 might be advantageous for observing the daily cycle of $CO_2$, but for other reasons, fast global coverage is important; for instance, in monitoring important events that only last a few days. Examples of these events are: biomass burning, (mud) volcanic eruptions and sudden release of $CH_4$ below ice/snow after melting in spring or ice break up (Siberia, Alaska). A constellation of exactly identical CarbonSats in essentially identical orbits has also the advantage of higher accuracy due to better (easier) intercalibration between the various satellites. In retrospect, we mentioned that we assumed data independence so that the off-diagonal elements of Eq. (4) are zero. This may hold true for configurations 001 and 003. But for a typical wind speed of about 3 m $s^{-1}$, an air parcel travels approximately 21.6 km within 2 h, i.e. it is still "close" to the power plant when the next CarbonSat overpass is to be expected. Under these circumstances, which may arise for configuration 002, non-diagonal elements may be relevant indicating positive correlations. In this case the precision reduction upon averaging will be smaller compared to uncorrelated observations. For these reasons, we therefore conclude that the preferred configuration is configuration 003, i.e. the one which achieved global coverage within the shortest time period (even if only one measurement per day can be taken).

CarbonSat can also serve as an independent verification system by checking the reported emissions at the hours of the overpasses for countries with an hourly reporting system as in the US. By comparing the routinely reported power plant emissions and the coincident CarbonSat measurements for that hour, the systematic errors from the sparse sampling will not be a significant error source anymore. Instead, other error sources such as aerosols, wind speeds, albedo, etc. will be more important. These can be improved through retrieval algorithm development.

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