

1 **The Orbiting Carbon Observatory (OCO-2) tracks 2-3**
2 **peta-gram increase in carbon release to the**
3 **atmosphere during the 2014-2016 El Niño**

4

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28 **ABSTRACT**

29 The powerful El Niño event of 2015-2016 – the third most intense since the 1950s –
30 has exerted a large impact on the Earth’s natural climate system. The column-
31 averaged CO₂ dry-air mole fraction (XCO₂) observations from satellites and ground-
32 based networks are analyzed together with in situ observations for the period of
33 September 2014 to October 2016. From the differences between satellite (OCO-2)
34 observations and simulations using an atmospheric chemistry-transport model, we
35 estimate that, relative to the mean annual fluxes for 2014, the most recent El Niño
36 has contributed to an excess CO₂ emission from the Earth’s surface (land+ocean) to
37 the atmosphere in the range of 2.4±0.2 PgC (1 Pg = 10¹⁵ g) over the period of July
38 2015 to June 2016. The excess CO₂ flux is resulted primarily from reduction in
39 vegetation uptake due to drought, and to a lesser degree from increased biomass
40 burning. It is about the half of the CO₂ flux anomaly (range: 4.4-6.7 PgC) estimated
41 for the 1997/1998 El Niño. The annual total sink is estimated to be 3.9±0.2 PgC for
42 the assumed fossil fuel emission of 10.1 PgC. The major uncertainty in attribution
43 arise from error in anthropogenic emission trends, satellite data and atmospheric
44 transport.

45

46 **Introduction**

47

48 Uncertainties in estimates of regional sources (+ve flux) and sinks (-ve flux) of CO₂
49 and other greenhouse gases, derived from direct inventory methods or inferred from
50 atmospheric observations, have hindered the development of effective policy for
51 reduction of emissions from anthropogenic activity¹. The large uncertainties obscure
52 the relative roles of management approaches for terrestrial biospheric fluxes and the
53 energy intensity of the industrial activities. For example, the sources and sinks of
54 CO₂ by the tropical land biosphere has remained uncertain² and the CO₂ emissions
55 from industries in China are frequently revised by the state and international research
56 communities³. While the inventory method suffers from a lack in completeness and
57 transparency, the atmospheric constraint has hitherto been compromised by both the
58 sparseness of observational network, and uncertainties in models employed for
59 regional CO₂ flux calculations⁴.

60

61 To improve the time and spatial coverage of the atmospheric CO₂ measurements,
62 NASA launched the OCO-2 satellite in July 2014^[5]. Since early September of 2014,
63 OCO-2 has been routinely returning almost one million soundings each day over the
64 sunlit hemisphere. While clouds and large aerosols abundances preclude full-column
65 measurements of CO₂ from most of these soundings, more than 10% (~100,000
66 soundings/day) yield estimates of the column-averaged dry air mole fraction, XCO₂.
67 The OCO-2 XCO₂ retrievals, after bias correction, agree well globally with the
68 TCCON for nadir, glint, and target observations, with median differences less than
69 0.5 parts per million (ppm) and root-mean-square differences typically below 1.5
70 ppm⁶. If regional scale biases are controlled to similar levels, these data can provide
71 the precision and accuracy needed to characterize CO₂ sources and sinks⁷.

72

73 The other factor that affects estimates of CO₂ fluxes from XCO₂ measurements is the
74 biases in the inverse methods using chemistry-transport models (CTMs). The role of
75 such bias has been illustrated using the XCO₂ observations from the first dedicated
76 Greenhouse Gases Observing Satellite "IBUKI" (GOSAT), which was launched on 23
77 January 2009 by the Japan Aerospace Exploration Agency (JAXA)⁸. Using multiple
78 flux inversions of in situ and satellite CO₂ data, Howeling et al. find that the model-
79 model flux differences quickly increase to >100% of the annual flux on the scale of
80 the subcontinental regions⁹. It is generally understood that the differences in
81 inversion-derived CO₂ fluxes are caused by a variety of the underlying modeling
82 components in the inversion systems, not the CTMs alone^{4,9}. The modeling
83 components include a priori flux and uncertainty assumptions, screening and
84 treatment of observational data, and uncertainties in transport models⁴.

85

86 The efficiency of the terrestrial ecosystem at absorbing atmospheric carbon dioxide
87 (CO₂) depends on the availability of sunlight, soil moisture (fed by precipitation), and
88 air temperature^{10,11}. Thus droughts and high temperatures associated with El Niño
89 reduce the ability of the terrestrial ecosystem to assimilate carbon while additional
90 release by frequent occurrence of fires further reduces the uptake of carbon by the
91 terrestrial biosphere¹²⁻¹⁶. The pyrogenic carbon flux of Indonesia during 2015 has
92 been estimated with bottom-up methods from fire observations by the MODIS
93 satellite instruments and with top-down, i.e. inversion, methods from atmospheric CO
94 observations by the MOPITT satellite instrument. The bottom-up methods yield
95 values of 340 TgC¹⁷, 380 TgC^{16,18} and 408 TgC¹⁹ for all of 2015, and of 250 TgC¹⁷
96 and 320 TgC¹⁹ for September-October 2015. The two CO inversions yield higher
97 estimates (501±170 TgC²⁰ for all of 2015 and 227±66 TgC²¹ for September-October

98 2015). The study regions are all dominated by the Indonesian fires despite varying in
99 their exact definitions ("Tropical Asia", "Maritime Southeast Asia" etc.). The range of
100 estimates provides some measure of the considerable uncertainty in our knowledge
101 of the pyrogenic carbon flux. However, each of these anomalies is smaller than those
102 estimated for the 1997/1998 El Niño event for Southeast Asia (~1 PgC)^{14,16}.
103 In addition to the relatively large uncertainties, the above-mentioned carbon flux
104 estimates are limited only to the emission mechanism of biomass burning. CO₂
105 observations, on the other hand, have the advantage of being more directly linked to
106 the net carbon flux to the atmosphere, i.e., they are not limited to a specific emission
107 mechanism like biomass burning.

108

109 Although the equatorial east Pacific Ocean experiences weaker ventilation of deep-
110 water CO₂ during an El Niño, thus a negative CO₂ flux anomaly²², but the effect of the
111 ocean component on global total CO₂ flux anomaly is not clear^{23,15}. For simplicity of
112 this work, no attempt is made to partition land and ocean fluxes.

113

114 Here, we analyze early OCO-2 observations of XCO₂ to quantify the impact of the
115 powerful El Niño event²⁴ on large scale CO₂ flux anomalies. A record CO₂ rise is
116 predicted for 2016, sufficient to keep the atmospheric level above 400 ppm at Mauna
117 Loa, Hawaii²⁵ for the foreseeable future. The OCO-2 observations along with CTM
118 simulations are used to make an impact assessment of the ongoing El Niño event on
119 the terrestrial carbon cycle. We estimated monthly CO₂ flux corrections from the
120 differences in OCO-2 measurements and transport model simulations. Comparisons
121 with in situ, ground-based remote sensing and GOSAT observations provide a test of
122 the robustness of the estimated carbon exchange based on the OCO-2 observations.

123

124 **Results**

125

126 **Model-observation comparison**

127 Figure 1 shows the latitude-time distributions of XCO₂ obtained from NASA's OCO-2
128 and JAXA's GOSAT instruments^{26,27} and the differences with JAMSTEC's
129 atmospheric chemistry-transport model (ACTM) simulations for the period from
130 September 2014 through October 2016 (up to May for GOSAT). Details on
131 observational data selection, ACTM simulations and their processing are given in the
132 Methods section. The OCO-2 minus ACTM results are shown for three combinations
133 of terrestrial and oceanic CO₂ fluxes, namely, CYC64 (Fig. 1b), IAV84 (Fig. 1c) and
134 IAV84+GFAS (Fig. 1d). The simulated XCO₂ growth rates by ACTM_CYC64 and
135 ACTM_IAV84 overestimated (typically by ~0.5 ppm) and underestimated (by up to
136 2.0 ppm), respectively, the observed growth rate over this 25-month period. The
137 underestimation of ACTM_IAV84 develops most strongly during Sep-Nov 2015. The
138 ACTM_IAV84+GFAS simulation most closely follows the OCO-2 observations,
139 compensating in particular for the underestimation after Nov 2015 (referred to as
140 'best' a priori for flux corrections). All ACTM simulations use the same emissions
141 from FFC at the rate of ~10 PgC yr⁻¹ (Table 1). However, the annual total land and
142 ocean fluxes vary, e.g., -2.86, -6.24, and -4.77 PgC yr⁻¹, respectively, for CYC64,
143 IAV84 and IAV84+GFAS cases for period July 2015 to June 2016. One striking
144 difference for the April-July period is that GOSAT – ACTM differences (Fig. 1f,g,h) in
145 the high northern latitudes (>30°N) are more negative than the OCO-2 - ACTM
146 differences (Fig. 1b,c,d). **This suggests a surface source inversion would produce**
147 **stronger sources in the northern high latitudes when GOSAT observations are used**
148 **compared to using the OCO-2 observations.**

149

150 Figure 2a,b,c show comparisons of XCO₂ as measured by OCO-2 and simulated by
151 ACTM as zonal means for three broad latitude ranges for the period from September
152 2014 through October 2016. The latitude bands of 10°S-10°N (hereinafter referred to
153 as tropics) and 10°-90° cover 88.6 and 210.7 million km², respectively. When
154 combined into 2.5°x2.5° grid boxes, the OCO-2 data coverage for the latitude bands
155 poleward of 10° varies from 30% to 50% of the total area. The region south of 10°S
156 has the largest model–observation mismatches, with values up to 2 ppm, with major
157 contributions from the American and Asian sectors, during April to August 2015. The
158 ACTM_IAV84 simulation, on the other hand, most closely follows the OCO-2
159 observations until July 2015 for the region north of 10°N (Fig. 2a), suggesting that the
160 FFC emissions are reasonably prescribed at an increase of 0.2 PgC yr⁻¹ during 2014-
161 2016 in the ACTM simulations and that the large model-observation mismatches at
162 the later time are arising from the deficiencies in biospheric fluxes, both from land
163 and ocean. The latest report of the Emissions Database for Global Atmospheric
164 Research (EDGAR)³ suggest no increase in FFC emissions during 2014-2015 (no
165 value for 2016 is yet available). Thus our estimation of biospheric emission during
166 October 2014 to October 2016 could be underestimated by up to 0.2 PgC, which is
167 assigned as FFC emission increase rate in our a priori model. The ACTM - OCO-2
168 differences show systematic decrease following the peak in February-March 2016, in
169 particular for the southern latitudes, until October 2016, as the El Niño condition
170 weakens (Fig. 2c).

171

172 Because the OCO-2 measurements started less than 6 months before the nominal
173 onset of the 2014-2016 El Niño this data alone cannot be used for calculating
174 anomalous CO₂ emissions. We have used longer time record from GOSAT, TCCON
175 (Total Carbon Column Observing Network)²⁸ and NOAA cooperative global air

176 sampling network²⁹ measurements since January 2013 for defining the baseline.
177 Here we report CO₂ flux anomalies with respect to 2013-2014 as the aim of this study
178 is to estimate anomalous CO₂ release for the whole El Niño period. The
179 ACTM_IAV84 simulation successfully simulated CO₂ growth rate during January
180 2013 to September 2014 (seen as the differences around the 0-line) as measured by
181 GOSAT (Fig. 2d,e,f), TCCON (Fig. 2g,h,i) and NOAA (Fig. 2j,k,l). For the October
182 2014 to October 2016 (El Niño) period, the ACTM_IAV84+GFAS simulation most
183 closely simulated the atmospheric XCO₂ measured by GOSAT and TCCON, and
184 also the NOAA flask observations (Fig. 2). Although the ACTM_IAV84+GFAS
185 simulation very well describes the time evolution of observed XCO₂ in the tropics and
186 most times for the region north of 10°N (mostly within 0.1 ppm), systematic
187 underestimations of up to ~2.0 ppm are seen in the region south of 10°S by April
188 2016. The larger variability in model-observation mismatches in the northern latitude
189 band (Fig. 2a,d,g) is probably an effect of strong terrestrial biospheric uptake and
190 release cycle, which are not very well constrained by ACTM inversion system using
191 in situ data only. This issue will be addressed later when flux corrections will be
192 validated using TCCON observation.

193

194 **Global CO₂ flux anomaly**

195 Comparing the 3 ACTM simulations with OCO-2 and other measurements, we find
196 that the global pyrogenic emission from GFAS of about 2.64 PgC, which in itself is
197 subject to considerable uncertainties, is similar to our XCO₂-based estimation for the
198 2015-2016 El Niño-induced extra carbon flux from vegetation fires, reduced net
199 primary productivity, and errors in the assumed trends of FFC emissions during the
200 period October 2014 – October 2016. Since the XCO₂ values consist of vertically-
201 integrated information for the whole atmospheric column, simple approximations can

202 be applied for estimating CO₂ flux corrections (in PgC month⁻¹) from meridional
203 atmospheric CO₂ burden differences (PgC) at monthly time interval (see Methods).
204 The estimated CO₂ flux corrections are summarized in Table 1. For the
205 ACTM_IAV84+GFAS fluxes, the anomalous CO₂ emissions aggregated over the
206 'main El Niño period' (defined by July 2015 to June 2016) are in the range of 2.23 -
207 2.55 PgC. Because the ACTM_IAV84+GFAS simulation generally follows the
208 observed OCO-2 XCO₂ (Fig. 2a-c), we use this as the 'best' prior for CO₂ flux
209 correction. The best prior case introduces less error in the flux corrections as the
210 transport of flux increments are ignored in our calculation method. The 0.32 PgC
211 difference in emissions is due to extrapolation of XCO₂ differences poleward in both
212 hemispheres (Fig. 1d). The lower range of values in the 3 right columns are obtained
213 without extending model-observation mismatches to the missing data grids. An effect
214 of decay in El Niño condition since April 2016 is seen in reduction of CO₂ flux
215 anomaly for October 2015 – September 2016 (1.20-1.34 PgC), compared to October
216 2014 – September 2015 (2.38-2.68 PgC).

217

218 The range of estimated CO₂ flux corrections is consistent with the empirical
219 calculation of the CO₂ flux anomaly (2.67-2.73 PgC) using its linear relationships with
220 the MEI trend (Table 1)¹⁵. Using the CO₂ flux anomaly and MEI trend relationship¹⁵,
221 the CO₂ flux anomaly for the 1997/1998 is estimated at 4.4-5.7 PgC, while that from
222 the atmospheric-CO₂ inversion was 6.7 PgC. A global CO₂ emission anomaly of ~2
223 PgC is estimated for July 1997 – June 1998 due to fires alone¹⁶.

224

225 The annual mean CO₂ residual land fluxes for the main El Niño period are then
226 estimated as -3.15 (=-2.86 - 0.29), -4.06 (=-6.24 + 2.18) and -3.68 (-4.77 + 1.09) PgC
227 yr⁻¹ for the simulation cases ACTM_CYC64, ACTM_IAV84 and ACTM_IAV84+GFAS

228 for the control data screening. The July 2015 to June 2016 aggregated fluxes for
229 ACTM_IAV84+GFAS (best a priori) case are only weakly sensitive when OCO-2 data
230 are screened for $AMF < 3.5$ and $WL < 6$ ($-3.83 = -4.78 + 0.95$ PgC) or $AMF < 2.5$ and
231 $WL < 6$ ($-3.75 = -4.78 + 1.03$ PgC; ref. Table S1). The consistency over data screening
232 and transport model cases provide us confidence on the adapted methodology for
233 calculation of flux correction from model-observation XCO_2 differences, and suggest
234 that treatment of the data gaps do not significantly affect the estimation CO_2 flux
235 anomaly (2.48 ± 0.07 PgC; mean and $1-\sigma$ standard deviation based on 3 sensitivity
236 cases for WL and AMF). The CO_2 flux anomalies estimated from ACTM and GOSAT
237 XCO_2 differences is 2.65 ($=1.70$ for GFAS + 0.95 from XCO_2 flux correction) PgC for
238 the IAV84+GFAS fluxes and period June 2015 to May 2016 (note one month
239 difference with OCO-2) are also found to be in good agreement with those estimated
240 using OCO-2.

241

242 Figure 3 shows the monthly variations in CO_2 flux corrections along with the number
243 of $\sim 1\text{km}^2$ pixels with fire, seen from the MODIS sensor onboard the Terra satellite³⁰.
244 The positive CO_2 flux corrections for both GOSAT and OCO-2 show high coincidence
245 with large fire counts, e.g., during September-October of 2014 and 2015, high CO_2
246 emissions are caused by fires in maritime tropical Asia (mainly Indonesia) and
247 America (mainly Brazil), and emissions during March-April 2015 can be linked to fires
248 in the continental tropical Asia (Thailand and the neighboring countries)¹⁴. As seen
249 from Fig. 3c, more than 90% of global fires (solid line) occur within the latitude band
250 of 30°S - 30°N (broken line), and are emitted as pulse in a one month time window.
251 This result of anomalous XCO_2 increase during the 2015-2016 El Niño can be
252 assigned to CO_2 emissions from the tropical land. Because the signal from the
253 enhanced fires is correlated with drought, the CO_2 observation based study cannot

254 quantitatively discriminate the relative roles of reduction in biospheric uptake due to
255 warmer and drier climate, and emissions from biomass burning. Interestingly,
256 although the time-integrated GFAS emissions are in good agreement with tropical
257 XCO₂ increase, the timing of pulsed CO₂ emissions during the fire events is not well
258 represented. However, as a first guess, we estimate fire emissions to be ~0.76 PgC
259 from the peaks in November 2015 and March 2016 (months following the large fire
260 counts as marked by the dotted lines vertical lines in Fig. 3), which is 30-34% of the
261 total flux anomaly for the main El Niño period.

262

263 **Meridional CO₂ flux anomaly and flux validation using TCCON**

264 Figure 4 shows the meridional distributions of annual mean a priori fluxes and flux
265 corrections using OCO-2 XCO₂ observations. The flux corrections are found to be
266 greatest at around 35-60°N (Fig. 4b,c), up to 10% of the rate of the total a priori
267 biospheric (non-fossil) fluxes, which are of the order of $\pm 20 \text{ gC m}^{-2} \text{ yr}^{-1}$ at these
268 latitudes. In general, the flux corrections at all latitudes are smallest for the
269 ACTM_CYC64 simulation and greatest for the ACTM_IAV84 simulation, but an
270 overall source or a weak sink is observed during October 2014 – September 2015
271 (Fig. 4b). A clear sink tendency is developed for the period October 2015 –
272 September 2016 for the ACTM_CYC64 case and slightly weaker source for the
273 ACTM_IAV84 or ACTM_IAV84+GFAS simulations (Fig. 4c). These suggest that the
274 effect of El Niño on CO₂ release from the biosphere has been moderated in the latter
275 part of 2016 compared to that in 2015 (ref. also Table 1).

276

277 Figure 5 shows the TCCON-ACTM mismatches for the simulations using a priori and
278 corrected fluxes, calculated using individual XCO₂ observations. We find that the best
279 flux corrections are obtained for the best a priori case (ACTM_IAV84+GFAS), where

280 the root-mean-square (RMS) differences of TCCON-ACTM XCO₂ are below 0.78
281 ppm for 5 out of 6 sites (except for Darwin at 1.07 ppm). A reduction in RMS differences
282 of 70-80% are found for this ACTM case. The simulation case of ACTM_CYC64 also
283 achieved RMS differences close to 1.0 ppm or lower following the flux correction.
284 However, the case of ACTM_IAV84 showed a mean RMS difference of 1.5 ppm after
285 flux corrections are applied. Thus a good a priori ACTM simulation is critical for
286 implementing this method of flux correction using OCO-2 measurements. One of the
287 most encouraging improvements in ACTM – OCO-2 difference is seen for Park Fall. At
288 this site, the differences were largest in July, which are reduced by half to ~1 ppm in
289 2015 and ~2 ppm in 2016 for the ACTM_CYC64 case (Fig. 5a), suggesting that the
290 CO₂ sinks should be increased in the northern mid-latitude region (green line in Fig.
291 4b,c). Such seasonal bias is not seen for ACTM_IAV84 case, but an overall reduction
292 in sink in the northern mid-latitudes is suggested (consistent with Fig. 4b,c). Both the
293 seasonal and annual biases are the lowest for the ACTM_IAV84+GFAS case.

294

295 Following this validation, we conclude the CO₂ flux anomaly to be 2.4 ± 0.2 PgC for
296 the July 2015 – June 2016 period using the flux corrections obtained for
297 ACTM_IAV84+GFAS case only. An annual total land and ocean sink of 3.9 ± 0.2
298 PgC yr⁻¹ during July 2015 – June 2016, for the assumed fossil fuel emissions of 10.1
299 PgC yr⁻¹, contrasts the average sink of 6.2 PgC yr⁻¹ during the reference year of
300 2014. This is in huge contrast to the July 1997 – June 1998 period, when the Earth's
301 surface acted as a net source of CO₂ to the atmosphere. Since the atmospheric
302 growth rate measured by the NOAA/ESRL at Mauna Loa is 3.05 ppm yr⁻¹ for the
303 main El Niño period, the global residual sink of 3.6 (=10.1-3.05*2.12) PgC yr⁻¹ is fairly
304 consistent with our results. The residual sink for 1998 based on Mauna Loa growth
305 rate was 0.5 (=6.7-2.93*2.12) PgC yr⁻¹.

306

307 In an attempt to gain further confidence in the ACTM corrected fluxes we compared
308 the meridional gradients in CO₂ fluxes from two other traditional inversions (Figure 6).
309 The traditional inversions are: CarbonTracker run from NOAA³¹ and Copernicus
310 Atmosphere Monitoring Service (CAMS)³². The comparison suggests large
311 differences between the inversion fluxes, and the differences showing strong
312 dependence on a priori FFC CO₂ emissions. Generally, the model assumed stronger
313 FFC emissions also suggest stronger biospheric uptake, with particular distinctions in
314 the northern mid-latitude region³³. This leads us to conclude that the simple inversion
315 system using XCO₂ observations and ACTM simulations is usable for global CO₂ flux
316 anomaly calculation.

317

318 Discussion

319

320 The powerful 2015-2016 El Niño has made a large impact on the Earth's natural
321 climate system, which in turn affected the terrestrial ecosystem. We analyzed the
322 column-averaged CO₂ dry mole fraction (XCO₂) estimates from NASA's OCO-2
323 observations collected between September 2014 and October 2016. We have also
324 used the longer measurement records from JAXA's GOSAT, TCCON ground-based
325 XCO₂ and NOAA in situ CO₂ measurements in the analysis. Global simulations using
326 JAMSTEC's ACTM are performed for three combinations of terrestrial and oceanic
327 CO₂ fluxes: CYC64, IAV84 and IAV84+GFAS, and a common field of emissions from
328 fossil fuel consumption and cement production. The XCO₂ and CO₂ growth rates are
329 slightly overestimated by ACTM_CYC64, but a greater underestimation was found for
330 ACTM_IAV84 while compared with OCO-2 observations. The ACTM_IAV84
331 simulation successfully simulated CO₂ growth rates during January 2013 to mid-

332 2014. Thus the IAV84+GFAS simulation produced the smallest model-data mismatch
333 over the tropics when GFAS emissions were added from October 2014 (total
334 emission of 2.64 PgC). We estimate that the El Niño event led to excess CO₂ release
335 to the atmosphere in the range of 2.23-2.55 PgC during July 2015 to June 2016,
336 compared to the reference period of 2014. This CO₂ release would be increased by
337 0.2 PgC if no increase in FFC emission was assumed.

338

339 In year 2015, about 0.76 PgC is emitted from fires, which is in the range of 30-34% of
340 total CO₂ flux anomaly. The OCO-2 based CO₂ flux anomaly of 2015-2016 El Niño is
341 comparable to that is estimated from an empirical relation of CO₂ flux anomaly and
342 ENSO index trends (2.67-2.73 PgC). Our estimated fire-induced CO₂ flux anomalies
343 disagree with those calculated from the GFED4.1s total fire CO₂ emissions of 1.64,
344 1.88 and 2.09 PgC for 2013, 2014 and 2015, respectively (anomaly ~0.2 PgC for
345 2015 relative 2014). and are more comparable to the 1997 and 1998 fire emission
346 anomalies (~1 PgC) with global emissions of 2.75 and 2.67 PgC, respectively
347 (http://www.falw.vu/~gwerf/GFED/GFED4/tables/GFED4.1s_CO2.txt)¹⁴.

348

349 The flux corrections based on OCO-2 measurements are validated using
350 independent TCCON measurements, which suggest systematic reductions in
351 TCCON-ACTM mismatches for the simulations using corrected fluxes compared to
352 the a priori fluxes. A mean 1- σ standard deviation of 0.7 ppm is achieved for 6
353 TCCON sites for the period of October 2014 to October 2016 using the corrected
354 fluxes. The flux correction method is applicable to satellite observations with near
355 global coverage to calculate global CO₂ flux anomalies at near real-time when a
356 suitable a priori model simulation of atmospheric-CO₂ is available, e.g.,
357 ACTM_IAV84+GFAS case in this study. Based on our best a priori case, the global

358 total flux anomaly is estimated to be 2.4 ± 0.2 PgC to the atmosphere as an effect of
359 the El Niño, while the Earth's surface acted as a net sink of CO₂ by 3.9 ± 0.2 PgC
360 during the period of July 2015 – June 2016.
361

362 **Methods**

363 We used the bias corrected measurements of XCO₂ from the 'OCO-2 7 LITE LEVEL
364 2' files²⁶ (updated document at [http://disc.sci.gsfc.nasa.gov/OCO-](http://disc.sci.gsfc.nasa.gov/OCO-2/documentation/oco-2-v7)
365 [2/documentation/oco-2-v7](http://disc.sci.gsfc.nasa.gov/OCO-2/documentation/oco-2-v7); last accessed: 5 December 2016). These files only
366 include those soundings that have passed the cloud screens and converged
367 (xco2_quality_flag = 0). In addition, only those soundings that have a warn level
368 (WL) less than 12 and air mass factor (AMF) less than 3.5 are used in this analysis
369 (Control case), but no distinction is made for the different viewing modes of nadir,
370 glint or target. All the data for the period extending from 06 September 2014 to 31
371 October 2016 are combined into 2.5°x2.5° grid boxes at monthly time intervals for the
372 convenience of analysis. Any grid containing less than 3 OCO-2 soundings (N) or an
373 absolute model (ACTM_IAV84+GFAS case) - observation XCO₂ difference greater
374 than 9 ppm is set to undefined. The limits for WL and AMF are chosen after testing
375 different cut-off levels for making the gridded dataset. For example, use of AMF < 2.5
376 or < 3.5 did not produce large number of zonal-mean XCO₂ differences greater than
377 ±1 ppm at most latitude bands (except at the high latitude edge of the satellite orbit)
378 in all months. Similarly XCO₂ differences greater than ±1 ppm were not found
379 frequently for selection of WL < 6 or WL < 12. Various sensitivities of these data
380 screening parameters are shown in the Supplementary Information (Fig. S1 and S1).

381 In addition, we have used selected measurements of XCO₂ from the ground-
382 based Total Carbon Column Observing Network (TCCON)²⁸ and CO₂ from the NOAA
383 cooperative global air sampling network²⁹ [Product: obspack_co2_1_CarbonTracker-
384 NRT_v2.0_2016-02-12]. We have used the XCO₂ data from TCCON sites at Lauder
385 (45°S, 170°E)³⁴, Reunion Is (21°S, 55°E)³⁵, Darwin (12°S, 131°E)³⁶, Ascension Is
386 (8°S, 14°W)³⁷, Lamont (37°N, 97°W)³⁸ and Park Falls (46°N, 90°W)³⁹. The in situ CO₂
387 data are taken from Cape Grim (41°S, 145°E), Samoa (14°S, 171°W), Ascension Is

388 (8°S, 14°W), Seychelles (5°S, 55°E), Barbados (13°N, 59°W), Mauna Loa (20°N,
389 156°W), Barrow (71°N, 157°W) and Alert (82°N, 62°W).

390 The four-dimensional (4D) distribution of CO₂ mole fractions are simulated using
391 the Center for Climate System Research/National Institute for Environmental
392 Studies/Frontier Research Center for Global Change (CCSR/NIES/FRCGC)
393 atmospheric general circulation model (AGCM)-based CTM (i.e., JAMSTEC's
394 ACTM)⁴⁰. ACTM is run at a horizontal resolution of T106 spectral truncations
395 (~1.125×1.125°), and 32 sigma-pressure vertical levels, and meteorology is nudged
396 to horizontal winds and temperature from the Japanese 55-year Reanalysis (JRA-
397 55)⁴¹. The following CO₂ flux tracers are simulated by ACTM with an aim to
398 encompass the observed CO₂ growth rates during October 2014 to February 2016
399 (Table 1):

400 *a. Flux CYC64*: This simulation is performed using the inverted land and ocean fluxes
401 for the year 2008 from 64 land and ocean regions⁴⁰. The global total flux for this
402 inversion is -2.86 PgC yr⁻¹ (Table 1), relatively weaker sink and thus over-predict
403 the atmospheric CO₂ growth rate for the decade of 2010s.

404 *b. Flux IAV84*: Monthly-mean CO₂ fluxes for 84 land and ocean regions
405 corresponding to year 2011 are taken from an 84-region inverse model⁴². The
406 global total flux for this inversion is -6.24 PgC yr⁻¹, relatively stronger sink and thus
407 under-predict the atmospheric CO₂ growth rate for the decade of 2010s.

408 *c. Flux GFAS*: The fire-related daily CO₂ emissions are taken from the Global Fire
409 Assimilation System (GFAS; version 1.2)¹⁹. The GFAS emissions are added to
410 IAV84 fluxes from October 2014 onwards, and is used here as a proxy for
411 anomalous CO₂ emission, not specifically as a quantification of fire emission.
412 Since more than 90% of GFAS emissions occur in the 20°S-20°N, this is regarded
413 as a surrogate for tropical land flux anomaly.

414 Interannually varying a priori emissions for fossil fuel consumption and cement
415 production (*FFC*) are taken from the Emissions Database for Global Atmospheric
416 Research (EDGAR, v4.2)³. Same for all 3 cases. The spatial distribution of emissions
417 for 2010 is repeated for all the later years with a 0.2 PgC yr⁻¹ increase globally. This
418 assumption of emission increase rate has identical, but compensating, effects on the
419 estimation of interannual variations in CO₂ fluxes.

420 The CO₂ flux tracer simulations are started on 01 January 2005. We then
421 combine the CO₂ flux tracers to get 4D CO₂ concentrations, as ACTM_CYC64
422 (=FFC+CYC64), ACTM_IAV84 (=FFC+IAV84), ACTM_IAV84+GFAS
423 (=FFC+IAV84+GFAS). These 3 combinations of model CO₂ concentrations allow us
424 to cover the whole range of XCO₂ increase observed by OCO-2 and TCCON, and
425 CO₂ at NOAA sites. The model CO₂ values are adjusted by -1.80, -1.45 and -1.45
426 ppm, respectively, for ACTM_CYC64, ACTM_IAV84 and ACTM_IAV84+GFAS on 01
427 September 2014, coinciding with the start of data collection by OCO-2. This
428 adjustment leads to no flux correction for September 2014. The vertical profiles of
429 CO₂ are first sampled at the location and time of individual OCO-2 measurements,
430 and then convolved with the a priori profiles and averaging kernels of OCO-2,
431 GOSAT and TCCON for calculating ACTM XCO₂ values⁴³.

432 Note that the ACTM_IAV84 simulation successfully simulated the CO₂
433 concentrations for the time evolution and tropospheric profiles over Asia for the
434 period 2007-2012⁴¹. Also shown here that the CO₂ growth rates are well simulated by
435 ACTM_IAV84 at the selected TCCON and NOAA ground-based measurement sites
436 for January 2013 to mid-2014. Thus any differences in time evolution during the
437 period September 2014 to February 2016 of OCO-2 data analysis can be attributed
438 to excess CO₂ releases associated with the El Niño event, relative to the 2014 mean.

439 Model XCO₂ are calculated⁴³ by convoluting model CO₂ profile (CO₂^{ACTM})
 440 with that of the a priori profile (CO₂^{prior}) and column averaging kernels (A_i) of
 441 instrumental sensitivity to different layers of the atmosphere (P_i, i=20, 20 and 71 for
 442 OCO-2, GOSAT and TCCON, respectively).

$$443 \quad XCO_2^{ACTM} = \sum_i (CO_2^{prior}_i \cdot dP_i) + \sum_i A_i (\sum_i CO_2^{ACTM}_i \cdot dP_i - \sum_i CO_2^{prior}_i \cdot dP_i) / (\sum_i dP_i / cH_2O_i)$$

444 (1)

445 dP_i is the thickness of each pressure layers. Water vapour corrections are applied to
 446 both the model and all TCCON column observations as are reported in dry air mole
 447 fractions. The correction term for each altitude level (*l*) is defined as:

$$448 \quad cH_2O = g \cdot M_{air} (1.0 + q^{dry} \cdot M_{H_2O} / M_{air})$$

449 (2)

449 Where, $q^{dry} = q / (1 - q)$ and *q* is specific humidity (mass fraction, kg/kg). M_{H₂O}=18.02 and
 450 M_{air} = 28.964 g/mole. Gravity 'g' is corrected for altitude (refer for further details:

451 https://tcon-wiki.caltech.edu/Network_Policy/Data_Use_Policy/Auxiliary_Data)

452 Since the XCO₂ values consist of vertically-integrated information for the
 453 whole atmospheric column, assuming that the simulated carbon atmospheric fluxes
 454 are perfect, simple approximations can be applied for estimating CO₂ flux corrections
 455 (in PgC month⁻¹) from sub-hemispheric atmospheric CO₂ burden differences (PgC) at
 456 monthly time interval.

$$457 \quad \text{Burden difference} = \Sigma (XCO_2 \text{ difference} \times \text{area of the grid} \times \text{air density}) \quad (3)$$

$$458 \quad CO_2 \text{ flux correction} = d(\text{Burden difference})/dt \quad (4)$$

459 Where the XCO₂ difference is the observed minus model values, area of the grid is
 460 latitude dependent and air density is calculated as the air mass overhead each 2.5 x
 461 2.5 grid from ACTM air density. The difference in the burden mismatches between
 462 October and September 2014 is assigned to the flux correction for October 2014. For
 463 these flux estimations in the control case, missing areas are filled by the mean values
 464 of the observed – model differences for the 3 latitude bands. This is done based on

465 an assumption that the mean differences will be transported within the semi-
466 hemispheric regions within months by the rapid zonal mixing. In this simple method,
467 we do not expect to resolve the evolution of flux corrections at less than a 1-month
468 time resolution or the contrast between the continents and between land-ocean.
469 However, this method is applicable for near real-time monitoring of biospheric health
470 of Earth's ecosystem without significant additional investment.

471 This method of flux corrections is valid only for sub-hemispheric scales since
472 the zonal transport circulates air masses several times around each of the 3 broad,
473 zonal bands within one month. This method suffers from the extrapolation of data to
474 the missing observation grid boxes. For example, OCO-2 soundings covered a
475 maximum of 70, 70 and 60% of the $2.5 \times 2.5^\circ$ grid cells in the latitudes bands of 90°S -
476 10°S , 10°S - 10°N , 10°N - 90°N , respectively. In the latitude bands poleward of 10° ,
477 monthly data coverage can be as low as 30% in the winter hemisphere. Data
478 coverage in the tropical latitudes suffers mainly from cloud cover (in addition to the
479 model transport error), sometimes for longer than a month, and are approximated at
480 modelers discretion by choosing not to modify the priors or applying a time
481 correlation. The fraction of missing data area will increase further when analyzed for
482 smaller than $2.5^\circ \times 2.5^\circ$ grid sizes. Note that this method cannot be employed for the
483 in situ measurement network without significant extrapolation in space and for the
484 fact that the ground measurement sites do not cover the majority of the continental
485 source regions⁴⁴.

486 As opposed to the site-based data analysis^{12,13,15} for CO_2 flux anomaly, this
487 method based on differences between the observation-model difference does not
488 require a long time series of data. As shown here, only one year of reference is
489 sufficient, (2014 used in this analysis). Another major advantage of this analysis
490 comes from the near uniform data coverage over the continents of tropical Asia,

491 Australia, South America and Africa, which are very sparsely observed by the in situ
492 measurement networks, providing a true global CO₂ flux signal. The traditional
493 analyses mentioned earlier in the Introduction focused on one site, which is often
494 under the influence of regional or local flux signals.

495 Finally, we are also able to validate the flux corrections from ACTM – OCO-2
496 XCO₂ differences using an independent set of TCCON observations. The zonal
497 mean flux corrections (Figure 4) are simulated using ACTM and XCO₂ signals added
498 to their respective a priori simulations. The results are presented in Figure 5, which
499 show clear reduction in ACTM – OCO-2 differences after the corrected flux
500 simulations (Table S2). Flux corrections using ACTM and OCO-2 XCO₂ are also
501 compared with CarbonTracker and CAMS traditional inversion results showing
502 greater influence of fossil fuel a priori emissions on the estimated biospheric flux
503 compared to the differences arising from flux estimation methods (Figure 6).

504
505

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631
632

633 **Acknowledgements**

634 This work is supported by the Environment Research and Technology Development
635 Fund (2-1401) of the Ministry of the Environment, Japan. PKP is grateful to
636 Christopher O'Dell for sharing user-friendly OCO-2 and GOSAT data in NetCDF. This
637 research has benefitted and inspired by discussions with Andrew Jacobson (also for
638 NOAA CarbonTracker inversion fluxes), David Baker, Frederic Chevallier (also for
639 CAMS inversion fluxes) and Sander Houweling. We thank Pieter Tans, Edward
640 Dlugokencky and team members at NOAA ESRL for allowing us to use the in situ
641 CO₂ measurements at the surface sites. The XCO₂ observation data were produced
642 by the OCO-2 project at the Jet Propulsion Laboratory, California Institute of
643 Technology, and obtained from the OCO-2 data archive maintained at the NASA
644 Goddard Earth Science Data and Information Services Center. Part of the analysis

645 described here was carried out at the Jet Propulsion Laboratory, California Institute
646 of Technology, under a contract with the National Aeronautics and Space
647 Administration. The GFAS dataset was produced by EU's Copernicus Atmosphere
648 Monitoring Service and distributed by the GEIA database ECCAD
649 (<http://eccad.sedoo.fr>). The TCCON data were downloaded from the TCCON archive,
650 hosted by CDIAC, at <http://www.tcon.ornl.gov>. The TCCON station on Ascension
651 Island has been funded by the Max Planck Institute for Biogeochemistry. The
652 TCCON site at Ile de la Réunion is operated by the Royal Belgian Institute for Space
653 Aeronomy with financial support in 2014 and 2015 under the EU project ICOS_Inwire
654 and the ministerial decree for ICOS (FR/35/IC2) and local activities supported by
655 LACy/UMR8105 - Université de La Réunion. TCCON data from Park Falls, Lamont,
656 and Darwin are made possible with support from NASA. TCCON data were obtained
657 from the TCCON Data Archive, hosted by the Carbon Dioxide Information Analysis
658 Center (CDIAC) at Oak Ridge National Laboratory, Oak Ridge, Tennessee, U.S.A.,
659 <http://tcon.ornl.gov>. We thank both the three reviewers for critical but constructive
660 comments, which have been very helpful for reshaping the contents of this article.

661

662 **Author contributions statement**

663 P.P., D.C. and J.K. conceived the experiments, P.P. conducted the model
664 experiments and data analysis, D.C. provided guidance on the use of OCO-2 data,
665 J.W. provided GFAS emissions, T.Sa. run ACTM inversions, T.Se. run tracer
666 simulation, K.Ic. and A.C. supported data analysis, and D.W., P.W., D.F., D.P., D.G.,
667 V.V., M.D., M.S., C.R. provided TCCON measurements and supported analysis. K.Ic.
668 prepared JRA55 meteorology. All authors reviewed the manuscript and contributed to
669 writing.

670

671 **Additional information**

672 All the model results and processed observational data as used in this article are

673 available from the lead author; Authors declare no competing financial interests.

674

Figure Captions

675

676

677 **Figure 1: Time evolution of XCO₂ from satellites and model.** Latitude-time
678 distribution of XCO₂ (in ppm) measured from OCO-2 (a) and GOSAT (e), and their
679 differences with 3 cases of ACTM simulations (b-d and f-h, respectively) for the
680 period of OCO-2 operation, from 07 September 2014 to 31 October 2016 (GOSAT
681 ACOS b7.3 are available until 31 May 2016). Note the striking similarities between
682 OCO-2 and GOSAT measurements and ACTM_IAV84+GFAS simulation case,
683 particularly over the tropics. Further detailed comparisons of GOSAT and ACTM, with
684 separation for soundings over land and water surfaces suggests the positive model
685 biases in the high latitude regions arise mainly over the ocean surface. Similar plots
686 cannot be made using data from the TCCON or NOAA network sites without
687 significant interpolation in space and time due to the geographically sparse sampling
688 of the ground-based networks.

689

690

691 **Figure 2: Observation-model comparisons of XCO₂ and CO₂ from different**
692 **measurement systems.** Time series of zonal mean differences in XCO₂
693 (observation – model) for three broad latitude bands (top two rows). The differences
694 in TCCON XCO₂ and NOAA CO₂ trends with ACTM simulations are shown in the
695 bottom two rows. All three cases of model simulations (ACTM_CYC64: green,
696 ACTM_IAV84: black, and ACTM_IAV84+GFAS: red) are matched with observations
697 on October 2014 (marked by vertical yellow line), which is chosen as the reference
698 point for the calculation of XCO₂ model-observation differences for calculating flux
699 corrections. Note that the OCO-2 measurements are started from September 2014,

700 GOSAT from 2009, TCCON from 2002, and MLO flask sampling from 1967.

701 Common legends to all the subplots are given in top-left panel.

702

703

704 **Figure 3: Global CO₂ flux corrections and fire count variability.** Global total CO₂
705 flux corrections for the extended global latitudes, estimated from the GOSAT and
706 ACTM (a; top), OCO-2 and ACTM (b; middle) differences and global total GFAS
707 emissions, and fire-pixel counts for global, tropics (30°S-30°N) and by continental
708 divisions for the tropics (c). Fire counts are taken from the Moderate-resolution
709 Imaging Spectroradiometer (MODIS) Active Fire Products³⁰
710 (<ftp://fuoco.geog.umd.edu/modis/C5/cm/monthly/hdf/>).

711

712

713 **Figure 4: Meridional distributions of CO₂ fluxes and flux corrections.** (a) A priori
714 fluxes for fossil-fuel and cement production, land and oceanic fluxes in
715 ACTM_CYC64 and ACTM_IAV84, GFAS fire emissions averaged over October 2014
716 – September 2015. The flux corrections for the two separate years (averaged over:
717 October – September) are shown for the 3 ACTM simulation cases (b, c; legends in b
718 are common to both panels).

719

720

721 **Figure 5: Comparisons of XCO₂ as measured by TCCON and simulated by**
722 **ACTM.** The XCO₂ time series are shown for 6 sites (as opposed to paired sites
723 shown in Fig. 2g-i) for two sets of simulations, solid and broken lines are for ACTM
724 runs using a priori and corrected fluxes, respectively. The statistics of TCCON-ACTM
725 mismatches are given in Table S2, which are calculated from individual TCCON data.

726

727 **Figure 6:** Comparison of a priori FFC CO₂ emissions and total natural/biospheric
728 (land+ocean) fluxes from inverse modelling. The fluxes from two independent
729 traditional inversions are taken from CarbonTracker by NOAA (CT-NOAA; Peters et
730 al., 2007; version: CT2016; www.esrl.noaa.gov/gmd/ccgg/carbontracker/) and
731 Laboratoire des Sciences du Climat et de l'Environnement (LSCE) inversion results
732 from CAMS (CAMS-LSCE; Chevallier et al., 2010; version: v15r4;
733 <http://apps.ecmwf.int/datasets/data/cams-ghg-inversions/>).

734

735

Time window	A priori CO ₂ fluxes used for ACTM simulations					Patra et al. # (2005b)	CO ₂ flux corrections from OCO-2 – ACTM differences [§]		
	FFC	CYC64	IAV84	IAV84 +GFAS	GFAS		CYC64	IAV84	IAV84+ GFAS
Oct 2014 - Sep 2015	9.93	-2.86	-6.24	-4.27	1.97	2.67 - 2.73	-0.13 - -0.23	1.17 - 2.04	0.41 - 0.71
Oct 2015 - Sep 2016	10.12	-2.86	-6.24	-5.57	0.67		-0.75 - -1.10	1.00 - 1.16	0.53 - 0.67
Jul 2015 - Jun 2016 (main El Niño period)	10.08	-2.86	-6.24	-4.77	1.46		-0.18 - -0.29	1.50 - 2.18	0.77 - 1.09

736 # Range estimated from two different fits, with (Flux anomaly = 0.3539 + 1.4935 ×
 737 MEI amplitude change) or without (= -1.0756 + 2.4579 × MEI amplitude change) the
 738 La Niña years.

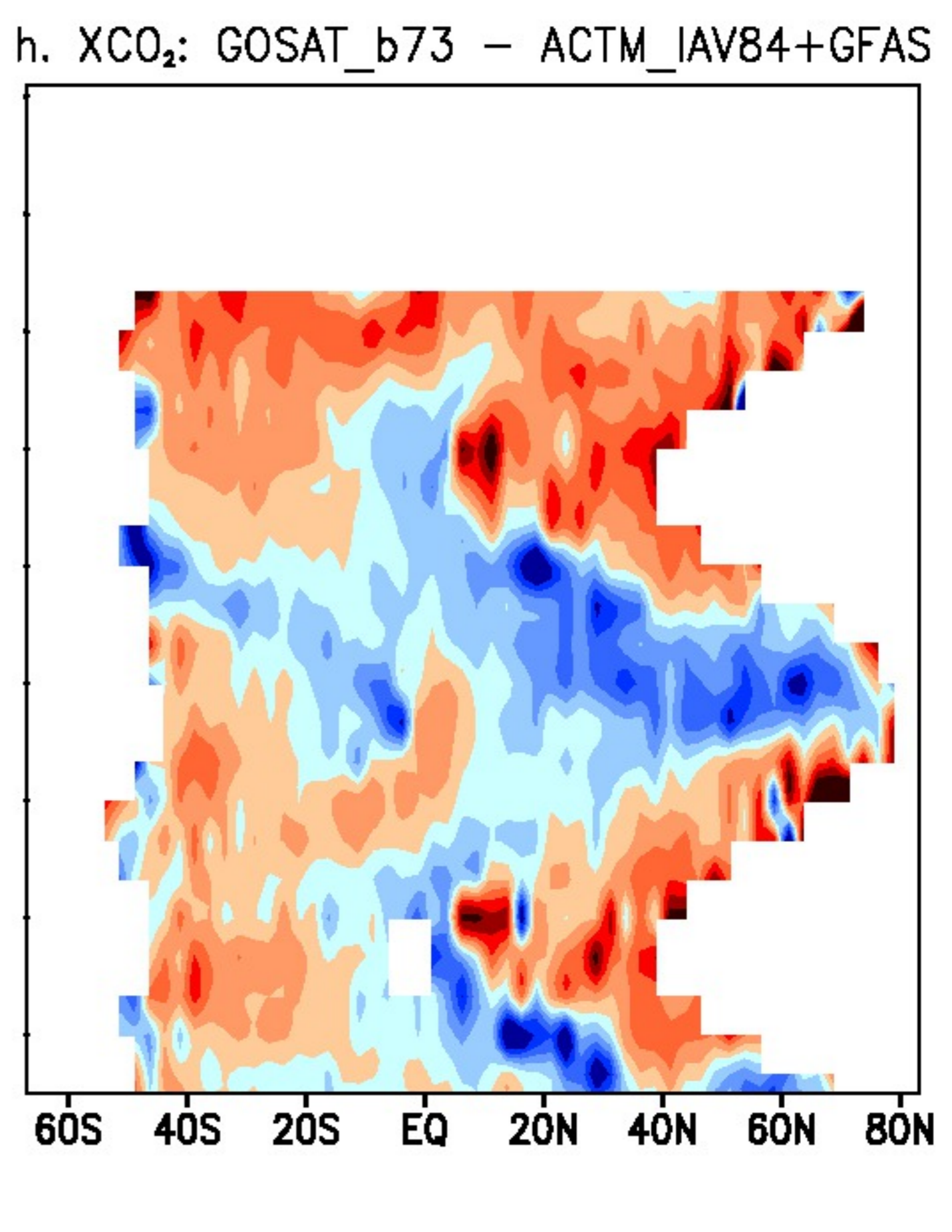
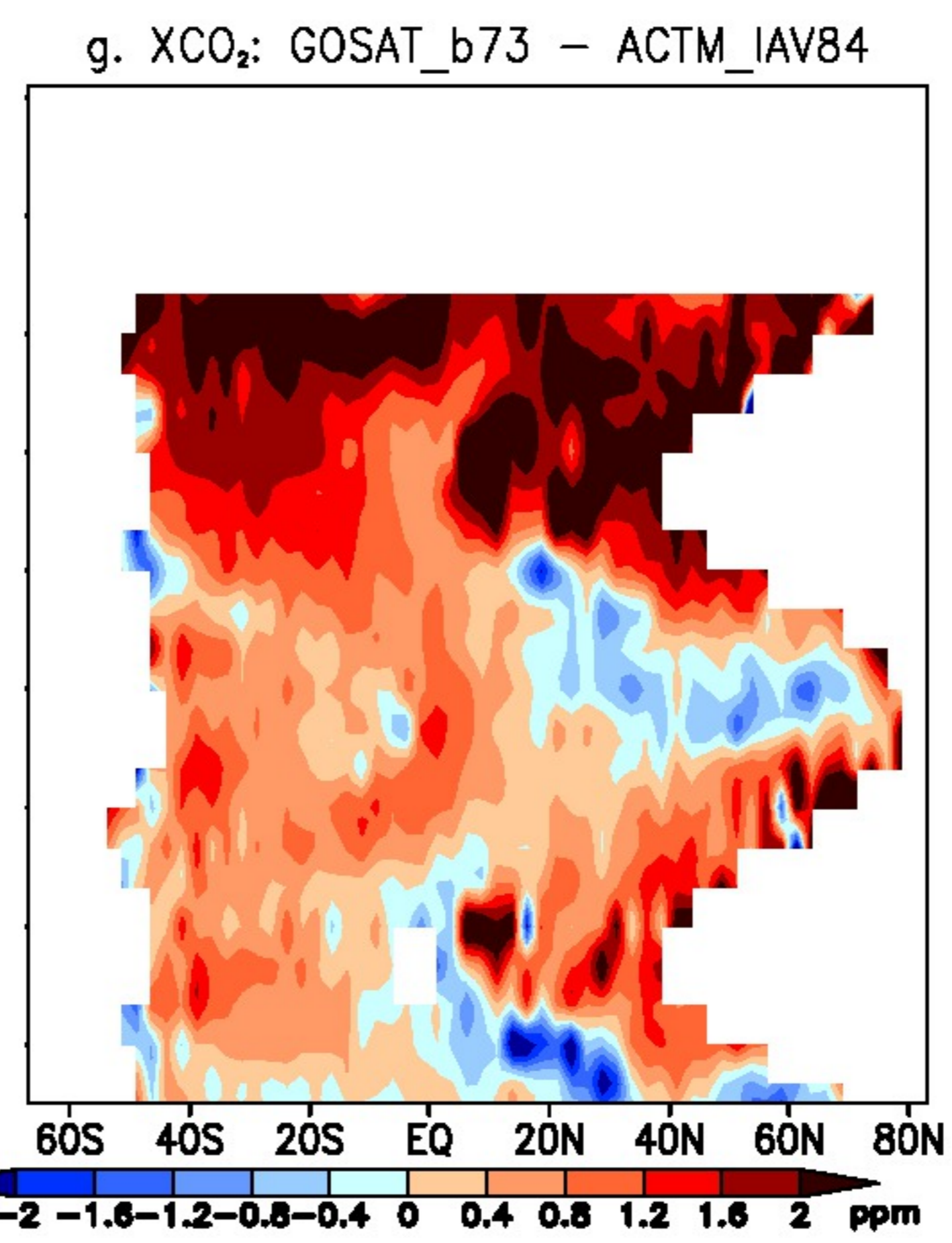
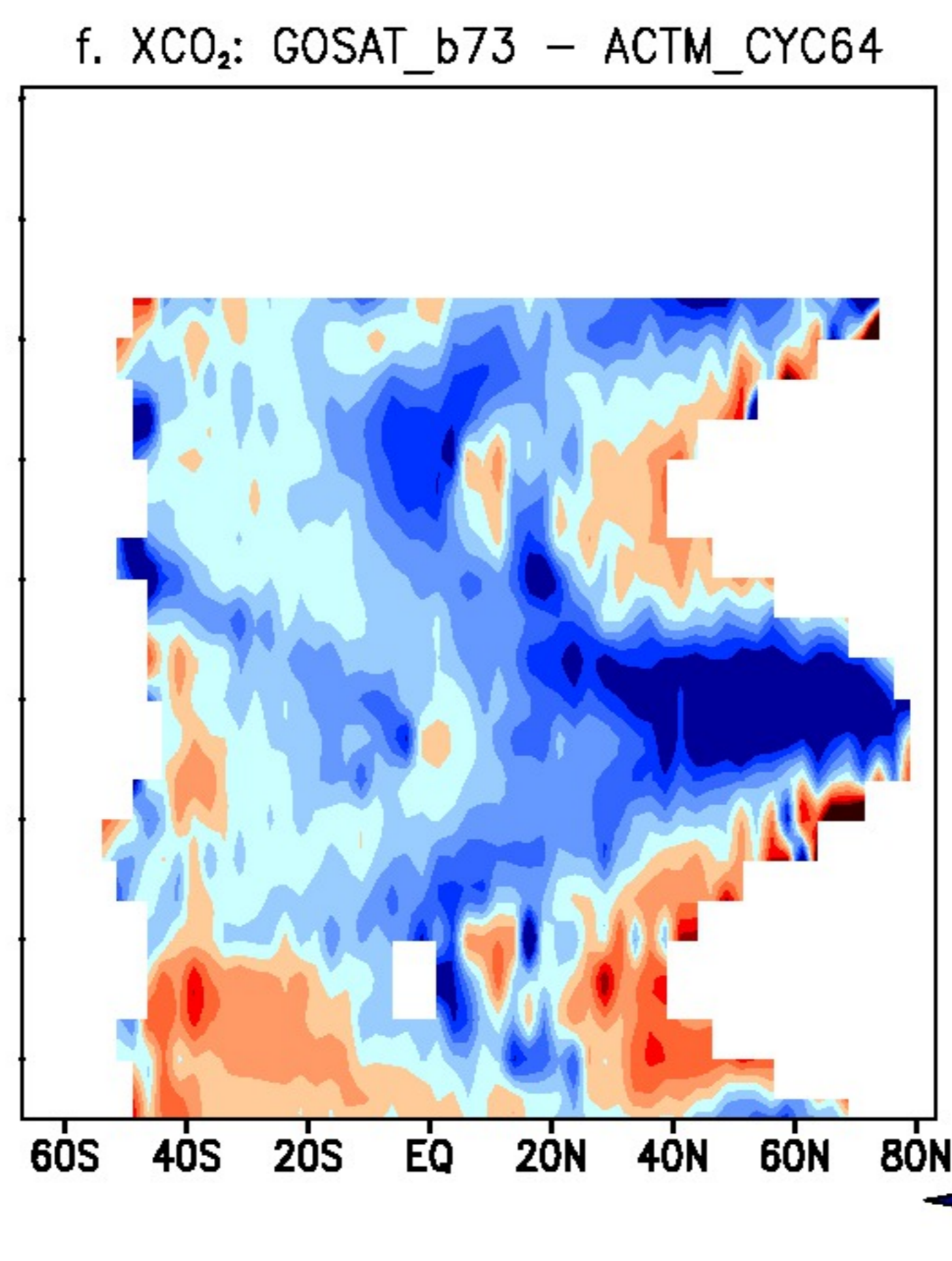
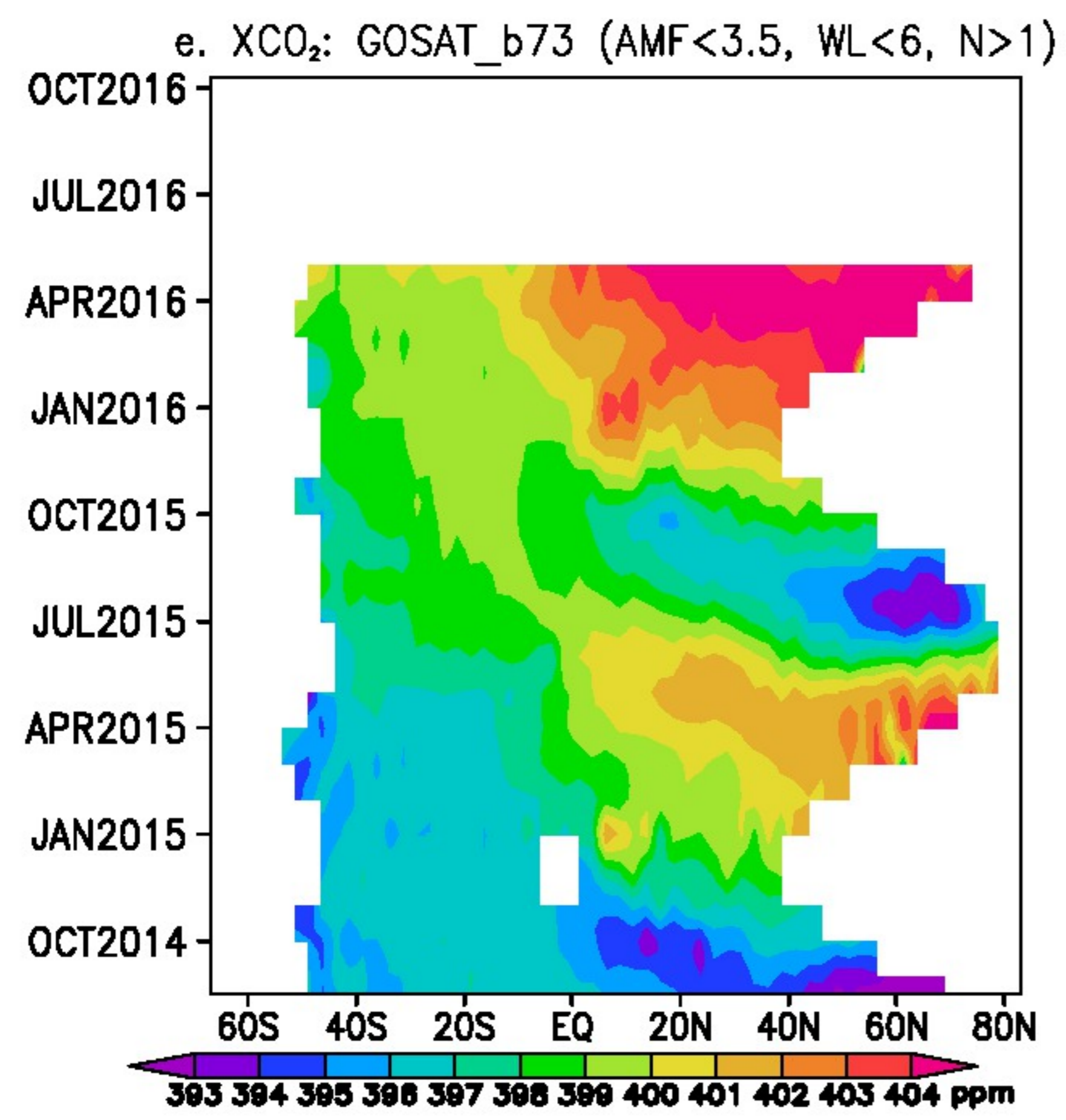
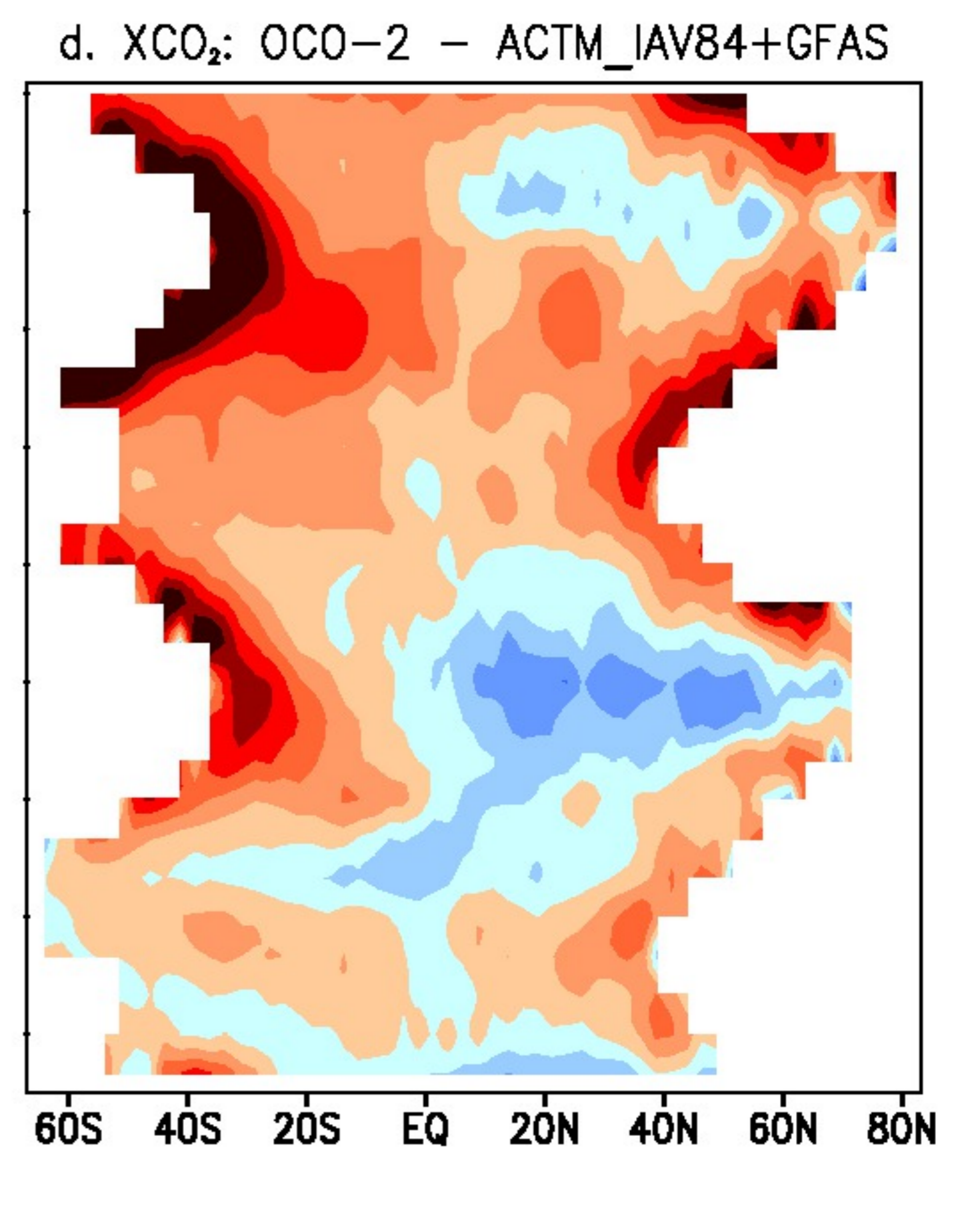
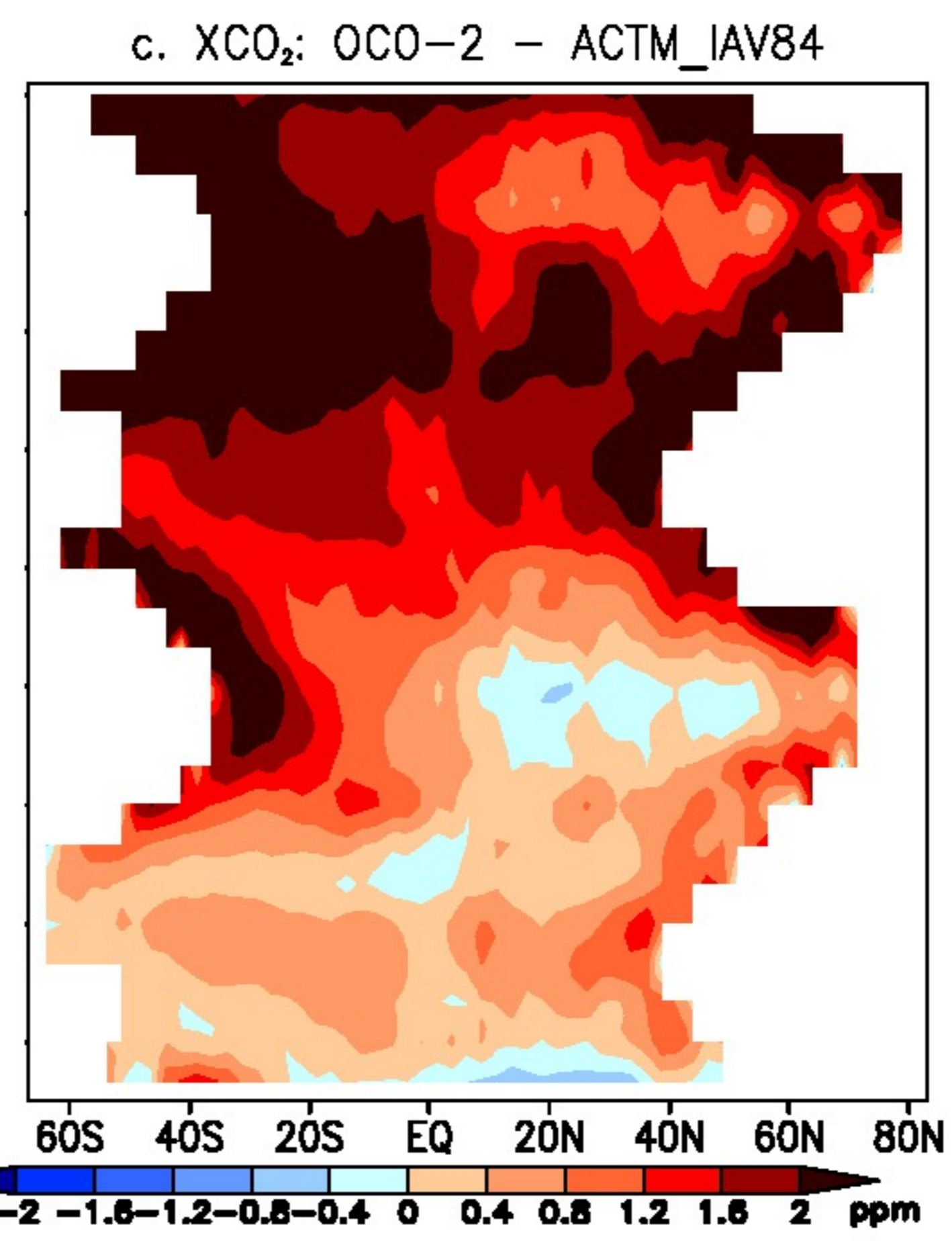
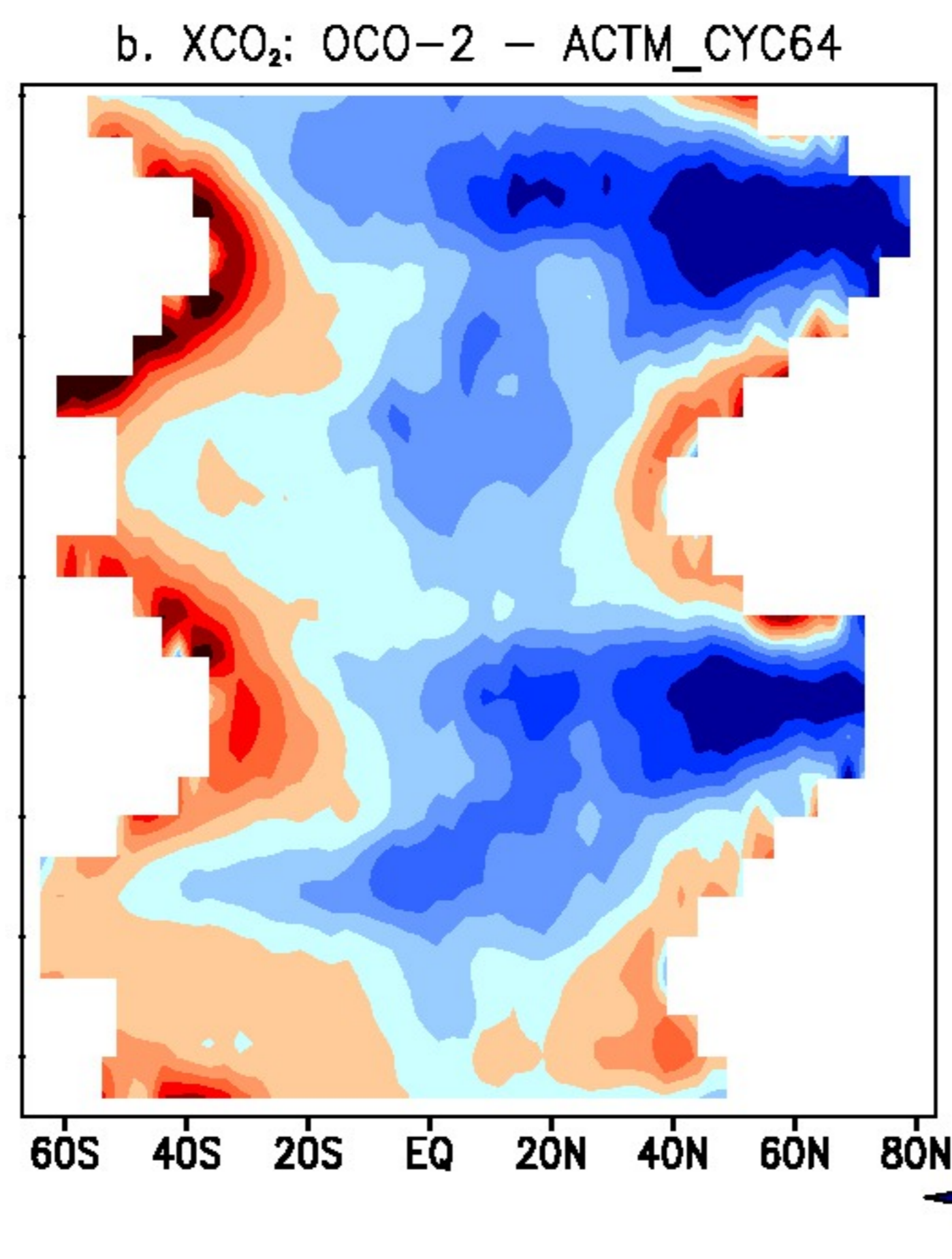
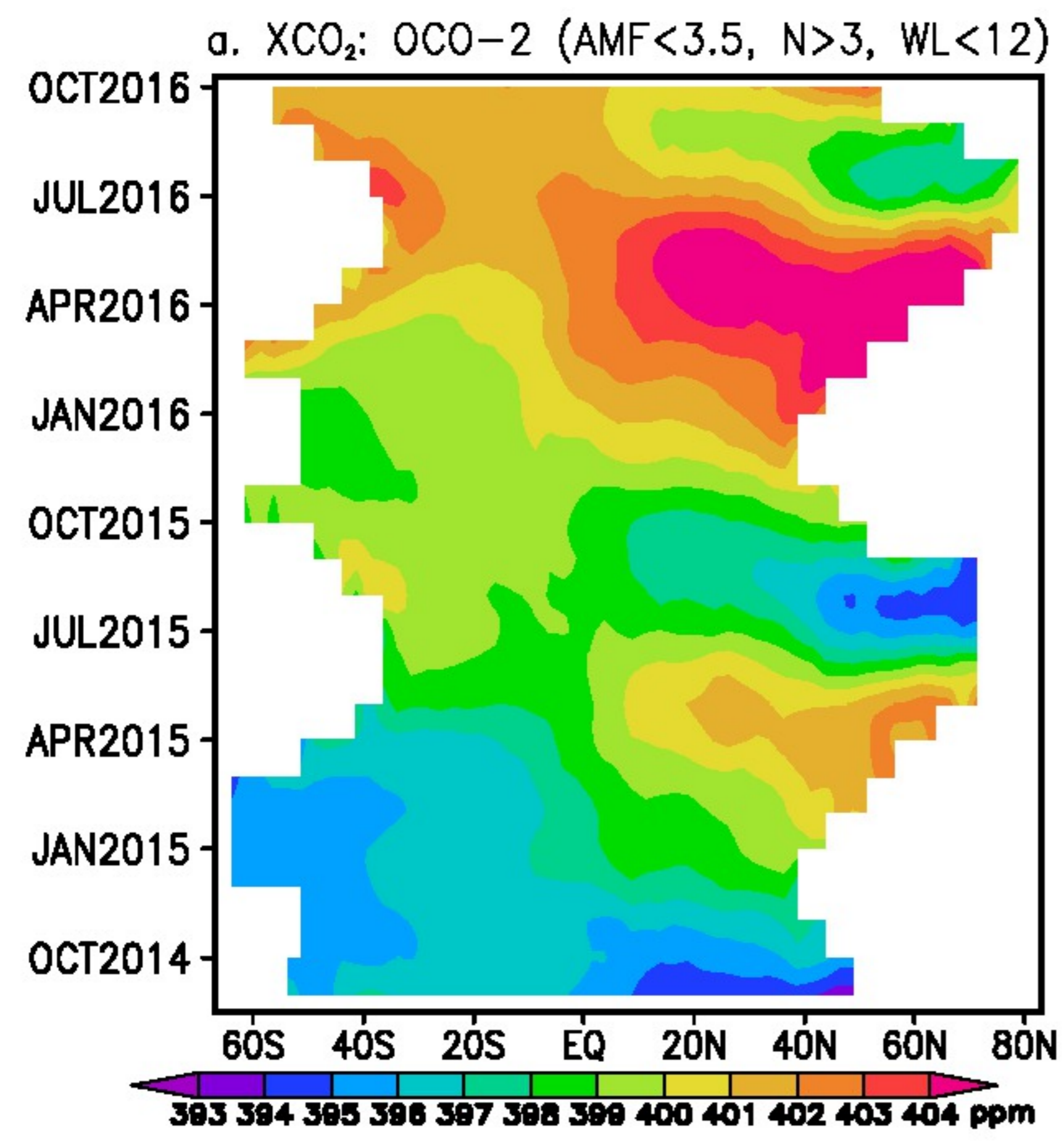
739 § Range of estimation using two different approximations on area coverage (lower:
 740 latitudes covered by measurements; higher: global; refer to the main text for details).

741

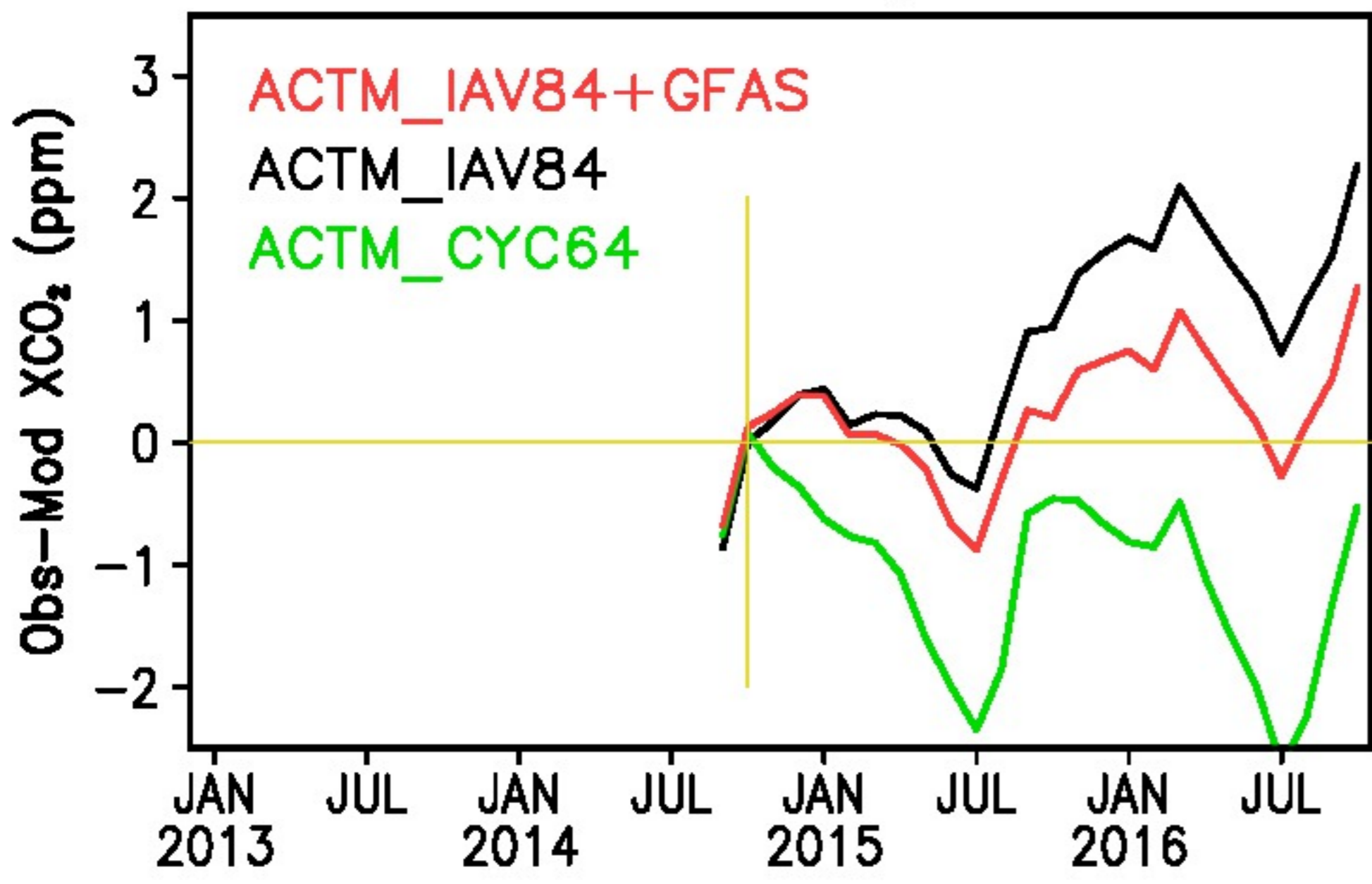
742

743 **Table 1:** Global total CO₂ fluxes used in the 3 ACTM simulations (column 2-6), and
 744 estimated flux corrections (column 7-10) for different time windows given in column 1
 745 (Units: PgC). Note here that these values are not strictly mass balanced as the XCO₂
 746 differences are weighted by area of the 3 latitude bands, without knowing whether
 747 the mismatches at high latitudes in particular extend to the poles on either side.

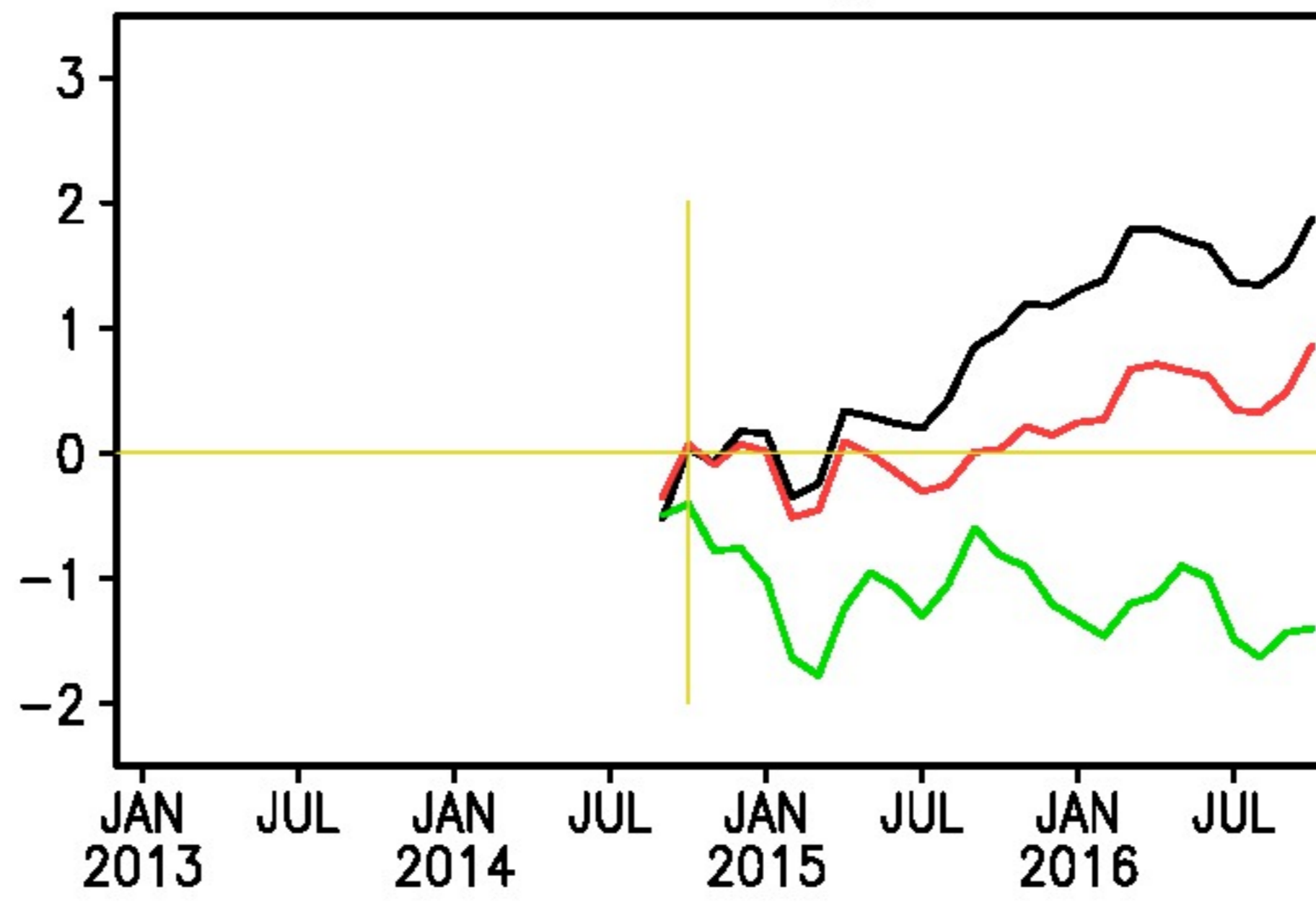
748



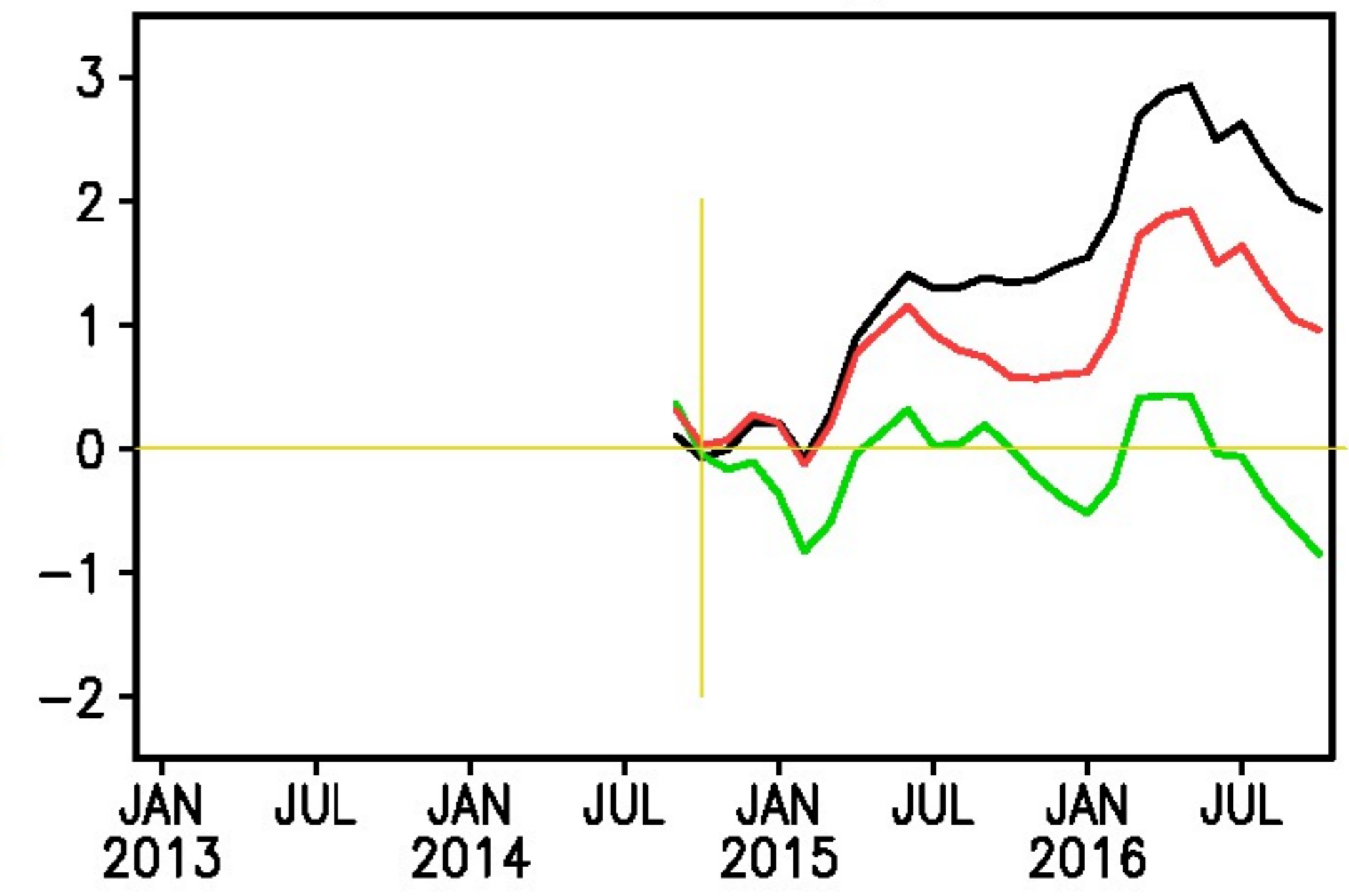
a. OCO-2 Zonal avg.: 10N-90N



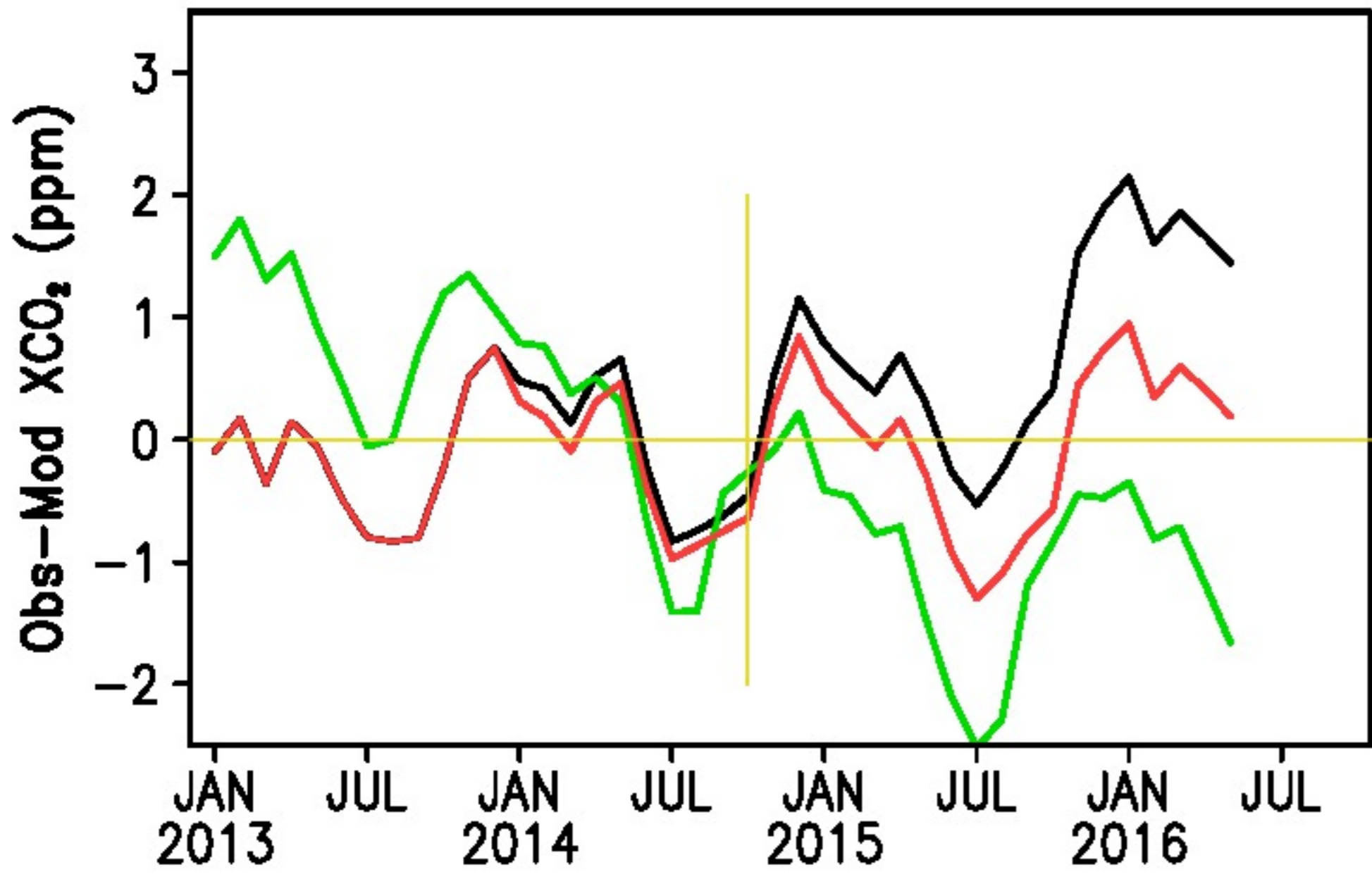
b. OCO-2 Zonal avg.: 10S-10N



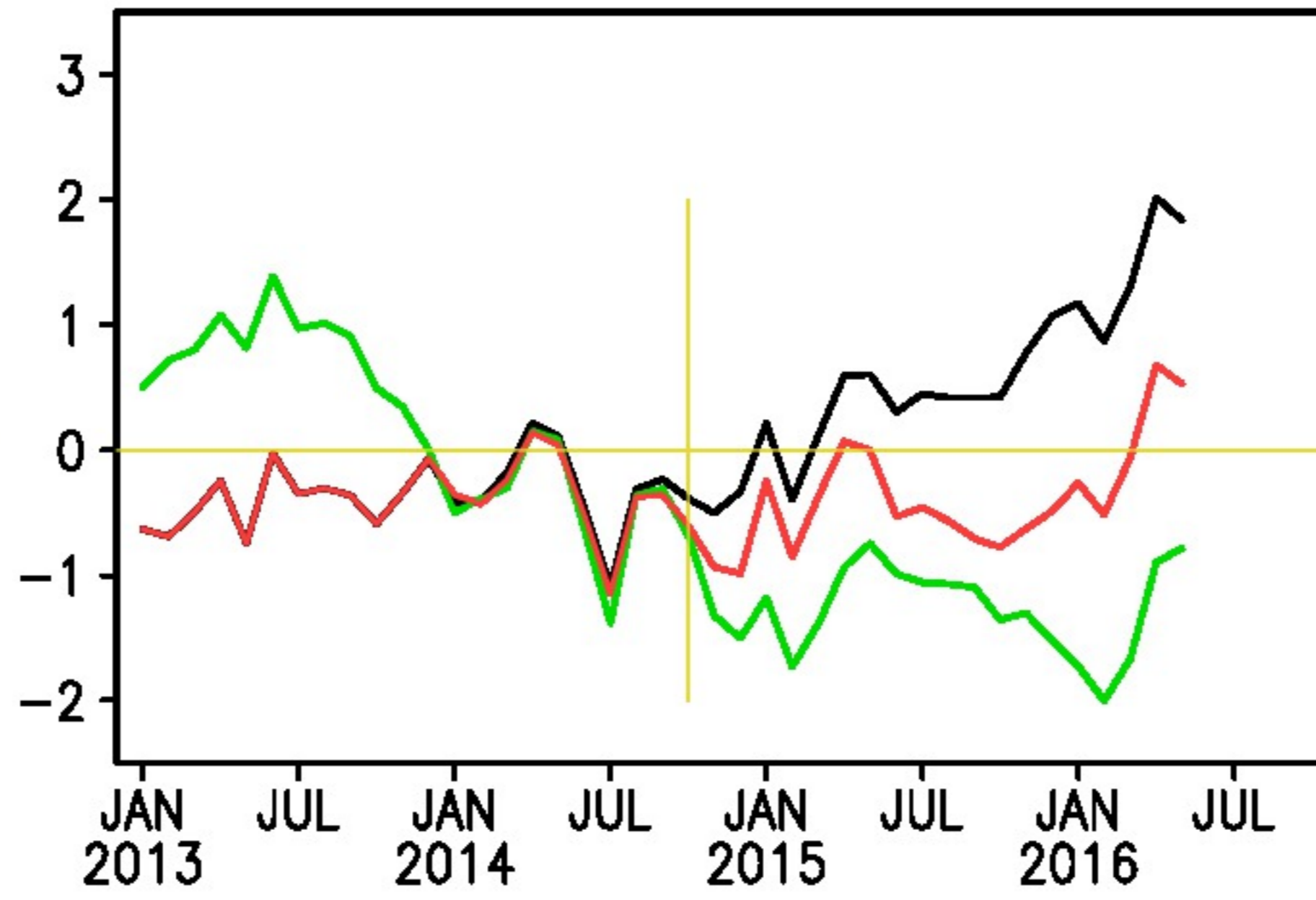
c. OCO-2 Zonal avg.: 90S-10S



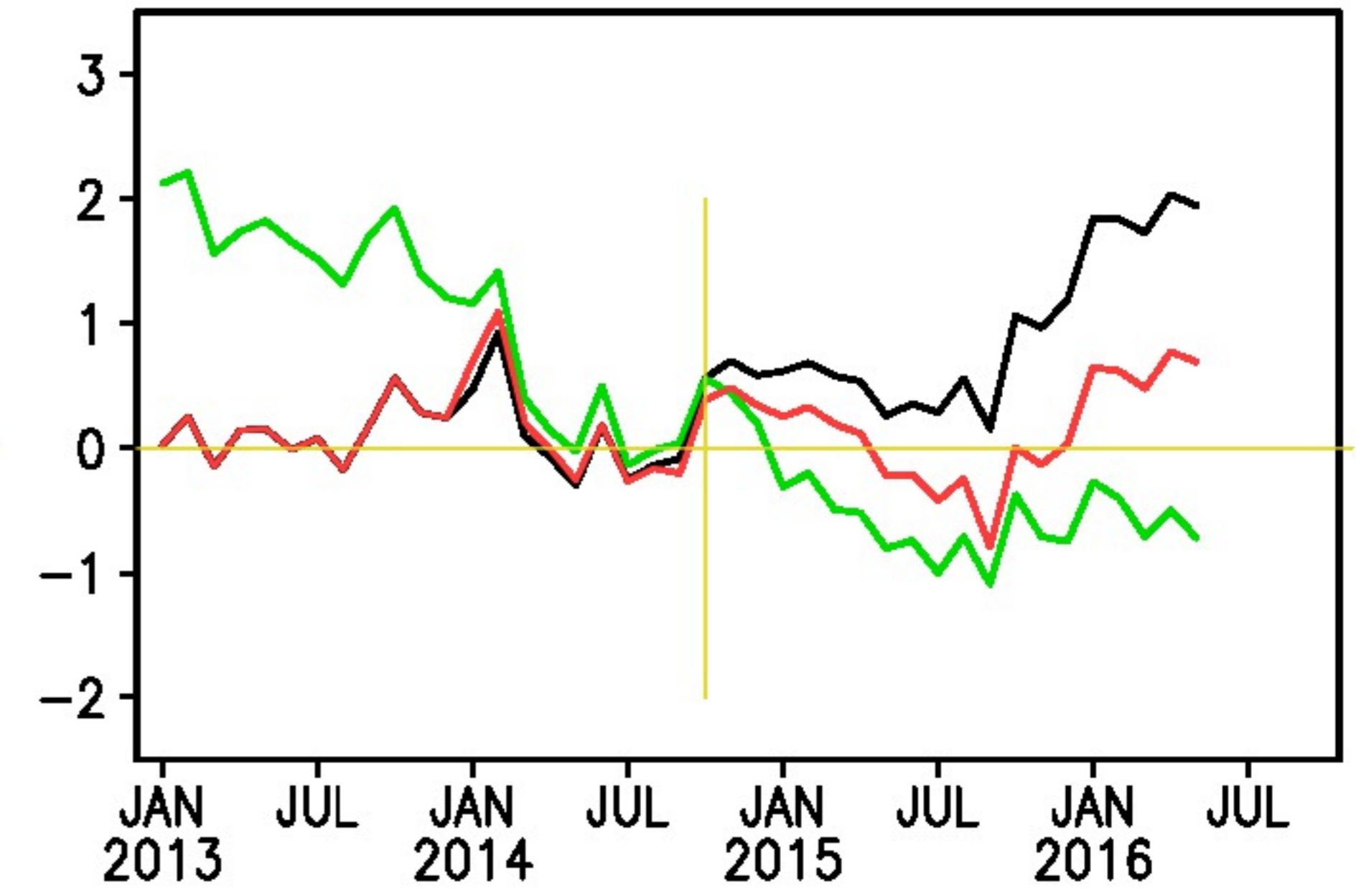
d. GOSAT Zonal avg.: 10N-90N



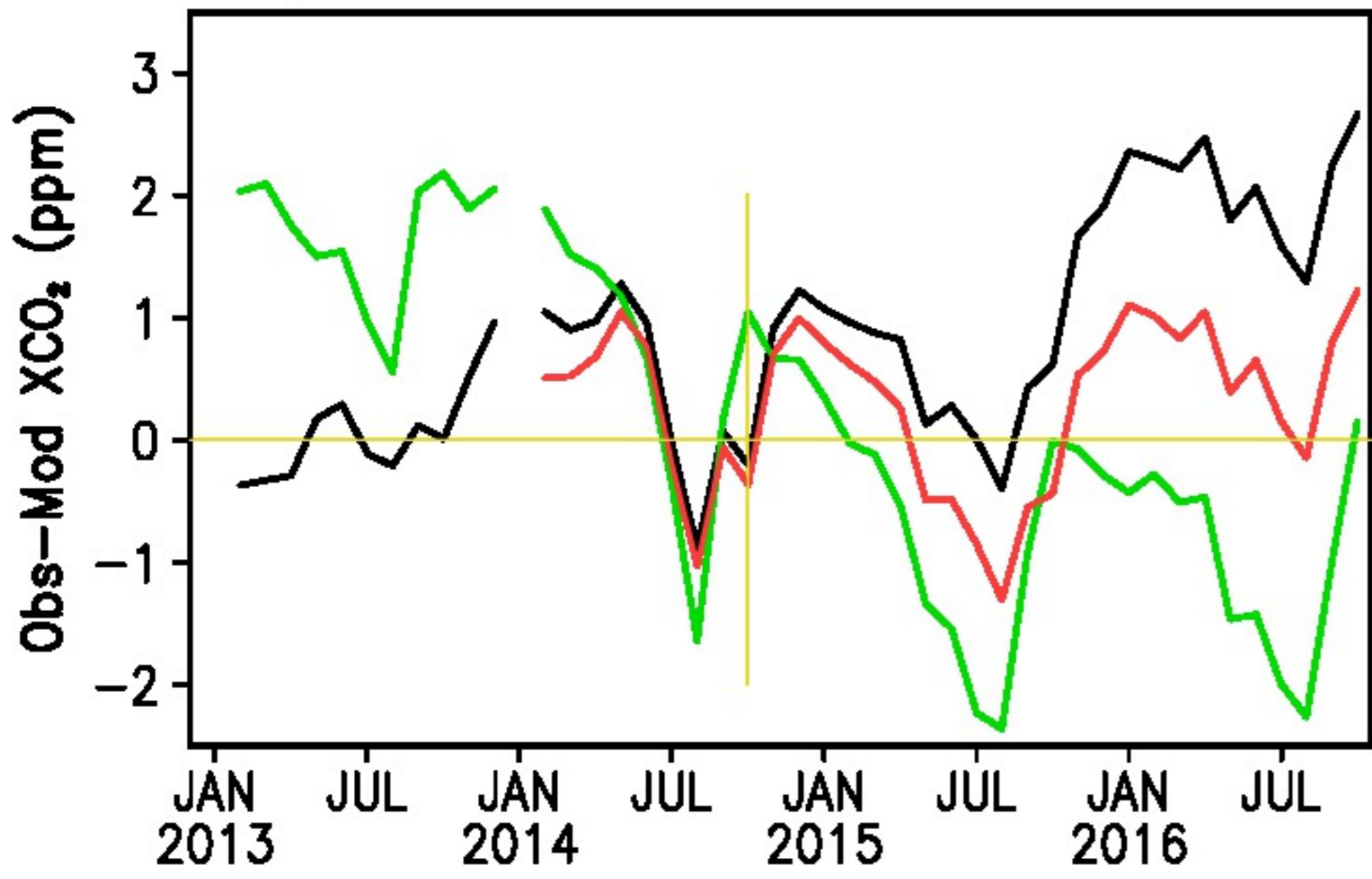
e. GOSAT Zonal avg.: 10S-10N



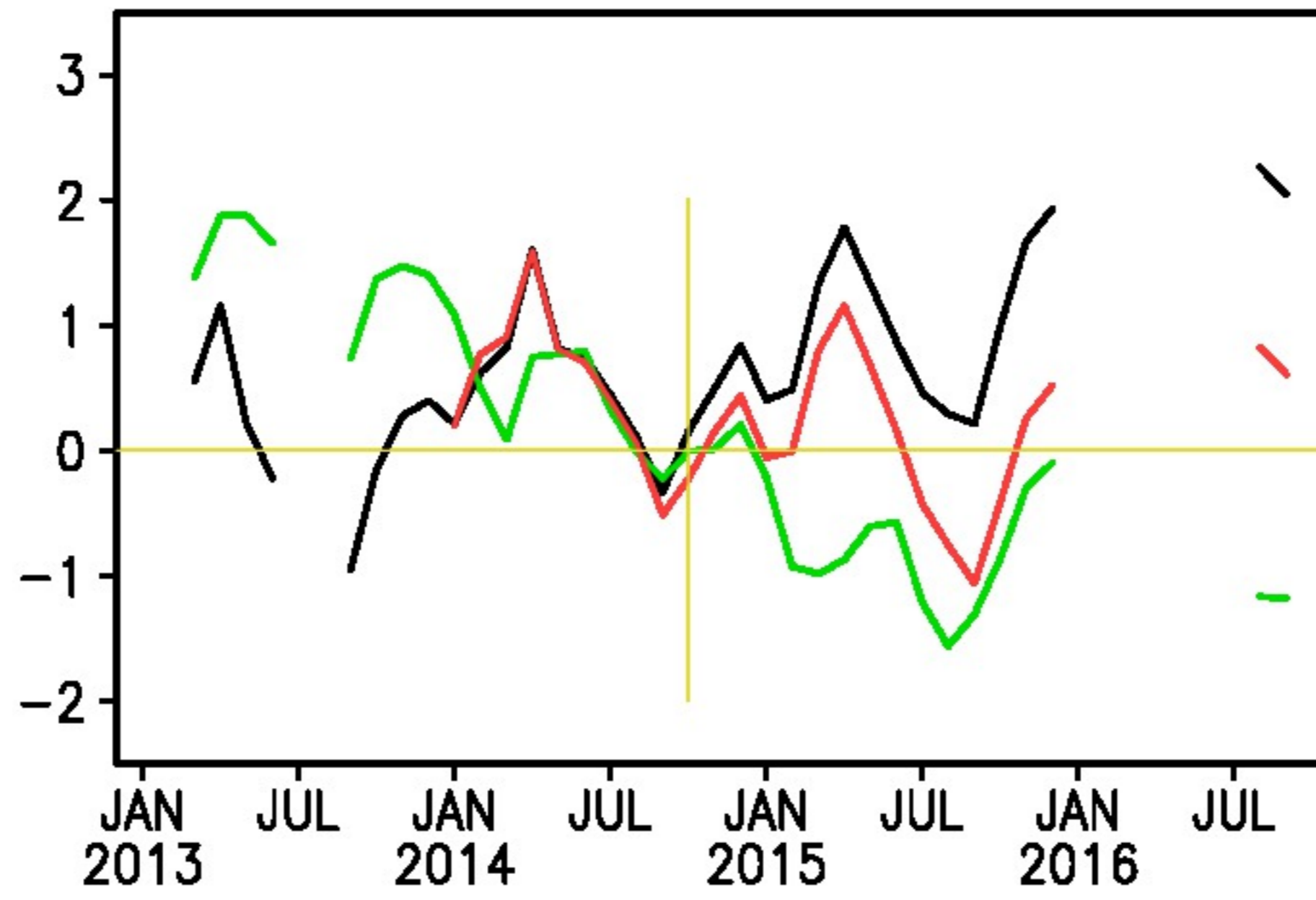
f. GOSAT Zonal avg.: 90S-10S



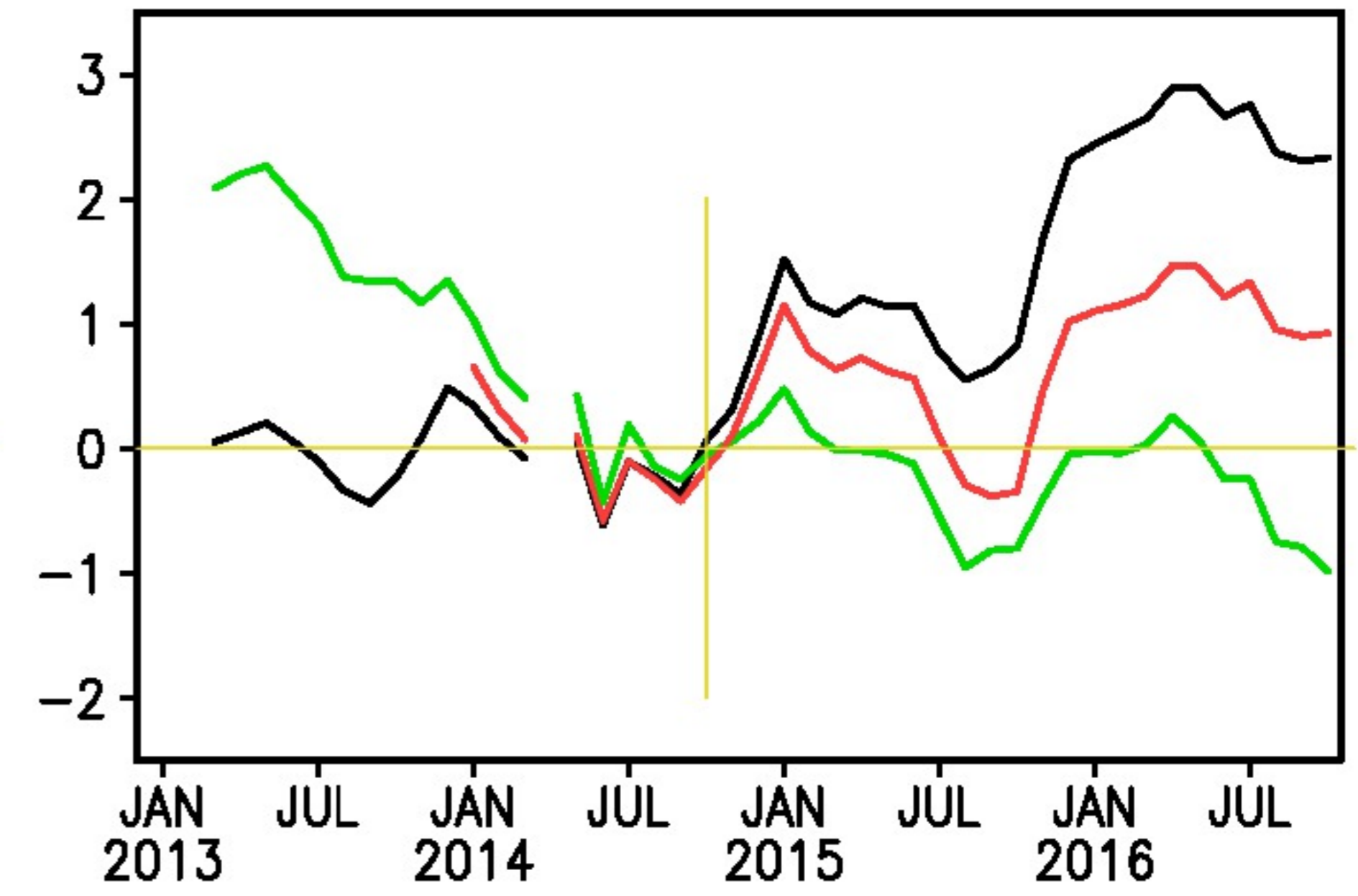
g. TCCON: Park Falls + Lamont



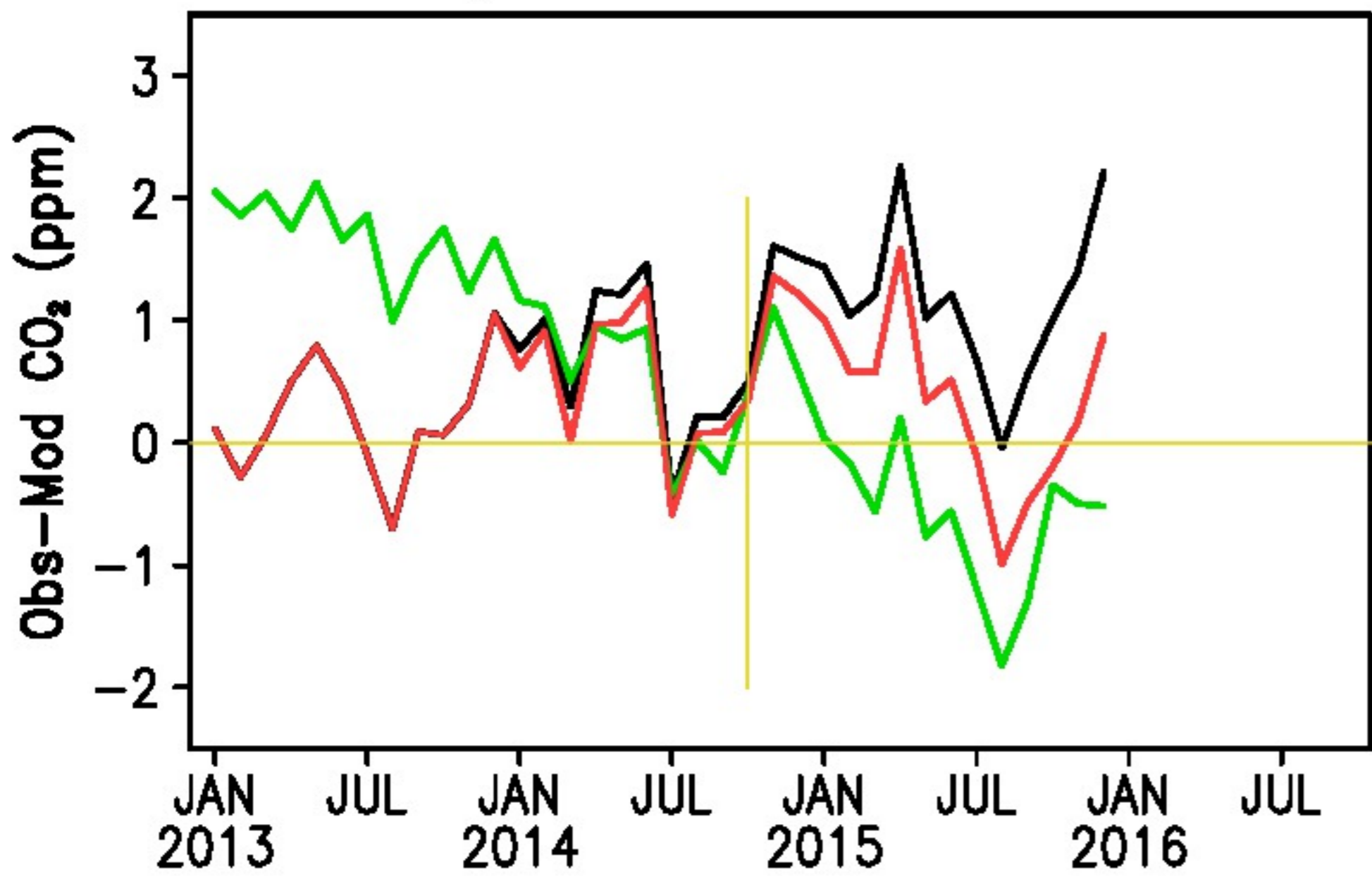
h. TCCON: Ascension + Darwin



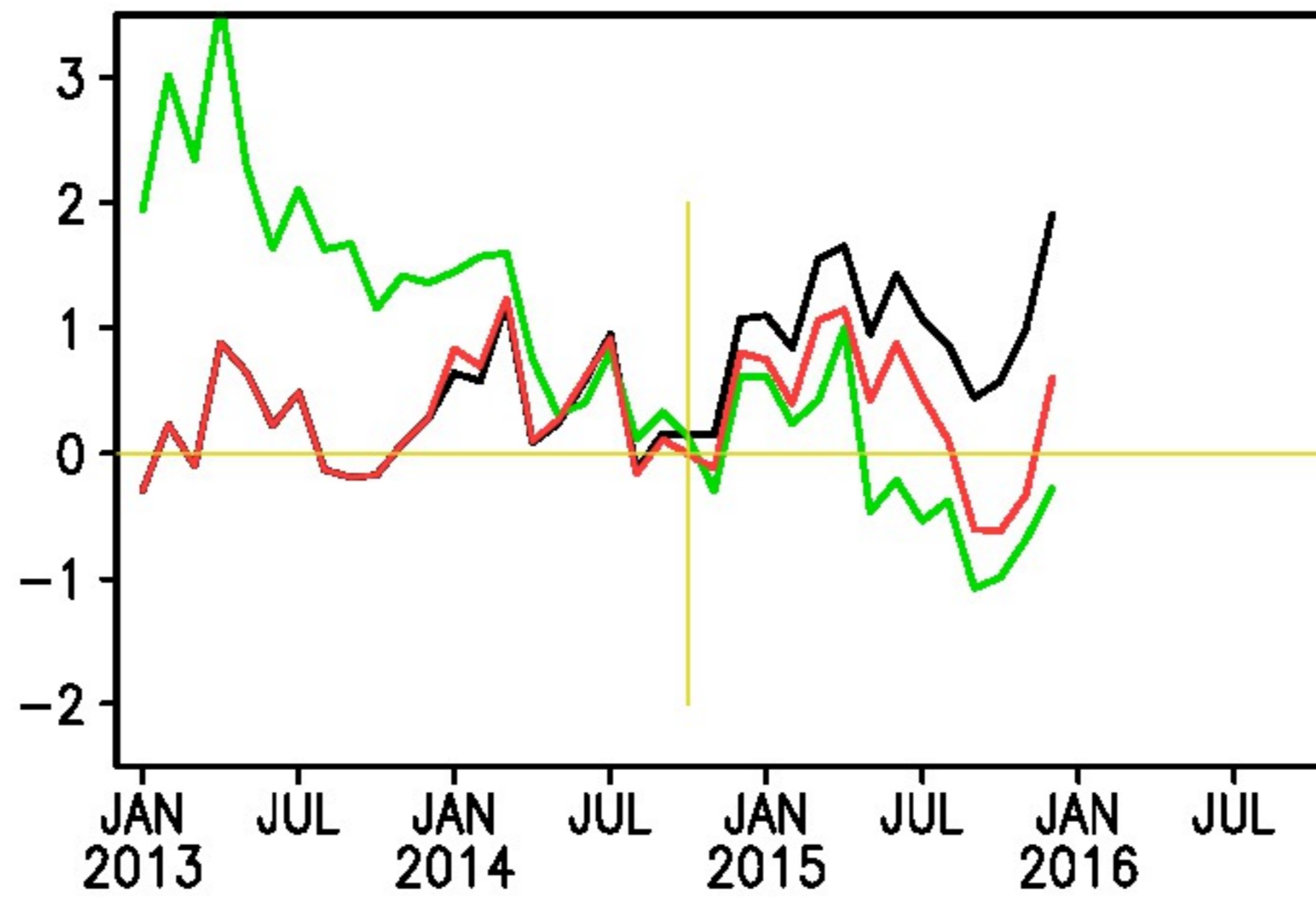
i. TCCON Reunion + Lauder



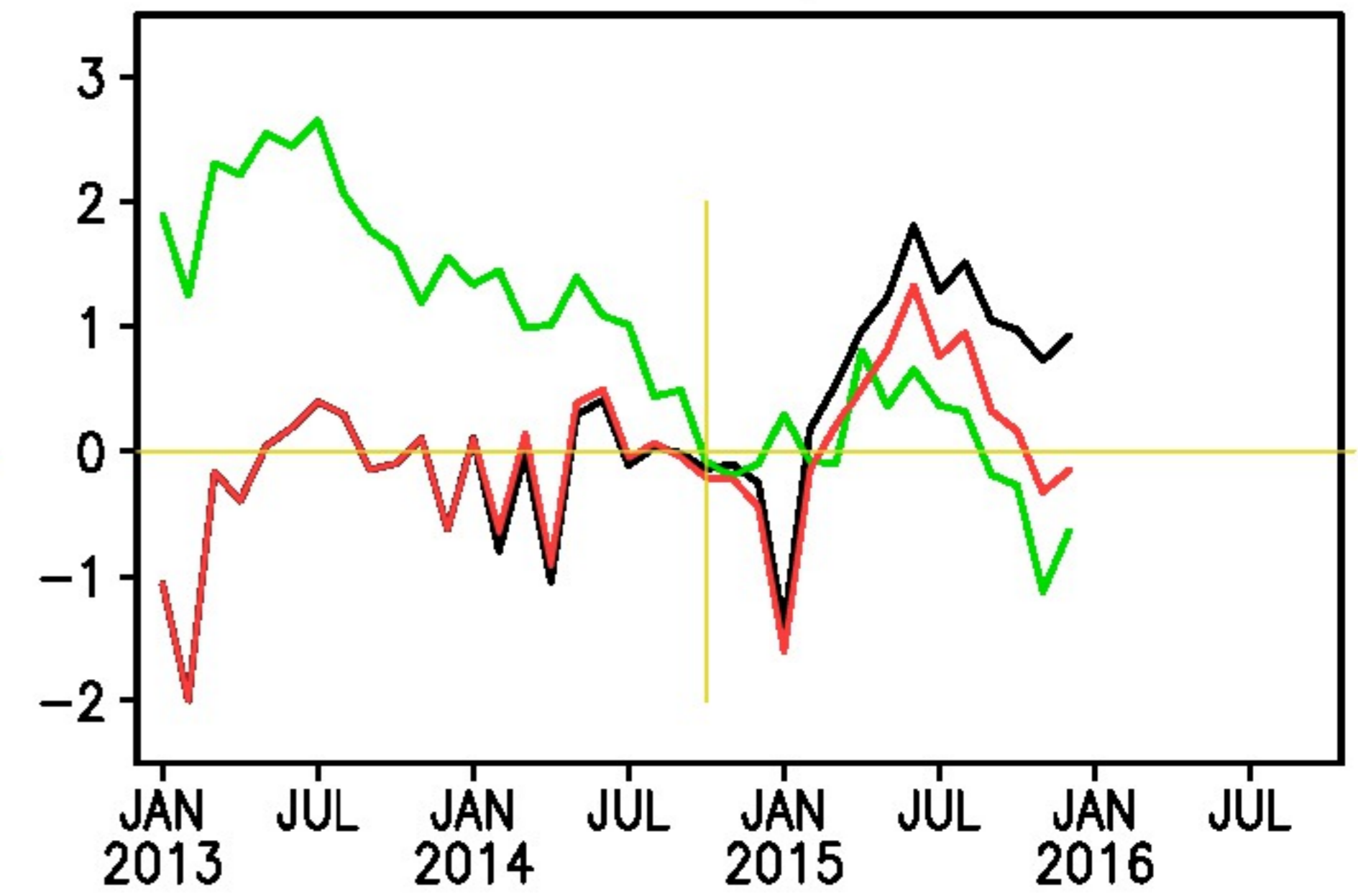
j. NOAA: Mauna Loa

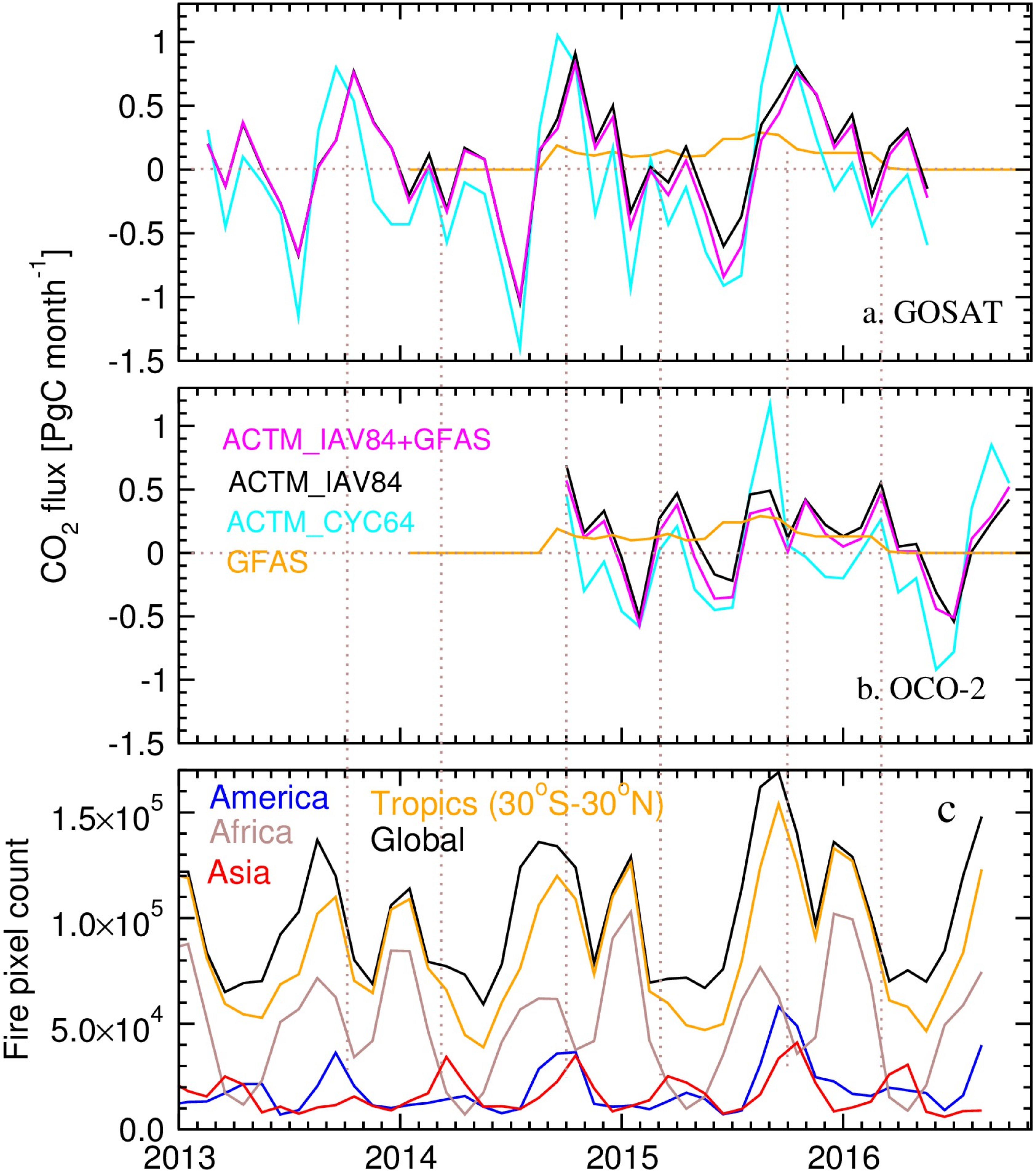


k. NOAA: Samoa

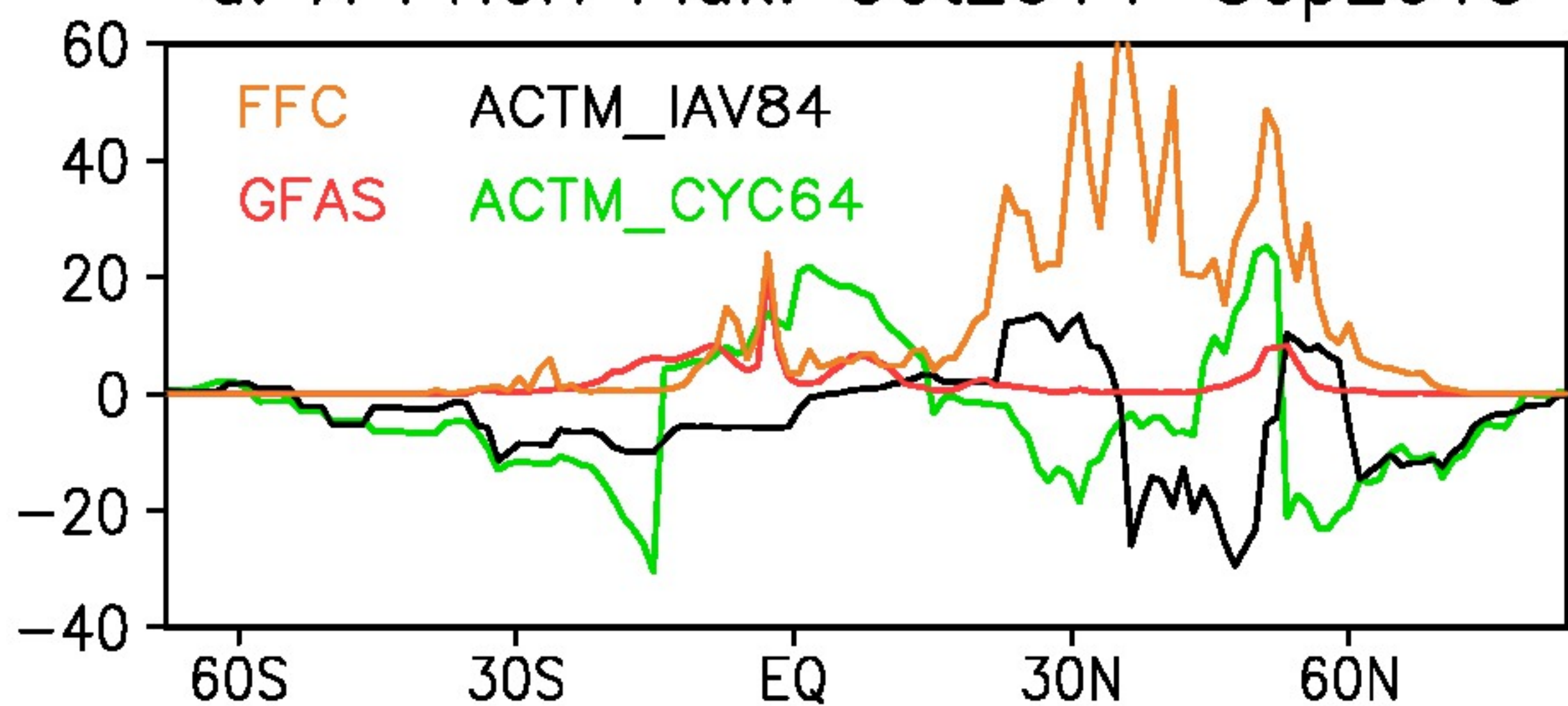


l. NOAA: Cape Grim

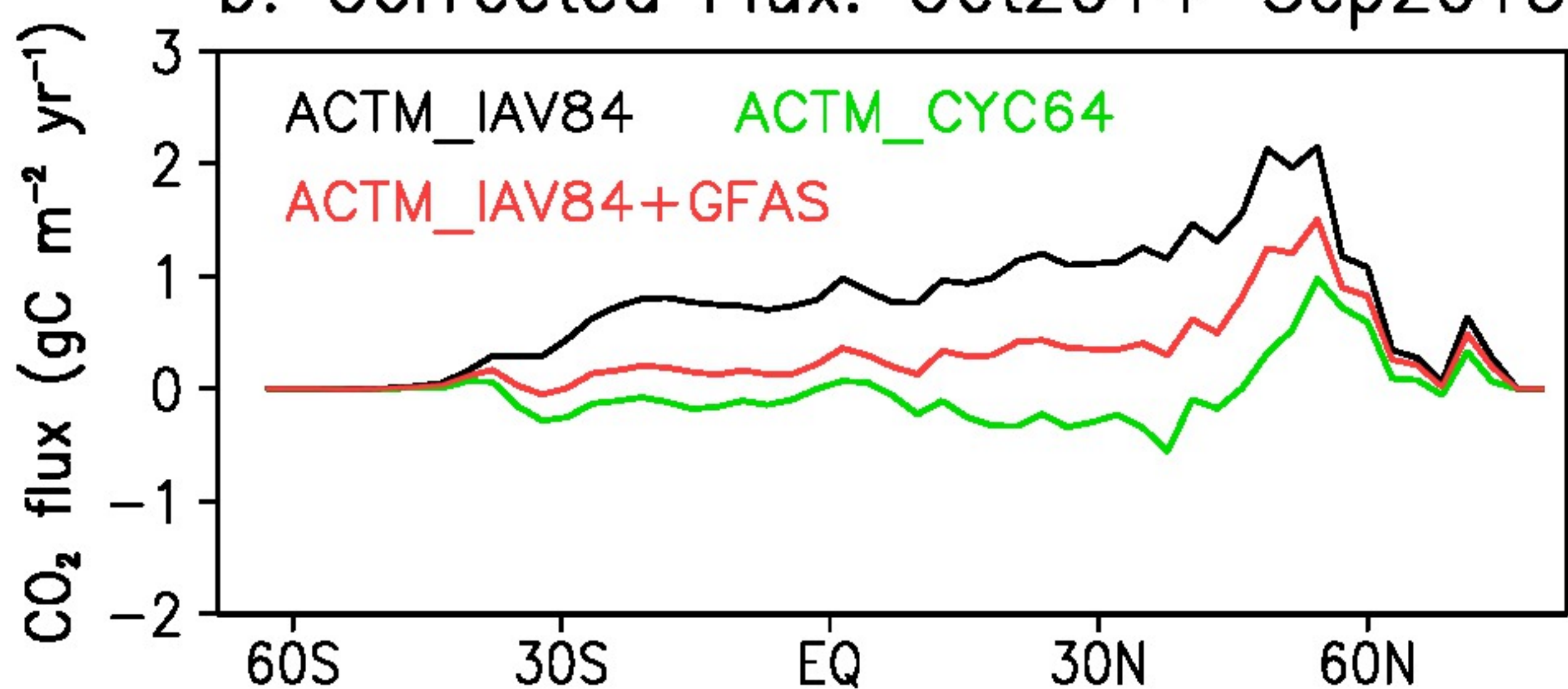




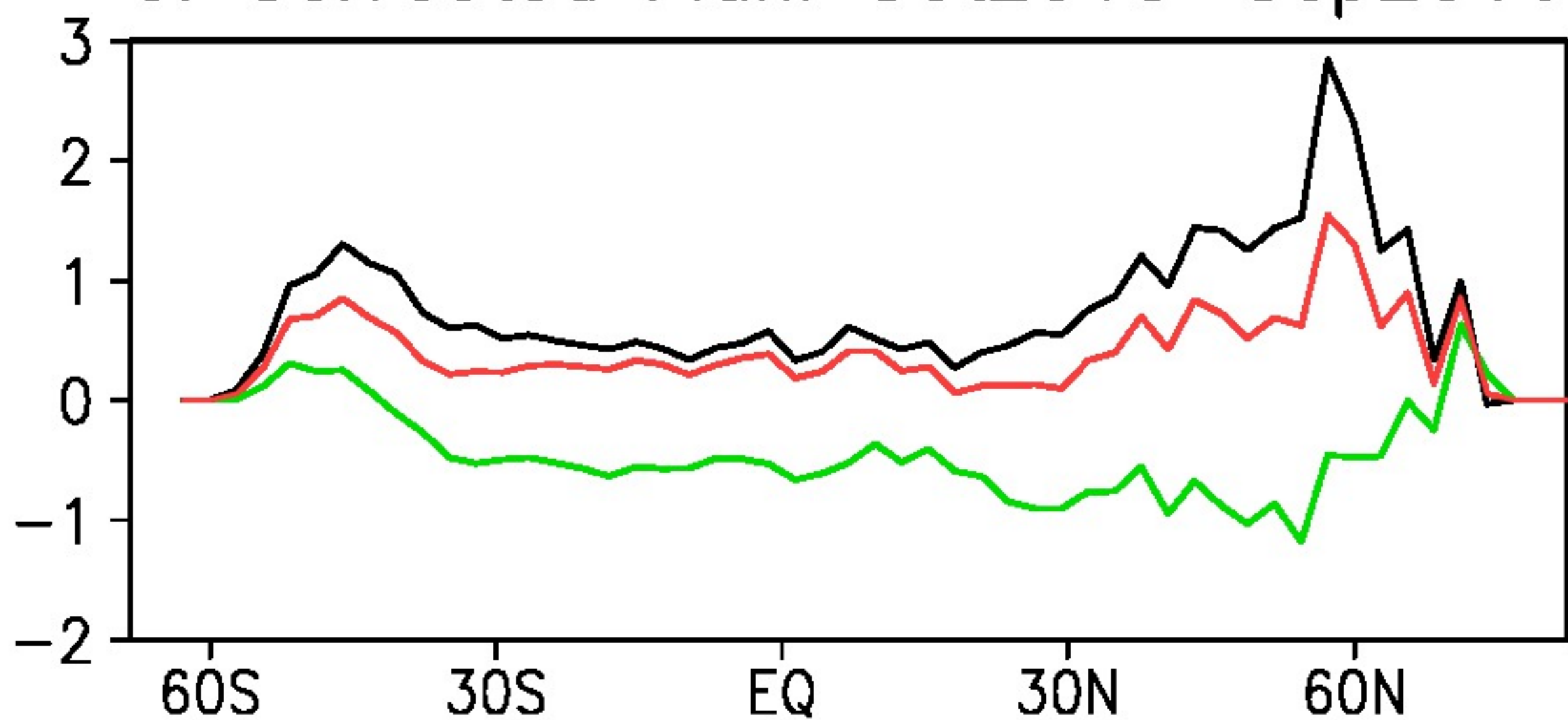
a. A Priori Flux: Oct2014–Sep2015



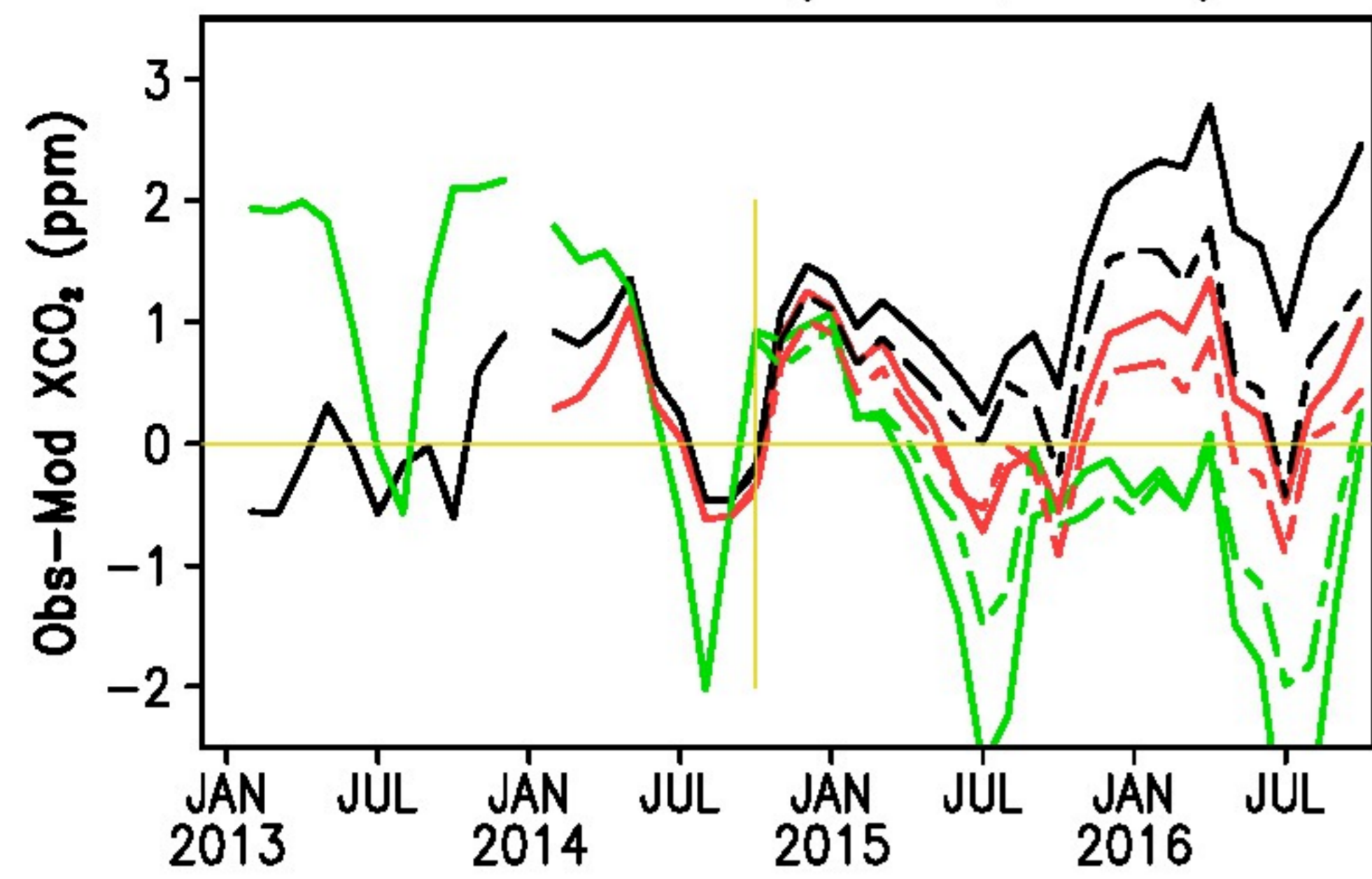
b. Corrected Flux: Oct2014–Sep2015



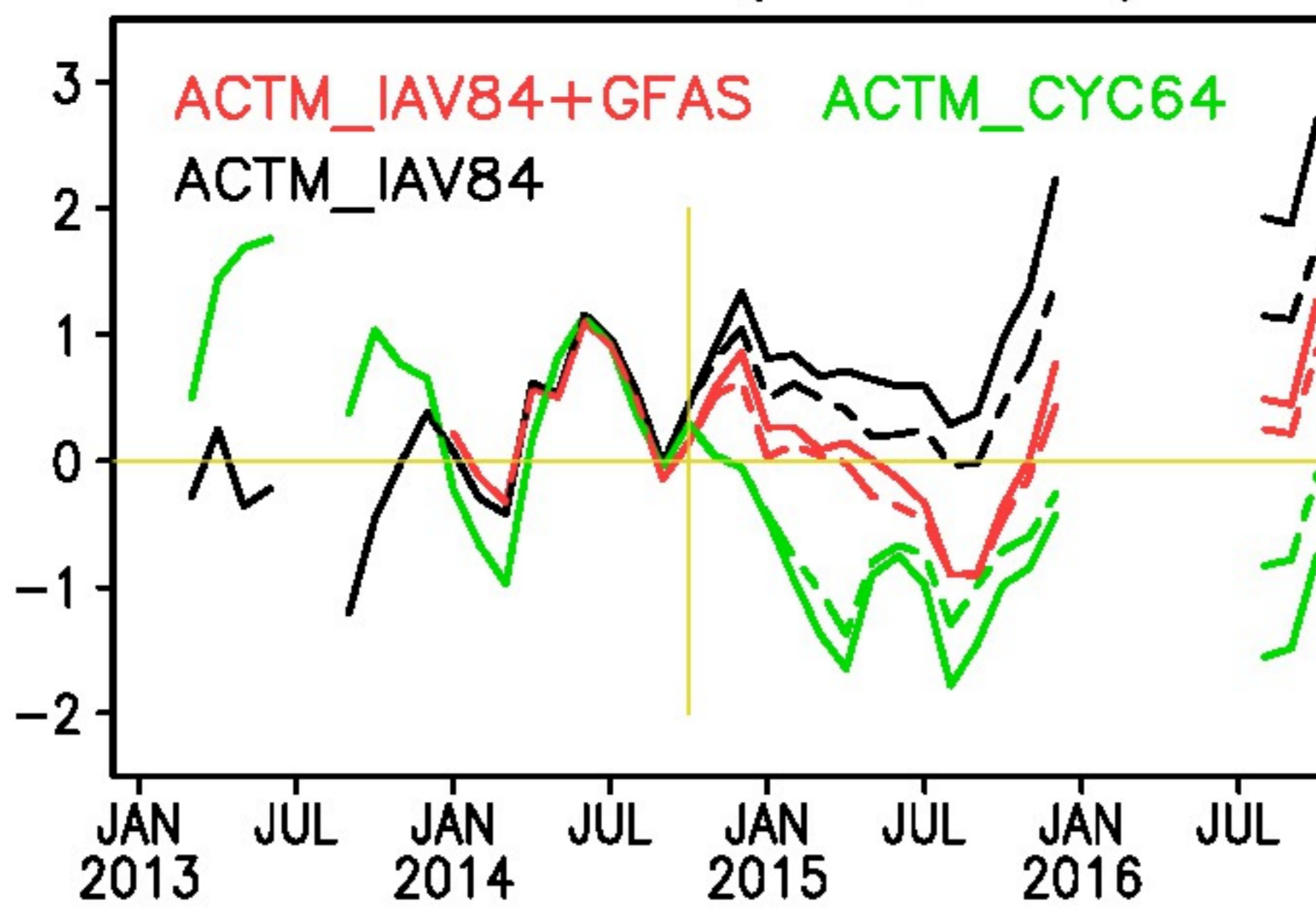
c. Corrected Flux: Oct2015–Sep2016



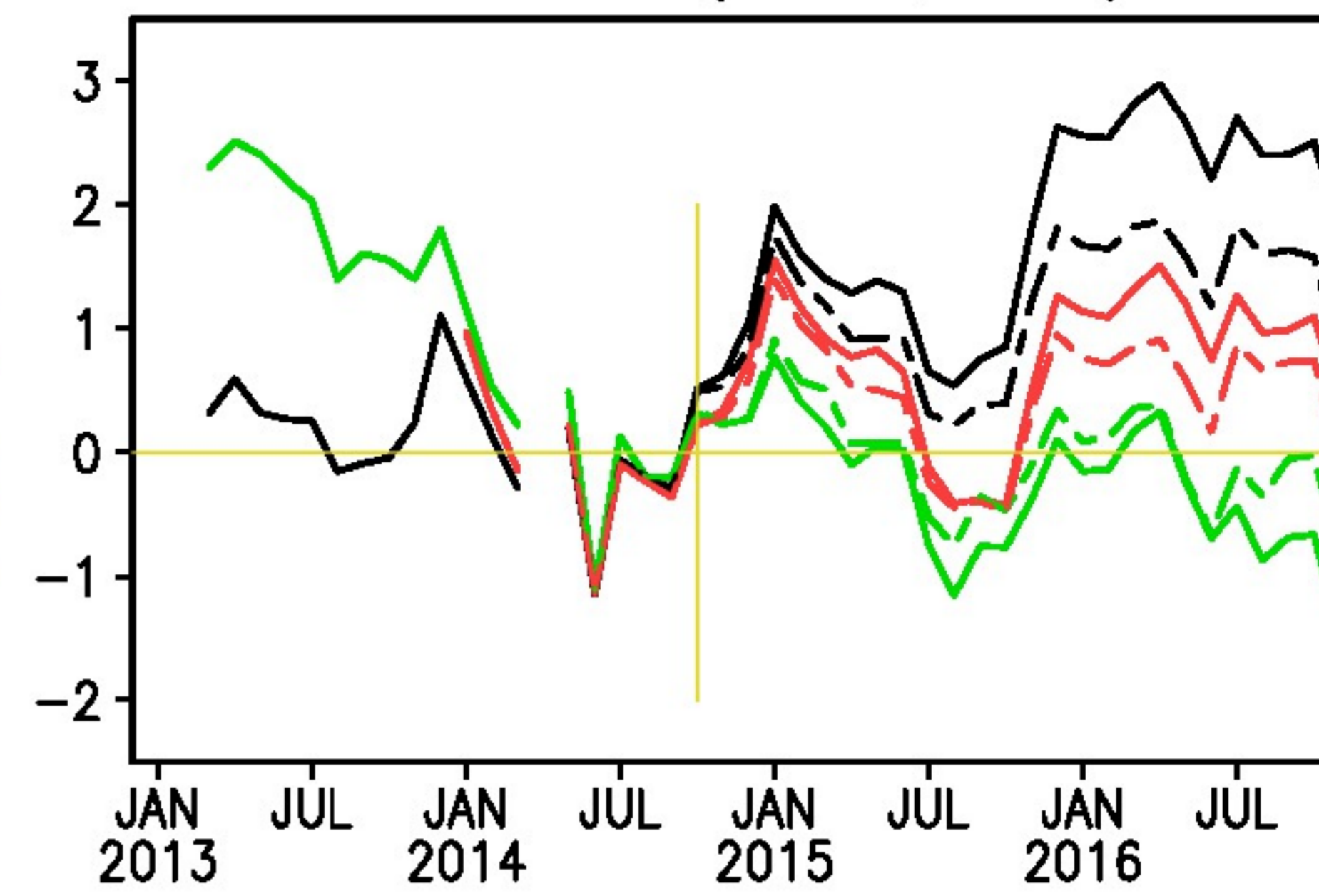
a. Park Falls (45.9N,90.3W)



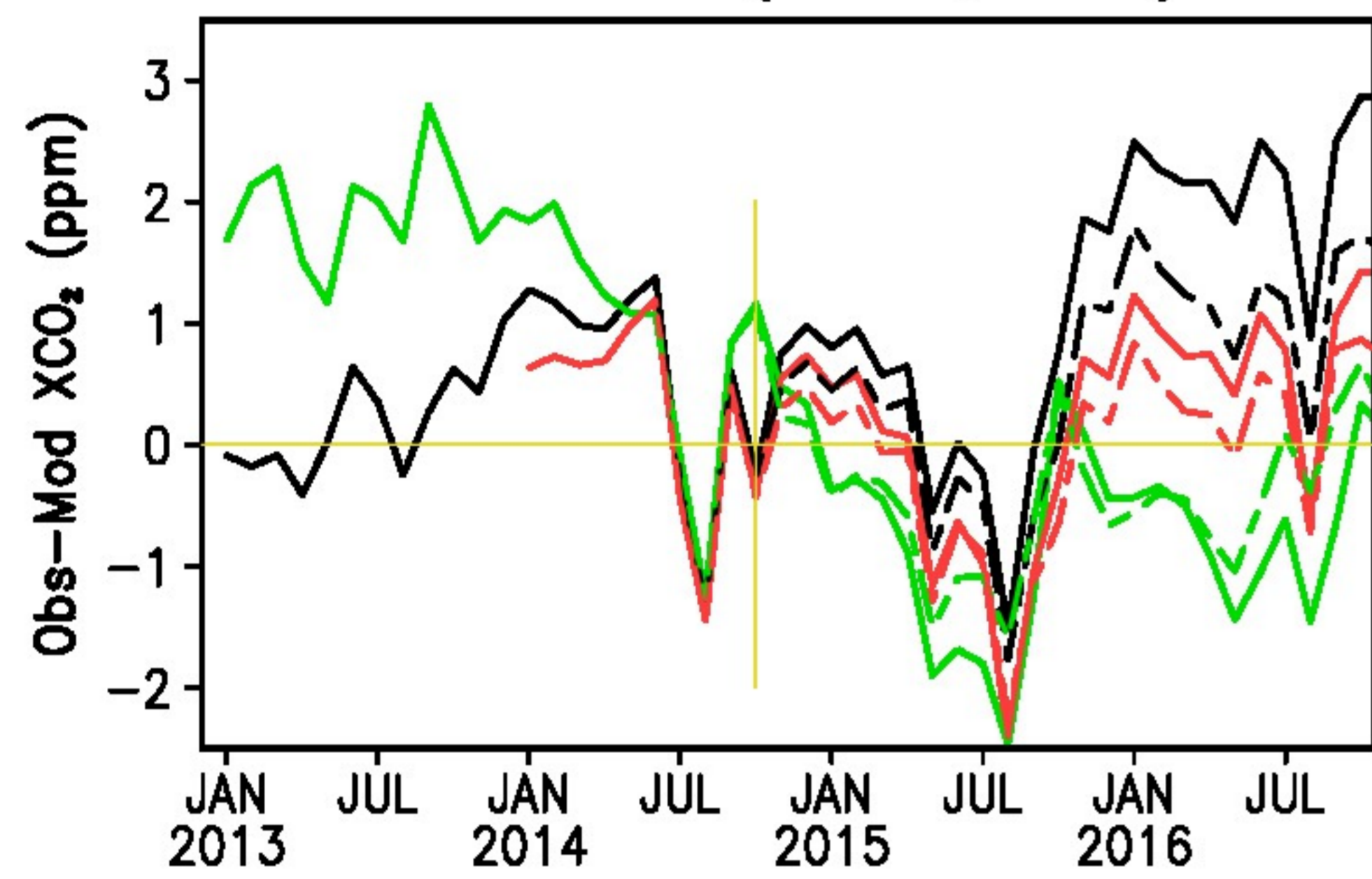
c. Ascension (7.9S,14.3W)



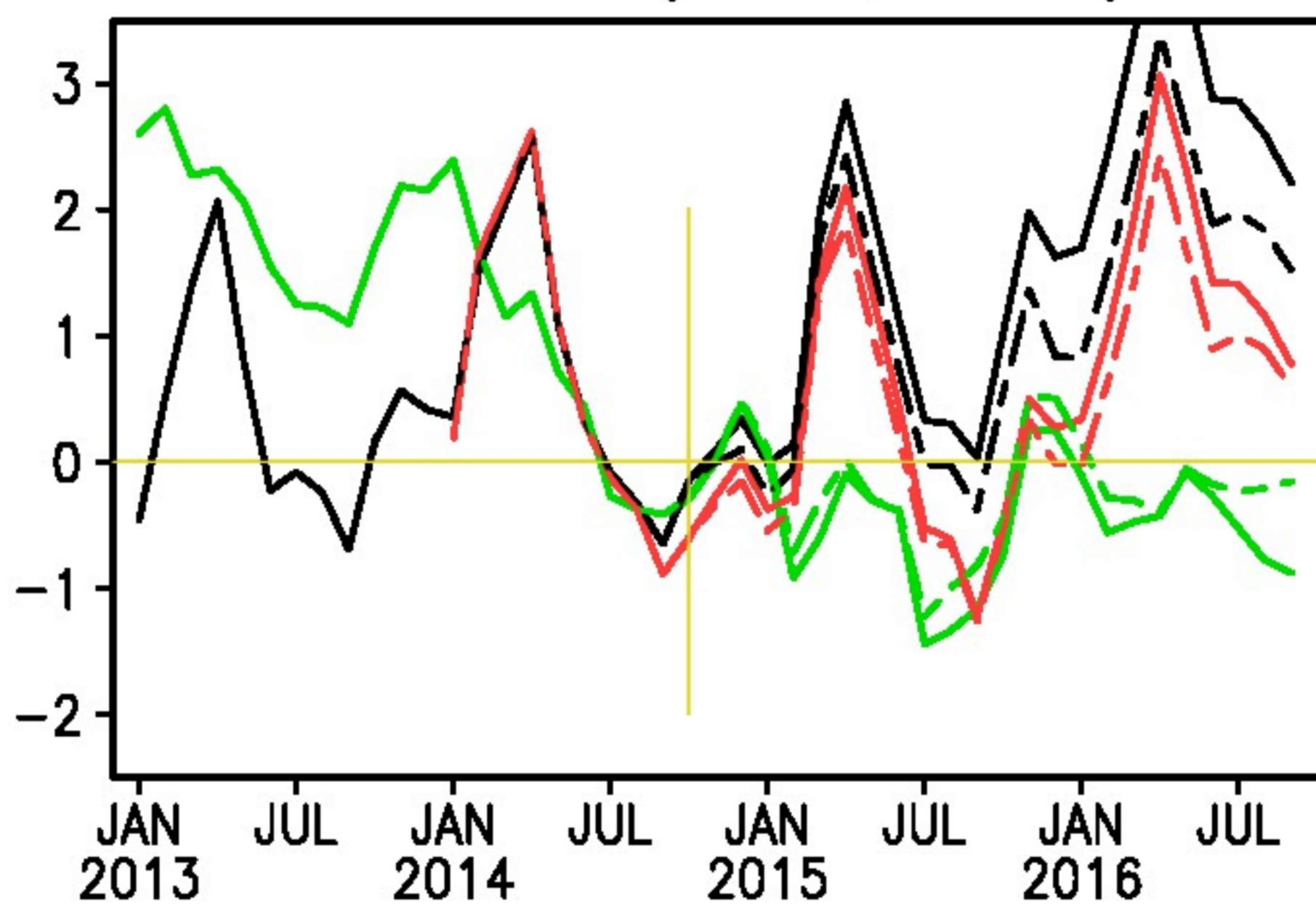
e. Reunion (20.9S,55.5E)



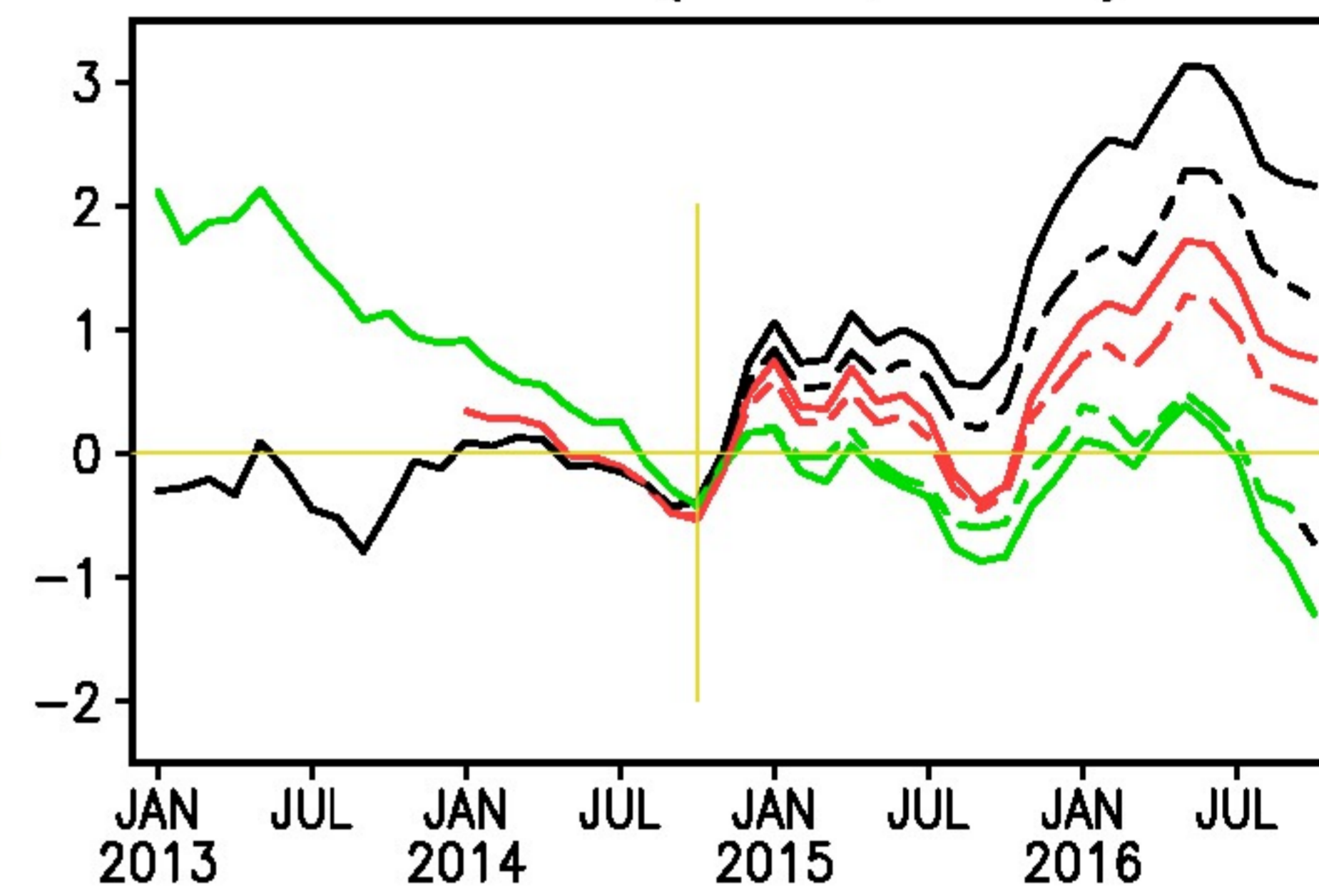
b. Lamont (36.6N,97.5W)



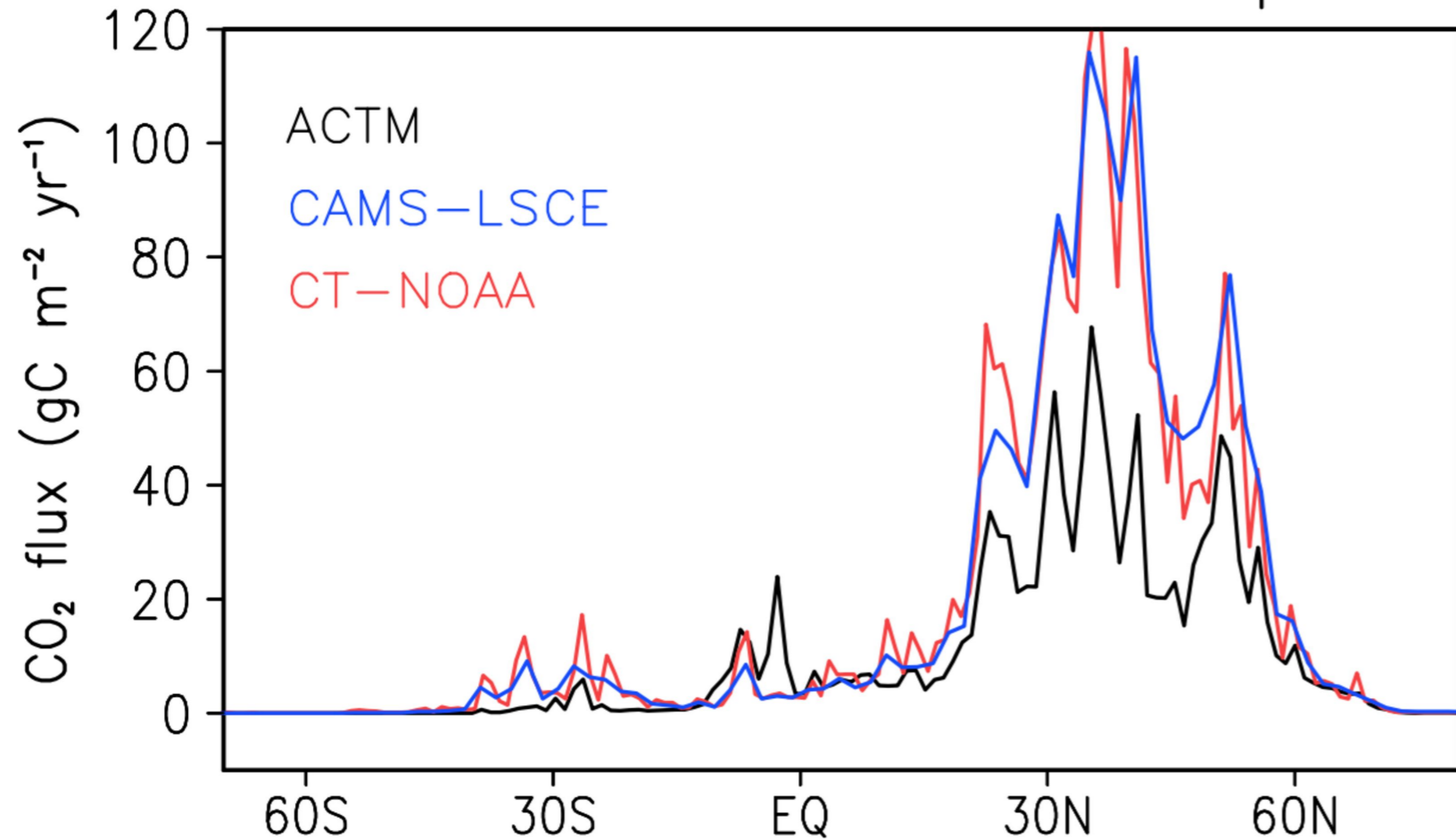
d. Darwin (12.4S,130.9E)



f. Lauder (45.0S,169.7E)



a. FFC emissions: Oct2014–Sep2015



b. Natural (land + ocean) flux

