LuftBlick Report 2016002

OMI validation support

Pandora-OMI NO_2 validation report

	Name	Company	Date
prepared by	Martin Tiefengraber	LuftBlick	03 Apr 2016
	Moritz Müller	LuftBlick	03 Apr 2016
checked by	Alexander Cede	LuftBlick	03 Apr 2016
approved by			

Contents

Document Change Record

Issue	Date	Section	Observations
1.0	03 Apr 2016	All	First draft version

1 Introduction

This report is deliverable TD3370-2.4 of the contract "OMI validation support" [?] within Task 3 of the ESA IDEAS+ project, addressing the validation of TotNO_2 OMI data with the Pandora instrument. Section 2 is a summary of the overall validation results, section 3 presents the materials and methods we applied for the validation data and section 4 shows the detailed validation results.

1.1 Applicable Documents

1.2 Reference Documents

2 Summary and Conclusions

This reports presents the validation results of the $TotNO_2$ product of OMI to the direct-sun $TotNO_2$ of Pandora. The validation period covers a maximum time range of more than 6 years and considers a maximum possible number of 81 validation locations (ValLoc).
For this study we chose a set of parameters where the validation quality is assessed on. These are

Validation parameter	Abbreviation
Correlation coefficient between OMI and Pandora data	CC
Median difference (= median$TotNO_2$(OMI - Pandora)) between OMI and Pandora data	MEDD
Root mean square error to a linear fit	RMS
Slope of linear fit Pandora vs. OMI	SLP
Offest of linear fit Pandora vs. OMI	OFF
Number of data points	Ndp

Table 1: Validation parameters used in this study to assess the validation quality.

n order to find proper filter parameters and thresholds, a sensitivity study on the validation parameters in Table 1 was carried out (details see section 4.1). The sensitivity study only comprises OMI related parameters since Pandora data are per se filtered by the strictest quality criteria. Only the Pandora data averaging time is considered.

OMI data showing cloud fractions < 0.1 and $TotNO_2$ uncertainties < 0.1 DU turned out to be suitable for the validation. Pandora data, averaged $\pm$ 15 min. around the OMI overpass time, also turned out to be the best choice. Further geolocation filtering (footprint pixel size and difference of footprint pixel center to Pandora location) strongly improves the validation quality but also strongly reduces the number of available validation locations from 50 to 10 locations. This emphasizes the necessity of long, continuous time series of ground based validation data.

Beside the data filtering two further correction steps are applied to the data. The validation geolocation of Pandora instruments are shifted to take into account the effective absorber height of NO_2 for direct-sun data, although we know the effect is small for NO_2 (explanation see section 3.2). OMI footprints are corrected based on a high resolution, time averaged climatological footprint map (ClimCor) of $TotNO_2$ (details see section 3.3). By this the varying position of the footprint pixels for different overpasses can be taken into account for sites with significant NO_2 gradients.

The validation results are summarized in Figure 1 and Figure 2, where results without and with applied geolocation filter are shown on the left figure panel, respectively. The filled cycles in the plot are green (red), when the validation parameter has been improved (worsened) by applying ClimCor. The data points without ClimCor are depicted as empty circles. The right figure panel summarizes all ValLocs in a box-whisker style plot, indicating the median value as red bar, the box as the 25 to 75 inter-quantile range, the vertical black bars as 10 respectively 90 percentile range and blue crosses as points lying outside this range. The detailed statistics and scatter plots for each ValLoc are given in section 4.3.

Since OMI is expected to underestimate NO_2 plumes due to averaging over the footprint pixel size, we include the consideration of the diurnal $TotNO_2$ variation (here) 4 hours before and after the OMI overpass time. This is expected to explain most of the outliers.

All ValLocs can basically be grouped in 3 categories. The members of group 1 show extraordinary good agreement between OMI and Pandora, expressed in high CC and SLP close to unity. We relate this good agreement to relatively low diurnal variation in NO_2. The minority of the ValLocs are part of this group. The members of group 2 comprise the majority of the ValLocs, with SLPs of about 0.2. This ValLocs are assumed to be affected by higher diurnal variation in NO_2, which forces OMI to underestimate $TotNO_2$. Group 3 embraces ValLocs with questionable validation results. Also ValLocs are included in that group, where the $TotNO_2$ calibration of the Pandora unit is maybe insufficient. This group is characterized by positive MEDD and/or negative SLP.

In terms of CLimCor, the majority of the ValLocs benefit from its application. Although all validation parameters could be slightly improved, we are confident to be able to further enhance the effect of the ClimCor (we are at the very beginning in utilizing this method). Especially striking is the ClimCor related improvement of ValLocs like Seoul and Niwot. CC of Seoul (highly polluted area) is improved from about 0.1 to more than 0.4 and SLP from Niwot could be lifted from 0.6 to 0.9.

Where geolocation filtering is used (Figure 2), the CC improves to approximately 0.6 for all locations, compared to a CC of 0.4 without geolocation filtering. SLP is also more close to unity, which we interpret as positive effect. On the other hand, the RMS gets worse for strict data filtering. The reason could be that many data points are filtered which enhances the data scattering. Another interesting fact which we want to point out is, that the ClimCor works better without geolocation filtering. This makes sense since both applying the ClimCor and geolocation filtering reduce the influence on varying positions of the overpass footprint pixels.

This study points out the importance of long, uninterrupted, well calibrated time series from ground based instruments for validation of $TotNO_2$. Only then, stringent data filter criteria, including geolocation filtering, can be applied without loosing strong statistics. The ClimCor method could be regarded as a workaround for locations with relatively short time series where no geolocation filtering can be applied. Further investigation of the group 1 locations once they show longer time series, may give more insight in the actual difference between OMI and Pandora $TotNO_2$.

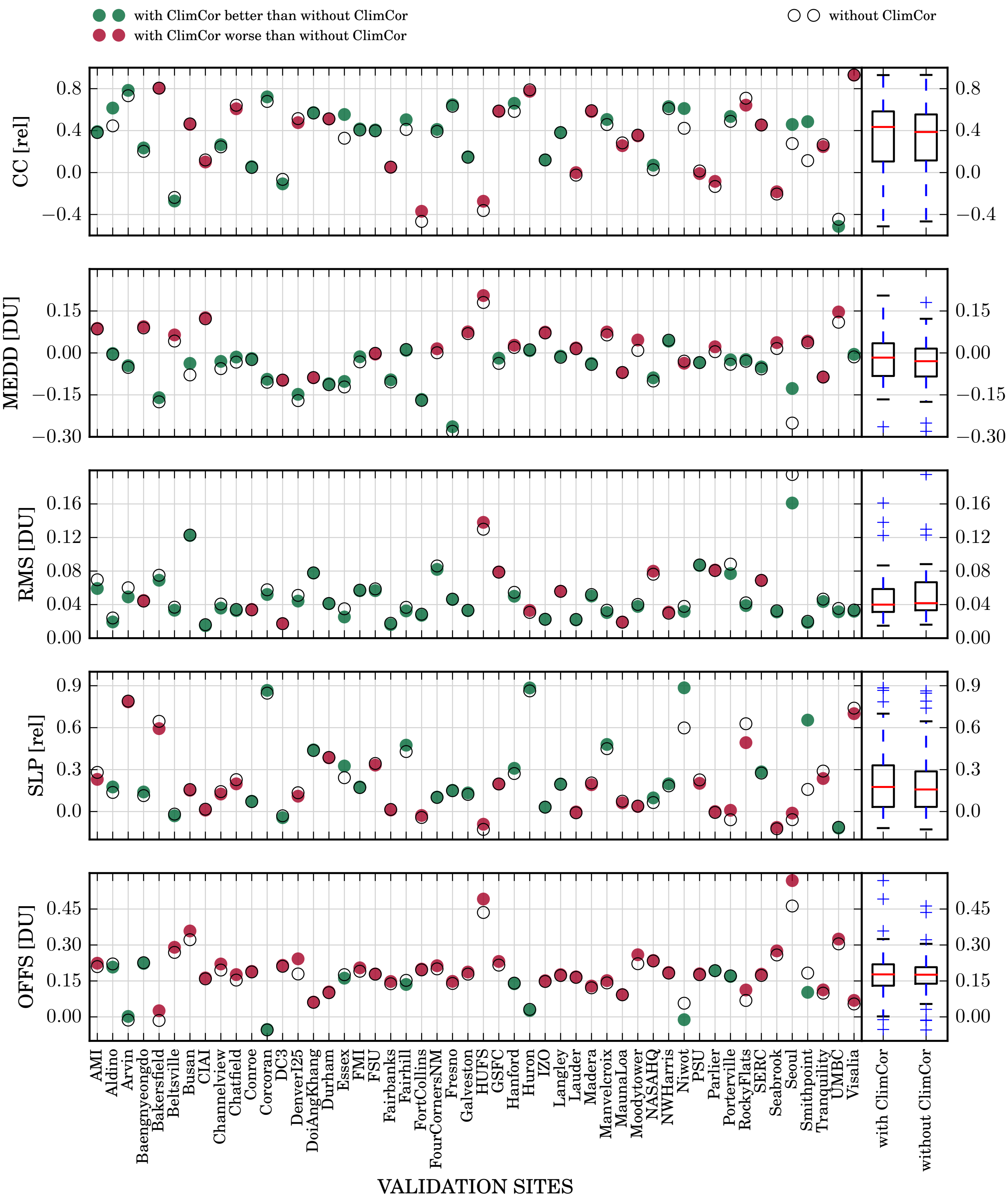


Figure 1: Validation locations showing the CC, MEDD, RMS, SLP and OFFS with and without the climatological footprint correction as outlined in 3.3

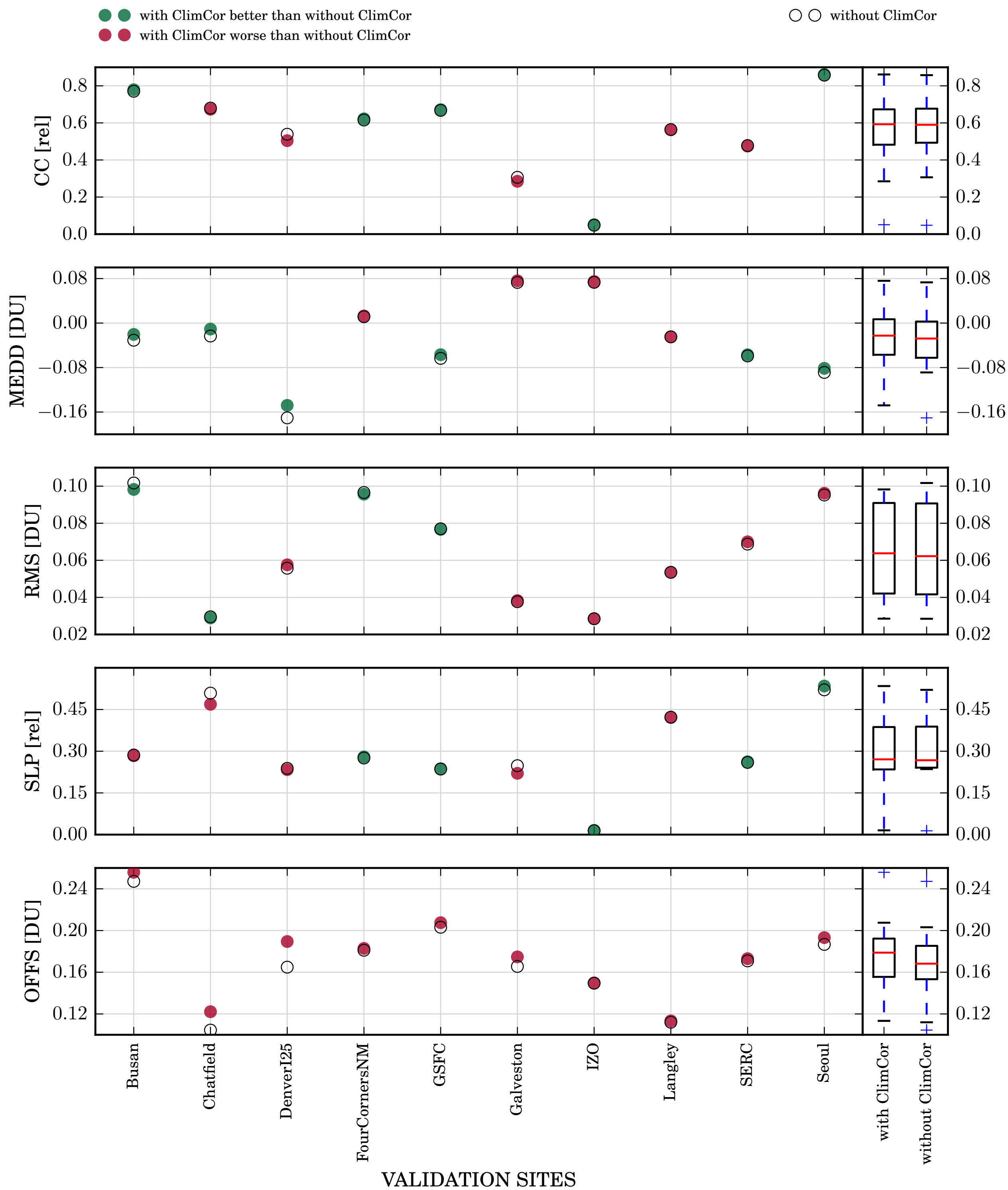


Figure 2: Validation locations with a strict geolocation filtering showing the CC, MEDD, RMS, SLP and OFFS and again with and without the climatological footprint correction as outlined in 3.3

3 Materials and Methods

3.1 Validation Data and Locations

The OMI overpass data are provided by the Aura Validation Data Center (AVDC) hosted by the National Aeronautics and Space Administration (NASA) and has been extracted by Michael M. Yan for each ValLoc in Figure 3. The NO_2 data product to be validated is the OMNO2 collection 3. This dataset is validated against the entire direct-sun Pandora dataset, which has recently been extended and refined from version 001 [**?**] to 002 [**?**]. The covered maximum time periods for each dataset are given in Table 2. The maximum time period is covered by the majority of the locations for OMI, but unfortunately not for all of them (difficulties with the overpass extraction). The covered time period is much more variable for Pandora, since part of the data have been collected during campaigns.

Data set	Version Number	Maximum time period	Data format
OMI	EOS Aura OMI OMNO2 (Collection 3)	2009-01-01 to 2015-09-30	GEOMS H5
Pandora	002	2009-01-01 to 2015-09-30	GEOMS H5

Table 2: Details on OMI and Pandora data sets.

Figure 3 gives an overview of the locations considered in this validation study, which is a subset of all possible locations introduced in **?**]. A ValLoc is accepted if significant temporal overlap is given and at least 10 data points are left after rigorous data filtering (details see section 4.1). If a validation location exhibits collocated and contemporary Pandora units, their data have been averaged for the validation study, which reduces both noise and potential systematic errors.

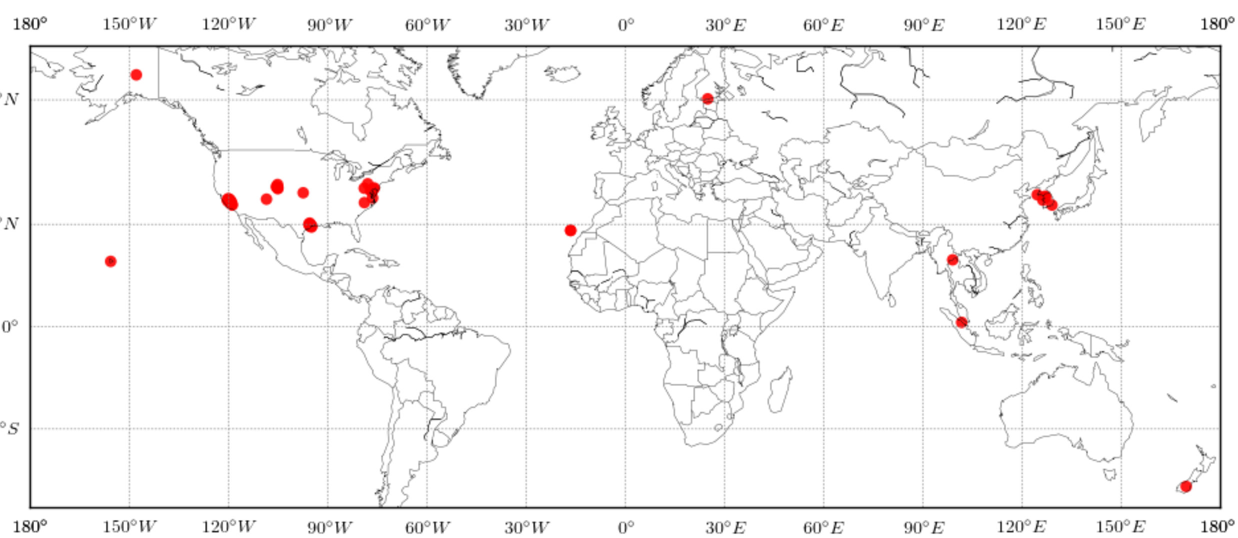


Figure 3: Validation locations.

3.2 Effective Validation Location

The SZA changes with the validation location and the overpass time of the Aura satellite, which carries the OMI. In the morning hours for example, the direct-sun data from Pandora are measured at moderate to high SZA. We assume the effective NO_2 absorption layer height to be at 1.0 km, so the effective validation location is not the ground geolocation itself. Instead, the effective location on the Northern Hemisphere is shifted towards the South-East direction. Although the spatial shift is much higher for totale ozone validation (due to its higher effective absorption layer height of about 20.1 km), we also refer to the effective Pandora locations for $TotNO_2$ in order to enhance the representativeness of this study.

3.3 Climatological Footprint Correction

If a ValLoc is located within an area of significant NO_2 gradients, the measured $TotNO_2$ by OMI is different for each overpass, since the actual position of the footprint pixel varies for each overpass. For illustration lets assume a NO_2 hot spot northeast of the ValLoc. If the footprint pixel covers the ValLoc only just with its bottom left (top right) corner the data would be biased high (low) compared to an average. We take this into account by compiling a significantly large number of overpass data to a high resolution climatological footprint map (ClCoRes = 0.05°). Significant means to have good statistics for each subgrid pixel in the high resolution map. The ClimCor is finally carried out by subtracting the mean value of a footprint pixel in the high resolution map from the value in the high resolution map where the Pandora is located.

We decided to calculate high resolution climatological footprint maps for each year from 2009 to 2015 to be able to take into account potential drifts between the years. The value used for the footprint correction is utilized on a yearly basis which means that a weighted average between the considered high resolution maps is calculated. For example, if the footprint has been measured at March the 1st 2014, we take 25 % of the 2014 map and 75 % of the 2013 map, for July the 1st we take 100 % of the 2014 map, for October the 1st 2014 we take 25 % of the 2014 map and 75 % of 2015 map, and so on.

We are at the very beginning in utilizing this ClimCor method and therefore have not yet quantified the influence of changing the resolution and the time slices of the high resolution map. We are sure that the impact of this method could be further improved. For example, increasing the resolution (finer) and/or considering seasonal high resolution maps rather than yearly maps may be advantageous.

3.4 Validation Strategy

The $TotNO_2$ validation has been carried out as follows:

- OMI validation data preparation

  1. For each ground location, the OMI overpass file provided by AVDC was reduced to those entries, where the Pandora geolocation is included in the satellite footprint.
     → SV0 data.
  2. Data quality filtering according to Table 4 and ClimCor is applied to the SV0.
     → SV1 data.

- Pandora validation data preparation

  3. For each footprint in SV1 spatially and temporally overlapping Pandora units are identified and combined.
     → PV0 data.
  4. Data quality filtering according to Table 4 and effective validation location correction is applied to PV0.
     → PV1 data.

- Validation procedure

  5. PV1 data points are averaged around SV1 footprint measurement times. The averaging time is PanAVG from Table 3.
     → PV2 data.
  6. SV1 is validated against PV2.

4 Results

4.1 Data Filtering

To include only reliable data in the validation study proper data filtering has to be applied. To be able to estimate the influence of a filter parameter threshold selection we carried out a simple sensitivity study. Pandora data filter parameters are not further tested, since we only accept data passing the strictest quality flag DQ0. This flagging procedure is explained in detail in **?**]. The filter parameters and thresholds are summarized in Table 3. For Pandora, we only tested for the effect of averaging the Pandora data around the overpass time (PanAVG). PanAVG is given as PanAVG/2 ± before the OMI overpass time.

Parameter	**Abbreviation**	**Threshold**
Pandora (DQ0)		
TotNO_2 uncertainty	PanUQ	0.05 DU
normalized rms of spectral fitting residual	PanWRMS	2.0×10^{-2}
wavelength shift	PanWVL	5.0×10^{-3} nm
direct sun air mass factor	PanAMF	7
enhanced data scatter	PanSCAT	4.0×10^{-4}

Table 3: Applied filters for Pandora DQ0.

For OMI data we selected two groups of filter parameters. From the first group, the geolocation filters, we tested for the longitudinal (latitudinal) distance of the footprint center to the Pandora location (dLON (dLAT)) and the footprint size (SatFPT). From the second group, the quality filters, we tested for cloud fraction (SatCF) and TotNO_2 uncertainty (SatUncNO2) from OMI.

The sensitivity of the selection of the filter parameter thresholds is validated against 4 of the validation parameters listed in Table 1: namely CC, MEDD (= medianTotNO_2(OMI - Pandora)), RMS and Ndp. Since we are interested in the relative change of the test parameters when altering the filter parameter thresholds, we express the test parameters as relative changes with respect to an initial guess (dCC, dMEDD, dRMS, dNdp). The initial guesses are given in the third column in Table 4.

The sensitivity test is carried out by varying only one of the filter parameter thresholds (values $<$ the threshold are accepted) at the same time and leave the others at the initial guesses. We applied the sensitivity tests on four locations with long time series, but with different characteristics. Langley (Fairfax, Virginia, USA) as a location considered to be rural and with the longest Pandora time series available, Los Alamos (Four Corners, USA) as a second rural site but with high NO_2 variability (nearby power plant), GSFC (Greenbelt, Maryland, USA) as an urban location and as the Pandora "headquarter" with the densest time series of Pandoras and finally Seoul (South Korea) due to its very high air pollution.

The results of the sensitivity study are shown in Figure 4 showing the different locations color coded. The columns in the plot refer to the test parameters and the rows to the filter parameters. Each subplot is visualized in a way to show 4 quarters (divided by the vertical and horizontal bar in gray) to give an immediate information about the improvement or deterioration of a test parameter by varying a selected filter parameter threshold. Improvement means, that positive values for e.g. dCC mean higher CC and positive values for dMEDD mean lower MEDD, since it is preferable. Hence the upper (lower) left quarter means improvement (deterioration) by reducing the filter parameter threshold and the upper (lower) right quarter means improvement (deterioration) by enhancing the threshold.

The geolocation filter parameters (dLAT, dLON, SatFPT) are especially dependent on the surroundings of the location and can strongly reduce Ndp. This filters can only be applied to ValLocs with long time series.

The dCC is higher for smaller pixel sizes and the latitude has a larger impact on the CC than the longitude because of the satellite footprint geometry. For Seoul, the geolocation filtering has a smaller impact than for the other three locations. This can be explained by the large spatial extension of the city and the throughout high values of NO_2.

SatCF has a similar impact on dCC and the dRMS for all locations, just Seoul is not affected too much by cloud filtering. SatCF 0.1 appears to to be a reasonable threshold for SatCF. A stricter value would reduce Ndp to much.

To be more stringent with SatUncNO2 may would reduce RMS but again at the cost of Ndp. The overall high SatUncNO2 for OMI at Seoul is illustrated by the strong increase in Ndp for less stringent filter thresholds.

We decided to increase the PanAVG from 20min to 30min because on average all test parameters increase and we assume that we do not blur the NO_2 information to much.

The final selection of the filter parameter thresholds applied for this validation study are summarized in Table 4 in the fourth column. The asterisks highlight filter parameters which can only be applied to ValLocs with long time series.

Sensitivity parameter	Abbreviation	Initial threshold	Best threshold
OMI geolocation filter			
lon. footprint center distance to Pandora *	dLON	0.3 °	0.14 °
lat. footprint center distance to Pandora *	dLAT	0.1 °	0.08 °
footprint area *	SatFPT	0.3 °x°	0.13 °x°
OMI quality filter			
cloud fraction	SatCF	0.3	0.1
TotNO_2 uncertainty	SatUncNO2	0.1 DU	0.1 DU
Pandora data averaging time			
data averaging time	PanAVG	20min	30 min

Table 4: Optimized filter parameter thresholds applied for the TotNO_2 validation. The best guess thresholds are the conclusions from the sensitivity test.

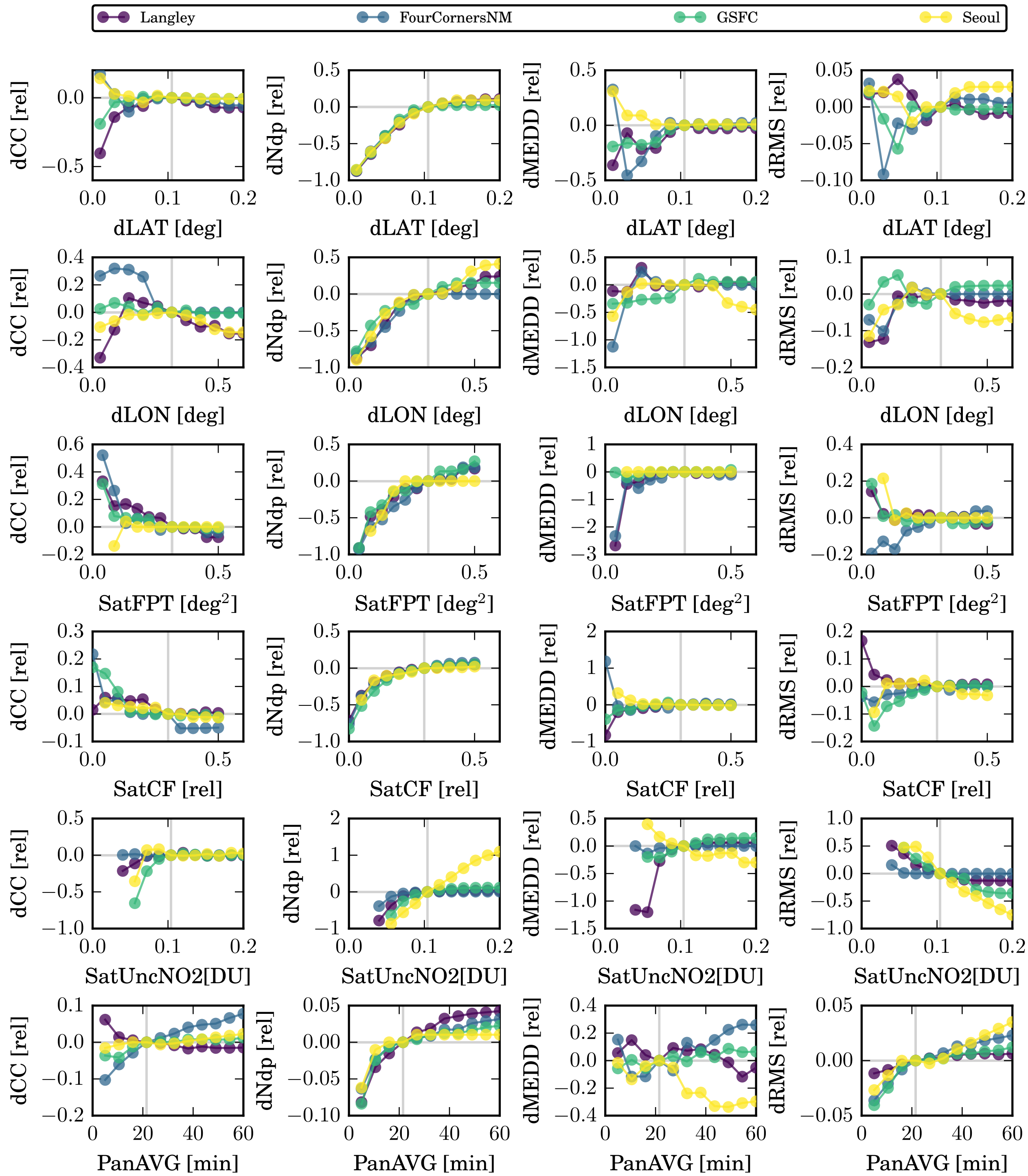


Figure 4: Filter parameter sensitivity test with four validation locations: GSFC, Langley, FourCornersNM and Seoul. The four different test parameters dCC, dNdp, dMEDD and dRMS in the columns and the filter parameters (dLat, dLon, SatFPT, SatCF, SatUncNO2 and PanAVG) in the rows.

4.2 Validation Results

4.3 Validation Results

In this section we present the OMI to Pandora validation for $TotNO_2$ for each ValLoc having time overlap with OMI. Each OMI footprint pixel underwent climatological correction (section 3.3) and Pandora locations are considered as effective locations (section 3.2). Results are shown for data filter criteria without and with geolocation filter applied. In the former case 50 ValLoc are shown and the latter case is represented by 10 ValLocs.

We state that outliers are often associated with restricted NO_2 plumes penetrated by the direct-sun beam, but underestimated due to the size of an OMI footprint pixel. To take this into account we also considered the approximated diurnal range of $TotNO_2$ (DNO_2R). It is estimated by the difference of the highest to the lowest value measured by the Pandora in the time range $\pm$ 4 hours of the OMI overpass time. This $TotNO_2$ range is given as color code in the scatter plots. Basically we can partition the ValLocs without geolocation filtering into 3 groups:

Group 1 comprises about 10 % of the ValLocs and show extraordinary good CC (≈ 0.8) with SLPs near 0.9. This very good agreement for OMI and Pandora may be a consequence of the relatively low DNO_2R. The high CC is, however, supported by the fact that only about 10 data points are the basis for the validation. These locations are e.g. Corcoran and Huron, both located in CA, USA and Niwot in South Korea, which strongly benefits from the ClimCor.

Group 2 comprises the major part of the ValLocs and can be further split up into densely and sparsely populated ValLocs. The main characteristic is a low SLP of ≈ 0.2. In both cases is an enhanced DNO_2R expected to be the major driver. In the case of the the sparsely populated ValLocs this manifests however still in a relatively high CC. Examples are e.g. Fresno CA and Denver CO in the USA. The densely populated ValLocs clearly show the low SLP driven by enhanced DNO_2R. Without the OMI underestimation the statistics would be rather good. Examples are Four corners NM, USA, Seoul and Busan in South Korea or FMI in Finland.

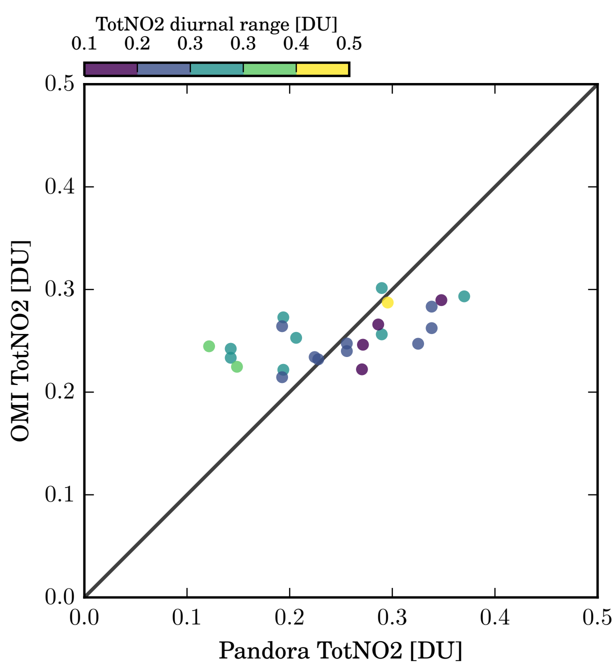
Group 3 comprises questionable ValLocs showing unexpected results. This group splits further up into ValLocs with probably insufficient Pandora $TotNO_2$ calibration and ValLocs with still missing explanation. Both subgroups show negative SLP and/or positive values for MEDD. This would mean that Pandora data underestimate the OMI data. Those cases would e.g. occur when a Pandora would be next to a large city. The error due to this cases should, however, be mitigated by the ClimCor. An obvious calibration issue is given for e.g. IZO Tenerife, Spain, with Pandora values near zero (not expected due to the rather constant stratospheric NO_2 background). IZO shows almost only stratospheric NO_2. An offset in the NO_2 calibration has a larger impact for low values. A representative of the second subgroup is e.g. UMBC MA, USA or Fort Collins CO, USA.

For locations indicated with an asterisk we applied the geolocation filtering.

Short Description	Long Description
longitude, latitude	ground geolocation of the Pandora unit (not its effective location)
num data points	number of data points passing the filter criteria
max Pan. (Pans.)	maximum number of Pandora units involved (name of Pandora(s) operating at this location)
CC	correlation coefficient between OMI and Pandora Tot NO_2
SLP	slope term in the linear fit including OMI uncertainty (Pandora uncertainty is omitted due to the large number of points)
OFFS	offset term in the linear fit including OMI uncertainty (Pandora uncertainty is omitted due to the large number of points)
RMS	root mean squre error to a linear fit in Pandora vs. OMI
mean	arithmetic mean of the difference OMI and Pandora
MEDD	median value for OMI and Pandora difference
25-75 percentile range	25 to 75 percentile range for OMI and Pandora difference
10-90 percentile range	10 to 90 percentile range for OMI and Pandora difference
min-max range	minimum value to maximum value range for OMI and Pandora difference
OMI CF	percentage of OMI data passing the OMI CF filter
Pandora DQ0	percentage of Pandora data passing the DQ0 filter

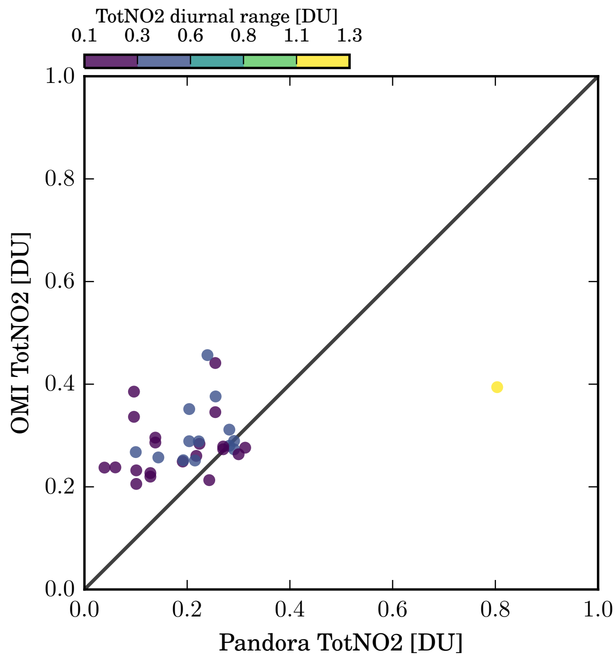
Table 5: Description on the additional information given for each location to validate.

Aldino



longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

AMI



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SLP	?? ± ??
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RMS	?? DU
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MEDD	?? DU
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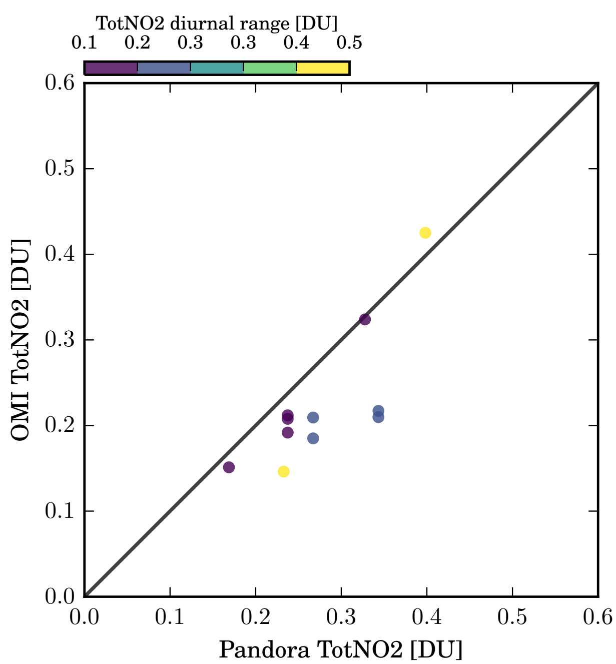
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Arvin



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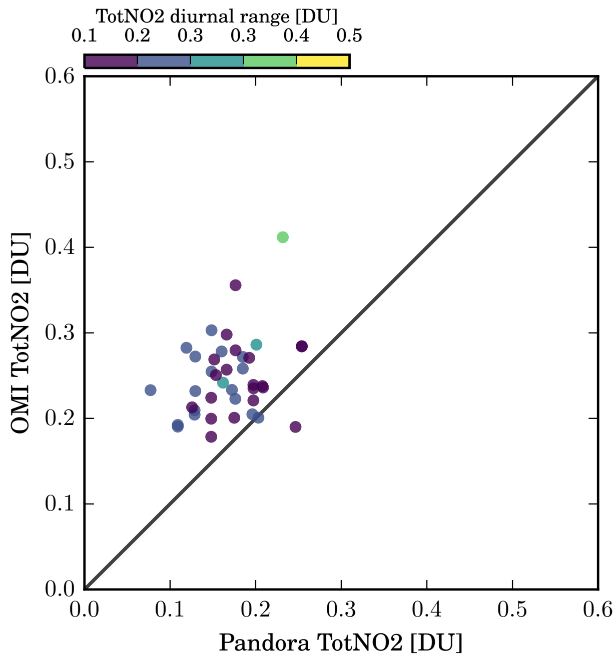
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Baengnyeongdo



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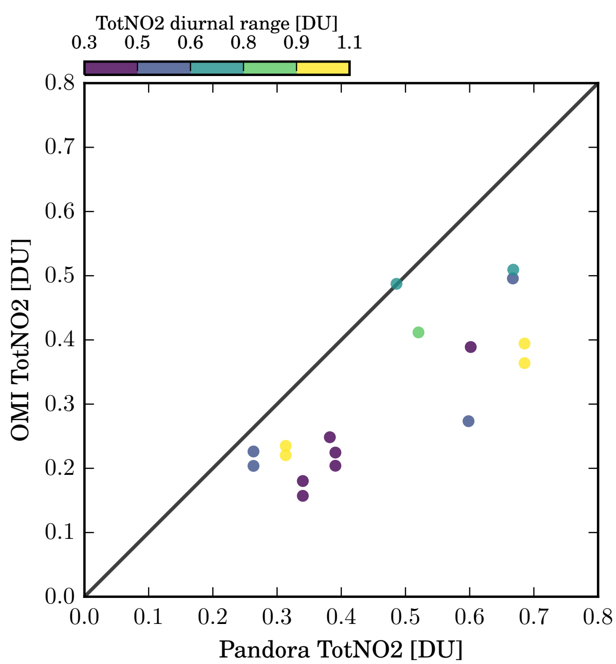
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Bakersfield



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RMS	?? DU
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MEDD	?? DU
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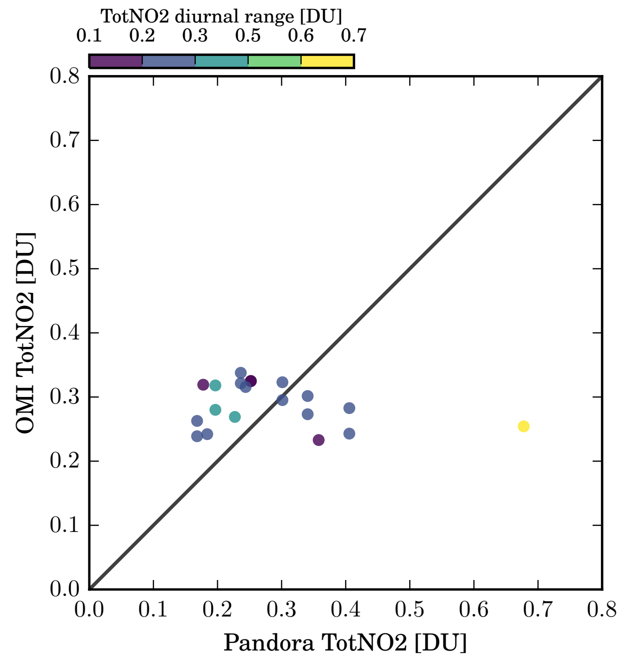
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Beltsville



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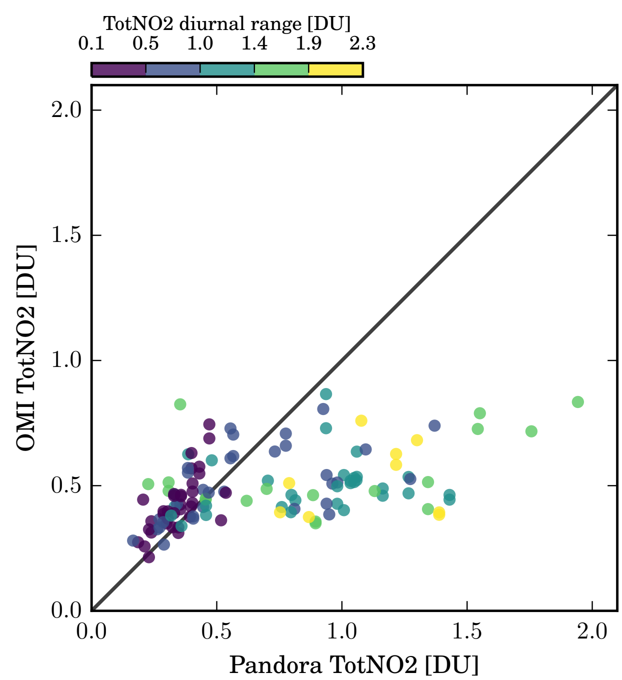
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Busan



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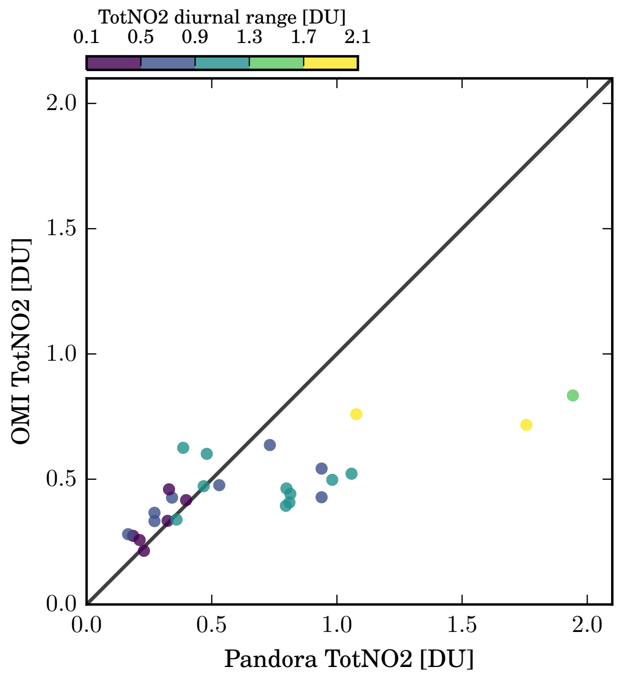
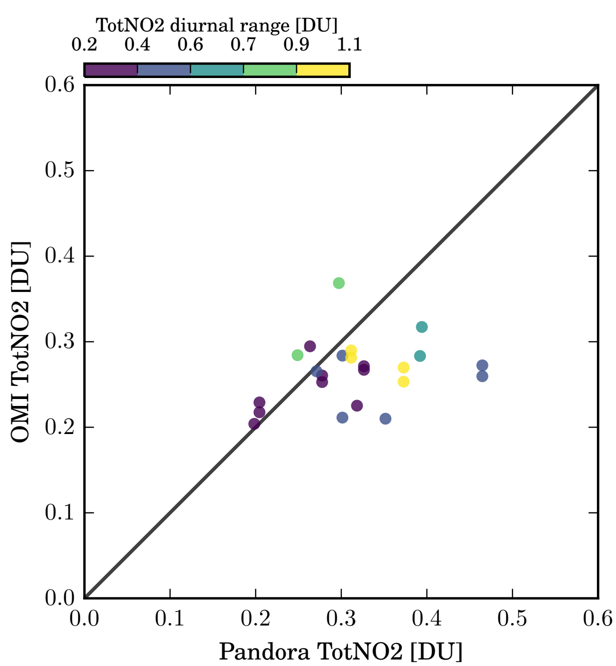
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Busan*



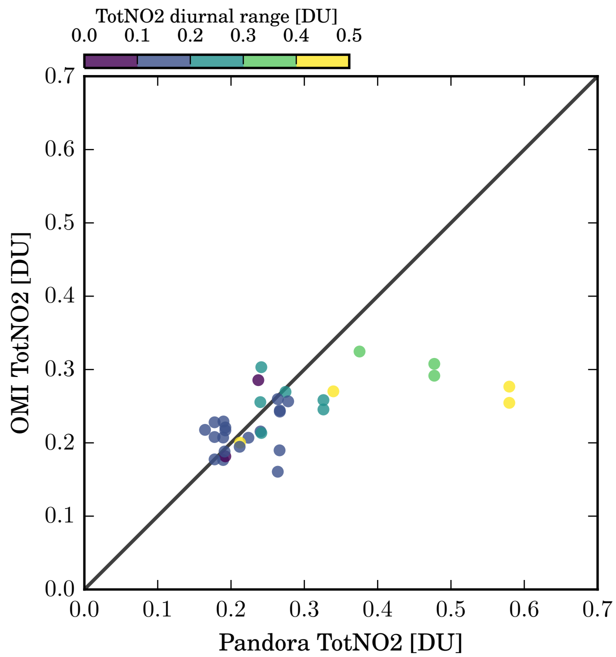
longitude, latitude	129.0825, 35.2353
num data points	27
max Pan. (Pans.)	1 (20)
CC	0.78
SLP	0.28 ± 0.03
OFFS	0.26 DU ± 0.02 DU
RMS	0.1 DU
mean	-0.19 DU
MEDD	-0.02 DU
25-75 percentile range	-0.40 DU to 0.07 DU
10-90 percentile range	-0.52 DU to 0.12 DU
min-max range	-1.11 DU to 0.24 DU
OMI CF	29.94 %
Pandora DQ0	69.68 %

Channelview



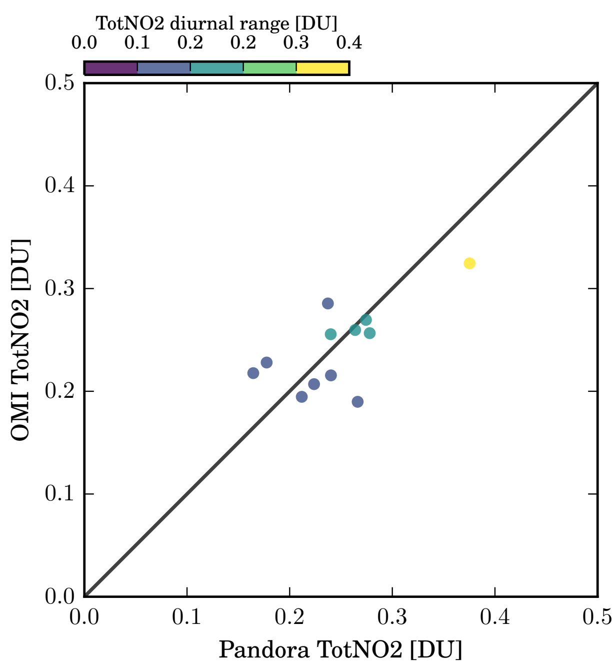
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Chatfield



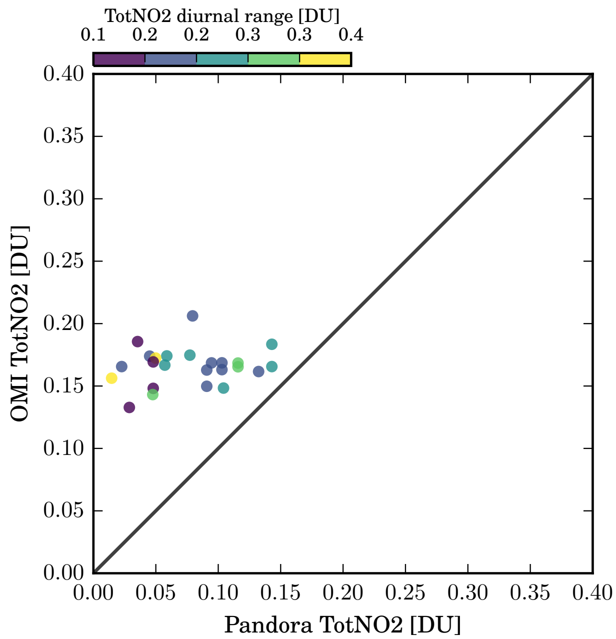
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Chatfield*



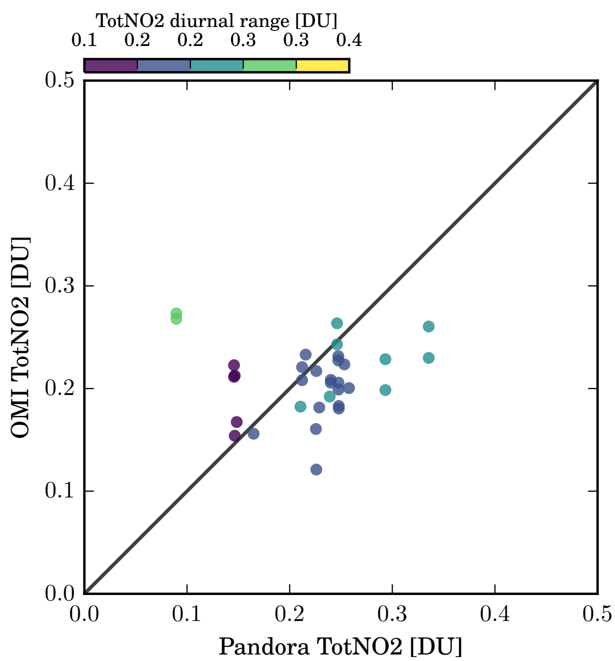
longitude, latitude	-105.07, 39.53
num data points	12
max Pan. (Pans.)	1 (26)
CC	0.67
SLP	0.47 ± 0.29
OFFS	0.12 DU ± 0.07 DU
RMS	0.03 DU
mean	-0.00 DU
MEDD	-0.01 DU
25-75 percentile range	-0.02 DU to 0.02 DU
10-90 percentile range	-0.05 DU to 0.05 DU
min-max range	-0.08 DU to 0.05 DU
OMI CF	22.41 %
Pandora DQ0	55.17 %

CIAI



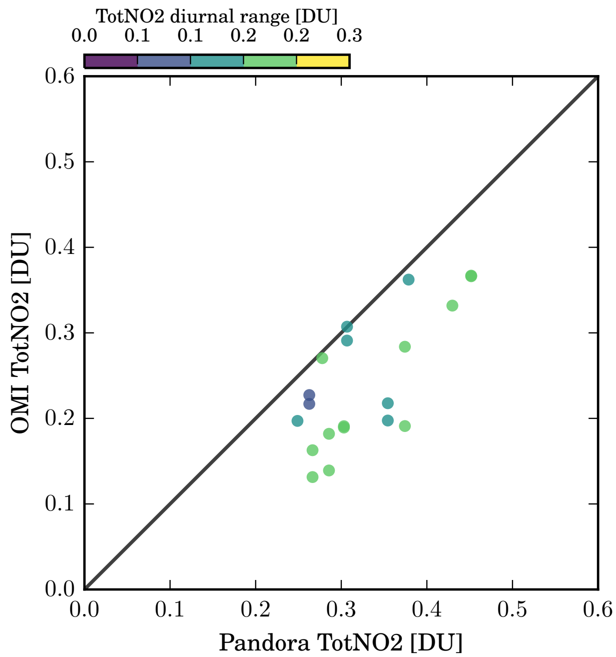
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Conroe



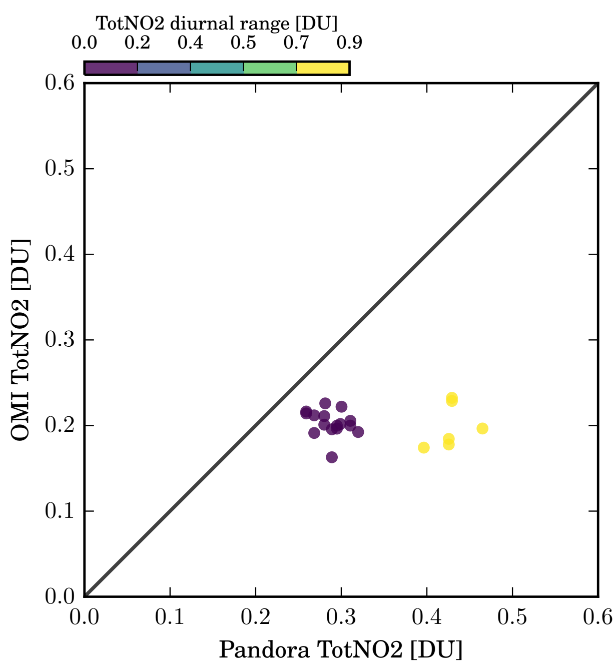
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Corcoran



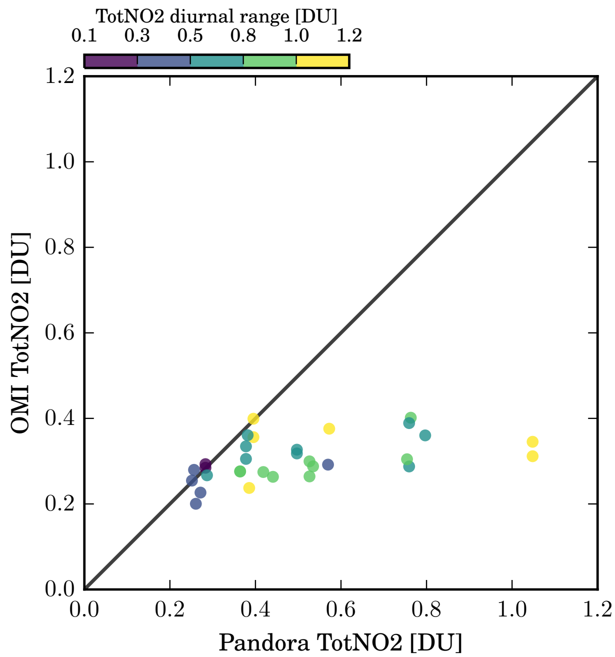
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

DC3



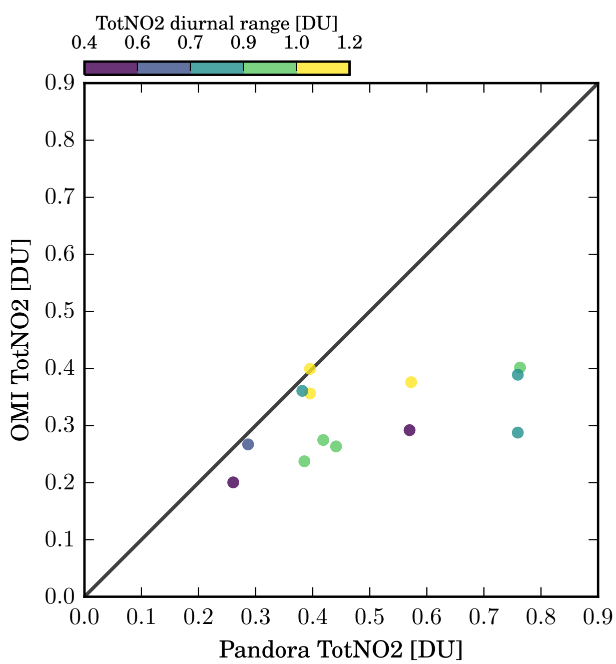
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

DenverI25



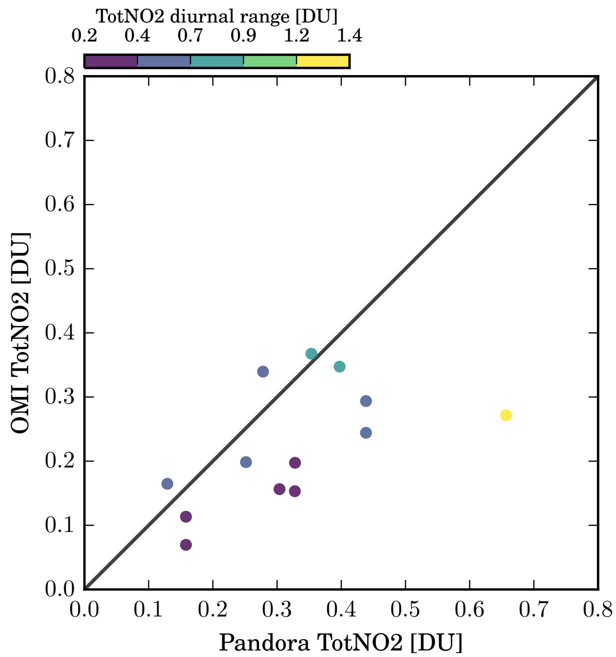
longitude, latitude	**??**, **??**
num data points	**??**
max Pan. (Pans.)	**??**
CC	**??**
SLP	**??** ± **??**
OFFS	**??** DU ± **??** DU
RMS	**??** DU
mean	**??** DU
MEDD	**??** DU
25-75 percentile range	**??** DU to **??** DU
10-90 percentile range	**??** DU to **??** DU
min-max range	**??** DU to **??** DU
OMI CF	**??** %
Pandora DQ0	**??** %

DenverI25*



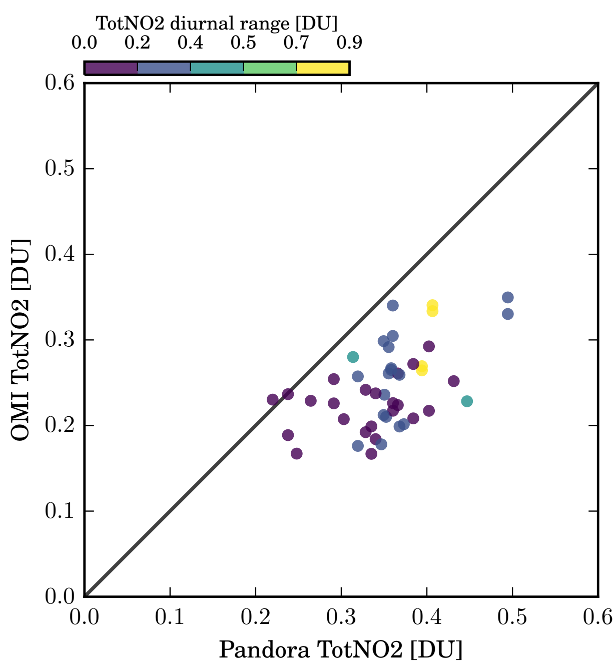
longitude, latitude	-105.015, 39.732
num data points	13
max Pan. (Pans.)	1 (27)
CC	0.50
SLP	0.23 ± 0.08
OFFS	0.19 DU ± 0.04 DU
RMS	0.06 DU
mean	-0.18 DU
MEDD	-0.15 DU
25-75 percentile range	-0.28 DU to -0.04 DU
10-90 percentile range	-0.37 DU to 0.02 DU
min-max range	-0.47 DU to 0.00 DU
OMI CF	22.67 %
Pandora DQ0	59.29 %

DoiAngKhang



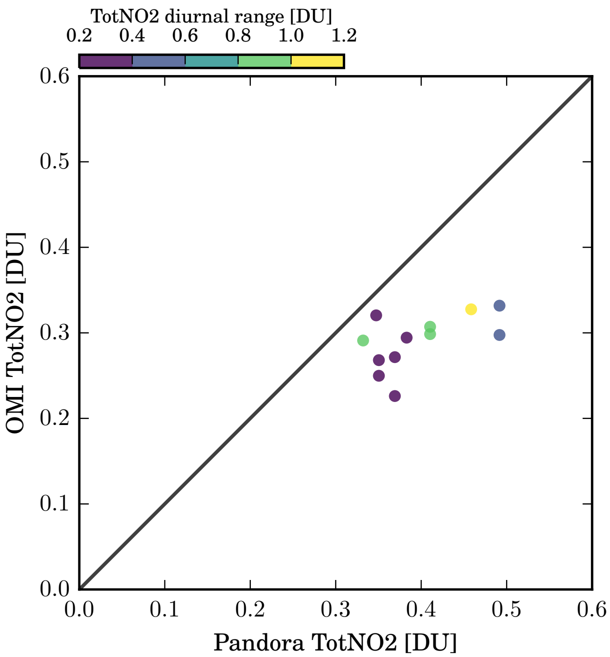
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Durham



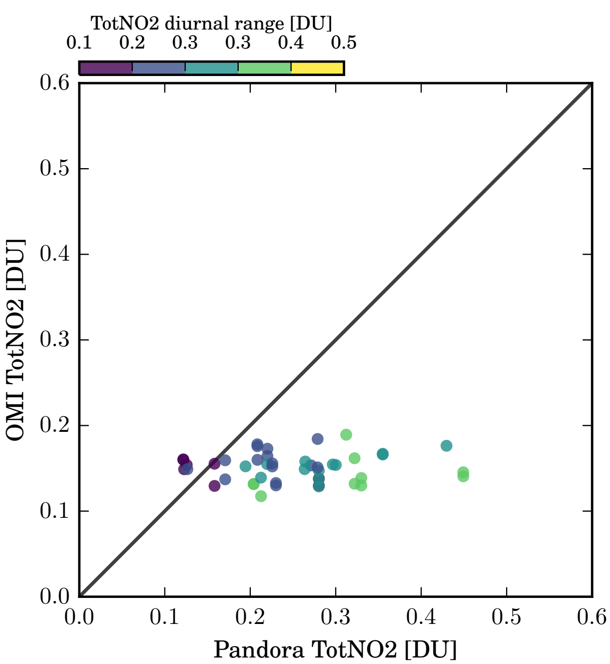
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Essex



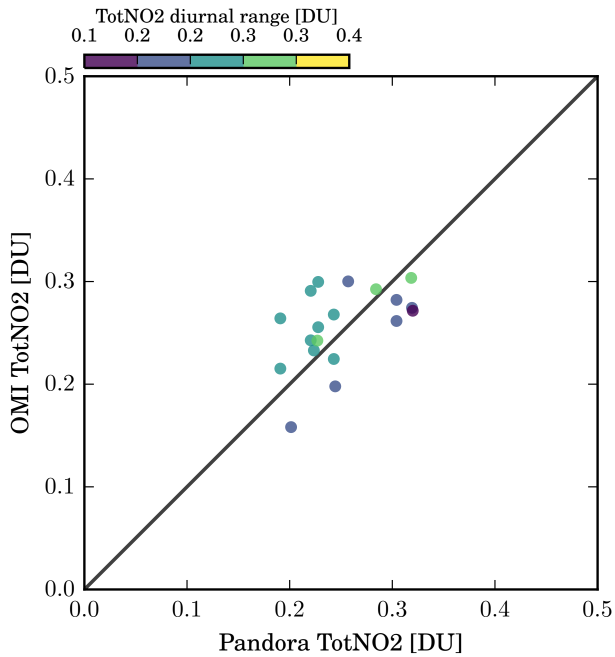
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Fairbanks



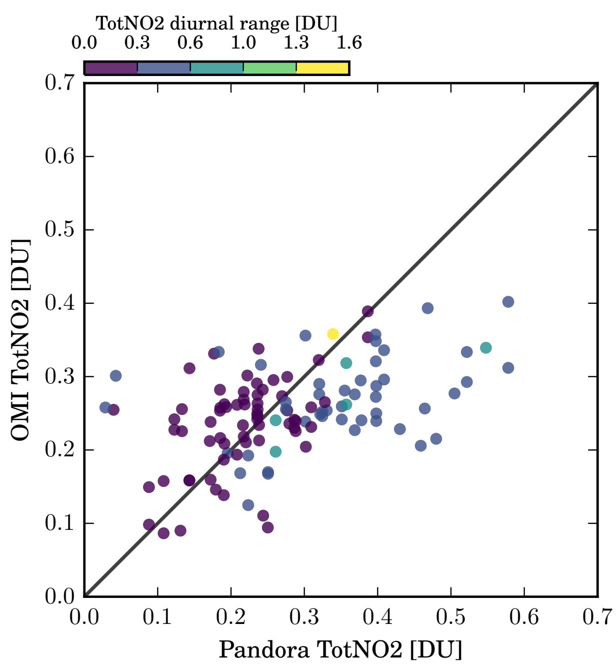
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Fairhill



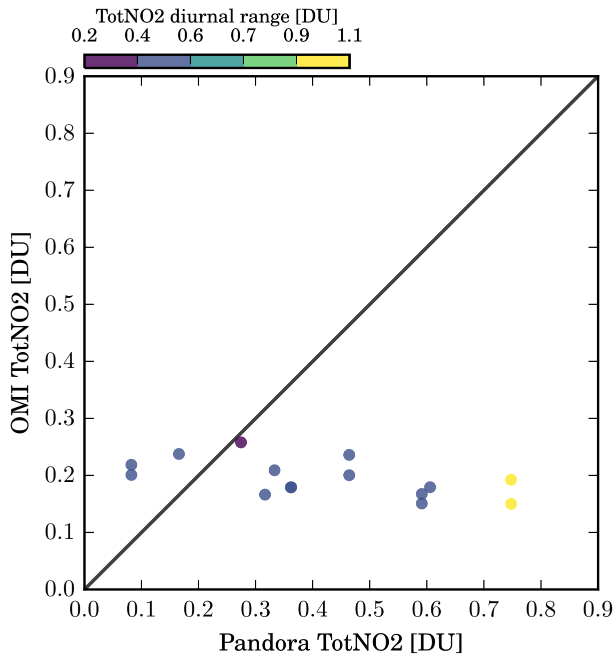
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

FMI



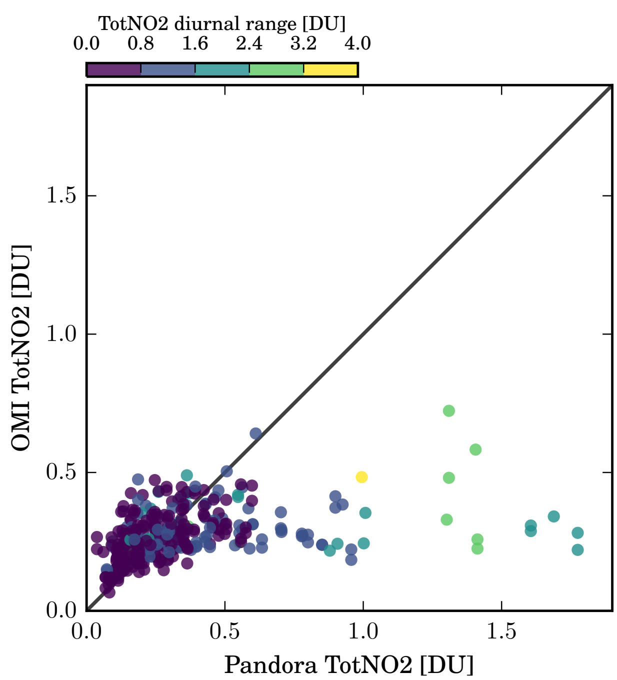
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

FortCollins



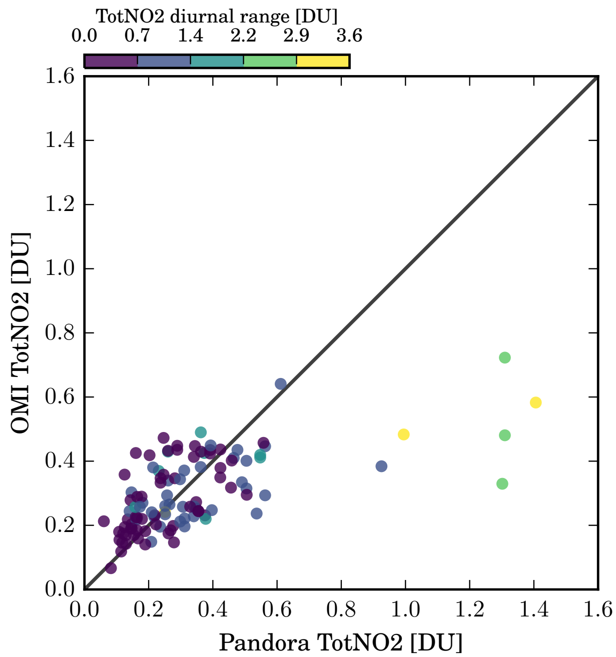
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

FourCornersNM



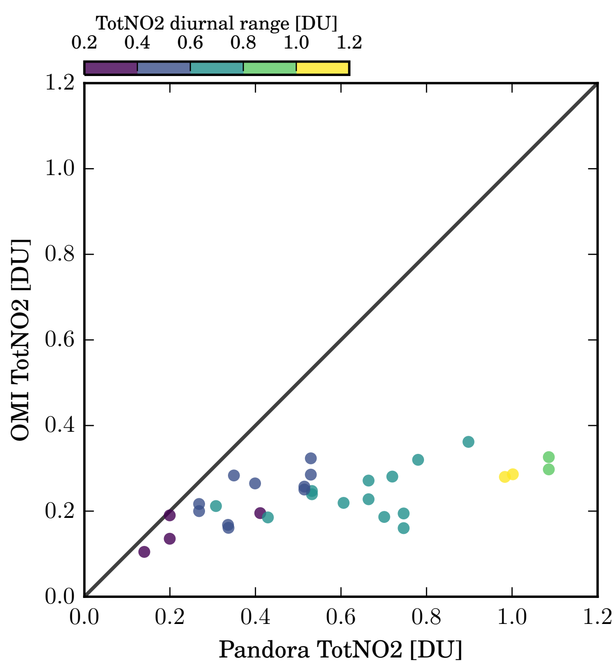
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

FourCornersNM*



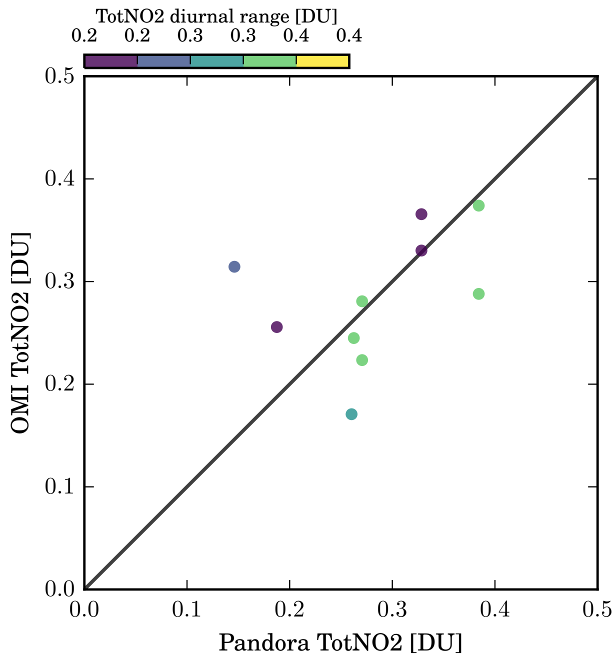
longitude, latitude	-108.480, 36.797
num data points	110
max Pan. (Pans.)	1 (23)
CC	0.62
SLP	0.28 ± 0.01
OFFS	0.18 DU ± 0.01 DU
RMS	0.10 DU
mean	-0.03 DU
MEDD	0.01 DU
25-75 percentile range	-0.09 DU to 0.07 DU
10-90 percentile range	-0.16 DU to 0.14 DU
min-max range	-0.97 DU to 0.27 DU
OMI CF	53.73 %
Pandora DQ0	58.54 %

Fresno



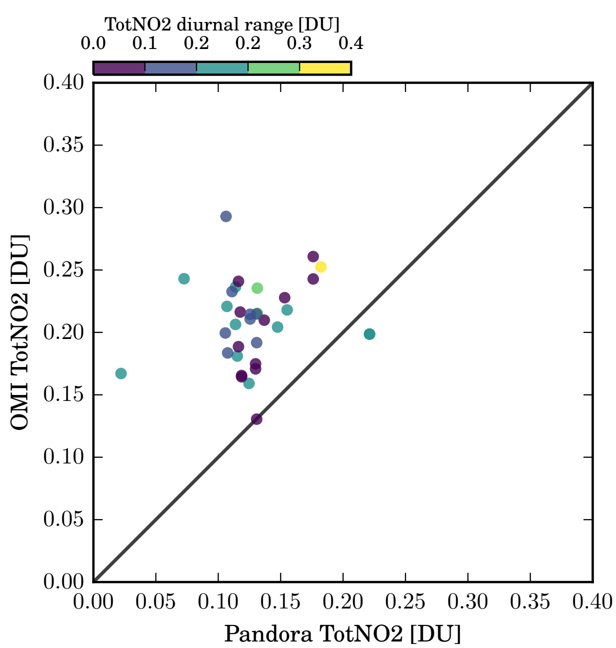
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

FSU



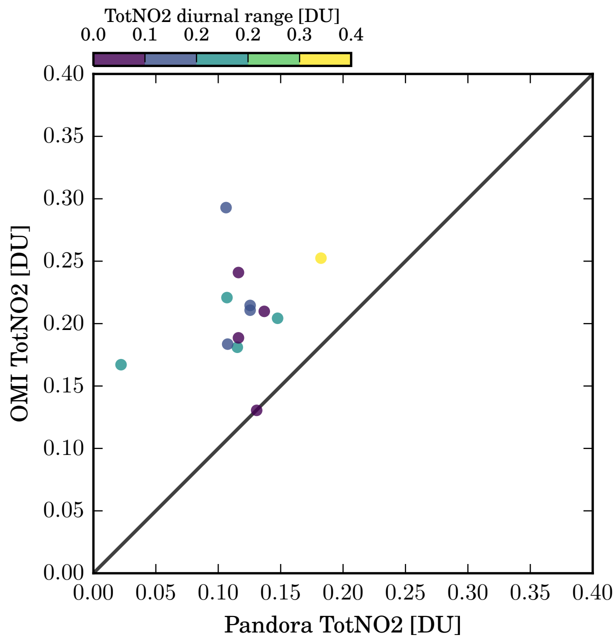
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RME	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Galveston



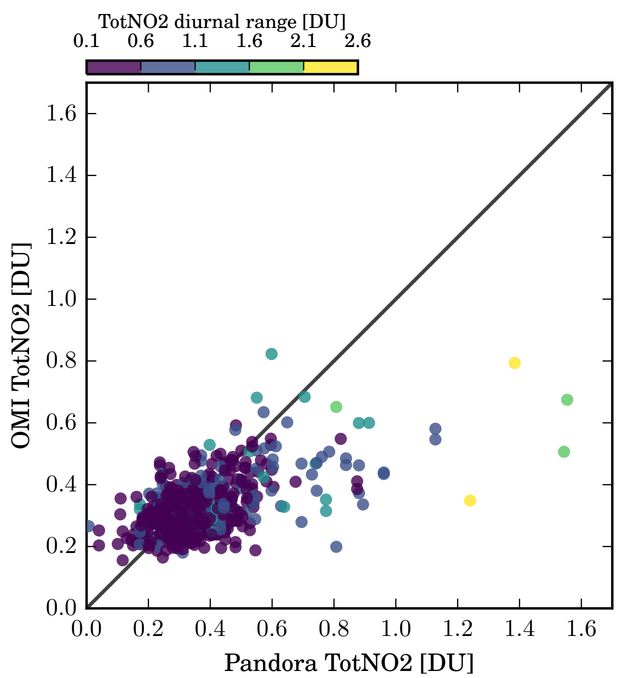
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Galveston*



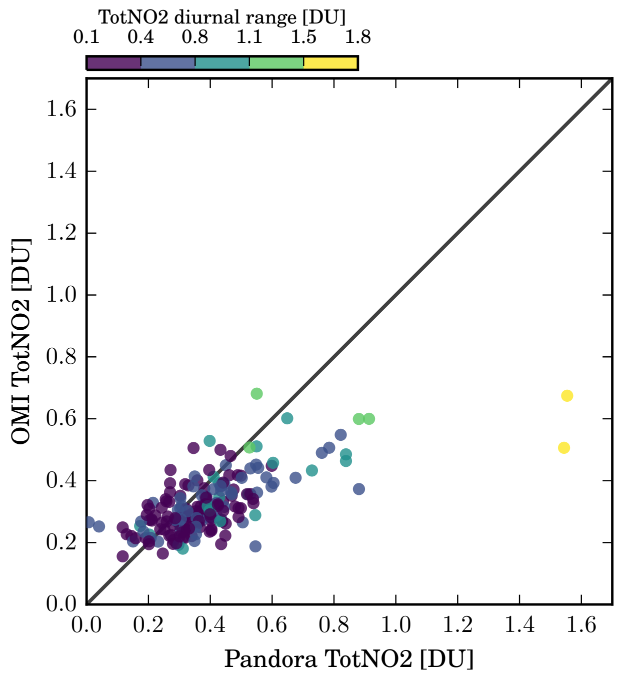
longitude, latitude	-94.8612, 29.2544
num data points	13
max Pan. (Pans.)	1 (34)
CC	0.28
SLP	0.22 ± 0.4
OFFS	0.17 DU ± 0.05 DU
RMS	0.04 DU
mean	0.09 DU
MEDD	0.08 DU
25-75 percentile range	0.07 DU to 0.11 DU
10-90 percentile range	0.06 DU to 0.14 DU
min-max range	-0.00 DU to 0.19 DU
OMI CF	38.30 %
Pandora DQ0	62.01 %

GSFC



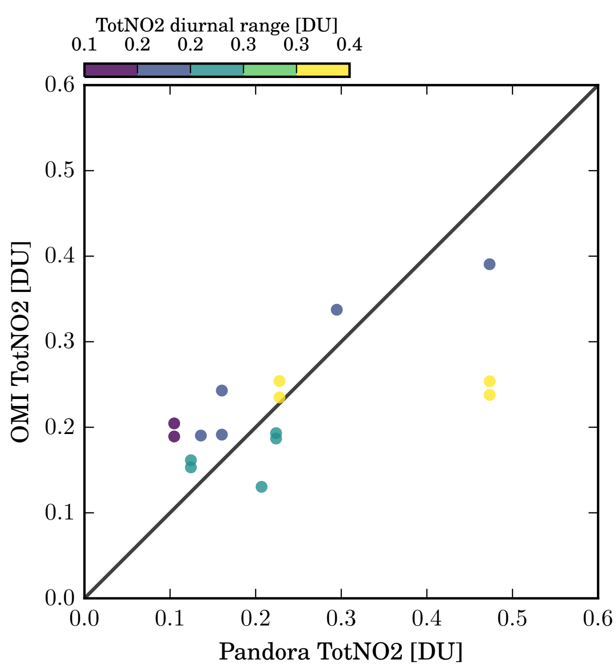
longitude, latitude	-76.8396, 38.9926
num data points	585
max Pan. (Pans.)	all Pandoras
CC	0.58
SLP	0.21 ± 0.02
OFFS	0.22 DU ± 0.01 DU
RMS	0.08 DU
mean	-0.05 DU
MEDD	-0.03 DU
25-75 percentile range	-0.10 DU to 0.04 DU
10-90 percentile range	-0.18 DU to 0.09 DU
min-max range	-1.04 DU to 0.26 DU
OMI CF	29.33 %
Pandora DQ0	40.20 %

GSFC*



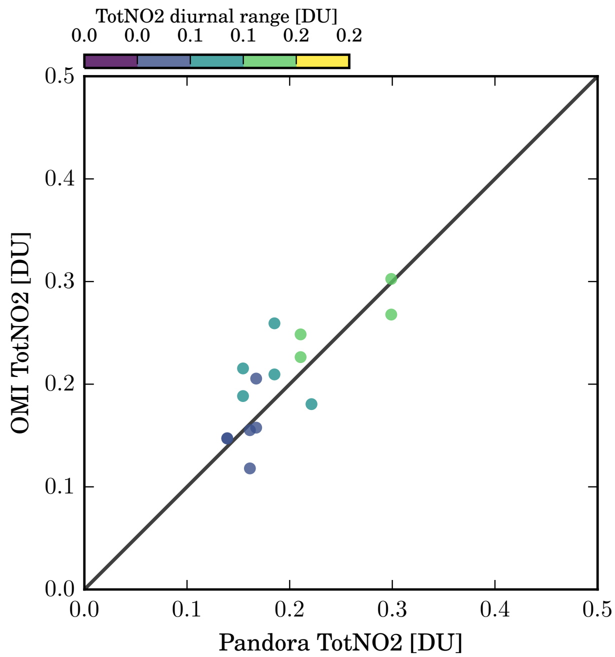
longitude, latitude	-76.8396, 38.9926
num data points	187
max Pan. (Pans.)	6 (18, 26, 2, 3, 7, 9)
CC	0.68
SLP	0.27 ± 0.02
OFFS	0.19 DU ± 0.01 DU
RMS	0.08 DU
mean	-0.07 DU
MEDD	-0.07 DU
25-75 percentile range	-0.12 DU to 0.01 DU
10-90 percentile range	-0.21 DU to 0.07 DU
min-max range	-1.04 DU to 0.26 DU
OMI CF	29.37 %
Pandora DQ0	40.20 %

Hanford



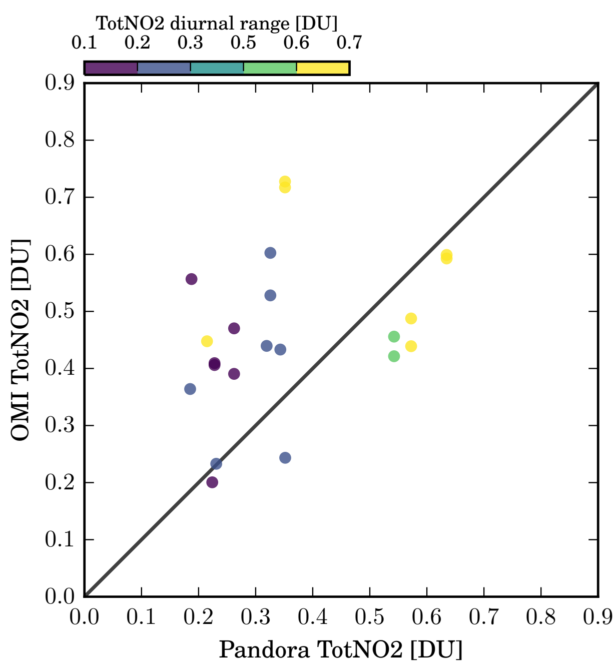
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Huron



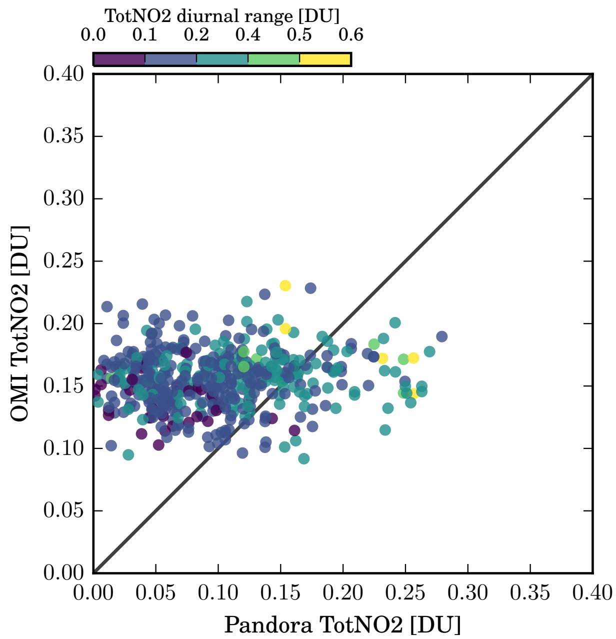
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

HUFS



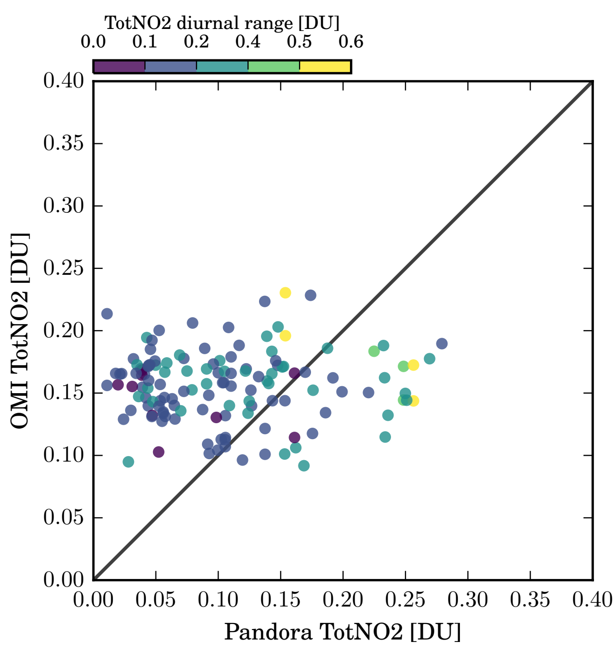
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

IZO



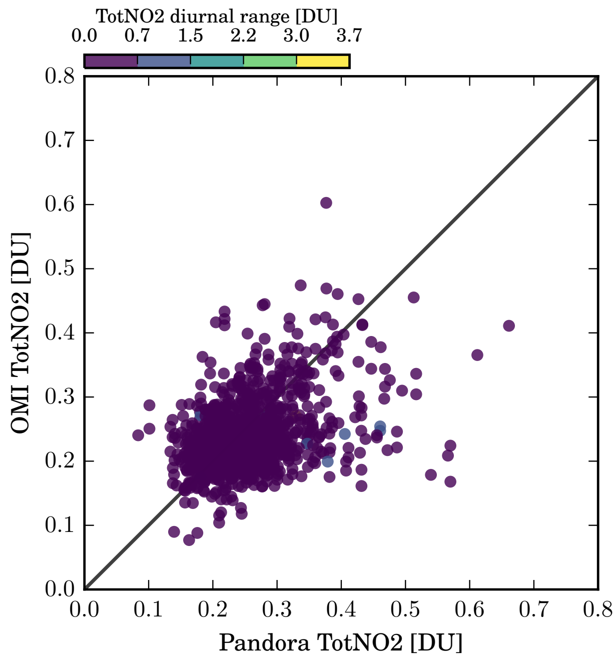
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

IZO*



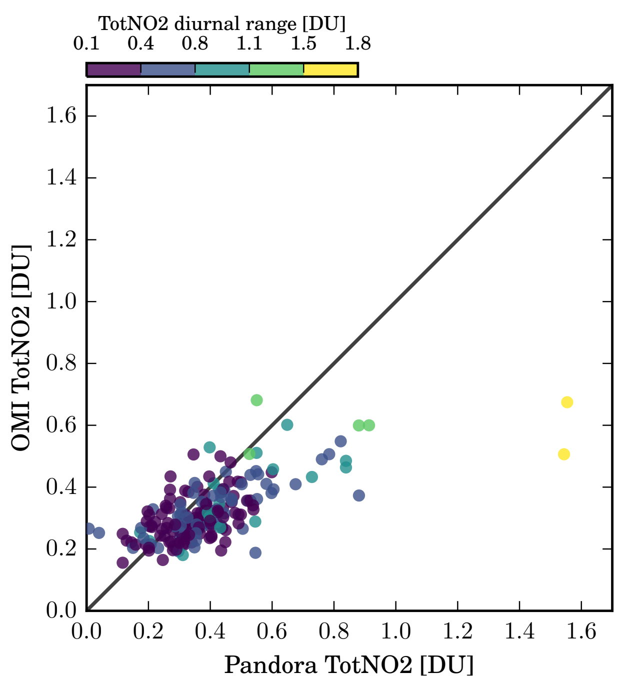
longitude, latitude	-16.4994, 28.309
num data points	134
max Pan. (Pans.)	1 (101)
CC	0.02
SLP	0.02 ± 0.04
OFFS	0.15 DU ± 0.01 DU
RMS	0.03 DU
mean	0.05 DU
MEDD	0.06 DU
25-75 percentile range	0.01 DU to 0.10 DU
10-90 percentile range	-0.06 DU to 0.13 DU
min-max range	-0.12 DU to 0.20 DU
OMI CF	32.97 %
Pandora DQ0	54.72 %

Langley



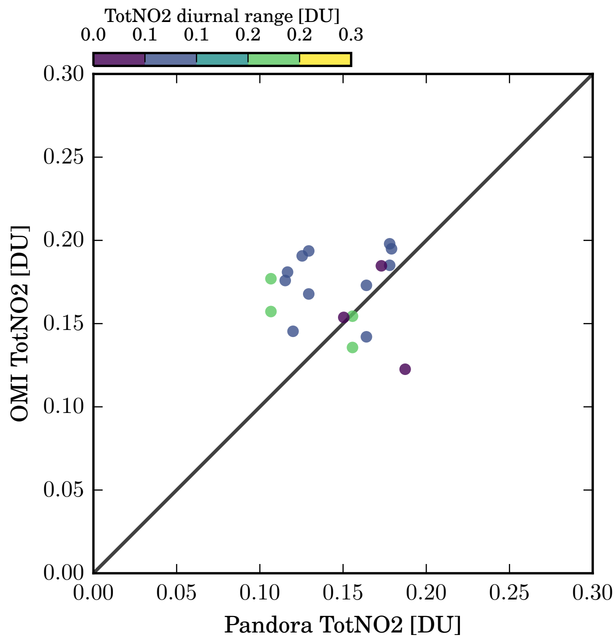
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Langley*



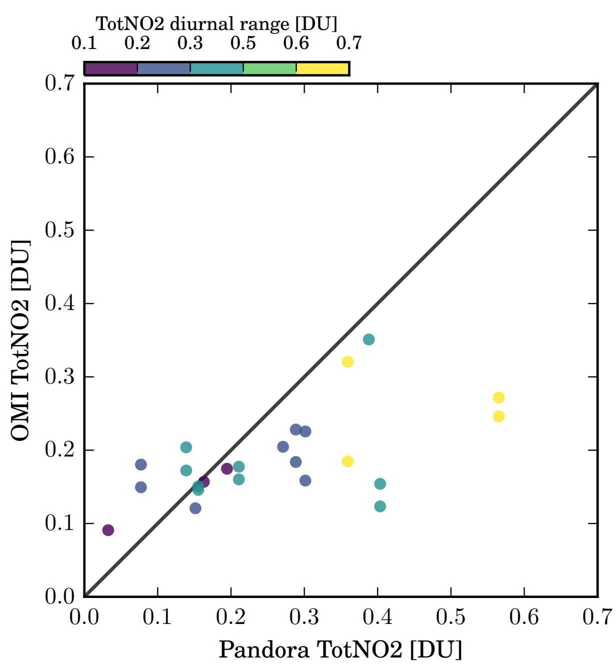
longitude, latitude	-76.8396, 38.9926
num data points	187
max Pan. (Pans.)	6 (18, 26, 2, 3, 7, 9)
CC	0.68
SLP	0.27 ± 0.02
OFFS	0.19 DU ± 0.01 DU
RMS	0.08 DU
mean	-0.07 DU
MEDD	-0.07 DU
25-75 percentile range	-0.12 DU to 0.01 DU
10-90 percentile range	-0.21 DU to 0.07 DU
min-max range	-1.04 DU to 0.26 DU
OMI CF	29.37 %
Pandora DQ0	40.20 %

Lauder



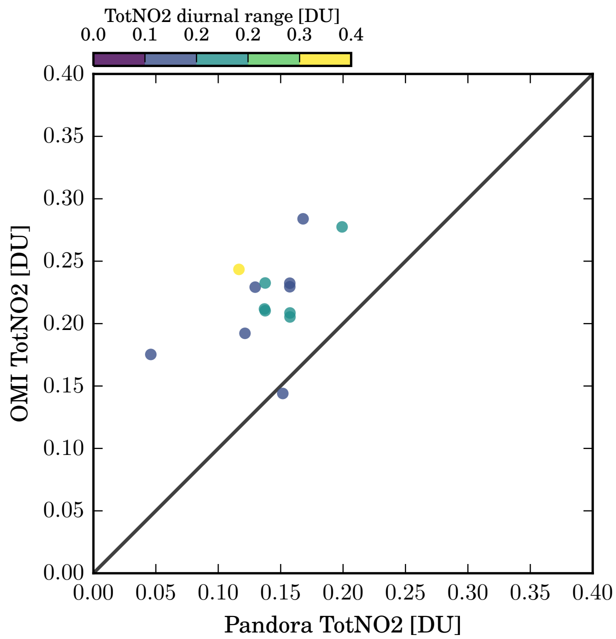
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Madera



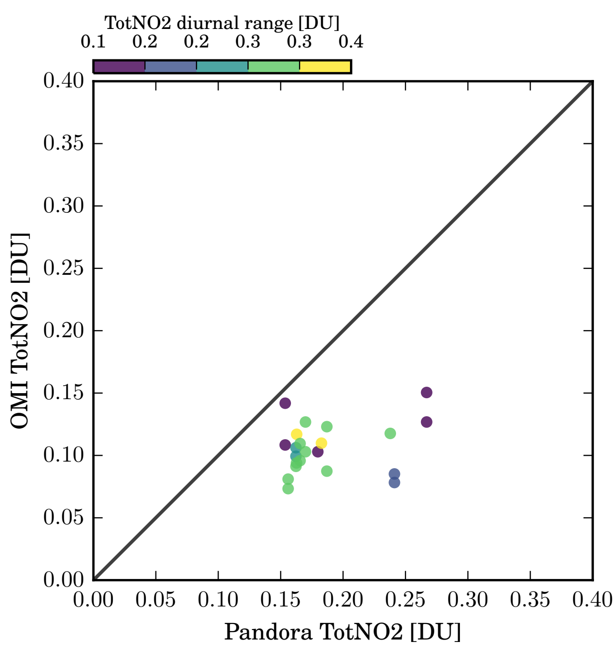
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Manvelcroix



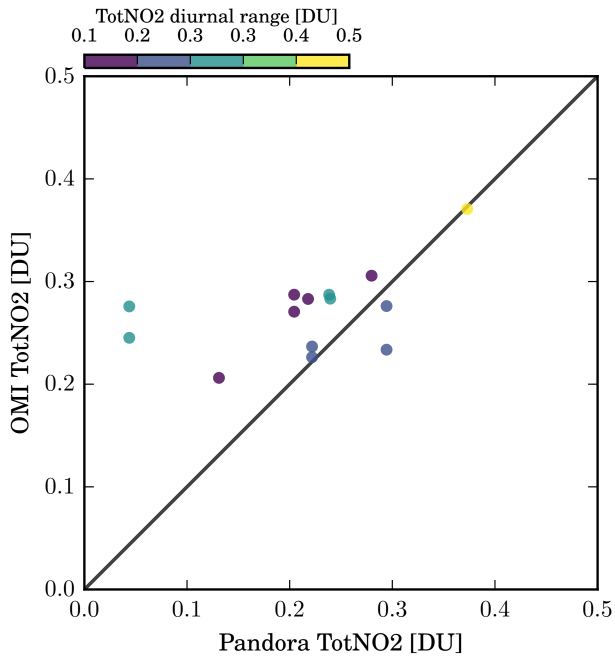
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

MaunaLoa



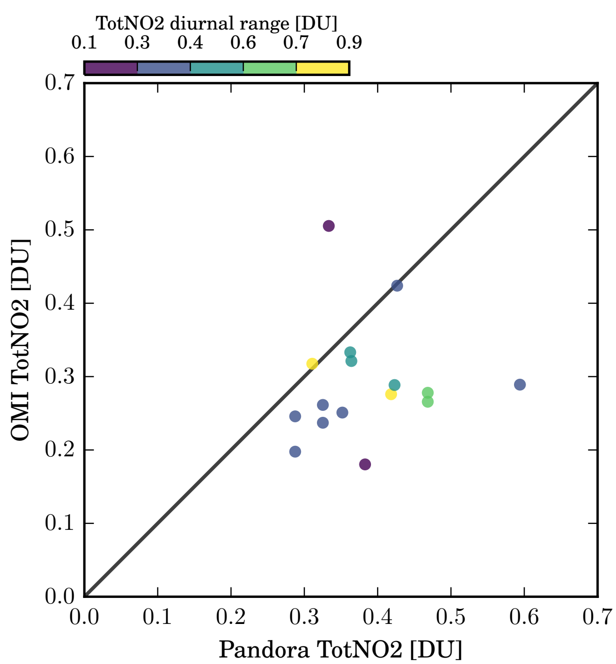
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Moodytower



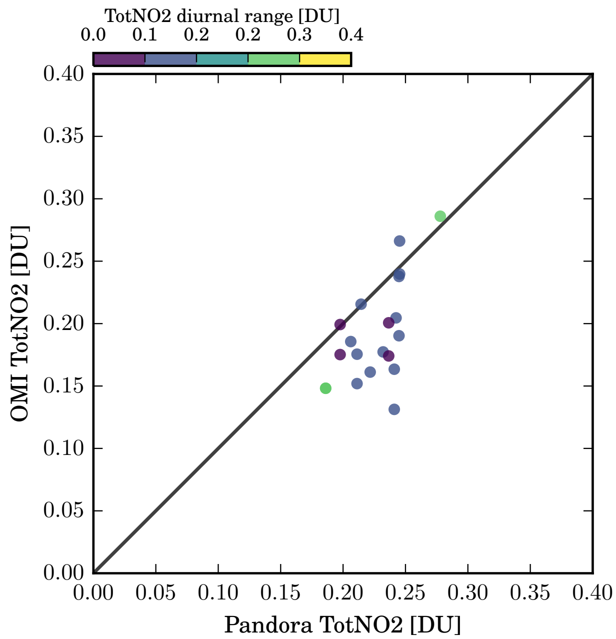
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

NASAHQ



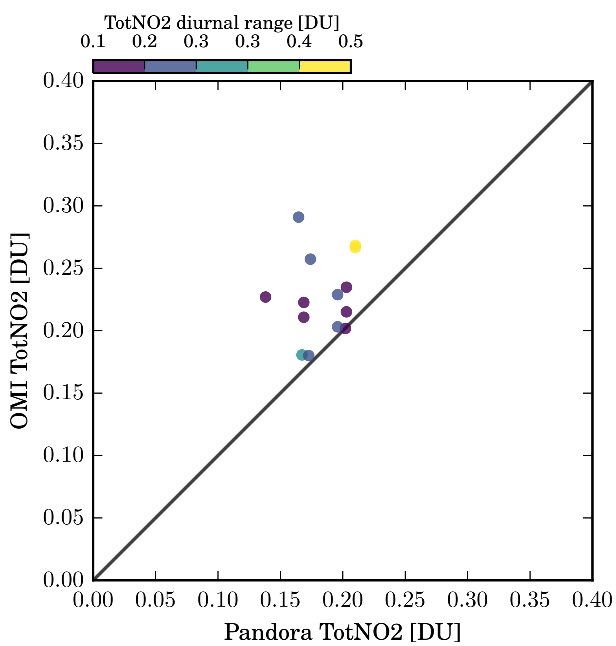
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
OFFS	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Niwot



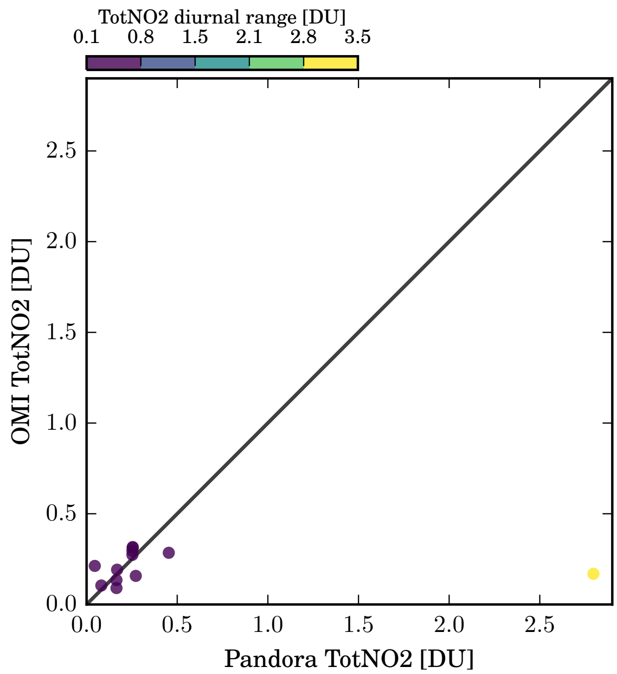
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

NWHarris



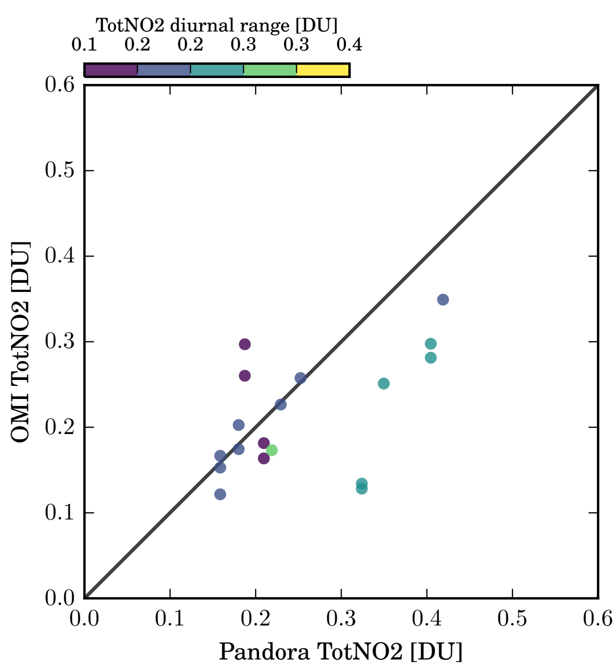
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Parlier



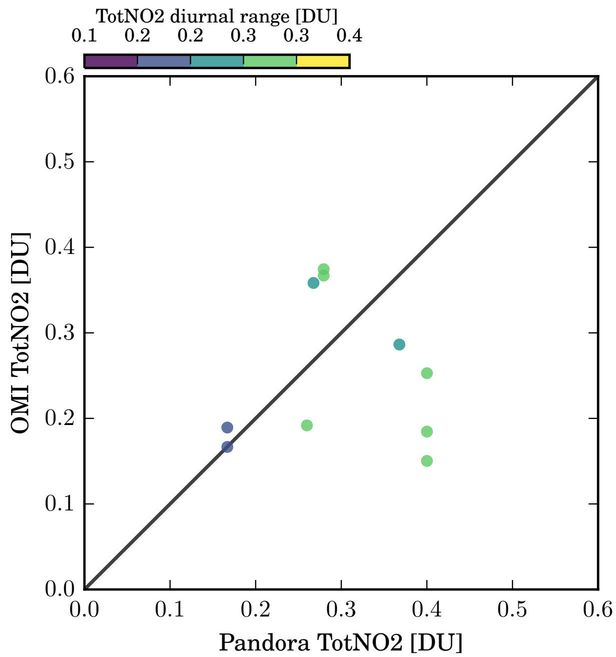
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Porterville



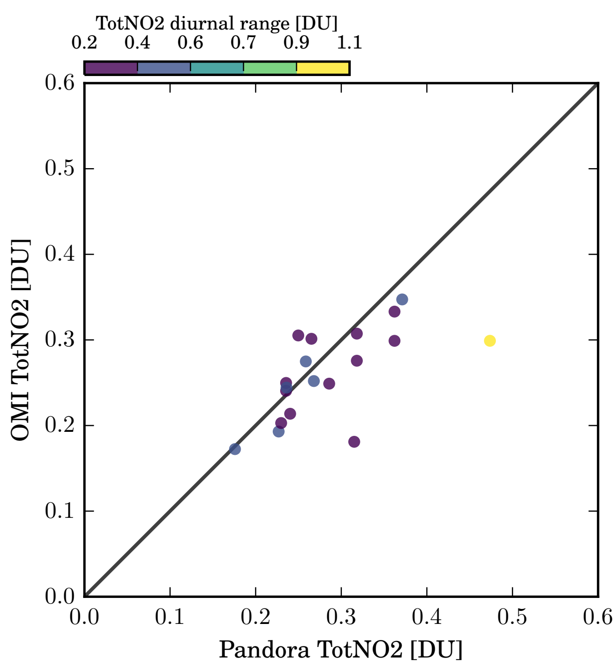
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

PSU



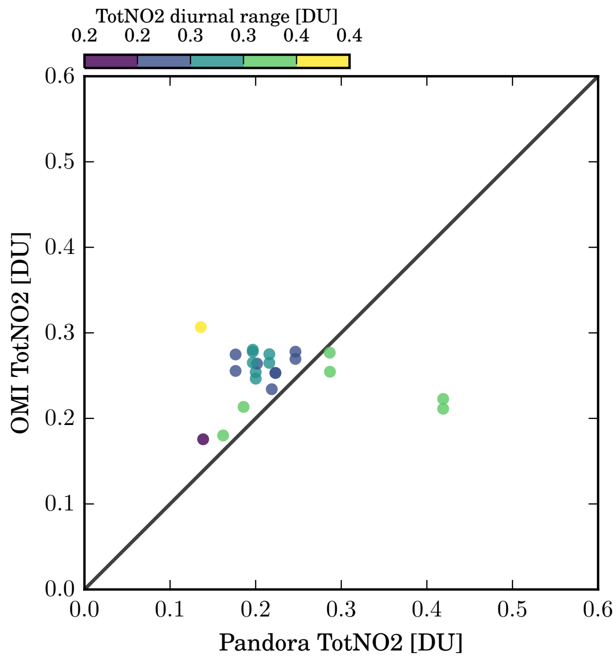
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

RockyFlats



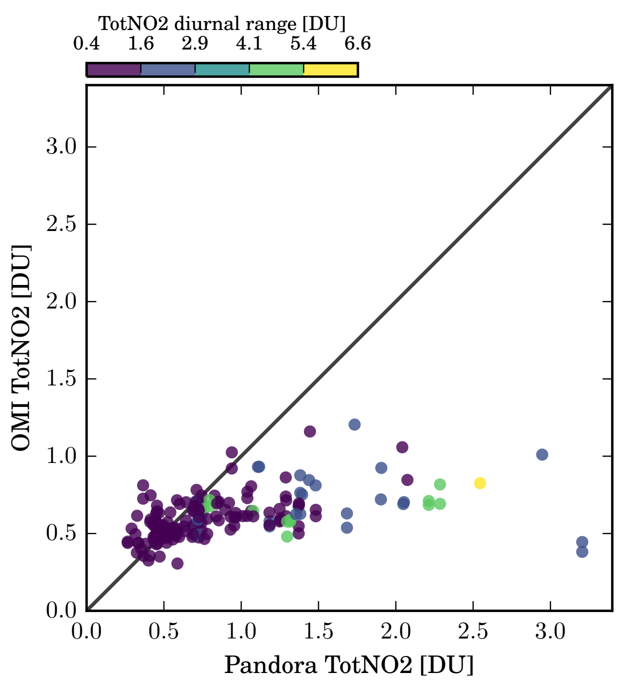
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Seabrook



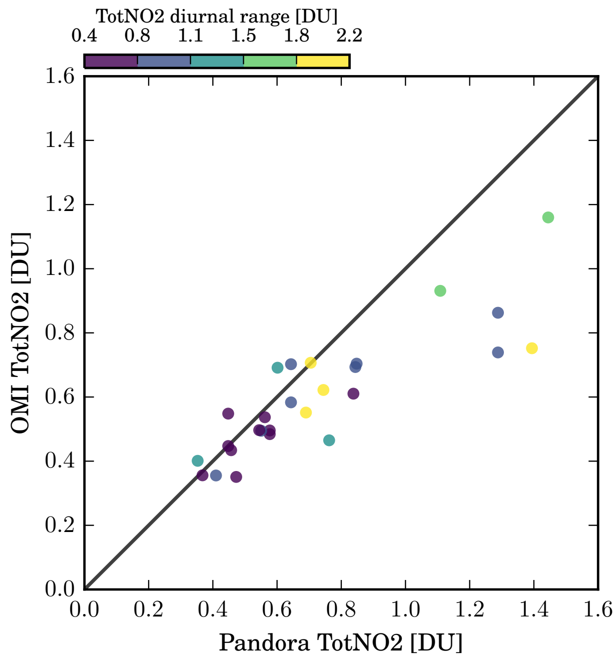
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Seoul



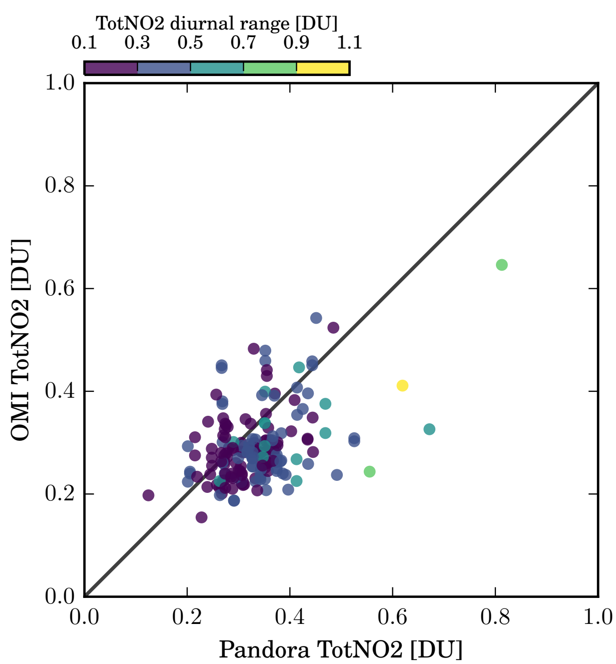
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Seoul*



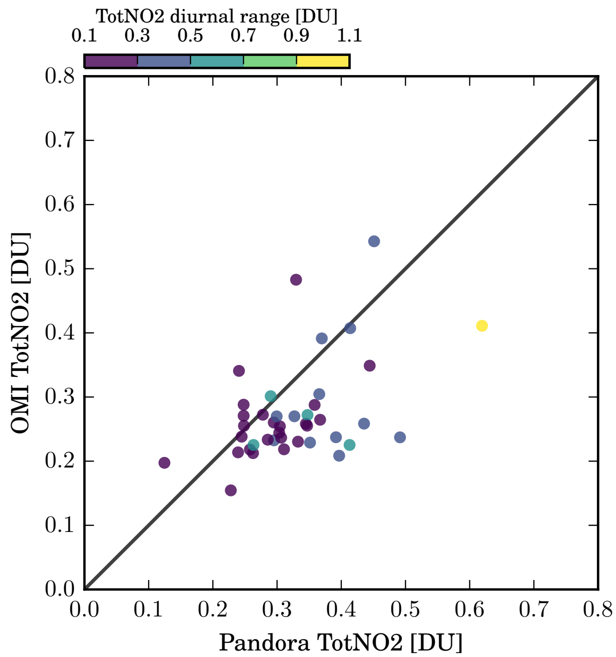
longitude, latitude	126.934, 37.5644
num data points	27
max Pan. (Pans.)	3 (27, 19, 29)
CC	0.86
SLP	0.53 ± 0.05
OFFS	0.19 DU ± 0.03 DU
RMS	0.10 DU
mean	-0.13 DU
MEDD	-0.08 DU
25-75 percentile range	-0.16 DU to -0.02 DU
10-90 percentile range	-0.35 DU to 0.05 DU
min-max range	-0.64 DU to 0.10 DU
OMI CF	23.90 %
Pandora DQ0	70.87 %

SERC



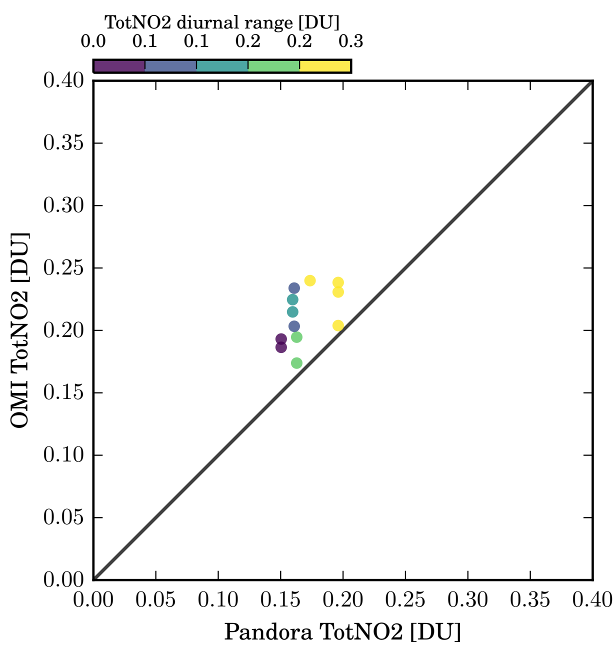
longitude, latitude	**??**, **??**
num data points	**??**
max Pan. (Pans.)	**??**
CC	**??**
SLP	**??** ± **??**
OFFS	**??** DU ± **??** DU
RMS	**??** DU
mean	**??** DU
MEDD	**??** DU
25-75 percentile range	**??** DU to **??** DU
10-90 percentile range	**??** DU to **??** DU
min-max range	**??** DU to **??** DU
OMI CF	**??** %
Pandora DQ0	**??** %

SERC*



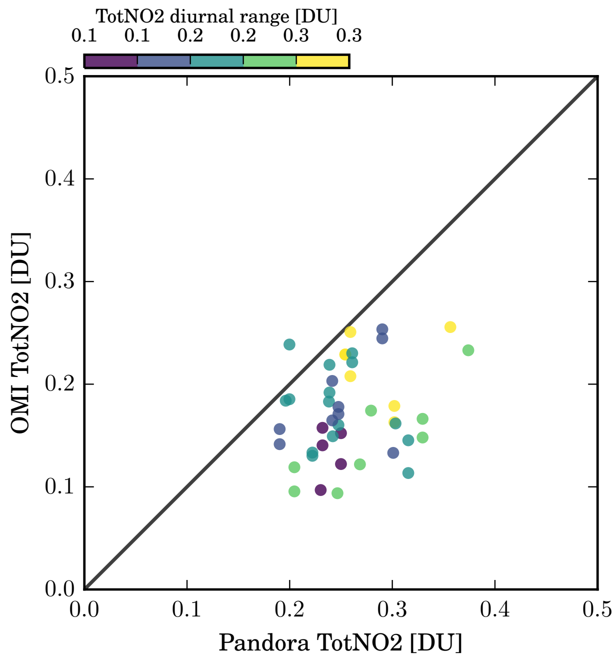
longitude, latitude	-76.55, 38.88
num data points	41
max Pan. (Pans.)	2 (24, 7)
CC	0.48
SLP	0.26 ± 0.10
OFFS	0.17 DU ± 0.03 DU
RMS	0.07 DU
mean	-0.05 DU
MEDD	-0.06 DU
25-75 percentile range	-0.09 DU to -0.01 DU
10-90 percentile range	-0.18 DU to 0.04 DU
min-max range	-0.25 DU to 0.15 DU
OMI CF	31.33 %
Pandora DQ0	44.09 %

Smithpoint



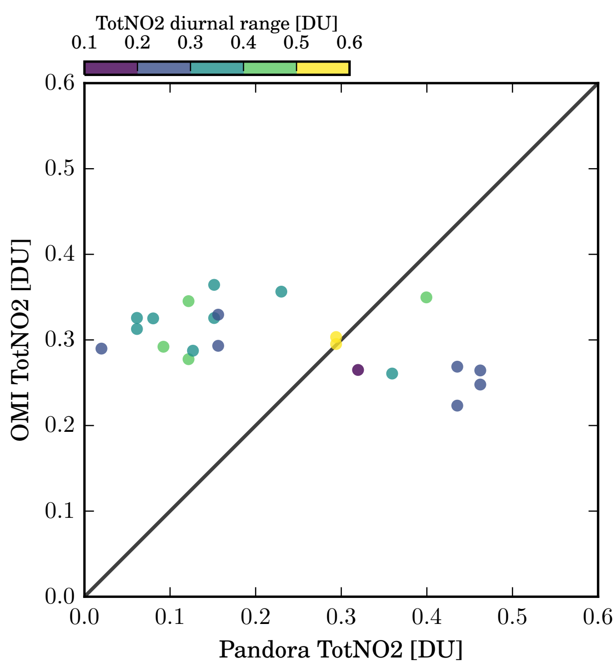
longitude, latitude	**??**, **??**
num data points	**??**
max Pan. (Pans.)	**??**
CC	**??**
SLP	**??** ± **??**
OFFS	**??** DU ± **??** DU
RMS	**??** DU
mean	**??** DU
MEDD	**??** DU
25-75 percentile range	**??** DU to **??** DU
10-90 percentile range	**??** DU to **??** DU
min-max range	**??** DU to **??** DU
OMI CF	**??** %
Pandora DQ0	**??** %

Tranquility



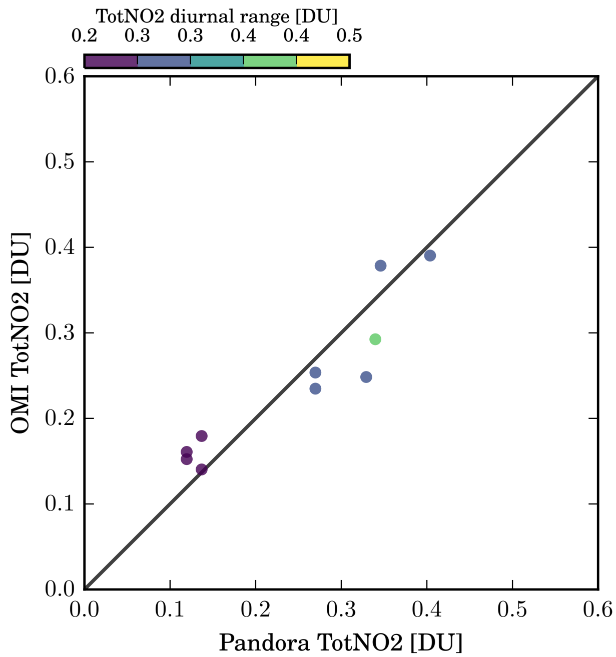
longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

UMBC



longitude, latitude	??, ??
num data points	??
max Pan. (Pans.)	??
CC	??
SLP	?? ± ??
OFFS	?? DU ± ?? DU
RMS	?? DU
mean	?? DU
MEDD	?? DU
25-75 percentile range	?? DU to ?? DU
10-90 percentile range	?? DU to ?? DU
min-max range	?? DU to ?? DU
OMI CF	?? %
Pandora DQ0	?? %

Visalia



longitude, latitude	-119.3930, 36.3141
num data points	585
max Pan. (Pans.)	1 (18)
CC	0.79
SLP	0.65 ± 0.05
OFFS	0.17 DU ± 0.04 DU
RMS	0.05 DU
mean	-0.05 DU
MEDD	-0.03 DU
25-75 percentile range	-0.07 DU to 0.02 DU
10-90 percentile range	-0.11 DU to 0.04 DU
min-max range	-0.12 DU to 0.04 DU
OMI CF	47.05 %
Pandora DQ0	98.25 %