

1 **GFIT2: An experimental algorithm for Vertical Profile**
2 **Retrieval from Near IR Spectra**

3

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12

13 **Abstract**

14 An algorithm for retrieval of vertical profiles from ground-based spectra in the near
15 IR is described and tested. Known as GFIT2, the algorithm is primarily intended for
16 CO₂, and is used exclusively for CO₂ in this paper. Retrieval of CO₂ vertical profiles
17 from ground-based spectra is theoretically possible, would be very beneficial for
18 carbon cycle studies and the validation of satellite measurements, and has been the
19 focus of much research in recent years. GFIT2 is tested by application both to
20 synthetic spectra, and to measurements at two TCCON sites. We demonstrate that
21 there are approximately 3 degrees of freedom for the CO₂ profile, and the algorithm
22 performs as expected on synthetic spectra. We show that the accuracy of retrievals of
23 CO₂ from measurements in the 1.61 μ (6220 cm⁻¹) spectral band is limited by small
24 uncertainties in calculation of the atmospheric spectrum. We investigate several
25 techniques to minimize the effect of these uncertainties in calculation of the spectrum.
26 These techniques are somewhat effective, but to date have not been demonstrated to
27 produce CO₂ profile retrievals with sufficient precision for applications to carbon
28 dynamics. We finish by discussing on-going research which may allow CO₂ profile
29 retrievals with sufficient accuracy to significantly improve on the results of column
30 retrievals, both in total column abundance and in profile shape.

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2 **1. Motivation**

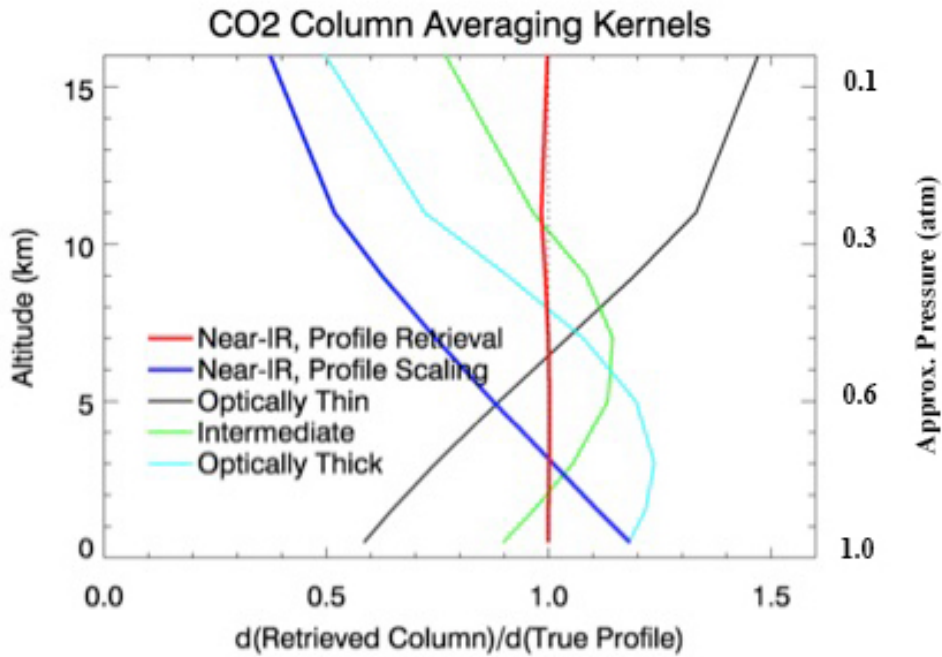
3 Since 2004 the Total Carbon Column Observing Network (TCCON) has measured
4 ground-based near-IR solar spectra. Their high spectral resolution and SNR allow
5 high precision measurements of total overhead column abundance of CO₂ and other
6 gases, which provide constraints on the global carbon budget, and also help validate
7 satellite measurements using the same spectral bands. The standard analysis consists
8 of least-squares spectral fitting to derive a multiplicative scale factor applied to an
9 assumed ('a priori') CO₂ profile shape. That analysis ('profile scaling') provides
10 column densities, from which dry air average mole fractions can be derived

11

12 Allowing the a priori CO₂ profile shape to vary in the retrieval process ('profile
13 retrieval') has several potential advantages. For one, it can be shown that such an
14 algorithm has more uniform sensitivity to CO₂ as a function of altitude, so should be
15 less sensitive to bias from the a priori profile (Fig. 1). Secondly, it has more freedom
16 to fit the observed spectrum, thus generally will leave smaller residuals, and may help
17 in understanding their origin. Finally, it would theoretically allow separation of the
18 boundary layer from the rest of the column, and helping to distinguish sources and
19 sinks at continental and sub-continental scales (Fig. 2). Profile retrieval at the
20 accuracy required is challenging, however. Profile retrieval requires that the factors
21 that affect the spectral line shape (e.g. ILS, spectroscopic widths) be accurately
22 known. And since profile retrieval attempts to extract more information from the
23 spectrum than profile scaling, there typically needs to be a priori constraints to keep
24 the retrieval stable (Rodgers, 1976, Solomon et al, 2000, Dohe, 2013).

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26



1

2 Fig. 1 Column averaging kernels for simulated retrievals. ‘Profile Retrieval’ and
 3 ‘Profile Scaling’ refer to a typical retrieval using GFIT2 on the 6220 cm⁻¹ CO₂ band
 4 observed operationally. ‘Optically Thin’, ‘Optically Thick’, and ‘Intermediate’ refer
 5 to an idealized, single, isolated spectral line. For these, we calculate a spectrum from a
 6 reference profile, perturb the profile at a single altitude, and calculate a new spectrum.
 7 We then perform a least-squares fit to this synthetic spectrum by deriving a scale
 8 factor for the reference profile. This scale factor, divided by the actual perturbation,
 9 produces a single element of the column averaging kernels shown.

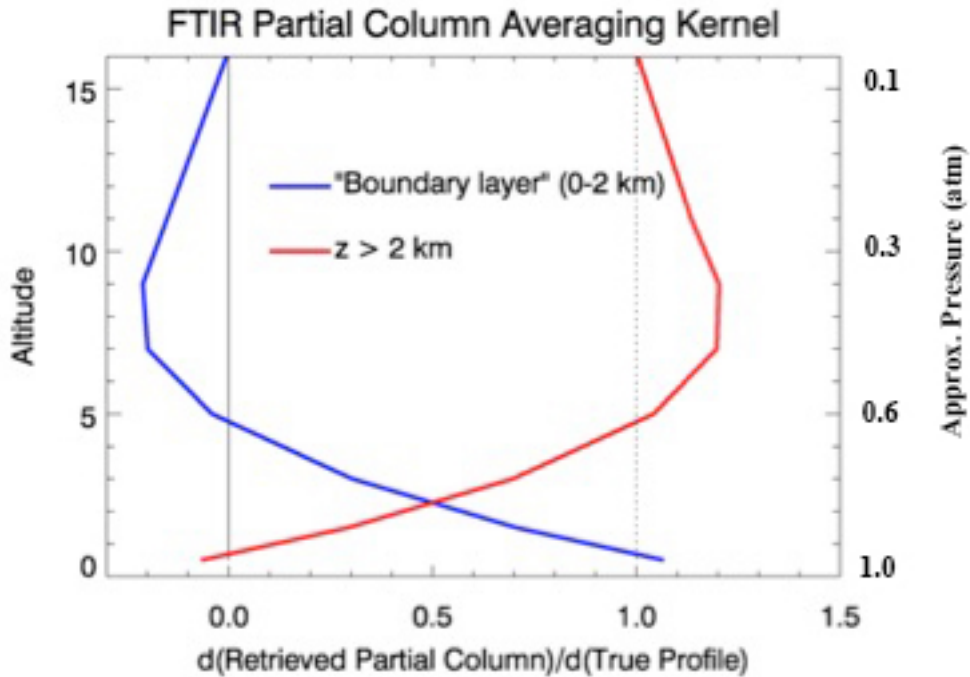
10

11 Recent work on profile retrieval development includes Kuai et al (2013), who
 12 retrieved CO₂ in three tropospheric layers using the 1.6 μ spectral band, and Dohe
 13 (2012) who studied a complete profile retrieval from measurements of the 2.1 μ band.

14

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16



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2 Fig. 2 Partial column averaging kernels for the profile retrieval algorithm of Fig. 1
 3 (GFIT2 applied to the 6220 cm^{-1} spectral band, with assumed signal-to-noise ratio =
 4 1000).

5

6 This paper describes the experimental implementation and early tests of a profile
 7 retrieval algorithm for TCCON spectra. Its layout is as follows. In section 2 we
 8 describe the standard algorithm used for TCCON and briefly discuss the history of
 9 profile retrieval and the chosen algorithm for similar measurements. Section 3
 10 describes implementation of the algorithm as GFIT2. Section 4 presents tests of
 11 GFIT2, both for synthetic spectra and for real spectra taken to coincide with
 12 overpasses by aircraft making in situ CO_2 measurements. Section 5 presents
 13 preliminary conclusions to date, and section 6 outlines future plans.

14

15

16 **2. Background and algorithm origins, history**

17 GFIT is the algorithm adopted by the TCCON for analysis of the spectra; it was
 18 developed over many years by Geoff Toon at JPL. GFIT is also used to analyze MkIV
 19 balloon spectra (e.g. Sen et al., 1996) and was used in the Version 3 processing of

1 ATMOS spectra (Irion et al., 2002). It is a profile scaling algorithm, employing a
2 quasi-linear regression to derive scale factors for all important absorbers as well as
3 other atmospheric and instrument parameters, such as continuum level and frequency
4 shift.

5

6 GFIT is designed in such a way that its ‘forward model’ is independent of and
7 separable from its ‘inverse method’. These terms are discussed in Rodgers (2000), but
8 briefly the forward model is an algorithm that calculates the atmospheric spectra
9 comparable to the observed spectra, incorporating radiative transfer and molecular
10 physics along with assumed gas distributions. The inverse method retrieves a state
11 vector of parameters, such as molecular mixing ratio, by finding values which provide
12 a best fit to the spectrum given other assumptions and constraints. The GFIT inverse
13 method is a form of ‘optimal estimation’ as described further below, which applies the
14 Gauss-Newton method, iteratively estimating the parameters by successive
15 approximation.

16

17 Ground-based spectra, at microwave, IR, and UV wavelengths, have been analyzed in
18 selected applications for limited altitude profile information, for many years (Connor
19 et al, 2007, 1995, Pougatchev et al, 1996, Schofield et al, 2004.) The physical origin
20 of the limited profile information in ground-base spectra is somewhat varied. Most
21 commonly, the pressure broadened line shape is exploited, however the use of lines of
22 varied opacity (see Fig 1) and the use of multiple atmospheric paths (Schofield, *ibid.*)
23 are also sources of profile information.

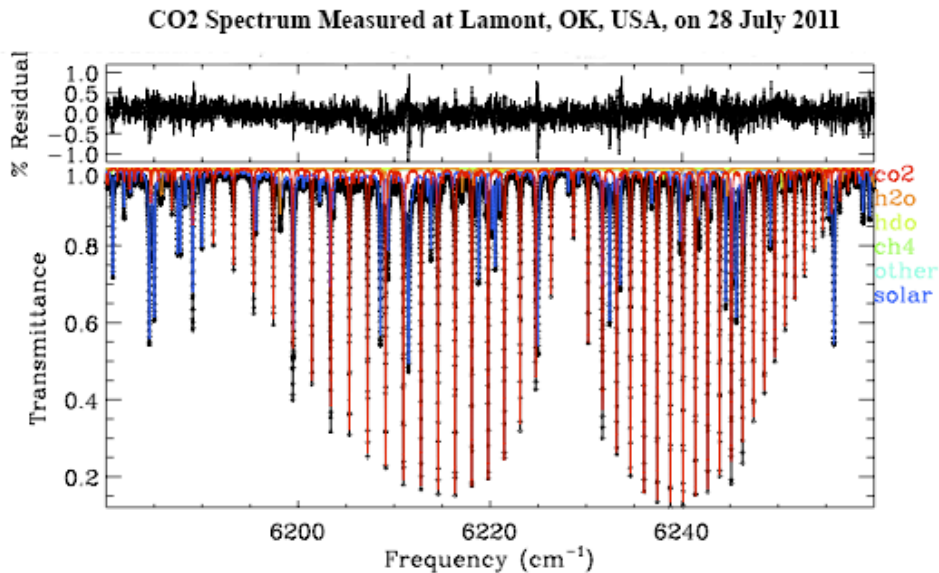
24

25 The most common algorithm for the inverse method used in these and other studies is
26 optimal estimation, formulated by Clive Rodgers (1976, 2000). That algorithm will be
27 described in detail in the following section.

28

29 Optimal estimation has been implemented as a user-selected option of inverse method
30 added to the version of GFIT publically released in 2012; no other changes to the
31 standard GFIT algorithm were made. The modified algorithm is known as GFIT2.

1 GFIT is designed to treat each spectral band independently. All calculations in this
2 paper are of the 1.61μ (6220 cm^{-1}) spectral band; the use of other bands will be
3 discussed briefly in section 5. Figure 3 shows a typical spectrum from the TCCON
4 site at Lamont, OK, USA.



5
6 Fig. 3. A typical spectrum in the 6220 cm^{-1} band. The calculated spectrum, produced
7 by GFIT in profile scaling mode, is superimposed, with the individual gas
8 contributions shown in color. CO_2 , solar lines, and H_2O dominate the visible features.
9 The residuals (also typical) are shown in the upper panel. This spectrum is one of the
10 atmospheric measurements used in section 4.2 and subsequently.

11

12 3. Algorithm and implementation

13 The optimal estimation formulation of Rodgers (2000) was adapted and applied for
14 use with the 'full physics' algorithm (inverse method plus forward model) developed
15 for the first Orbiting Carbon Observatory (OCO) satellite, which failed to reach orbit
16 in 2009. The OCO inverse method, as it existed in 2007, is described in Connor et al
17 (2008) and was used as a starting point for the development of GFIT2. Much of the
18 discussion in section 2 of Connor et al (2008) is directly applicable.

19

20

1 3.1 Inverse Method

2 The OCO inverse method was adapted for use with GFIT, and is briefly described
3 here. We use the notation and concepts of Rodgers (2000). The spectrum, or
4 measurement vector \mathbf{y} , is expressed symbolically as $\mathbf{y} = \mathbf{F}(\mathbf{x}) + \boldsymbol{\varepsilon}$ where \mathbf{x} is the state
5 vector, \mathbf{F} is the forward model, and $\boldsymbol{\varepsilon}$ is the vector of measurement errors.

6 The solution of the GFIT2 inverse method is the state vector $\hat{\mathbf{x}}$ with maximum *a*
7 *posteriori* probability, given the measurement \mathbf{y} . We solve for the state vector update
8 \mathbf{dx}_{i+1} , using a slightly modified form of Rodgers' Eq. 5.8, to improve numerical
9 accuracy by avoiding the inversion of a large matrix:

$$11 \quad (\mathbf{S}_a^{-1} + \mathbf{K}_i^T \mathbf{S}_\varepsilon^{-1} \mathbf{K}_i) \mathbf{dx}_{i+1} = [\mathbf{K}_i^T \mathbf{S}_\varepsilon^{-1} (\mathbf{y} - \mathbf{F}(\mathbf{x}_i)) + \mathbf{S}_a^{-1} (\mathbf{x}_i - \mathbf{x}_a)] \quad (1)$$

12
13 where \mathbf{K} is the weighting function matrix, or Jacobian, $\mathbf{K} = \frac{\partial \mathbf{y}}{\partial \mathbf{x}}$, \mathbf{x}_a is the *a priori* state
14 vector, \mathbf{S}_a is the *a priori* covariance matrix, and \mathbf{S}_ε is the measurement covariance
15 matrix.

16
17 After each iteration, we test for convergence. To facilitate that, we compute the
18 change in the solution scaled by its estimated variance:

$$20 \quad d\sigma_i^2 = \mathbf{dx}_{i+1}^T \hat{\mathbf{S}}^{-1} \mathbf{dx}_{i+1} \quad (2)$$

21
22 where $\hat{\mathbf{S}}$ denotes the covariance of the retrieved state, using the relation

$$24 \quad \hat{\mathbf{S}}^{-1} \mathbf{dx}_{i+1} \cong [\mathbf{K}_i^T \mathbf{S}_\varepsilon^{-1} (\mathbf{y} - \mathbf{F}(\mathbf{x}_i)) - \mathbf{S}_a^{-1} (\mathbf{x}_i - \mathbf{x}_a)] \quad (3)$$

25
26 $d\sigma_i^2$ is effectively the square of the state vector update in units of the solution
27 variance.

1

2 If $d\sigma_i^2 < fn$ (where n is the number of state vector elements, and f is an adjustable
3 convergence parameter), convergence is reached.

4

5 Lastly, we compute the retrieval covariance matrix, $\hat{\mathbf{S}}$, and the averaging kernel
6 matrix \mathbf{A} . $\hat{\mathbf{S}}$ is given by

7

$$8 \quad \hat{\mathbf{S}} = (\mathbf{K}^T \mathbf{S}_e^{-1} \mathbf{K} + \mathbf{S}_a^{-1})^{-1} \quad (4)$$

9

10 The averaging kernel matrix \mathbf{A} is given by

11

$$12 \quad \mathbf{A} = \hat{\mathbf{S}} \mathbf{K}^T \mathbf{S}_e^{-1} \mathbf{K} \quad (5)$$

13

14 Finally, the degrees of freedom for signal are given by the trace of the matrix \mathbf{A} ; the
15 degrees of freedom for the CO_2 profile are the trace of the CO_2 -only sub-matrix of \mathbf{A} .

16

17 To enable use of the Rodgers' algorithm, a modified GFIT code was developed which
18 completely separates the forward model and inverse method, and allows integration of
19 optimal estimation profile retrieval with the existing code. Conceptually, the
20 experimental, integrated GFIT allows selection of the existing (profile scaling) or
21 modified (profile retrieval) algorithm. This is simply accomplished by setting a
22 parameter in an input file. The integrated algorithm has input and output files identical
23 to the existing GFIT, plus new input and output files specific to profile retrieval,
24 which are not required unless the modified algorithm is selected.

25

26 3.2 Measurement Error

27 A critical input to the algorithm of Eq. (1) is the measurement error covariance, \mathbf{S}_e . It
28 is assumed to be diagonal, and the simplest assumption is that the error is entirely

1 random noise independent of frequency. As we will see later, in all real spectra there
2 are systematic residuals, larger than the actual noise level, due to spectral features that
3 can only be imperfectly modeled in the algorithm. If these features are not taken into
4 account in constructing \mathbf{S}_g , the retrieved profile develops severe oscillations.

5

6 The simplest way of ‘de-weighting’ spectral features which remain in the residuals is
7 to increase the estimated measurement error estimate (equivalently, reduce the
8 assumed signal-to-noise ratio, SNR) at all frequencies, so that residual features are
9 ignored (treated as measurement error) (e.g. Connor et al, 1995). As we will see, in
10 practice this is somewhat effective at damping oscillations, but only at the cost of
11 losing most of the profile information in the spectrum.

12

13 An alternative approach we have attempted to avoid profile oscillations is to vary the
14 assumed spectral error to reflect the real residuals obtained by spectral fits (Rodgers
15 & Connor, 2003). A two-stage retrieval is run, in which stage 1 is profile scaling. The
16 residuals from stage 1 are then used to estimate the spectral error as a function of
17 frequency, and inserted on the diagonal of \mathbf{S}_g . This procedure greatly reduces profile
18 oscillations in many synthetic retrievals. We refer to it as ‘variable SNR’.

19

20 A third approach to the problem of systematic residuals is to estimate them
21 empirically, and then to include them in the forward model, multiplied by a scale
22 factor retrieved as part of the state vector (JPL, 2015). Perhaps the simplest approach
23 is to estimate the systematic component by averaging the residuals over the entire set
24 of spectra under study. This technique and simple variants on it will be described in
25 section 4.4 below.

26

27 3.3 State Vector and A priori Uncertainties

28 The full state vector consists of the CO₂ profile, scale factors for the other gas profiles
29 contributing to the spectrum in the band pass (H₂O, HDO, and CH₄ in the 6220 cm⁻¹
30 band), the background continuum level, tilt, and curvature, a frequency shift and a
31 zero level offset. This is identical to the standard GFIT scale factor, except for the

1 CO₂ profile itself. A scale factor multiplying a vector of systematic residuals, as
2 described in 3.2, has been added to the state vector for the retrieval tests of section
3 4.4.

4

5 A critical input is the *a priori* covariance matrix \mathbf{S}_a , specifying assumed uncertainties
6 in the state vector and their correlations. The retrievals in this paper assume that \mathbf{S}_a is
7 diagonal. The *a priori* uncertainties assumed are guided by those used in the standard
8 GFIT scaling, namely 1 for the three interfering species and the continuum level, 0.1
9 for the continuum tile and curvature, 2 for frequency shift, and 0.5% for zero level
10 offset (which is expected to be approximately zero). The uncertainty in each of the 70
11 levels in the CO₂ profile is set independently. These uncertainties range from 1-5%,
12 are largest near the surface, and have been adjusted to improve the test results where
13 possible. Finally the residual scale factor, when in use, has been assigned an
14 uncertainty of 10%, based on the observed variability of the systematic residuals.

15

16 3.4 Other input parameters

17 The only other input parameters specific to profile retrieval concern convergence and
18 goodness-of-fit. They include the convergence parameter defined in section 3.1, the
19 maximum acceptable X^2 of the spectral fit, and the maximum number of iterations
20 allowed.

21

22 **4. Testing GFIT2**

23

24 4.1 Synthetic Spectra

25 The algorithm was first tested by retrievals on synthetic spectra, where the ‘true’
26 atmospheric profile is known. In these tests, the forward model (used by the
27 algorithm) may be the same as the forward function (which includes all ‘true’
28 physics), or may differ from it in a controlled way.

29

30

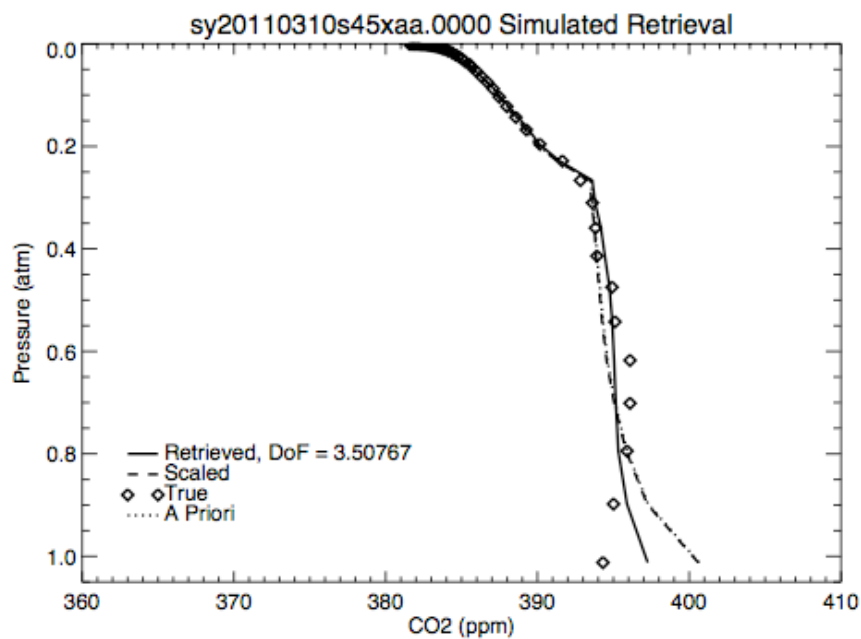
1 4.1.1 No Forward Model Error

2 We illustrate the most basic test in Fig. 4. Here a synthetic spectrum was calculated
3 from the profile labeled 'True' (diamonds), then GFIT2 was run on the calculated
4 spectrum without modification, using the a priori profile shown. (The a priori profile
5 is selected on the basis of climatology.)

6

7 The assumed signal-to-noise ratio was 1000. The solid lines in Fig. 4 show the
8 retrieved profile, and the degrees of freedom for the profile are shown in the legend.
9 The two results shown in Fig 4a and 4b are typical. The retrieved profile has 3.3-3.5
10 degrees of freedom (DoF), and follows the departure of the true profile from the a
11 priori reasonably well. This behavior is consistent with previous experience and with
12 expectations, and leads to the conclusion that the algorithm is working as designed.

13

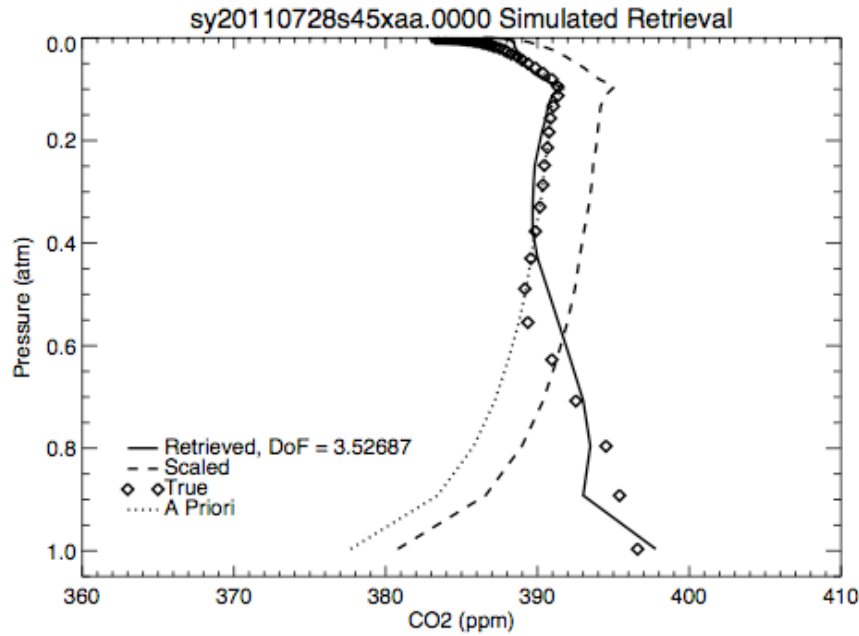


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15 Fig 4a Retrievals from a synthetic spectrum with no forward model error

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17



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2 Fig 4b As in Fig 4a, assuming different true and a priori profiles

3

4

5 4.1.2 Pointing Error

6 Next we used a known instrumental limitation to test the skill of the variable SNR
 7 technique. Namely, while the instrument nominally points at the center of the solar
 8 disk, it is common for some error to be introduced by patchy cloud cover or simply by
 9 tracking hardware problems. The effect of such pointing error is to introduce a
 10 Doppler shift due to solar rotation, making calculations of the solar Doppler shift
 11 inaccurate, and thus result in an uncompensated shift in the position of solar lines
 12 relative to telluric lines.

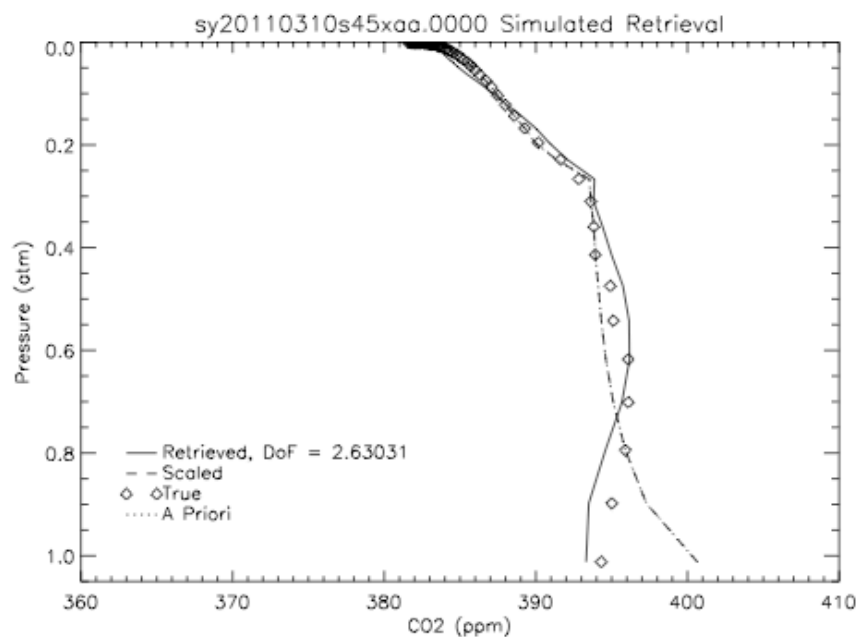
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14 To assess the effect of pointing error, we assumed that an error was present equal to
 15 10% of the solar diameter, which produces an error in the solar Doppler shift of ~1.3
 16 ppm. We then applied the ‘variable SNR’ modification to the measurement error
 17 covariance S_{ϵ} , as described in section 3.2. Retrievals with this assumed error are
 18 shown in Fig 5. There is a significant decrease in the degrees of freedom, from ~3.3-
 19 3.5 to ~2.6. This occurs because the apparent SNR decreases in the regions of the
 20 solar lines. That is, the assumed measurement error is increased at all frequencies

1 where the Doppler shift error causes an increased residual spectrum, and in some
2 cases the solar lines and CO₂ features overlap; the increased measurement error
3 reduces the algorithm's sensitivity to the measured spectrum, corresponding to lower
4 DoF.

5

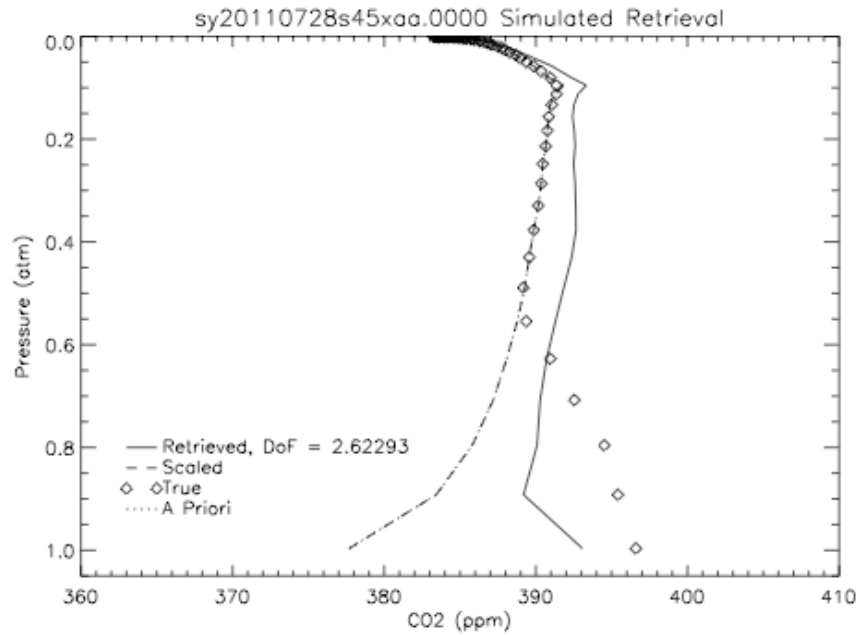
6 The retrieval in Figure 5a is qualitatively similar to the one with higher DoF in Fig 4a.
7 The retrieved profile in Figure 5b spreads the increased CO₂ in the lower troposphere
8 over a broad range of altitude, showing the effect of poorer vertical sensitivity
9 compared to Figure 4b, but does detect the presence of enhanced CO₂ in the
10 troposphere. Overall, we believe the variable SNR modification is shown to be
11 effective in coping with systematic residuals due to the level of solar pointing error
12 introduced.



13

14 Fig 5a As Fig 4a, with telescope pointing error assumed.

15



1

2 Fig 5b As Fig 4b, with telescope pointing error assumed.

3

4 4.1.3 Linewidth Error

5 Error in spectroscopic parameters is an important cause of systematic error in the
 6 calculated spectra, leading to systematic structures in the spectral residuals. Since the
 7 profile retrieval depends critically on the spectral lineshape, spectroscopic errors will
 8 limit its performance, possibly severely. The most obvious source of spectroscopic
 9 error affecting lineshape is the pressure broadening coefficient, which simply scales
 10 the linewidth at a given pressure. It is arguably the largest source of lineshape error as
 11 well. We will use synthetic spectra and simulated retrievals to evaluate its effects.

12

13 For this purpose we have multiplied the pressure broadening coefficients in the
 14 relevant CO₂ bands near 1.6 microns by 1.01, thus modeling a 1% error in linewidth,
 15 and used these modified coefficients to calculate sets of ~100 synthetic spectra on
 16 specific days at Lamont, using actual SZA and modeled temperature, etc. We have
 17 then run both the scaling and profile retrievals with the original unmodified
 18 coefficients. The average profiles for one day are shown in Fig. 6a.

19

1 The scaling retrieval reduces the CO₂ mixing ratio slightly to compensate for the 1%
2 linewidth error, producing a net error in XCO₂ (and mixing ratio) of 0.2%. The profile
3 retrieval, on the other hand, produces large oscillations, of ~5% at the surface and
4 ~2% in the upper troposphere and stratosphere. Despite these large errors in profile,
5 the net error in XCO₂ is of similar magnitude (but opposite sign) to the scaling
6 retrieval.

7

8 Fortunately, errors in real retrievals are unlikely to be as large as in these simulations.
9 Much effort in recent years has gone into refining knowledge of the spectroscopic
10 parameters needed for modeling atmospheric CO₂. Devi et al (2007) state typical
11 uncertainty in the pressure broadening coefficient of strong lines in the 1.6 micron
12 CO₂ bands is only approximately 0.1%. Admittedly, this is a formal uncertainty
13 derived from their spectral fits, and may not include some sources of absolute
14 uncertainty. However even an absolute uncertainty that small would produce an error
15 in CO₂ at the surface of ~ 2 ppm.

16

17 The extreme sensitivity of the CO₂ profile to errors in the pressure broadening
18 coefficient, and by extension to other sources of lineshape error, motivates a search
19 for ways to ‘correct’ the forward model spectra to minimize such effects. Since the
20 (unknown) true error in a spectroscopic parameter is constant, it may be expected to
21 produce a spectral signature which is very similar from measurement to measurement,
22 over many measurements. If we can isolate and remove that signature, the profile
23 retrieval may be able to capture variations in profile shape within that set of
24 measurements.

25

26 As a preliminary test, we assume that the spectroscopic error signature is given by the
27 residuals of the scaling retrieval, and add those to the calculated spectrum in the
28 profile retrieval. The average profiles, corresponding to Fig 6a, are shown in Fig. 6b.

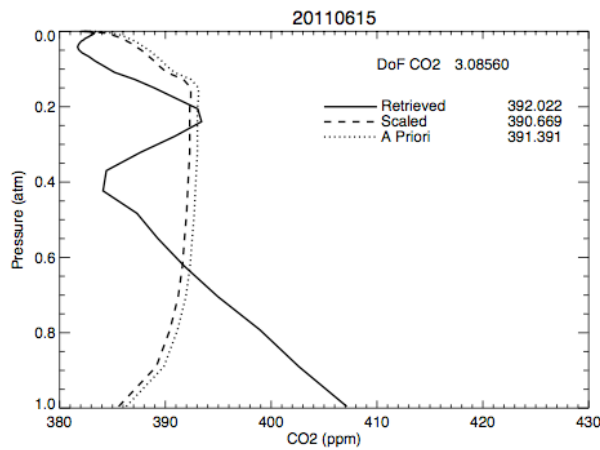
29 The average retrieved profile is nearly identical to the scaling retrieval; no spurious
30 changes in profile shape are introduced. The derived XCO₂ mole fractions differ by
31 only 0.01 ppm.

1

2 Of course, for real measurements, the signature of spectral error is not so easily
3 derived. Later, in section 4.4, we calculate the mean residual vector for large sets of
4 real measurements, and attempt profile retrievals including a scale factor applied to
5 the mean residual vector.

6

7



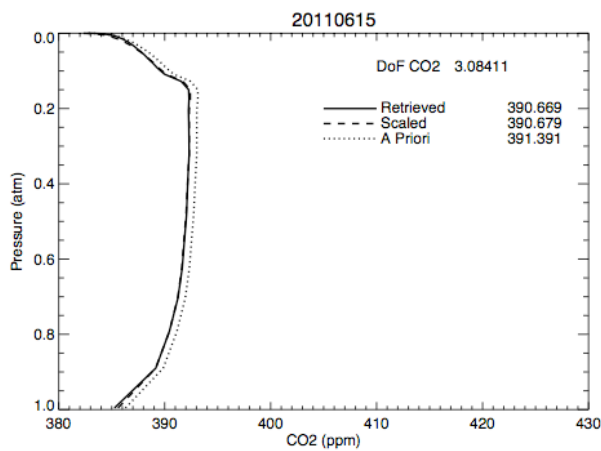
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10 Fig 6a. Retrievals with a 1% error in pressure broadening coefficient assumed

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1 Fig 6b. As Fig 6a, except the residuals of the scaling retrieval are included in the
2 profile retrieval's forward model

3 4.1.4 ILS Error

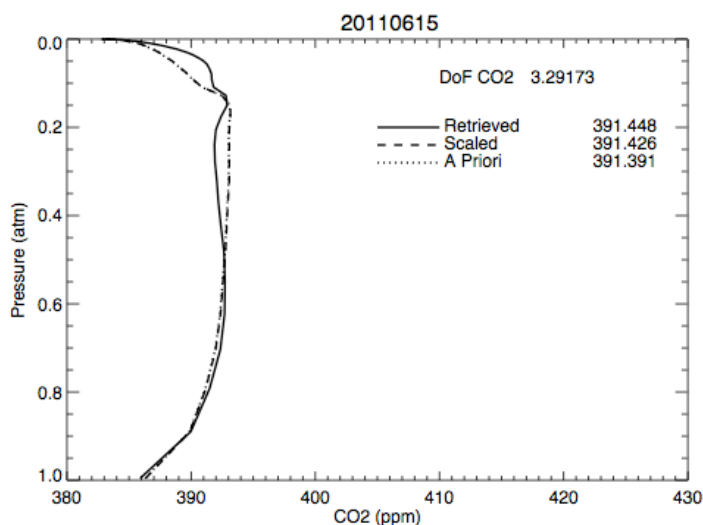
4 Another potentially significant source of error is distortion of the measured line shape
5 itself. For Fourier transform spectrometers (FTS, as used by TCCON) the instrument
6 line shape (ILS) is a convolution of contributions from the finite path difference and
7 the finite field-of-view (FOV) of the FTS. The path difference and its ILS
8 contribution (a sinc function) are well known, but the FOV, which contributes a
9 rectangular shape, has an uncertainty we estimate as 7%. This causes the observed
10 line to be broader and weaker than the atmospheric line, and progressively has a
11 larger effect as the line is narrower. I.e. the error due to finite aperture becomes more
12 important at lower pressure where the intrinsic line shape is narrower. (See for
13 example Davis, Abrams, and Brault, 2001.)

14

15 We illustrate this effect in Fig. 7, which is calculated for the same spectra as Fig. 6,
16 and so is directly comparable to Fig. 6a. The net effect of this error is very small in
17 the lower troposphere, and grows only to ~1% in the stratosphere. We conclude that
18 error in the measured line shape is unlikely to dominate error in the calculated line
19 shape (section 4.1.3).

20

21



22

1 Fig. 7 Retrievals of the spectra used for Fig. 6, with an assumed error of 7% in the
2 instrument field-of-view.

3

4 4.2 Atmospheric Measurements

5 Atmospheric spectra are routinely measured in Lamont, Oklahoma, at the Southern
6 Great Plains site of the Dept. of Energy Atmospheric Radiation Measurement
7 network. A Cessna aircraft equipped with air sampling in situ detectors is flown there
8 on a regular basis, and produces CO₂ profiles from ~0-5 km altitude. (Biraud et al,
9 2013). Although these profiles include only about half the total column of
10 atmospheric CO₂, it is in the lowest few kilometers that CO₂ is most variable and least
11 predictable. Therefore the Cessna measurements, coupled with climatological
12 estimates at higher altitudes, are expected to produce reasonable estimates of the full
13 CO₂ profile. In particular, they can test the profile retrieval algorithm's ability to
14 detect variations from climatology in the lower troposphere.

15

16 With this in mind, we have chosen several days for study. On these days, Cessna
17 flights were made, atmospheric conditions were excellent, and many high quality
18 near-infrared spectra were recorded. We selected days from various times of year to
19 allow conditions as variable as possible. The specific days chosen are 20110615,
20 20110705, 20110728, 20110826, 20111224, 20120114, and 20120115.

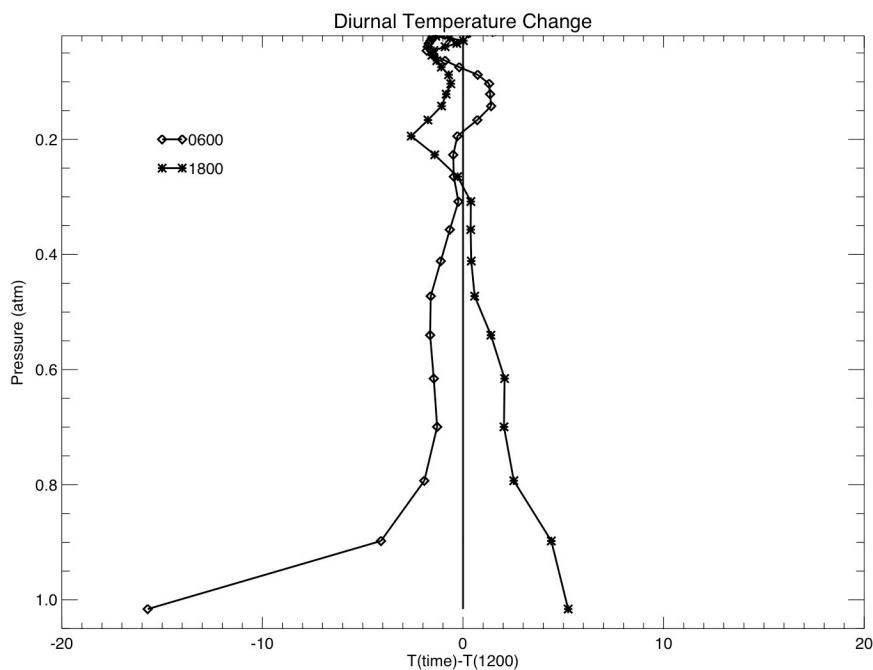
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22 Analysis of the data from these days immediately revealed significant errors in the
23 solar Doppler shift. This is shown not only by simple examination of the residuals, but
24 is also formally calculated, as the difference in the frequency shift observed for solar
25 lines (after correcting for the calculated Doppler shift) and telluric lines. GFIT does
26 not automatically take this error into account, by recalculating the spectrum with the
27 correct Doppler shift. However, these errors can be corrected by using the retrieved
28 solar/telluric difference to correct the calculated Doppler shift, and then re-running the
29 retrieval. All measured spectra and retrievals used and/or shown in this paper have
30 been 'Doppler shift corrected' in this way.

31

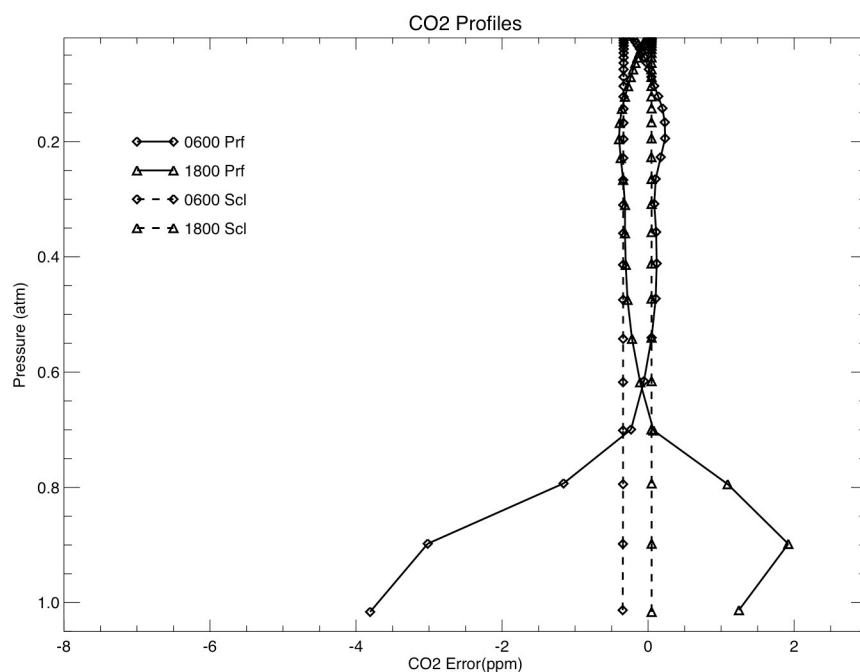
1 Another potential issue is the temperature profile used in performing each retrieval.
2 In clear, dry conditions, the temperature at the surface will sometimes vary by as
3 much as 20 K during daylight. This has an important impact on retrieval of
4 tropospheric CO₂, as shown in Fig 8. Fig 8a shows the difference in temperature
5 between 1200 LMST and 0600 and 1800 of the same day. Fig 8b shows the effect of
6 not correctly including this temperature variation. In particular Fig 8b shows the
7 difference between profiles retrieved assuming the 1200 temperature profile and those
8 using the temperatures of 0600 and 1800. Two sets of curves are shown, one for
9 profile scaling and one for profile retrieval.

10



11

12 Fig 8a. NCEP temperature profiles at 0600 and 1800 for a single day, less the profile
13 at 1200 on the same day.



1

2 Fig 8b. Error in CO₂ retrievals produced by not accounting for the temperature
 3 changes of Fig 8a. Dashed lines for profile scaling, solid for profile retrieval.

4

5 Note that the CO₂ errors produced by imposing an error in surface temperature are
 6 largely confined to the lowest 2 km. To minimize this effect, we have used the NCEP
 7 profiles at 0600, 1200, and 1800 LMT, and interpolated between them to the
 8 approximate time of the Cessna overflights. These interpolated temperature profiles
 9 have been used in all the retrievals shown subsequently in this section

10

11 4.2.1 SNR = 100

12 As described in section 3.2, we first attempted retrievals by setting the signal-to-noise
 13 (SNR) low enough to avoid trying to fit systematic spectral residuals. The SNR
 14 observed to achieve this for the current data set is approximately 100. Two examples
 15 are shown in Fig. 9. Fig. 9a may be compared directly to Figs. 4b and 5b. A smoother
 16 version of the Cessna data is the ‘true’ profile in Figs. 4b and 5b. The a priori profile
 17 is the same. Note that the degrees of freedom for the CO₂ profile (‘DoF CO₂’) is 1.4-

1 1.5, implying there is only at best slightly more information about the profile than the
2 1 degree of freedom available to the scaling retrieval.

3

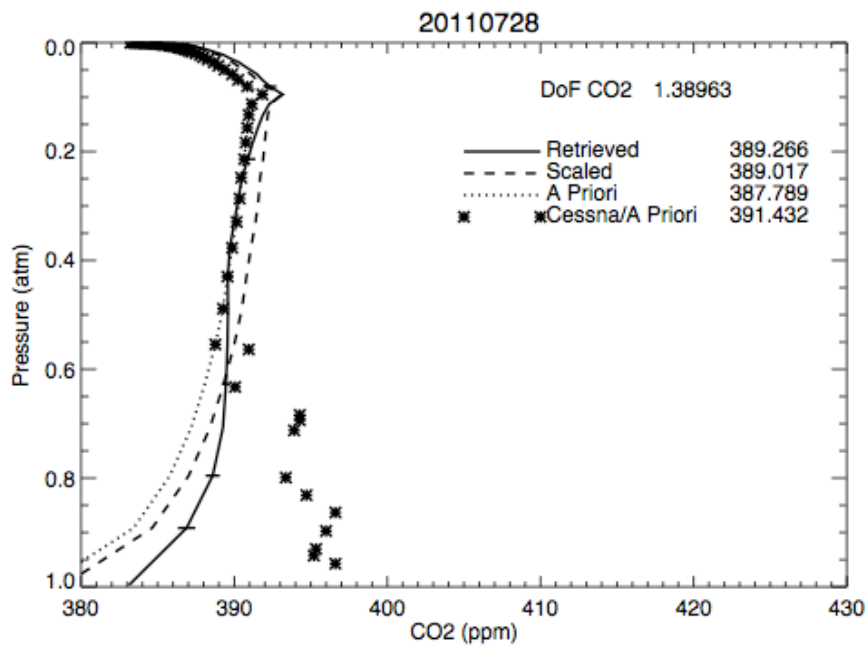
4 We see that the retrieval in Fig 9a poorly matches the Cessna profile in the lower
5 troposphere, although it is a small improvement on the a priori. The profile in Fig. 9b
6 matches CO₂ at p > 0.5 atm reasonably well, though that may be fortuitous.

7

8 For present purposes the thing to note is that assuming SNR=100 largely masks
9 information on the altitude profile, but also avoids profile oscillations (e.g. Fig. 6a), at
10 least for these two days.

11

12

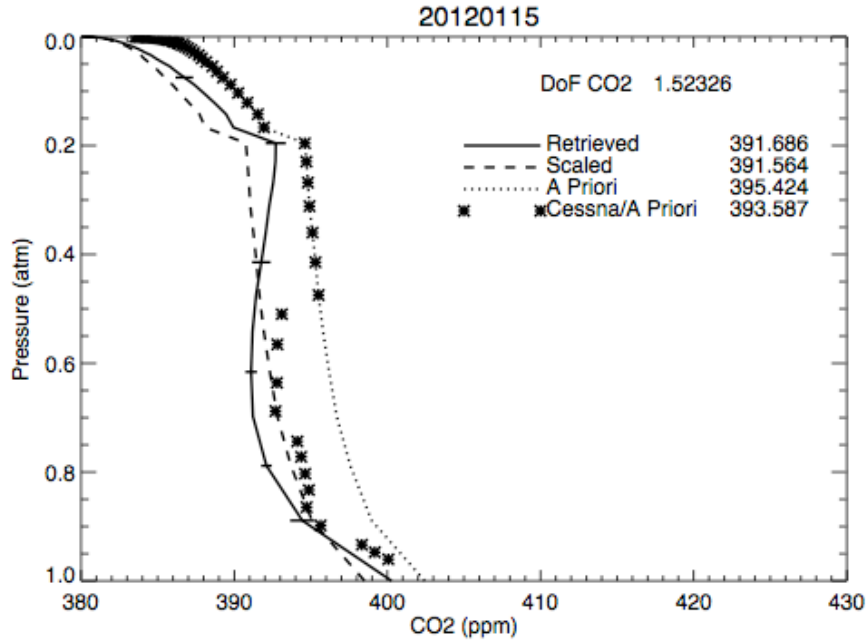


13

14 Fig. 9a Average retrieval within about 1 hour of a Cessna overflight, assuming
15 SNR=100, on 28 July 2011

16

17



1

2

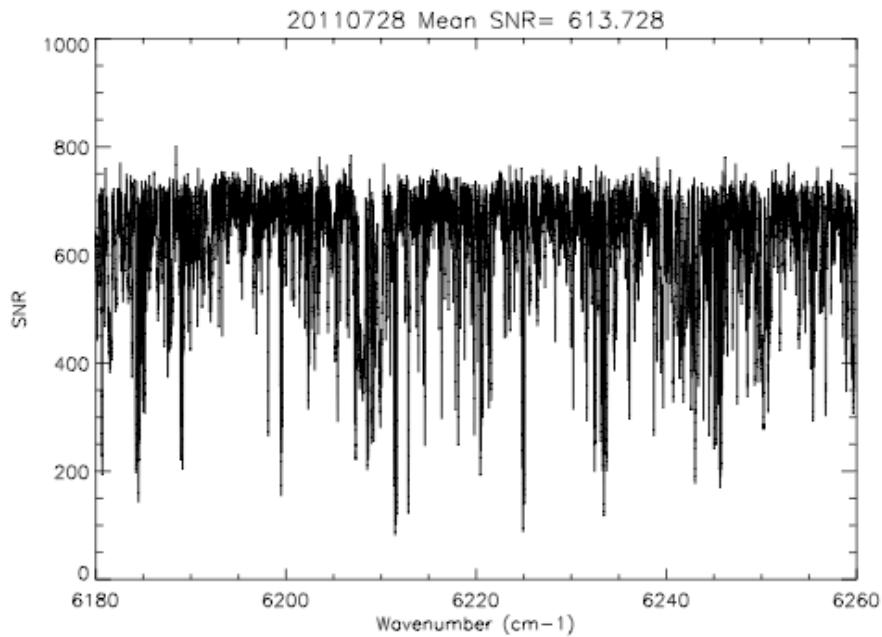
3 Fig. 9b As Fig. 9a, for 15 Jan 2012.

4

5 4.2.2 Variable SNR

6 We attempted to include as much profile information as possible while avoiding
 7 ‘over-fitting’ the spectral regions with the poorest residuals, by using the variable
 8 SNR as described in section 3.2. We illustrate by showing results for the same days as
 9 in the preceding section, 20110728 and 20120115. We show in Fig. 10 the effective
 10 SNR on which we based the diagonal of \mathbf{S}_ε for use in Eq. (1), for the day 20110728.

11 Note that the effective SNR varies from ~100-750. The mean value is shown in the
 12 title, and is a bit over 610. This is to be compared to SNR=1000 in Fig. 4 and
 13 SNR=100 in Fig 9.



1

2 Fig. 10 Signal-to-noise ration (SNR) derived for July 28, 2011 from the variable SNR
 3 technique (see text).

4

5 Examples of profiles retrieved with variable SNR are given in Fig. 11. CO₂ DoF has
 6 increased to ~ 2.9-3.3, compared to Fig 9. Fig 11a is directly comparable to Fig. 9a.

7 There appears to be some improvement in the lower troposphere, but also degradation
 8 in the upper troposphere, with a suggestion of an incipient oscillation. Fig 11b shows

9 a runaway oscillation. This result shows that the fundamental instability of the
 10 retrieval has not been adequately mitigated by the application of the variable SNR

11 technique. It is worth pointing out that these 2 days are ‘typical’ of the 7 days studied.

12 In particular, the 2 other winter days show oscillations much like in Fig 11b, the 3
 13 other summer days do not, but show little if any improvement vs. the Cessna profile.

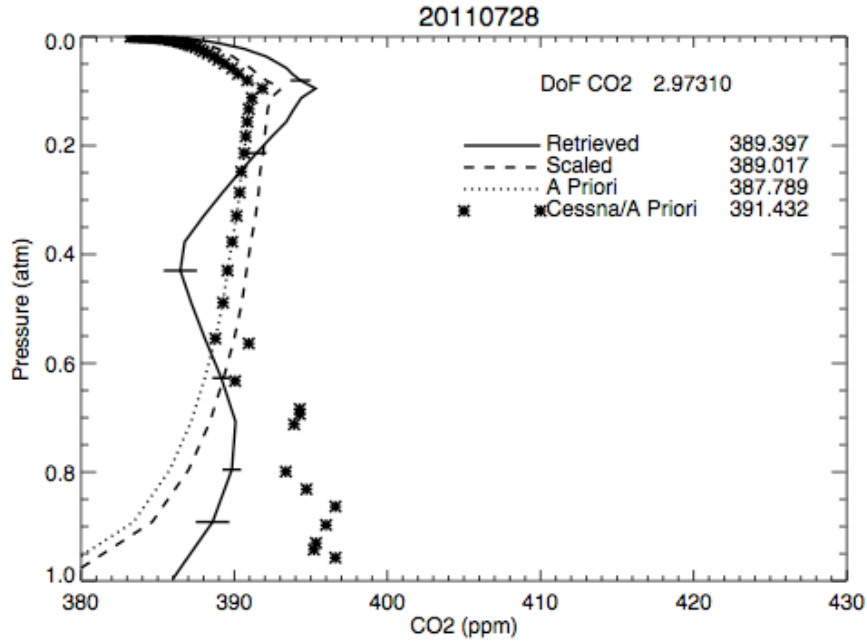
14

15

16

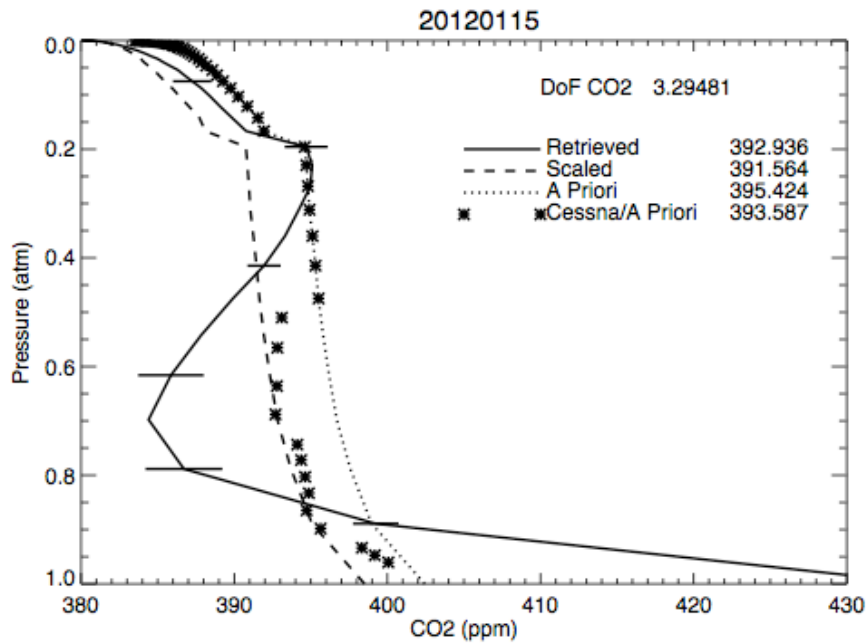
17

18



1

2 Fig 11a Average retrieval within about 1 hour of a Cessna overflight, assuming
 3 variable SNR, on 28 July 2011



4

5 Fig 11b. As Fig. 11a, for 15 Jan 2012.

6

7 The performance of the profile retrieval algorithm with variable SNR on the measured
 8 spectra tested is clearly unsatisfactory. In an effort to understand this limitation we

1 next closely examine the spectral residuals the algorithm produces, as described in the
2 next section.

3

4 4.3 Spectroscopic Residuals

5 Past experience indicates that the oscillatory behavior of the profiles seen in Fig. 11 is
6 most likely driven by a failure of the forward model to adequately reproduce the
7 measured spectrum. This of course may reflect systematic error either in the model or
8 the instrument. To isolate the spectral signature of the error we calculated mean
9 residuals from many spectra. We further expanded our study to examine the residuals
10 produced by the same model instrument at a different site, namely Lauder, New
11 Zealand.

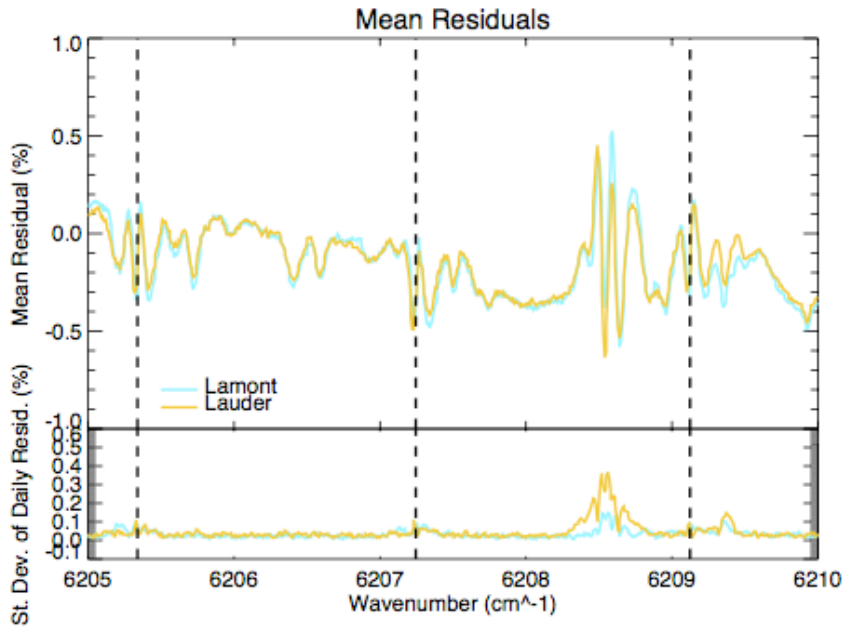
12

13 On the 7 days examined in section 4.2, a total of 5946 good quality spectra were
14 recorded at Lamont. There were ~600 spectra/day in winter and up to ~850/day in
15 summer. We have performed retrievals on all of these spectra, and calculated the
16 mean residual for each day, and the overall mean residual, in an attempt to isolate
17 systematic spectral features which the GFIT forward model cannot reproduce.

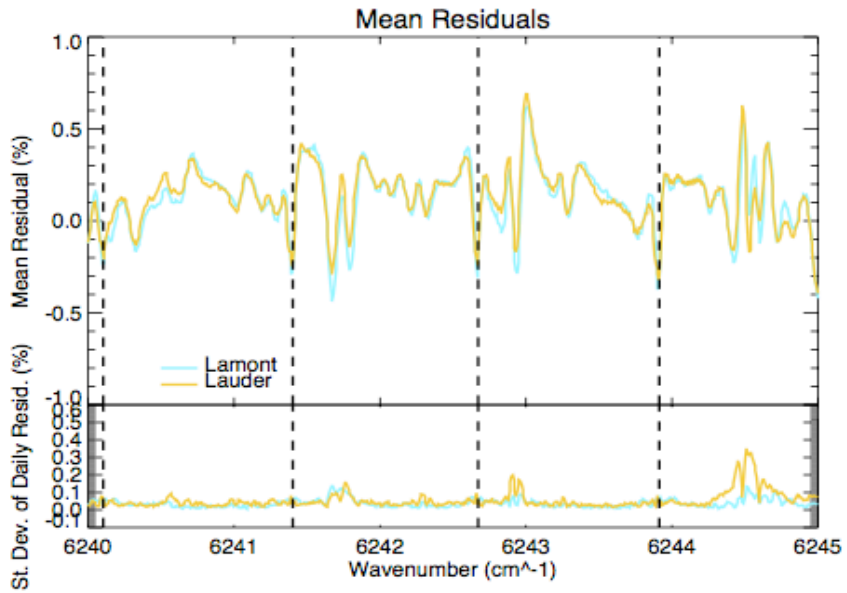
18 At Lauder we examined every tenth spectrum recorded on 13 days selected for clear
19 sky and seasonal coverage. The days were 20100710, 20100711, 20100730,
20 20100824, 20100908, 20101102, 20101107, 20101108, 20110204, 20110216,
21 20110401, 20110521, and 20110928. A total of 621 spectra were included; the
22 number of spectra/day ranged from ~10-70.

23

1

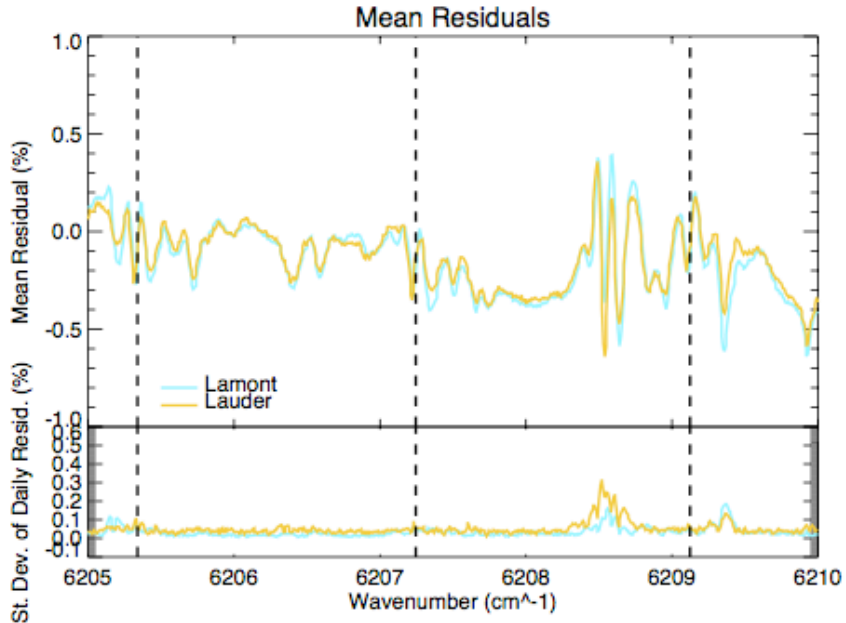


2



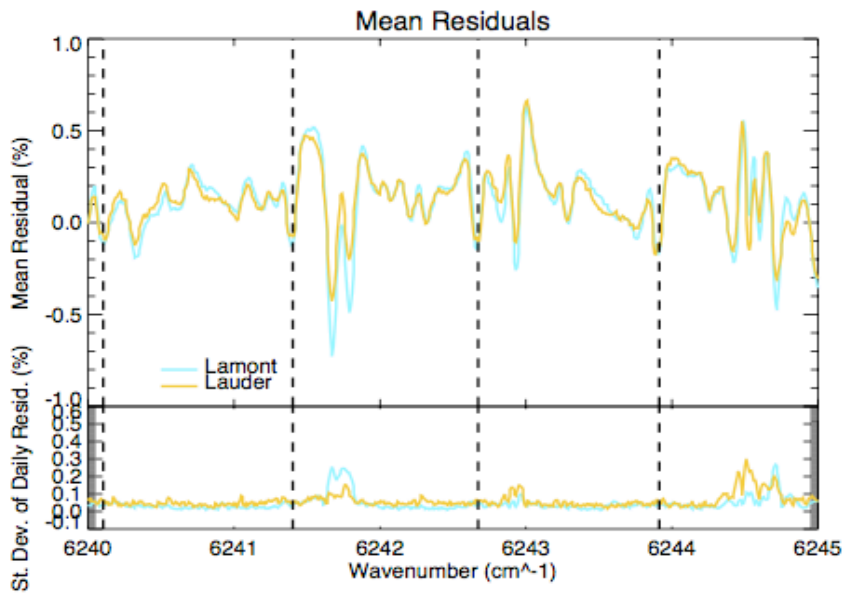
3 Fig. 12 Mean and standard deviation of residuals in selected spectral intervals, for
4 measurements with airmass < 2.

5



1

2



3

4 Fig. 13 Mean and standard deviation of residuals in selected spectral intervals, for
 5 measurements with $2 < \text{airmass} < 4$.

6

7 Figs. 12-13 show expanded views of portions of the mean residuals for the 2 sites, for
 8 airmass < 2 (Fig 12) and for $2 < \text{airmass} < 4$ (Fig. 13). A pair of two (upper and lower)
 9 panels is shown for each spectral interval, 6205-6210 cm^{-1} and 6240-6245 cm^{-1} . The
 10 upper panel shows the mean residual. The dashed vertical lines indicate the positions

1 of CO₂ spectral lines. The lower panel shows the standard deviation of the daily mean
2 residual vectors.

3

4 It is immediately clear that there are systematic residuals of ~0.5% depth at all of the
5 CO₂ positions. Also, the CO₂ residuals are very similar at Lauder and Lamont, and for
6 both ranges of airmass. Closer examination shows that the residuals are slightly
7 asymmetric, such that the line center is at slightly higher frequency than the center of
8 the residual.

9

10 While to first order all the CO₂ residuals in Figs. 12-13 are very similar, there are also
11 differences. The systematic residuals are broader at higher airmass, and the same
12 features are somewhat broader at Lauder than at Lamont.

13

14 4.4 Mean Bias Correction

15 We strongly suspect that a stable profile retrieval is not possible in the presence of
16 systematic spectral errors as suggested by the residuals of section 4.3, and that these
17 will readily produce the unsatisfactory oscillations seen in Fig. 11. This systematic
18 spectral signature might be thought of as a ‘bias’ of the GFIT forward model which
19 prevents it from fitting the measured spectra precisely enough. The GFIT forward
20 model, as with most practical atmospheric spectral line models, uses the Voigt profile
21 as its lineshape. However, it has recently become well understood that the Voigt
22 lineshape is inadequate to model atmospheric spectra at the sub-percent level. See, for
23 example, Fig. 1 of Long et al., 2011. Unfortunately, improved line shape functions are
24 far more complex, and, while several of them are known to improve spectral fits in
25 the laboratory (ibid.) there is no agreement as to which of them contains the best
26 physical description of the line formation. Since atmospheric spectra are formed in far
27 different physical conditions than laboratory spectra, it is unclear how to modify the
28 forward model to improve the observed spectral fits.

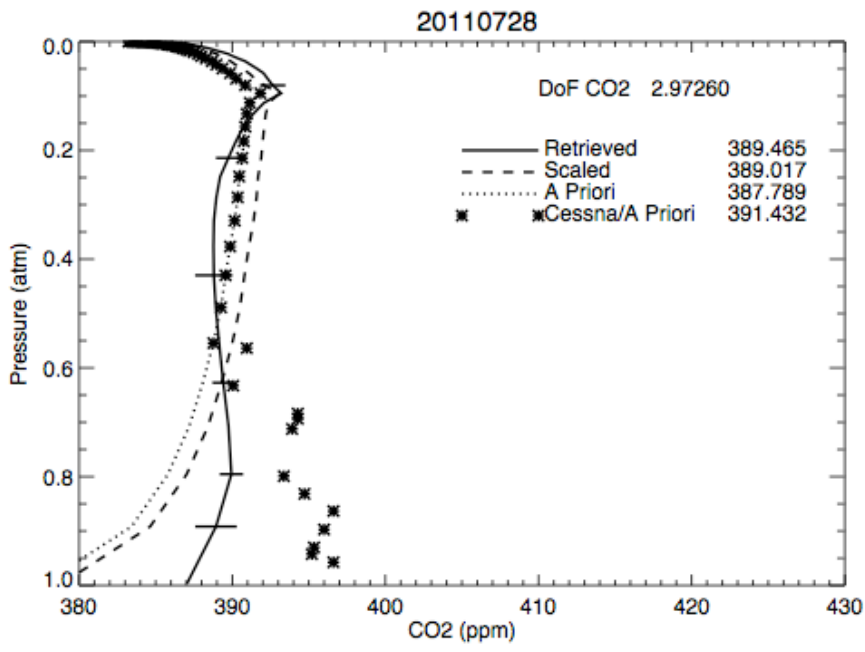
29

30 Pending a future clarification of the physics of line formation, we have attempted to
31 stabilize the algorithm by performing simple ‘corrections’ to the forward model to

1 remove, as far as possible, the spectral ‘bias’. In the first instance, we have performed
 2 retrievals on the Lamont spectra discussed in section 4.2, accounting for systematic
 3 spectral residuals as follows. We have modified the forward model to include addition
 4 of a spectral basis vector, multiplied by a scale factor, to the modeled spectrum. We
 5 calculate the mean residual spectrum from a large set of the Lamont retrievals (the set
 6 to be defined shortly). We then use those mean residuals as the basis vector to be
 7 added to the modeled spectrum. The scale factor which multiplies the basis vector is
 8 incorporated in the state vector, to be retrieved for each measured spectrum. It is
 9 typically ~ 1 .

10

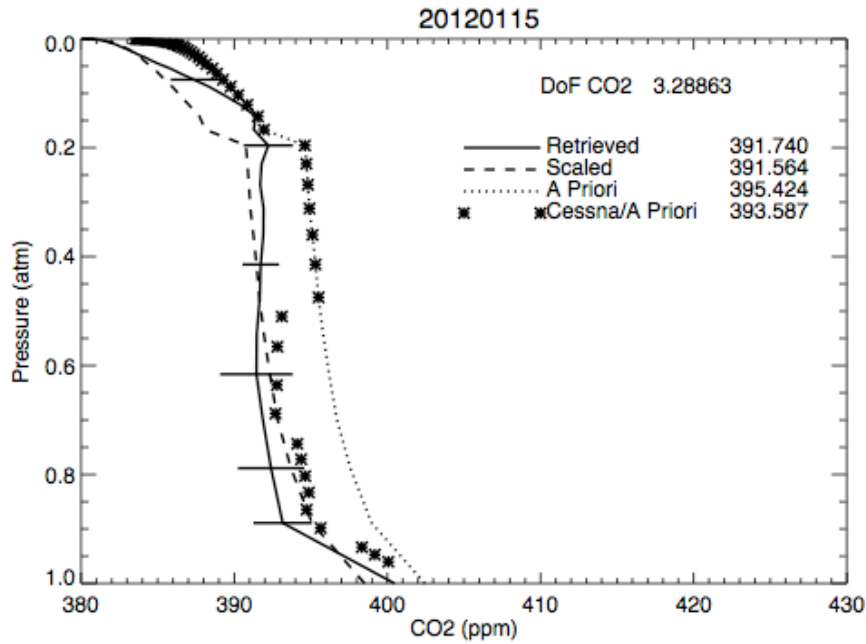
11 In the first instance, we derive the mean residual from the full set of 7 days data, and
 12 use this as the basis vector in retrievals from each measured spectrum. We show two
 13 of the daily retrieved profiles (each the average of ~ 80 individual retrievals) in Fig.
 14 14.



15

16

17 Fig. 14a. As Fig 11a, but including a basis vector of mean residuals in the forward
 18 model.



1

2 Fig 14b. As Fig. 14a, for 15 Jan 2012.

3

4 Figs. 14a and 14b are directly comparable to Figs. 11a and 11b. The same data and
 5 algorithm are used, except for the addition of the scaled mean residual as just
 6 discussed.

7

8 The comparison of Figs 11 and 14 shows a dramatic improvement on 20120115,
 9 eliminating the large oscillation of Fig 11b. Also on 20110728, the profile of Fig 14a,
 10 after subtracting the mean residual, is less oscillatory than previously (Fig 11a). On
 11 both days, the integrated column from the profile retrieval, represented by XCO_2 , is
 12 slightly closer to the estimated true value. This is promising and suggests further
 13 development of the ‘bias correction’ procedure.

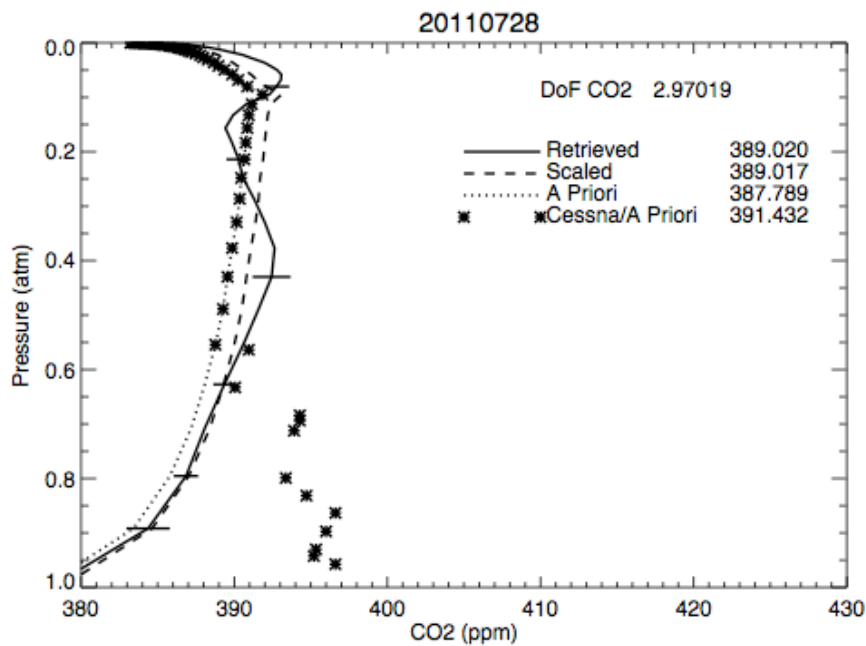
14

15 Deriving the residual vector from the full 7 days of measurements implicitly assumes
 16 that the residuals are independent of seasonal effects and instrumental adjustments
 17 over a long period. This is unlikely to be the case; in fact we have already noted in
 18 discussing Figures 12-13 that the residuals depend to some degree on airmass. The
 19 mean airmass of a set of spectra will vary with season and times of day. To lessen the
 20 impact of both airmass and potential instrumental variations in the residuals, we have

1 used monthly residuals calculated in a limited range of airmass (1-2 or 2-4) as the
2 spectral correction vectors, and run the retrievals once more. The results are shown in
3 Fig. 15.

4

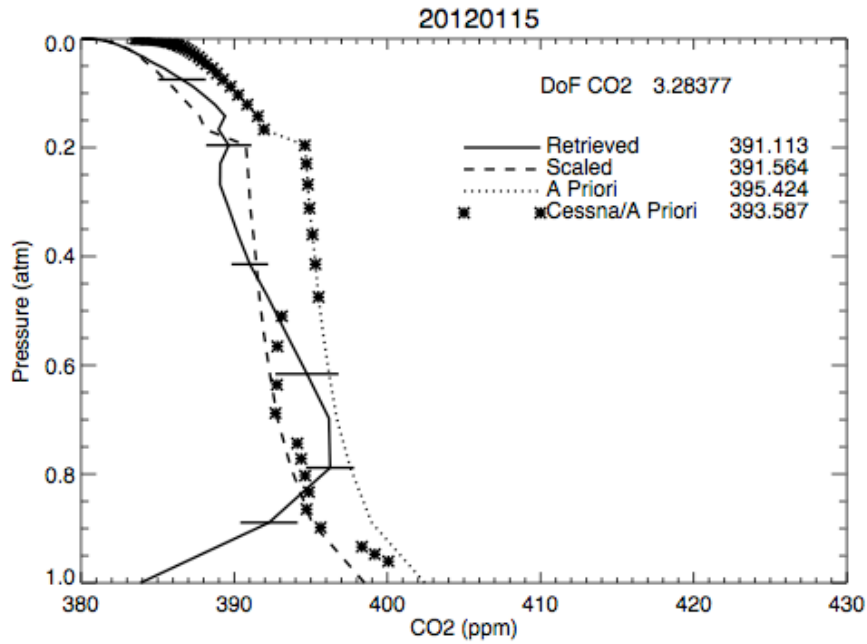
5 Unfortunately these results are a clear step backward. Fig. 15a shows no sensitivity to
6 the enhanced lower tropospheric CO₂, and in Fig. 15b we see the return of oscillatory
7 behavior. The XCO₂ value from the profile retrieval minus the estimated true value is
8 similar to the scaled minus true value on 20110728, and somewhat larger than scaled
9 minus true value on 20120115. It should be noted that the final residuals resulting
10 from addition of the scaled, monthly mean residuals are better (the RMS fit is smaller)
11 than those which result from use of the overall mean residuals. Despite that, the
12 profiles are worse, suggesting that spectral features relevant to the CO₂ profile are
13 being removed by the attempt at spectral ‘bias correction’.



14

15

16 Fig. 15a. As Fig. 14a, with a different residual basis vector

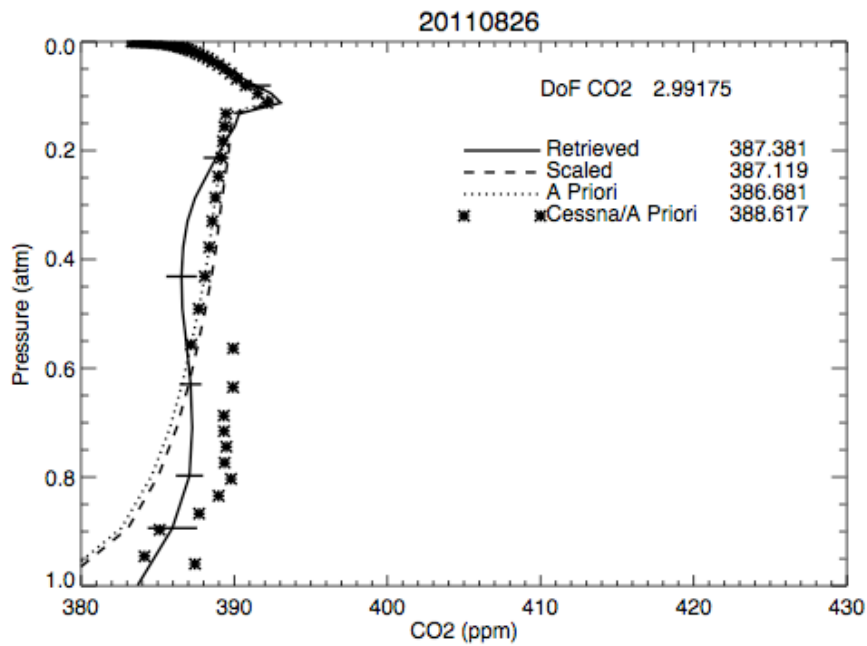


1

2 Fig. 15b As Fig. 14b, with a different residual basis vector

3

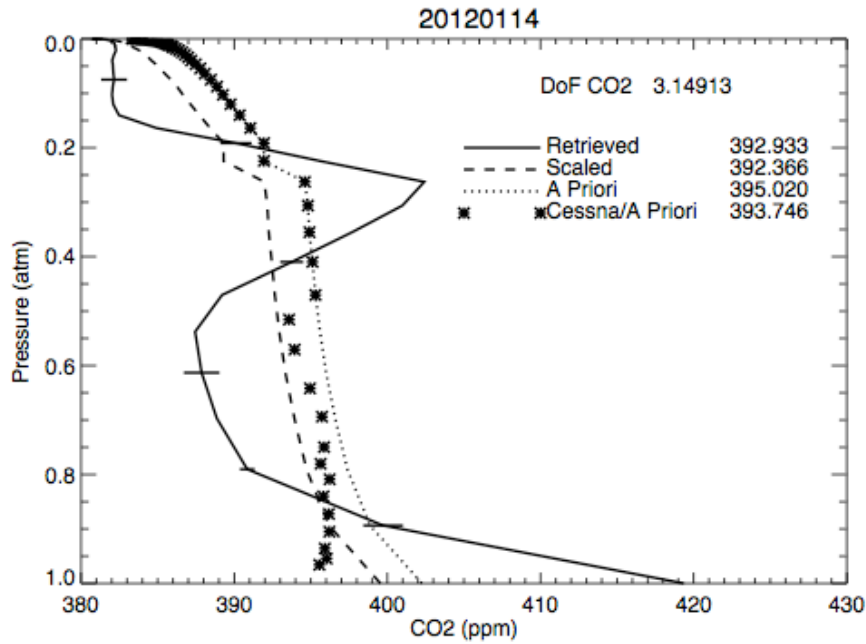
4 Our best results to date come from adding the scaled mean residuals of the set of days
 5 under study. With that in mind we will expand the discussion to include days other
 6 than the 2 illustrations used so far.



7

8

9 Fig 16a As Fig 14a., for 28 Aug 2011



1

2 Fig 16b As Fig 14b., for 14 Jan 2012

3

4 Fig. 16a and 16b show results for 20110826 and 20120114. They were produced in
 5 the same way as Fig. 14a and 14b, that is, including addition of a scaled mean
 6 residual. The two dates are chosen to illustrate two features of the full set of retrievals.
 7 Namely, on 26 Aug we see a smooth profile with only a suggestion of oscillation,
 8 which seems (maybe fortuitously) to track some enhanced CO₂ in the lower
 9 troposphere. This description is similar to one for 28 July (Fig 14a); in fact it is
 10 typical of all four summer days of this group. Conversely, 14 Jan shows a serious
 11 oscillation in the profile, unlike 15 Jan (Fig 14b). The third winter day studied, 24 Dec
 12 2011 (not shown), has an oscillation similar to 14 Jan. On both days, XCO₂ from the
 13 profile retrieval is slightly closer to the true value than is the scaled value.

14

15 In summary these results fall into 2 classes. In one, the retrieved profile is reasonably
 16 well behaved, but offers little if any improvement on the profile scaling version. In the
 17 other, the retrieved profile suffers serious oscillations. XCO₂ from the profile retrieval
 18 is similar to that from the scaling retrieval.

19

20

1 5. Conclusions

2 The algorithm behaves as expected on synthetic data. On real data, results are usually
3 worse than scaling, given our a priori knowledge of the CO₂ distribution with altitude.
4 Spectral residuals are generally poor. When modifications to the spectra and/or tight
5 constraints force residuals to be small, profile oscillations tend to be severe. Based on
6 the tests shown in section 4.1, it would seem that our theoretical knowledge of the
7 atmospheric spectra is inadequate to provide useful CO₂ profiles at the accuracy
8 required. It is important to consider the word ‘useful’: the required accuracy for
9 ‘useful’ measurements of CO₂ in the troposphere is very high, (~0.1 - 0.2%) relative
10 to other atmospheric species and altitude regions. Demands on our knowledge of the
11 spectra are correspondingly high.

12

13 There are at least two directions to follow in pursuit of useful profile retrievals. One is
14 improvements to the forward model. These could be in the form of more accurate
15 values of spectral parameters, more appropriate models of spectral line shape, and/or
16 knowledge of the instrument line shape. All of these areas have however already been
17 the focus of intense work over an extended period of time, and breakthroughs may be
18 slow in coming.

19

20 A second alternative is to exploit profile information from sources other than the
21 pressure broadened line shape. An immediately accessible source is spectral regions
22 of higher and lower opacity than the spectral band considered here. In particular,
23 several other CO₂ bands of varying opacity are routinely measured simultaneously
24 with the 1.61 micron (6220 cm⁻¹) band by the TCCON FTS. A profile retrieval using
25 several bands simultaneously should be explored. For example, the 2.06 micron (4852
26 cm⁻¹) band has much higher opacity while the 1.65 micron (6073 cm⁻¹) band has
27 lower opacity than the 1.61 micron band we have used. As shown in Fig. 1, regions of
28 high opacity are very sensitive to the lower troposphere, while more optically thin
29 regions are sensitive to the upper troposphere and stratosphere. Simultaneous
30 retrievals using all 3 bands would be far less sensitive to details of the spectral line
31 shape, and thus might avoid the difficulties described earlier. A complicating factor,
32 however, is the likelihood of different errors in band strength in the 3 regions. A

1 strategy for self-consistent scaling the band strengths might be required before
2 performing a simultaneous profile retrieval.

3

4 A simple alternative has been suggested, namely imposing a priori constraints on the
5 profile shape by experimenting with explicit interlayer correlations in the a priori
6 covariance matrix S_a . However it has been our experience in similar retrieval
7 problems that interlayer correlations are best used to fine tune a successful algorithm,
8 and may not be needed at all. This is fundamentally because in the Rodgers'
9 algorithm the a priori profile shape implicitly imposes the profile fine structure, which
10 is not strongly influenced by the measurement (see Rodgers, 1990). So, for example,
11 the algorithm developed at Stony Brook University for ground-based microwave
12 measurements of CIO has been used successfully for more than 20 years and has
13 always used a diagonal S_a matrix (Solomon et al, 2000, Connor et al, 2013), and the
14 OCO algorithm of Connor et al, 2008, on which the current OCO-2 algorithm is
15 based, included interlayer correlations as a refinement after successful initial testing.

16

17 In light of past experience therefore we have deferred serious experimentation with
18 interlayer correlations in the a priori of GFIT2, until either the forward model can be
19 improved, or the sensitivity of the retrieval to forward model errors can be reduced, as
20 described earlier in this section.

21

22 Finally, it is our intention to release GFIT2 to the community, as an option within the
23 public version of GFIT. That would allow testing and development by a wider range
24 of experienced researchers. So far that has proven impractical, but we hope to do so in
25 the near future.

26

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29 Institute of Technology, under contract with NASA. We thank NASA's Carbon Cycle
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32 NASA's OCO-2 project in collaboration with the DOE ARM program. Cessna data

1 from the SGP are available through the ARM archive (www.archive.arm.gov). We
2 thank Sebastien Biraud for his assistance in interpreting the aircraft data.

3
4

5 References:

6 Biraud, S. C., M. S. Torn, J. R. Smith, C. Sweeney, W. J. Riley, and P. P. Tans (2013),
7 A multi-year record of airborne CO₂ observations in the US Southern Great Plains,
8 *Atmos. Meas. Tech.*, 6(3), 751–763, doi:10.5194/amt-6-751-2013.

9

10 Connor, B. J., H. Bösch, G. Toon, B. Sen, C. Miller, and D. Crisp (2008), Orbiting
11 Carbon Observatory: Inverse method and prospective error analysis, *J. Geophys.*
12 *Res.*, 113, D05305, doi:10.1029/2006JD008336.

13 Connor, B.J., T. Mooney, J. Barrett, P. Solomon, A. Parrish, and M. Santee,
14 Comparison of ClO measurements from the Aura Microwave Limb Sounder to
15 ground-based microwave measurements at Scott Base, Antarctica, in spring 2005.
16 *J. Geophys. Res.*, 112, D24S42, doi:10.1029/2007JD008792, 2007.

17 Connor, B.J., A. Parrish, J.-J. Tsou, and M.P. McCormick, Error analysis for the
18 ground-based microwave ozone measurements during STOIC, *J. Geophys. Res.*,
19 100, 9283-9292, 1995.

20 Connor, B.J., D.E. Siskind, J.J. Tsou, A. Parrish, A.E.E. Remsberg, Ground-based
21 microwave observations of ozone in the upper stratosphere and mesosphere. *J.*
22 *Geophysical Res.*, 99, 16,757-16,770, 1994.

23 Davis, S.P., M.C. Abrams, and J.W. Brault, *Fourier Transform Spectroscopy*,
24 Academic Press, 2001.

25 Devi, V.M., D.C. Benner, L.R. Brown, C.E. Miller, and R.A. Toth (2007), Line
26 Mixing and Speed Dependence in CO₂ at 6227.9 cm⁻¹: Constrained multispectrum
27 analysis of intensities and line shapes in the 30013 – 00001 band. *J. Mol. Spec.* 245
28 (2007) 52-80.

29 Dohe, Susanne, Measurements of atmospheric CO₂ columns using ground-based
30 FTIR spectra (2013), Doctor of Science dissertation, Karlsruhe Institute of
31 Technology

1 JPL, Jet Propulsion Laboratory, Orbiting Carbon Observatory – 2, Level 2 Full
2 Physics Algorithm Theoretical Basis Document (2015),
3 <http://disc.sci.gsfc.nasa.gov/OCO-2/documentation/oco-2->
4 [v6/OCO2_L2_ATBD.V6.pdf](http://disc.sci.gsfc.nasa.gov/OCO-2/documentation/oco-2-v6/OCO2_L2_ATBD.V6.pdf)
5

6 Irion, F.W., M.R. Gunson, G.C. Toon, A.Y. Chang, A. Eldering, E. Mahieu, G.L.
7 Manney, H.A. Michelsen, E.J. Moyer, M.J. Newchurch, G.B. Osterman, C.P.
8 Rinsland, R.J. Salawitch, B. Sen, Y.L. Yung, and R. Zander, Atmospheric Trace
9 Molecule Spectroscopy (ATMOS) Experiment Version 3 data retrievals, *Appl.*
10 *Opt.*, 41(33), 6968-6979, 2002.

11 Kuai, Le, Debra Wunch, Run-Lie Shia, Brian Connor, Charles Miller, Yuk Yung
12 (2012), Vertically constrained CO₂ retrievals from TCCON measurements. *J.*
13 *Quant. Spec. & Rad. Trans.*, 113 (14), 1753-1761.

14 Long, David A., Katarzyna Bielska, Daniel Lisak, Daniel K. Havey, Mitchio
15 Okumura, Charles E. Miller, and Joseph T. Hodges (2011). The air-broadened,
16 near-infrared CO₂ line shape in the spectrally isolated regime: Evidence of
17 simultaneous Dicke narrowing and speed dependence. *J. of Chem Phys.* 135,
18 064308

19 Pougatchev, N.S., B.J. Connor, N.B. Jones, and C.P. Rinsland, Validation of ozone
20 profile retrieval from infrared ground-based solar spectra, *Geophys. Res. Lett.*, 23,
21 1637-1640, 1996.

22 Rodgers, C.D.; Connor, B.J. (2003). Intercomparison of remote sounding instruments.
23 *Journal of Geophysical Research* 108(D3), 4116, doi:10.1029/2002JD002299.

24 Rodgers, C.D., *Inverse Methods for Atmospheric Sounding: Theory and Practice*,
25 World Scientific Publishing Co. Ltd., 2000.

26 Rodgers, C. D., Retrieval of Atmospheric Temperature and Composition From
27 Remote Measurements of Thermal Radiation, *Rev. Geophys. and Space Phys.*, 14,
28 p609-624, 1976.

29 Schofield, R.; Connor, B.J.; Kreher, K.; Johnston, P.V.; Rodgers, C.D. (2004). The
30 retrieval of profile and chemical information from ground-based UV-Visible

1 DOAS measurements. *Journal of Quantitative Spectroscopy and Radiative*
2 *Transfer* 86, 115-131.

3 Sen, B., G.C. Toon, J.-F. Blavier, E.L. Fleming, and C.H. Jackman, Balloon-borne
4 observations of mid-latitude fluorine abundance, *J. Geophys. Res.*, 101(D4), 9045-
5 9054, 1996.

6 Solomon, P.M.; Barrett, J.; Connor, B.J.; Zoonematkermani, S.; Parrish, A.; Lee, A.;
7 Pyle, J.; Chipperfield, M. Seasonal observations of chlorine monoxide in the
8 stratosphere over Antarctica during the 1996-1998 ozone holes and comparison
9 with the SLIMCAT 3D model. *Journal of Geophysical Research* 105: 28979-
10 29001.

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12