1   **OMI Total Column Water Vapor Version 4 Validation and Applications**

2   Huiqun Wang[1], Amir Hossein Souri[1], Gonzalo González Abad[1], Xiong Liu[1] and Kelly Chance[1]

3   [1]. Smithsonian Astrophysical Observatory, 60 Garden Street, Cambridge, Massachusetts 02138,
4   USA

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6   *Correspondence to: Huiqun (Helen) Wang (hwang@cfa.harvard.edu)*

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8   **Abstract**

9   Total Column Water Vapor (TCWV) is important for the weather and climate. TCWV is
10   derived from the Ozone Monitoring Instrument (OMI) visible spectra using the Version 4.0
11   retrieval algorithm developed at the Smithsonian Astrophysical Observatory. The algorithm uses
12   a retrieval window between 432.0 and 466.5 nm and includes updates to reference spectra and
13   water vapor profiles. The retrieval window optimization results from the trade-offs among
14   competing factors.

15   The OMI product is characterized by comparing against commonly used reference datasets –
16   Global Positioning System (GPS) network data over land and Special Sensor Microwave Imager
17   / Sounder (SSMIS) data over the oceans. We examine how cloud fraction and cloud top pressure
18   affect the comparisons. The results lead us to recommend filtering OMI data with cloud fraction
19   less than f = 0.05 - 0.25 and cloud top pressure > 750 mb (or stricter), in addition to the data
20   quality flag, fitting RMS and TCWV range check. Over land, for f = 0.05, the overall mean of
21   (OMI-GPS) is 0.32 mm with a standard deviation (σ) of 5.2 mm, the smallest bias occurs when
22   TCWV = 10 – 20 mm, and the best regression line corresponds to f = 0.25; Over the oceans, for f
23   = 0.05, the overall mean of (OMI-SSMIS) is 0.4 mm (1.1 mm) with σ = 6.5 mm (6.8 mm) for
24   January (July), the smallest bias occurs when TCWV = 20 – 30 mm, and best regression line
25   corresponds to f = 0.15. For both land and the oceans, the difference between OMI and the
26   reference datasets is relatively large when TCWV is less than 10 mm. The bias for Version 4.0
27   OMI TCWV is much smaller than that for Version 3.0.

28   As test applications of the Version 4.0 OMI TCWV over a range of spatial and temporal
29   scales, we find prominent signals of the patterns associated with El Niño and La Niña, the high

30 humidity associated with a corn sweat event and the strong moisture band of an atmospheric

31 river (AR). A data assimilation experiment demonstrates that the OMI data can help improve the

32 Weather Research and Forecasting model (WRF)'s skill at simulating the structure and intensity

33 of the AR and the precipitation at the AR landfall.

1 Introduction

35 Water vapor is of profound importance for weather and climate. Through condensation, it

36 forms clouds that modify albedo, affect radiation and interact with particulate matter. In addition,

37 latent heat released from water vapor condensation can influence atmospheric energy budget and

38 circulation. Water vapor is the most abundant greenhouse gas, accounting for ~50% of the

39 greenhouse effect (Schmidt et al., 2010). Thus, monitoring the spatial and temporal distributions

40 of water vapor is crucial for understanding water-vapor related processes.

41 Water vapor has been measured using a variety of in situ and remote sensing techniques from

42 the ground, air and space. Satellite data provide global perspective and are indispensable for

43 constraining reanalysis products (Dee et al., 2011; Gelaro et al., 2017). The current satellite

44 water vapor datasets are evaluated through the Global Energy and Water cycle Exchanges

45 (GEWEX) Water Vapor Assessment program (Schröder et al., 2019). These datasets are derived

46 from visible, near infrared (NIR), Infrared (IR), microwave and Global Positioning System

47 (GPS) measurements. Each dataset has its own characteristics and contributes to the

48 understanding of water vapor in its own way. For example, microwave data are useful for both

49 clear-sky and cloudy-sky conditions, but are best suited for non-precipitating ice-free oceans due

50 to the complications associated with land surface emissivity; NIR data are best suited for the

51 land, as the surface albedo is low over the oceans; IR data are available over all surface types,

52 but are strongly influenced by clouds and less sensitive to the planetary boundary layer; visible

53 data are sensitive to the boundary layer over both land and the oceans, but are complicated by

54 uncertainties in clouds and aerosols (Wagner et al., 2013).

55 Total Column Water Vapor (TCWV, also called Integrated Water Vapor - IWV, or

56 Precipitable Water Vapor - PWV) can be retrieved from the 7ν water vapor vibrational polyad

57 band (around 442 nm) despite the weak absorption (Wagner et al., 2013). This made it possible

58 to derive TCWV from instruments measuring in the blue wavelength range. Since water vapor is

59 a weak absorber here, saturation of spectral lines is not of concern (Noël et al., 1999). Moreover,

60   the similarity between the land and ocean surface albedo in the blue wavelength range suggests a

61   roughly uniform sensitivity of the measurement over the globe (Wagner et al., 2013). However,

62   weaker absorption tends to result in larger relative uncertainties, especially for low TCWV

63   amount.

64   Using the visible spectra measured by the Ozone Monitoring Instrument (OMI), Wang et al.

65   (2014) retrieved Version 1.0 TCWV from 430 – 480 nm and publically released the data on the

66   Aura Validation Data Center (AVDC, https://avdc.gsfc.nasa.gov). Wang et al. (2016) found that

67   the Version 1.0 data generally agree with ground-based GPS data over land, but are significantly

68   lower than the microwave observations over the oceans. They found that using a narrower

69   retrieval window (427.7 – 465 nm) in Version 2.1 could improve the data over the oceans

70   without adversely affecting the results over land much. However, the Version 2.1 data were only

71   generated for a few test months and not released to the public. An interim Version 3.0 OMI

72   TCWV product is available at AVDC. Compared with Version 2.1, Version 3.0 uses the

73   reference spectrum for water vapor from the latest HITRAN database (Gordon et al., 2016) and

74   that for liquid water from Mason et al. (2016), as well as the newest cloud product (Veefkind et

75   al., 2016). The Version 3.0 retrieval window (427.0 – 467.0 nm) is adjusted from that for

76   Version 2 within 2 nm on each end based on fitting uncertainty for a randomly selected test orbit.

77   This paper focuses on Version 4.0 OMI TCWV which has replaced Version 3.0 on AVDC.

78   We present the Version 4.0 retrieval algorithm which incorporates a more vigorous systematic

79   optimization for the retrieval window and miscellaneous updates. We characterize the

80   performance of the Version 4.0 dataset by comparing with well-established references, such as

81   the GPS network data and the Special Sensor Microwave Imager / Sounder (SSMIS)

82   observations. We also assess the performance of Version 4.0 against that of Version 3.0. To

83   provide practical guide to users of the new data, we investigate the influence of cloud fraction

84   and cloud top pressure on the comparisons. Based on the results, data filtering criteria are

85   recommended. As an additional check on the Version 4.0 product, we show test applications of

86   the data to a range of spatial and temporal scales, including El Niño / La Niña, a corn sweat

87   event and an atmospheric river (AR) event. For the first time, a data assimilation experiment for

88   the AR event demonstrates that the OMI TCWV data can provide useful constraint for weather

89   prediction.

2 Retrieval Algorithm

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91   OMI on board the Aura spacecraft is a UV/Visible imaging spectrometer (Levelt et al.,

92   2006). It has been making daily global observations at a nominal 13×24 km nadir resolution

93   from a 1:30 PM equator crossing time polar orbit since October 2004. The UV-Visible channel

94   of OMI covers 350-500 nm at a spectral resolution of about 0.5 nm.

95   TCWV is derived from the OMI visible spectrum using a commonly used two-step approach.

96   First, the Slant Column Density (SCD, molecules/cm^2) is retrieved from a spectral fitting

97   algorithm. Then, the Vertical Column Density (VCD, molecules/cm^2) is calculated from the ratio

98   of SCD and Air Mass Factor (AMF) (Palmer et al., 2001). VCD can be converted to TCWV

99   using 10^{23} molecules/cm^2 = 29.89 mm. The details of the two-step procedure can be found in

100   González Abad et al. (2015). The specifics of Version 4.0 are discussed below.

101   The Version 4.0 spectral fitting parameters are summarized in Table 1. In the nonlinear least

102   square fitting, we consider wavelength shift, under-sampling, closure polynomials (3rd order

103   multiplicative and additive), reference spectroscopic spectra of water vapor, interfering

104   molecules (O_3, NO_2, O_4, liquid water, $C_2H_2O_2$ and IO) and Raman scattering (the Ring effect,

105   vibrational Raman scattering of air and the water Ring effect). In comparison with previous

106   versions, Version 4.0 no longer fits common mode (i.e. the mean of the fitting residual, González

107   Abad et al., 2015). It turns out that the common mode for land is different than that for ocean

108   (Wang et al., 2014). Previous retrievals derive a common mode for each orbit swath using the

109   pixels in the low latitudes which often includes both land and ocean scenes. Thus, the derived

110   common mode depends on the proportion of land versus ocean pixels of the spacecraft orbit and

111   is not universally suitable for all the pixels of the swath. Statistics for Orbit 10423 show that

112   although the mean of SCD differs little between the retrievals with and without common mode in

113   the fitting (0.1 mm), the standard deviation of SCD between them can be significant (1.7 mm).

114   Most of the settings in Table 1 are shared between Version 3.0 and 4.0, except that Version 3.0

115   uses HITRAN 2016 (Gordon et al., 2016) as the water vapor reference spectrum, includes

116   common mode in the fitting, but does not consider vibrational Raman scattering of air (Lampel et

117   al., 2015a). We revert to the HITRAN 2008 water vapor spectrum (Rothman et al., 2009) in

118   Version 4.0 because validation results show that it leads to better agreements with the GPS and

119   SSMIS TCWV data (Section 3). We did not apply the correction of Lampel et al. (2015b) to the

120 HITRAN 2008 water vapor spectrum. It is recently found that HITRAN 2016 is adversely

121 affected by an issue with line broadening for water vapor in the blue wavelength range and

122 improvements are being made for the next HITRAN release (the HITRAN group, personal

123 communication).

124 **Table 1.** Parameters used in Version 4.0 spectral fitting for OMI total column water vapor.

Wavelength shift	Solar reference spectrum	Dobber et al. (2008)
Target	H_2O	288K, Rothman et al. (2009)
Interference molecules	O_3	228K, Brion et al. (1993)
	NO_2	220K, Vandaele et al. (1998)
	O_4	293K, Thalman and Volkamer (2013)
	Liquid water	Mason et al. (2016)
	$C_2H_2O_2$	296K, Volkamer et al. (2005)
	IO	298K, Spietz et al. (2005)
Raman scattering	Ring effect	Chance and Spurr (1997)
	Water Ring	Chance and Spurr (1997)
	Air Vibrational Raman	Lampel et al. (2015a)
Other	Additive polynomial	3rd order
	Multiplicative polynomial	3rd order
	Under-sampling	Chance et al. (2005)

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126   To optimize the retrieval window, we randomly selected OMI Orbit number 10426 (on July

127 1, 2006) to examine the effect of varying the starting and ending wavelengths around the 7ν

128 water vapor absorption band. The orbit swath contains 60×1644 ground pixels and covers parts

129 of Australia, the Pacific, China and other areas. We systematically adjust the starting wavelength

130 within 426.0-435.0 nm and the ending wavelength within 460.0-468.5 nm, both at 0.5 nm steps.

(a) median(rms × 10⁴)

(b) median SCD uncertainty (mm)

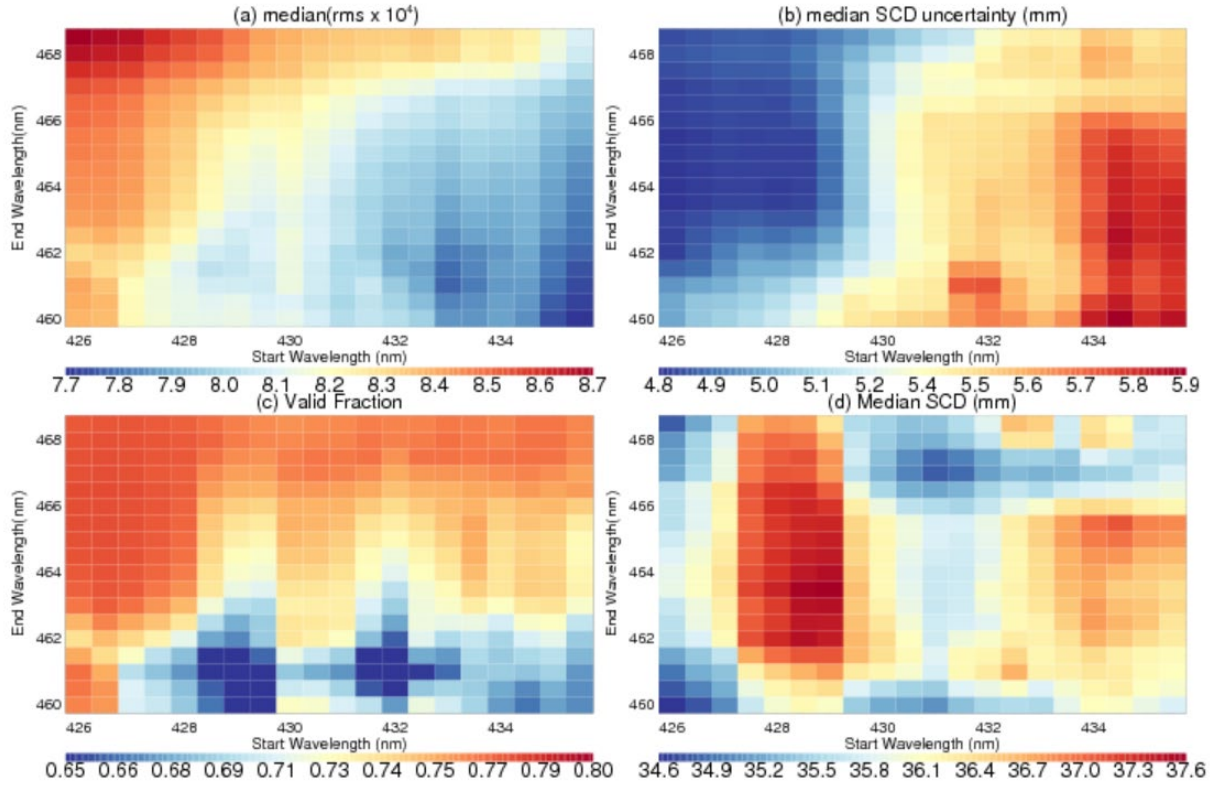(c) Valid Fraction

(d) Median SCD (mm)

Figure 1. Sensitivity of the retrieval to the start and end wavelengths (nm) of the retrieval window for OMI Orbit number 10426. (a) Median of fitting RMS×10^4; (b) median of water vapor SCD fitting uncertainty in mm; (c) valid fraction for retrievals; (d) median SCD in mm.

In previous versions, the fitting window is selected based on the fitting uncertainty (Wang et al., 2014, 2016). For Version 4.0, we consider the following four factors. (1) Figure 1a shows that the median of the fitting Root Mean Squared error (RMS) is smaller toward the lower right corner of the domain (i.e., longer start wavelength and shorter end wavelength); (2) Figure 1b shows that the medium fitting uncertainty of water vapor SCD decreases toward the upper left corner; (3) Figure 1c shows that the fraction of valid retrievals for the orbit generally increases toward the upper part of the domain. Valid retrievals here refer to those that pass the main data quality check (MDQFL = 0) and have positive SCDs. The main data quality check ensures that the fitting has converged, the SCD is < 5×10^{23} molecules/cm^2 (149.45 mm) and within 2σ of the fitting uncertainty. The SCD threshold here is meant to filter out large outliers. For reference, the largest TCWV of the GPS and SSMIS datasets used in Section 3 is about 75 mm. At low latitudes where TCWV is large, more than 90% of the OMI AMFs are between 0.5 and 2.0; (4) The length of the retrieval window increases with the difference between the end and start

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148   wavelengths. The general patterns exhibited by Orbit number 10426 in Figure 1 also hold for

149   Orbit number 10423 which cuts across the Pacific near the dateline.

150   Ideally, we would like to have small fitting RMS to reduce the residual's amplitude and

151   structure, a small fitting uncertainty to reduce error, a large fraction of valid data to increase data

152   volume and a long retrieval window to include more information into the fitting. However, these

153   criteria cannot be met simultaneously. As a compromise, we select the wavelength interval

154   between 432.0 nm and 466.5 nm as the retrieval window for Version 4.0. For Orbit number

155   10426, this leads to a median fitting RMS of 8.1×10^{-4}, a median SCD uncertainty of 5.4 mm, a

156   valid fraction of 0.75 and a window length of 34.5 nm (Figure 1). Figure 1d shows that the

157   median SCD for Orbit number 10426 varies between 34.6 mm and 37.6 mm. This 3 mm

158   difference corresponds to an 8% variation and exhibits a complex pattern within the domain. The

159   Version 4.0 retrieval window leads to a median SCD of 35.5 mm for Orbit number 10426 which

160   is near the beginning of the middle third of the SCD range. The ratio between the median SCD

161   uncertainty and the median SCD (i.e., the relative SCD uncertainty) is about 0.15. Note that this

162   value is for the whole orbit which includes a wide range of SCDs. As shown in Supplementary

163   Figure 1, the relative SCD uncertainty is >1.2 for SCD = 0 – 10 mm, drops to about 0.4 for SCD

164   = 10 – 20 mm, and to about 0.1 for SCD > 40 mm.

165   The AMF is calculated by convolving scattering weights with the shape of water vapor

166   vertical profile (González Abad et al., 2015). The scattering weight is interpolated from the same

167   look-up table as that used in Wang et al. (2016). The scene specific information used in the AMF

168   calculation is listed in Table 2. By propagating typical errors for surface albedo (15%), cloud

169   fraction (10%) and cloud top pressure (15%), we find that the AMF error for a typical orbit

170   (number 10426) is mostly < 3%, though for cloudy pixels over land, the AMF error can be up to

171   15%. Version 4.0 uses the 0.5°×0.667° monthly mean MERRA-2 water vapor profile (Gelaro et

172   al., 2017) for the month and year corresponding to the retrieval, while previous versions used the

173   monthly mean of 2007 for all years. To evaluate the error associated with gas profiles, we

174   compare the TCWV calculated using the daily MERRA-2 profile against that calculated using

175   the monthly MERRA-2 profile for July 2006 (for TCWV within the 0 – 75 mm range). Results

176   show that TCWV(daily) – TCWV(monthly) has a mean (median) of 0.3 mm (0 mm) with a

177   standard deviation of 5.0 mm. When comparing the TCWV calculated using the daily MERRA-2

178   profile against that calculated using the daily ERA-Interim profile for July 2006, we find that

179 TCWV(MERRA-2) – TCWV(ERA-Interim) has a mean (median) of -0.1 mm (0 mm) with a

180 standard deviation of 2.8 mm. Thus, gas profiles can introduce substantial scatter to the retrieved

181 TCWV. AMF is highly sensitive to clouds (Wang et al., 2014; Vasilkov et al., 2017). Version 4.0

182 uses the cloud information from Veefkind et al. (2016). The primary difference with the Acarreta

183 et al. (2004) cloud product used in Version 1.0 and 2.1 is in the cloud top pressure for cloud

184 fraction f < 0.3. In addition to the factors in Table 2, aerosol and surface bi-directional

185 reflectance distribution function (BRDF) influence the AMF (Lorente et al., 2017; Vasilkov et

186 al., 2017), but have not been considered in the retrieval yet.

187 **Table 2.** Parameters used in AMF calculation

Solar Zenith Angle	OMI L1B data
View Zenith Angle	
Relative Azimuth Angle	
Surface Albedo	OMLER (Lambert equivalent reflectance) Kleipool, et al. (2008)
Cloud fraction	OMCLDO2 (derived from O_2-O_2) Veefkind et al. (2016)
Cloud top pressure	
Surface pressure	MERRA-2 monthly data (0.5°×0.667°), Gelaro et al. (2017)
Water vapor profile	

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189 **3 Validation**

190   To validate the Version 4.0 OMI TCWV data, we compare them against two commonly used

191 reference datasets – a GPS network dataset for land and a microwave dataset for the oceans.

192 **3.1 OMI and GPS over land**

193   To assess the Version 4.0 OMI TCWV over land, we compare against the GPS network data

194 downloaded from NCAR (rda.ucar.edu/datasets/ds721.1). The GPS data are composed of 2-

195 hourly TCWV at International GNSS Service (IGS), SuomiNet and GEONET stations, and have

196 an estimated error of < 1.5 mm (Wang et al., 2007; Ning et al., 2016). The subset of IGS-

197 SuomiNet data for the whole year of 2006 is used in this paper. The geographical distribution of

198 the stations can be found in Wang et al. (2016). Most of the stations are concentrated in North

199 America and Europe, fewer are scattered on other continents.

200   OMI TCWV data are filtered using the following criteria. The stripes in Level 2 swaths due

201 to systematic instrument error are removed using the SCD scaling procedure described in Wang

202   et al. (2016). The pixels affected by OMI's row anomaly are filtered out

203   (projects.knmi.nl/omi/research/product/rowanomaly-background.php), as well as negative or

204   extremely large (i.e., TCWV > 75 mm) values. For the clear-sky comparison in Figure 3, we

205   require cloud fraction < 5% and cloud top pressure > 750 mb, in addition to MDQFL = 0 and

206   fitting RMS < 0.001. The cloud fraction and cloud top pressure are from the OMCLDO2 cloud

207   product (Veefkind et al., 2016) and are included in the Level 2 OMI product for ease of data

208   filtering. On a typical day of July 1, 2006, among the OMI data that pass the MDQFL and

209   TCWV range test, cloud fraction < 0.05 accounts for 35% of the data, cloud top pressure > 750

210   mb accounts for 53% of the data and RMS < 0.001 accounts for 72% of the data.

211   To co-locate GPS and OMI data, we select the GPS data observed between 1200 LT and

212   1500LT. This 3-hour local time range covers the OMI overpass time. We average the qualified

213   OMI data within 0.25° longitude × 0.25° latitude of the GPS stations for each day. To minimize

214   the influence of local topography (e.g., mountain peaks, river valleys), if a station's elevation is

215   more than 250 m different than the mean elevation within the corresponding 0.25°×0.25° grid

216   square, then it is excluded from the analysis. The 0.25°×0.25° topography was downloaded from

217   www.temis.nl/data/topo/dem2grid.html. The comparison between OMI and GPS is made for

218   TCWV within the range of 0 – 75 mm as the largest TCWV for the GPS data is about 75 mm.

219   The co-locating procedure leads to about 11,000 co-located data points for the entire year of

220   2006.

221   Figure 2 shows the comparison between the resulting co-located GPS and Version 4 OMI

222   TCWV. The top panel shows the histogram of OMI-GPS (in 0.5 mm bins). The bin from -0.5 to

223   0.0 mm corresponds to the peak of the distribution. The overall mean (median) of OMI-GPS is

224   0.32 mm (0.35 mm), with a standard deviation of 5.2 mm. The mean (median) absolute error is

225   3.9 mm (3.0 mm).

226   The bottom panel of Figure 2 shows the joint distribution of the co-located GPS and Version

227   4.0 OMI data. The count for each 0.5 mm bin is normalized by the maximum of all bins. About

228   34% of the data have TCWV < 10 mm, 72% have TCWV < 20 mm and 90% have TCWV < 30

229   mm. There is a general linear correlation between GPS and OMI data, with a correlation

230   coefficient of r = 0.87 (R^2 = 0.76). The linear regression line (OMI = 2.22 + 0.88 * GPS, where

231   OMI and GPS TCWV are in mm) has a significant positive intercept and a slope that is less than

232   one. This indicates a positive bias of OMI against GPS for small TCWV and a negative bias for

233   large TCWV. Indeed, as indicated at the top of the panel, the mean of OMI-GPS for each 10 mm

234   GPS TCWV bin decreases from 1.7 mm for TCWV = 0 – 10 mm to -2.3 mm for TCWV = 40 –

235   50 mm, though the fraction of data for TCWV > 40 mm is < 3%. The corresponding standard

236   deviation (σ) increases from 3.5 mm to 7.9 mm. The minimum bias of 0.2 mm occurs for TCWV

237   in the 10 – 20 mm bin. The large positive bias of the 0 – 10 mm bin (as compared with the

238   TCWV of the bin) has significant adverse effect on the regression line. For TCWV > 10 mm, the

239   regression line (OMI = 1.51 + 0.91 × GPS) is better.

240   In comparison, although Version 3.0 OMI is similarly correlated with GPS (correlation

241   coefficient r = 0.86), it has a much larger positive bias of 2.8 mm (with a standard deviation of

242   5.5 mm). The large bias is attributed to the much larger SCD of Version 3.0 (Supplementary

243   Figure 2b), as the AMFs of both versions roughly follow the 1:1 line (Supplementary Figure 2a).

244   Sensitivity tests show that the larger Version 3.0 SCD is primary due to the water vapor

245   reference spectrum. If the water vapor reference spectrum in Version 4.0 is replaced with that of

246   Version 3.0 (Test 1), then the median SCD increases by about 4.5 mm for Orbit 10423

247   (Supplementary Figure 2c). Modifying the retrieval window for Version 3.0 cannot sufficiently

248   reduce the retrieved SCD, therefore cannot make significantly better agreement with the

249   reference TCWV data. As Version 4.0 shows better performance, this paper focuses on

250   characterizing Version 4.0 to provide useful information to potential users. In subsequent

251   discussions, OMI data refer to Version 4.0 unless specified otherwise.
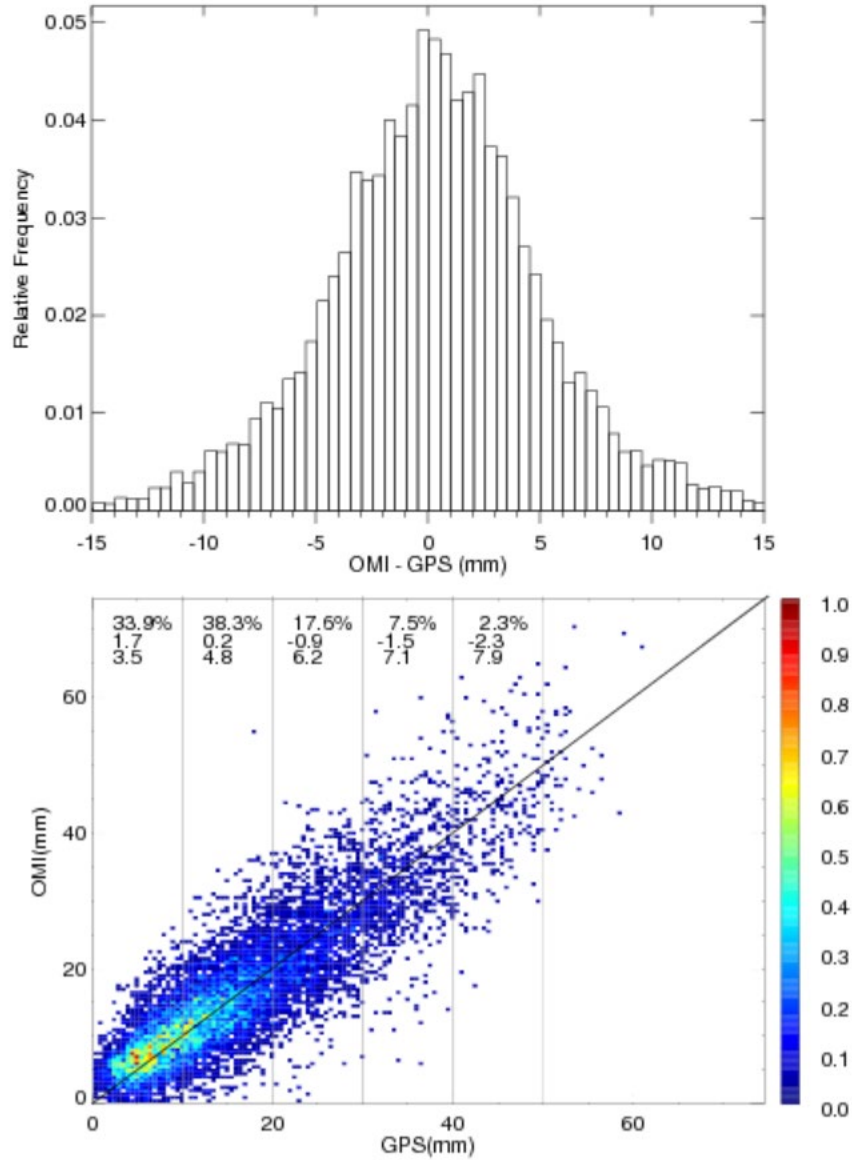
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Figure 2. Comparison between co-located GPS and OMI TCWV (mm) for all days in 2006. The
data filtering criteria include cloud fraction < 5%, cloud top pressure > 750 mb, and others
discussed in the text. (Top) Relative frequency of occurrence for OMI-GPS (mm). (Bottom)
Normalized joint distribution of GPS versus OMI TCWV (mm). The three lines of text from top
to bottom indicate the percentage of data points (1st), the mean of OMI-GPS in mm (2nd), and
the standard deviation of OMI-GPS in mm (3rd) for each 10 mm GPS TCWV, respectively. The
1:1 is plotted for reference.

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262   OMI TCWV retrieval is highly sensitive to clouds (Wang et al., 2014). In Figure 3, we

263   examine the effect of OMI cloud fraction threshold (f) on the comparison while keeping other

264   data filtering criteria the same as those for Figure 2 (i.e., cloud fraction < f, cloud top pressure <

265   750 mb, MDQFL = 0, fitting RMS < 0.001 and 0 < TCWV<75 mm). From f = 0.05 to f = 0.55,

266   the number of co-located data pairs (N) more than triples, the mean of OMI-GPS increases from

267   0.32 mm to 1.66 mm, the standard deviation of OMI-GPS increases from 5.2 mm to 6.1 mm. The

268   linear correlation coefficient (r) increases from r = 0.87 at f = 0.05 to r ~ 0.90 at f = 0.15, then

269   levels off for larger cloud fraction thresholds. It should be noted that the error in cloud top

270   pressure decreases with cloud fraction in the OMCLDO2 product (Veefkind et al., 2016). As a

271   result, f = 0.05 corresponds to the largest uncertainty in cloud top pressure, and the error will

272   propagate into OMI TCWV through AMF, leading to smaller correlation coefficient than those

273   for larger f values.

274   In addition, as shown by the GPS versus OMI joint distributions for different cloud fraction

275   thresholds in Figure 4, the f ≥ 0.15 cases have larger effective dynamical ranges which tend to

276   favor better correlations. For example, there is a larger fraction of data pairs with TCWV > 30

277   mm for f = 0.15 than for f = 0.05. The regression line for f = 0.15 (OMI = 1.26 + 0.96 * GPS)

278   shows an apparent improvement over that for f = 0.05 (OMI = 2.22 + 0.88*GPS). The best

279   regression line is arguably that for f = 0.25 (OMI = 1.16 + 0.99*GPS) or f = 0.35 (OMI = 1.19 +

280   1.00*GPS), though the mean bias and scatter are larger than those for f < 0.25 (Figure 4).

281   In brief, f = 0.05 leads to the lowest overall bias and scatter of the co-located data; f = 0.15

282   doubles the number of co-located data pairs and leads to the largest improvement in the

283   correlation coefficient; f = 0.25 (or 0.35) leads to the best linear regression line; the bias and

284   standard deviation increase with cloud fraction threshold. Hence, cloud fraction thresholds in the

285   range of f = 0.05 – 0.25 seems reasonable for filtering OMI TCWV, depending on applications.
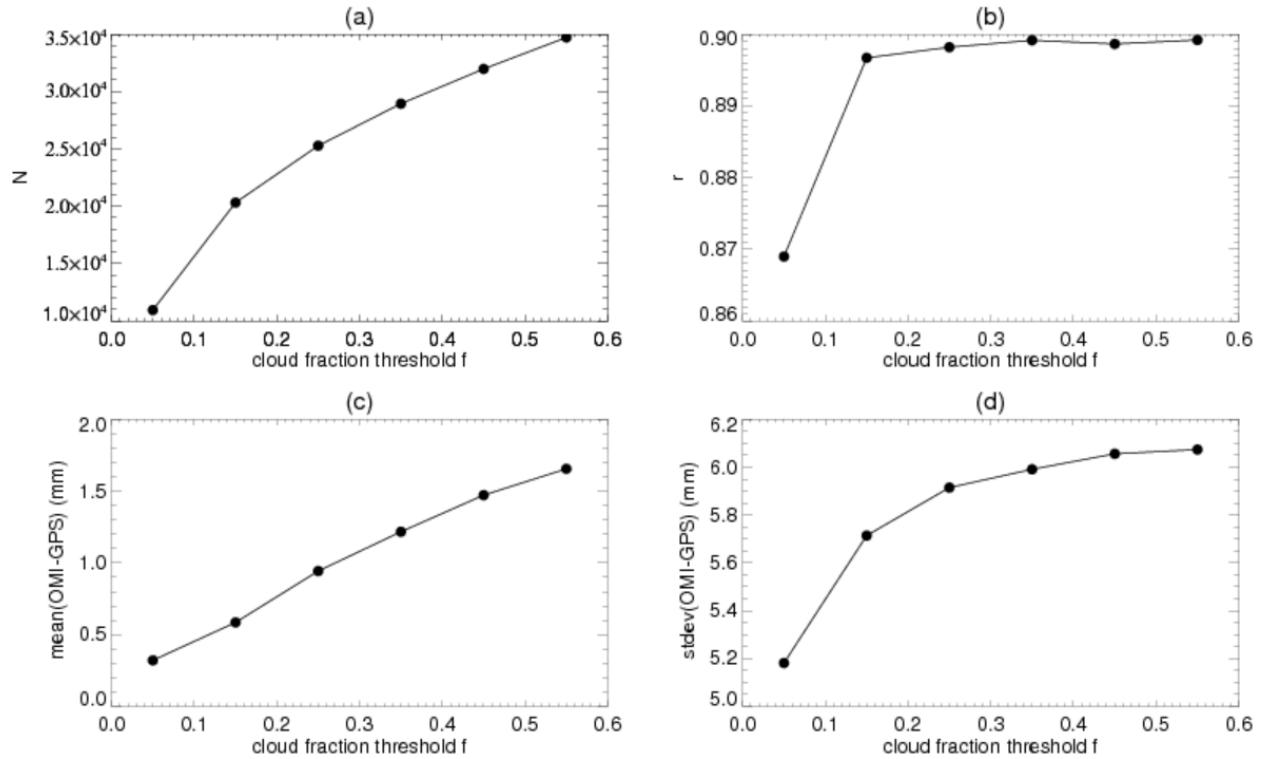
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Figure 3. Dependence of various parameters on the cloud fraction threshold (f) used for filtering

287   OMI data. Other filtering criteria remain the same as those for Figure 2. The parameters are (a)

288   number of co-located OMI and GPS data pairs; (b) linear correlation coefficient between OMI

289   and GPS TCWV; (c) mean of OMI-GPS in mm; (d) standard deviation of OMI-GPS in mm.

290   Results are derived from the co-located Version 4.0 OMI and GPS data for the whole year of
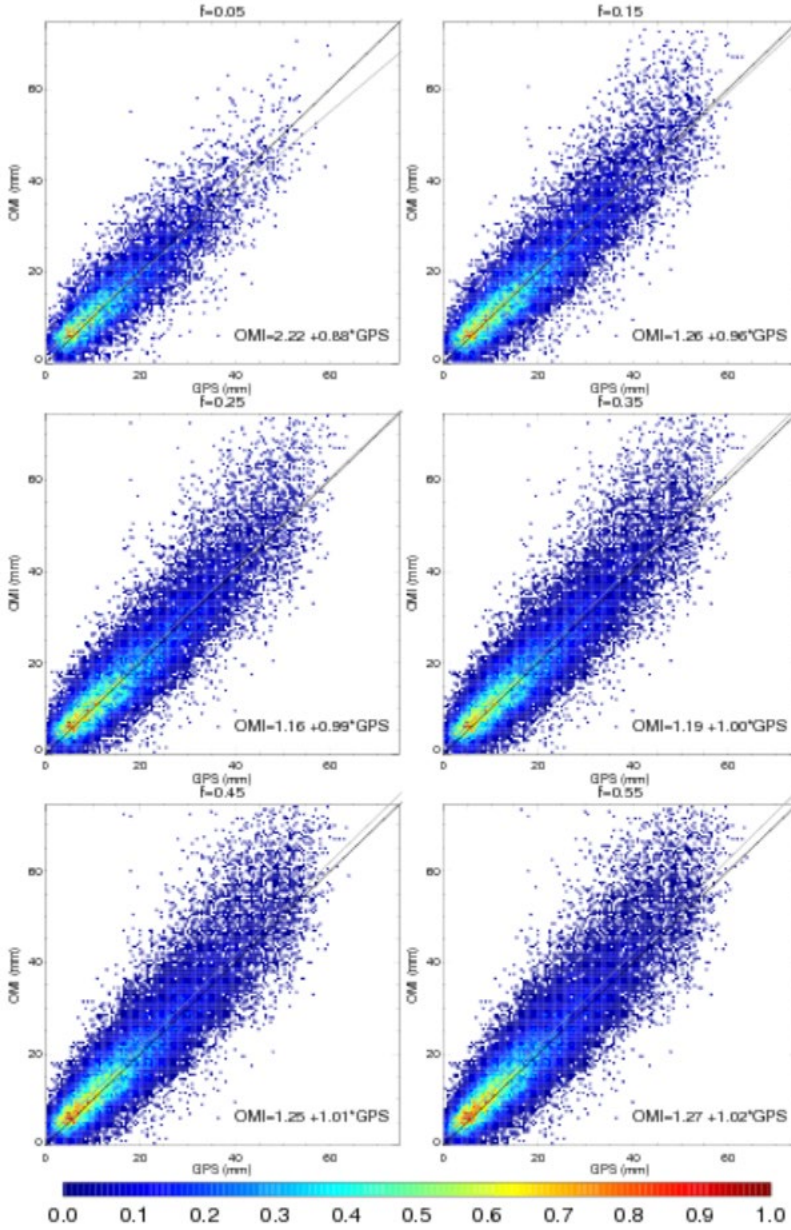
291   2006.

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Figure 4. Normalized joint distributions of GPS versus Version 4.0 OMI TCWV for different cloud fraction thresholds. Results are derived from the co-located data pairs for 2006. The OMI data filtering criteria are the same as those for Figure 3. In each panel, the 1:1 line is plotted in black, the linear regression line is plotted in gray and indicated by the formula in the lower right corner.

To further characterize the effect of cloud fraction threshold on the comparison between GPS and OMI, in Figure 5, we examine the mean and standard deviation (σ) of OMI-GPS for each 10 mm GPS TCWV bin. The results are derived from the same sets of co-located GPS and OMI

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302   data as those used in Figure 3 and Figure 4. The filled symbols are for the cases where the

303   number of GPS and OMI data pairs within the corresponding TCWV bin is > 1% of the total

304   number of data pairs, and the open symbols are for < 1%. As the filled symbols represent better

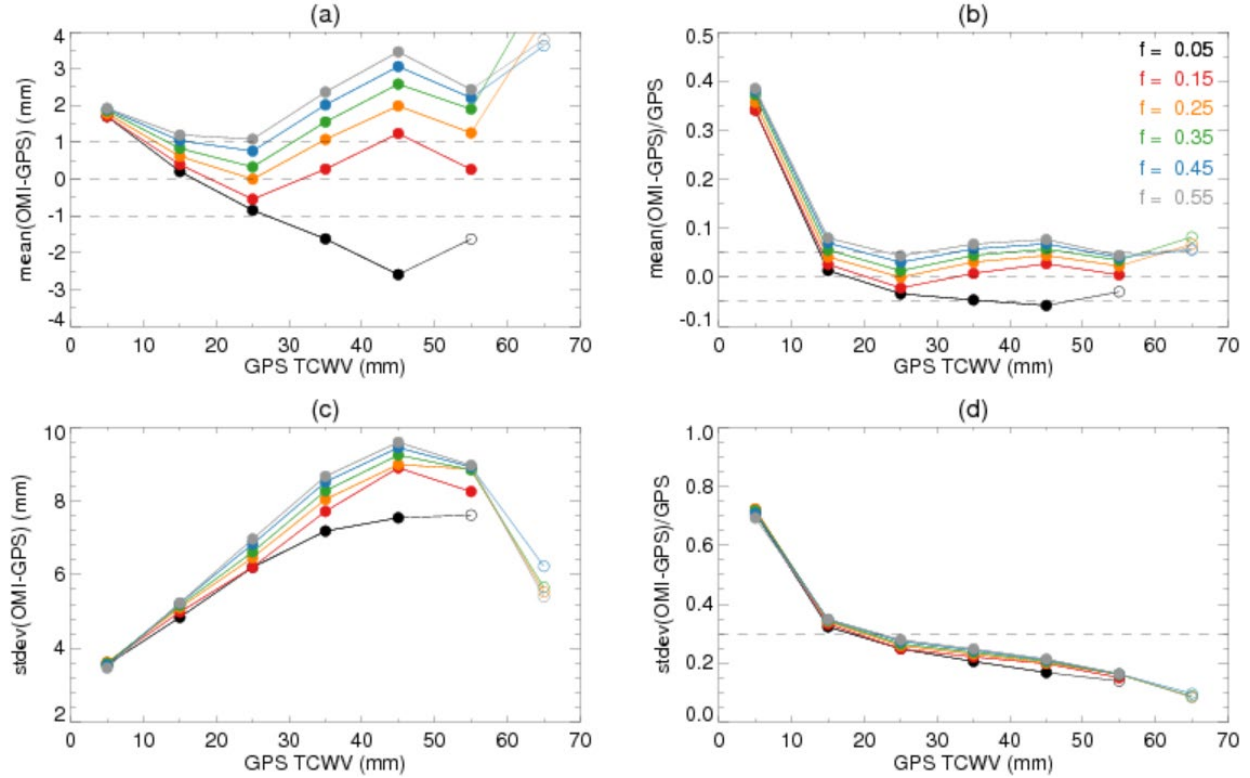305   statistics, we will focus on them below.

307   **Figure 5.** Parameters for each 10 mm TCWV bin. Curves with different colors are for different

308   cloud fraction thresholds (f) as indicated in Panel (b). The OMI filtering criteria remain the same

309   as those for Figure 3 and 4. Symbols are filled if the fraction of data pairs within the TCWV

310   interval is > 1% of all the available data pairs, and are open otherwise. The parameters are (a)

311   mean of OMI-GPS in mm, (b) relative bias defined as (OMI-GPS)/GPS, (c) standard deviation

312   (σ) of OMI-GPS in mm, and (d) relative scatter defined as σ/GPS. Results are for all days in

313   2006. Dashed lines are meant to facilitate visualization.

314

315   Figure 5(a) shows that the means of OMI-GPS vary between ±4 mm following "V"-shaped

316   curves whose minima occur in the TCWV = 20 – 30 mm bin except for f = 0.05. The curves shift

317   upward with increasing cloud fraction thresholds, suggesting that OMI cloudy-sky TCWV is

318   generally larger than OMI clear-sky TCWV. Other things being equal, cloud formation indicates

15

319   water vapor saturation and therefore a larger amount of TCWV than that under clear-sky

320   condition. The smallest absolute bias for 10 < TCWV < 20 mm occurs at f = 0.05, that for 20 <

321   TCWV < 30 mm occurs at f = 0.25, and that for 30 < TCWV < 40 mm occurs at f = 0.15. The f =

322   0.15 and f = 0.25 curves show the best overall performance according to Figure 5(a) as they are

323   within 1 mm of zero for 10<TCWV<40 mm, while other curves come within 1 mm of zero in

324   narrower TCWV ranges. Figure 5(b) shows the relative bias which is defined as the mean of

325   (OMI-GPS)/GPS. The relative biases decrease sharply from ~40% to ~5% as GPS TCWV

326   increases from the TCWV = 0 – 10 mm bin to the TCWV = 10 – 20 mm bin, and generally stay

327   less than ~5 – 10 % for larger TCWV values. Figure 5(c) shows that σ increases from ~3.5 mm

328   for TCWV = 0 - 10 mm to ~9.5 mm for TCWV = 40 - 50 mm (the percentage of data with

329   TCWV > 50 mm is very small). In most cases, larger cloud fraction thresholds correspond to

330   larger σ values. This is consistent with the larger dynamical range (due to a larger fraction of

331   data with high TCWV) for larger cloud fraction threshold (Figure 4). In fact, the relative scatter,

332   defined as the mean of σ/TCWV, shows little difference among the f values (Figure 5d). The

333   relative scatter decreases with TCWV, with the sharpest decrease from ~0.7 to ~0.3 between

334   TCWV = 0 – 10 mm and TCWV = 10 – 20 mm (Figure 5d).

335   In short, Version 4.0 OMI agrees with GPS within 1 mm for 10<TCWV<40 mm when f =

336   0.15 and f = 0.25 are used; when f = 0.05 is used, the bias and scatter are the smallest for

337   10<TCWV<20 mm; but, for TCWV < 10 mm, OMI TCWV is too high and has large relative

338   scatter. The latter is expected from the low signal-to-noise ratio when TCWV < 10 mm in the

339   OMI retrieval.

340   **3.2 OMI and SSMIS over ocean**

341   To evaluate Version 4.0 OMI TCWV over the oceans, we compare against the microwave

342   TCWV data from SSMIS on board the Defense Meteorological Satellite Program (DMSP)'s F16

343   satellite. The SSMIS data are derived by Remote Sensing Systems (RSS) using their Version 7

344   algorithm (www.remss.com) and have a retrieval accuracy of better than 1 mm (Wentz, 1997;

345   Mears et al., 2015). For clear-sky comparison, we use the daily 0.25°×0.25° SSMIS data for

346   January and July 2006 and filter out the pixels affected by rain and cloud liquid water. Diedrich

347   et al. (2016) found that the diurnal cycle in TCWV is generally within 1% to 5% of the daily

348   mean, with a minimum between 0600 LT and 1000 LT and a maximum between 1600 LT and

349   2000 LT. To reduce the influence of diurnal cycle, we average the SSMIS data for the ascending

350   and descending orbits of F16 (~2000 LT and 0800 LT in 2006).

351   We generate daily 0.25°×0.25° Level 3 OMI TCWV from the de-striped Level 2 OMI

352   swaths, with the requirement that MDQFL = 0, fitting RMS < 0.001, 0<TCWV<75 mm, cloud

353   fraction < 0.05, and cloud top pressure > 750 mb. There are typically 15 Level 2 swaths per day.

354   The gridding program uses a tessellation method that weighs the contribution of a Level 2 data

355   point by its area within the Level 3 grid square and its spectrum fitting uncertainty (Wang et al.,

356   2014, 2016). The filtered daily Level 3 SSMIS and OMI data are compared for each month. We

357   find 548,223 and 847,678 co-located data pairs for January and July 2006, respectively.
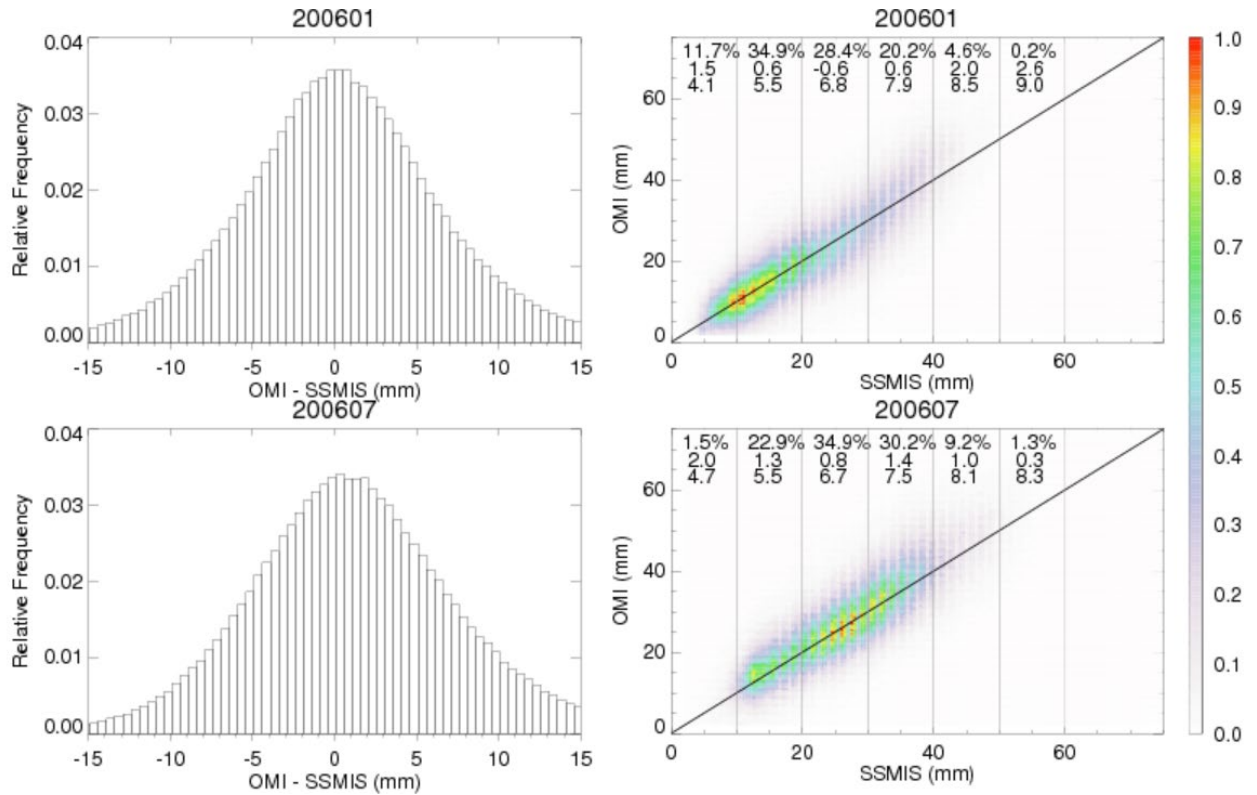

359   **Figure 6.** Comparisons between Version 4.0 OMI and SSMIS over the oceans for (top) January

360   2006 and (bottom) July 2006. Panels in the left column show the relative occurrence frequency

361   of OMI-SSMIS (mm). Panels in the right column show the normalized joint distribution of

362   SSMIS versus OMI TCWV (mm).

363

364   The left column of Figure 6 shows the distribution of OMI-SSMIS for January and July

365   2006. For July, the mean of OMI-SSMIS is 1.1 mm with a standard deviation of 6.8 mm, the

366   mean absolute error |OMI-SSMIS| is 5.2 mm; for January, the mean error, standard deviation and

367   mean absolute error are 0.4 mm, 6.5 mm and 5.0 mm, respectively. This suggests a slightly better

368   agreement for January than for July. In comparison with the (OMI-GPS) over land (Section 3.1),

369   OMI-SSMIS over the oceans has somewhat larger bias and standard deviation. However, as

370   TCWV over the oceans are generally larger than that over land (compare Figure 6 with Figure

371   2), the relative bias and scatter are actually similar.

372   The right column of Figure 6 shows the normalized joint distribution of SSMIS versus OMI

373   for January and July 2006. The correlation coefficients are r = 0.84 and 0.82 for January and

374   July, respectively. For January, OMI-SSMIS remains within 0.6 mm of zero for TCWV in the 10

375   – 40 mm range, but is 1.5 mm for TCWV in the 0 – 10 mm range (only a small fraction of data

376   pairs have TCWV > 40 mm); for July, OMI-GPS is 0.8 mm for the TCWV = 20 – 30 mm bin,

377   and varies between 0.8 and 1.4 mm for TCWV in the 10 – 50 mm range (only a small fraction of

378   data pairs have TCWV < 10 mm or > 50 mm). For TCWV bins that have > 5% of the data pairs,

379   the standard deviation of OMI-SSMIS vary between 4.1 and 8.1 mm. Overall, Version 4.0 OMI

380   data compare reasonably well with SSMIS data for TCWV in the 10 – 40 mm range, with the

381   smallest bias occurring in the TCWV = 20 – 30 mm bin.

382   The agreement between Version 4.0 OMI with SSMIS is better than that between Version 3.0

383   OMI and SSMIS. For July 2007, using the same data filtering criteria as before, we find that

384   Version 3.0 OMI – SSMIS has a mean of 3.2 mm with a standard deviation of 7.8 mm. The bias

385   is much larger than that for Version 4.0 OMI – SSMIS. Again, this is because of the much larger

386   SCD of Version 3.0 OMI TCWV due to the water vapor reference spectrum (Supplementary

387   Figure 1).

388   Table 3 shows the effect of cloud fraction threshold (f) on the comparison between SSMIS

389   and Version 4.0 OMI TCWV. The comparisons are performed using daily filtered Level 3 data

390   for July 2006. For SSMIS, we filter out pixels affected by rain. This is less restrictive than that

391   used for Figure 6 as pixels with cloud liquid water are kept here. For OMI, we require MDQFL =

392   0, RMS < 0.001, 0 < TCWV < 75 mm, cloud top pressure > 750 mb and cloud fraction < f.

393   Results show that OMI is higher than SSMIS by 0.02 – 3.07 mm for f = 0.05 – 0.45. The

394   difference between the f = 0.05 case of Table 3 and the f = 0.05 case of Figure 6 is due to the

395   relaxed SSMIS filtering criteria. The closest agreement in terms of the mean and standard

396   deviation of OMI-SSMIS occurs when f = 0.05. The number of SSMIS and OMI data pairs more

397   than doubles between f = 0.05 and f = 0.15. The linear correlation coefficient varies between

398   0.82 and 0.85 within the range of f values considered. The best linear regression line (OMI =

399   0.70 + 1.02 * SSMIS) occurs when f = 0.15. Therefore, for OMI over the oceans, we recommend

400   using cloud fraction threshold f = 0.05 – 0.15, in combination with the other usual data filtering

401   criteria, though users are advised to make their own decisions based on their tolerance and

402   applications.

403   **Table 3.** Effect of cloud fraction threshold on the comparison between SSMIS and Version 4.0

404   OMI TCWV for July 2006. f: OMI cloud fraction threshold; N: number of qualifying data pairs;

405   P: Percentage of qualifying data pairs with respect to the total number of qualifying SSMIS data

406   points; Mean: mean of OMI-SSMIS in mm; σ: standard deviation of OMI-SSMIS in mm; MAE:

407   Mean absolute error |OMI-SSMIS| in mm; r: correlation coefficient between SSMIS and OMI;

408   R^2: coefficient of determination for linear regression OMI = b + k * SSMIS, where OMI and

409   SSMIS are in mm; b: Intercept of linear regression; k: slope of linear regression.

f	N	P (%)	Mean	σ	MAE	r	R^2	b	k
0.05	1,048,879	7.4	0.02	7.11	5.39	0.82	0.67	1.43	0.95
0.15	2,837,032	20.0	1.38	7.82	5.84	0.84	0.71	0.70	1.02
0.25	3,932,468	27.8	2.20	8.09	6.09	0.84	0.71	1.11	1.04
0.35	4,819,185	34.0	2.73	8.22	6.24	0.85	0.72	1.45	1.05
0.45	5,537,003	39.1	3.07	8.26	6.32	0.85	0.72	1.62	1.06

410

411   Lowering the value for cloud top pressure threshold also leads to larger bias and scatter. For

412   example, when cloud fraction threshold f = 0.05 and cloud top pressure > 500 mb are used, the

413   mean and standard deviation of OMI-SSMIS become 0.80 mm and 7.9 mm, both are larger than

414   those for f = 0.05 in Table 3, though the linear regression line improves to OMI = 0.63 + 1.01 *

415   RSS due to an increase in the dynamical range of TCWV. It should be noted that the OMCLDO2

416   cloud product shows good agreement with ground-based observations for clouds at altitudes

417   lower than 2.5 km where single cloud layers dominate, but shows significant bias and large

418   scatter for clouds at altitudes higher than 2.5 km where multi-layer clouds dominate (Veefkind et

419   al., 2016). Thus, OMI TCWV data corresponding to low cloud top pressure (high altitude)

420   should be used with caution. Relaxing the filtering criteria for both cloud fraction and cloud top

421   pressure will lead to larger bias and scatter, therefore, it is not recommended. As an example, for

422   cloud fraction < 0.15 and cloud top pressure > 300 mb, the mean (standard deviation) of OMI-

423   SSMIS becomes 2.8 mm (9.0 mm) for July 2006.

424   **4 Application**

425   **4.1 El Niño / La Niña**

426   In Figure 7, we examine the signals associated with El Niño and La Niña in Version 4.0 OMI

427   TCWV. Panel (a) shows the Multivariate ENSO Index (MEI) from NOAA (Wolter and Timlin,

428   1998) (https://www.esrl.noaa.gov/psd/enso/mei/). Positive (negative) values correspond to El

429   Niño (La Niña) conditions. We examine the anomalies in TCWV for July 2010 (MEI = -1.103,

430   La Niña) and July 2015 (MEI = 1.981, El Niño) in the bottom row. Although these events are

431   strong within the OMI record (from 2005 to the present), they are mild in comparison with the

432   extrema. Between 1950 and 2018, the maximum MEI is 3.008 (in March 1983) and the

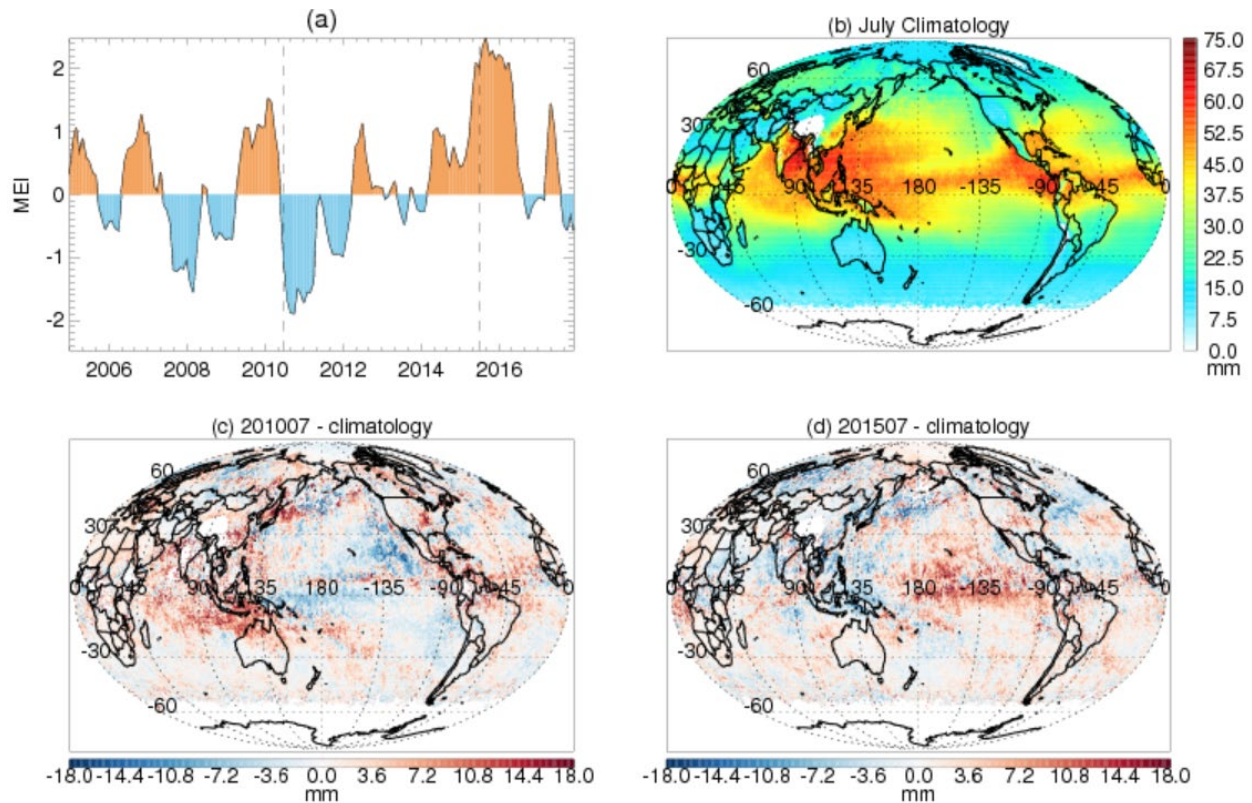433   minimum MEI is -2.247 (in June 1955).

434

Figure 7. Top row: (a) Multivariate ENSO Index. Dashed vertical lines indicate July 2010 and July 2015; (b) TCWV (mm) climatology for July derived from Version 4.0 OMI data. Bottom row: TCWV anomaly (mm) with respect to the climatology for (c) July 2010 and (d) July 2015.

To examine the changes in OMI TCWV under different conditions, we first generate the monthly Level 3 (0.5°×0.5°) OMI TCWV using the Level 2 data for July 2005 and July 2015 using the method described in Section 3.2 (with a cloud fraction threshold of $f = 0.15$ and a cloud top pressure threshold of 750 mb). Then, using the same data filtering criteria, we derive the climatology for July using all the Level 2 July data between 2005 and 2015 (Figure 7b). Finally, we plot the deviations from the climatology (mm) for July 2010 and July 2015 in Figure 7(c) and 7(d), respectively.

The TCWV anomalies exhibit large-scale patterns. The pattern for July 2015 largely opposes that for July 2010. Particularly, in July 2015 under El Niño conditions, TCWV are higher in the equatorial central and eastern Pacific and lower in the Indonesia region; while in July 2010 under La Niña conditions, TCWV are lower in the tropical eastern Pacific and equatorial western

451 Pacific and higher in Indonesia and the Indian Ocean. The overall patterns largely conform to the

452 results derived from the Hamburg Ocean Atmosphere Parameters and Fluxes from Satellite Data

453 (HOAPS) data (Shi et al., 2018).

454 **4.2 Corn Sweat**

455 "Corn sweat" refers to a hot and humid condition associated with heat waves which results in

456 large evapotranspiration rate in the Midwestern United States where cropland is often the

457 dominant land usage type. Besides evaporation, transpiration by plants, such as corn, draws

458 water from the soil to the atmosphere, enhancing the humidity and increasing the heat index. A

459 corn sweat event from July 18 to July 24 in 2016 made news in the US. This event is examined

460 in Figure 8 using the Version 4.0 OMI TCWV.

461 Figure 8 (a) and 8(b) show the Level 3 (0.25°×0.25°) OMI TCWV for July 18 - July 24

462 (7-day) and June 1 – August 31 (JJA) in 2016, respectively. The 7-day period corresponds to the

463 corn sweat event. The 0.25°×0.25° Level 3 data are derived using the same filtering criteria as

464 those used for Figure 7. Figure 8(c) indicates the anomaly associated with the corn sweat event

465 relative to the JJA mean. High TCWV is observed for the 7-day period from the Gulf coast to the

466 Midwestern US. Besides the Gulf region, the largest TCWV enhancements (of up to 18+ mm)

467 occur in parts of Iowa (IA), Missouri (MO), Illinois (IL) and Indiana (IN). Elevated TCWV is

468 also observed by several GPS stations in the general area during the same time period, though

469 coincident OMI data are not found at the stations (Supplementary Figure 3). At a few stations,

470 high TCWV persisted a couple more days after July 24 which is most likely related to a change

471 in the weather. As shown by the surface pressure observations at the GPS stations, the Midwest

472 is under the control of a high-pressure system during the corn sweat period and a low-pressure
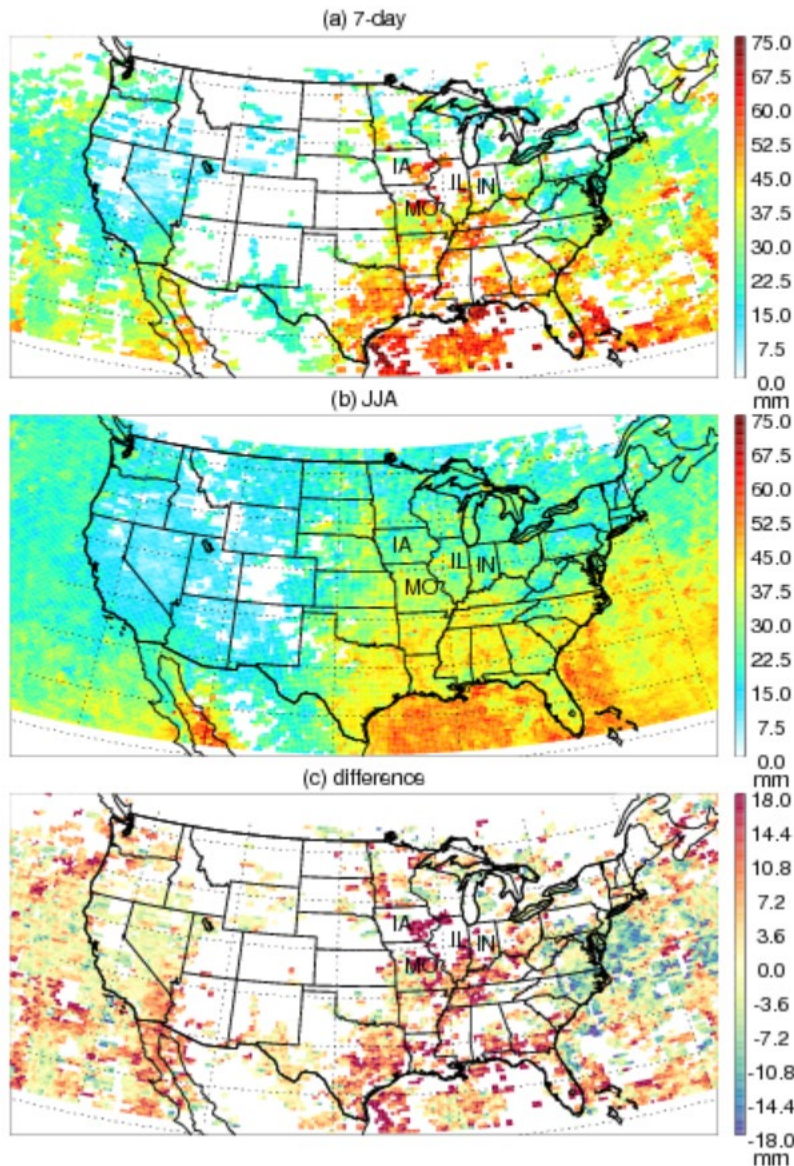
473 system afterwards (Supplementary Figure 4).

474

Figure 8. Level 3 (0.25°×0.25°) OMI TCWV (mm) generated using the Level 2 data during (a) July 18 - July 24, 2016 and (b) June 1 - August 31, 2016. (c) The difference of (a) - (b) in mm. The abbreviations for the states most affected by the event are indicated in the map.

To assess the significance of evapotranspiration for the Midwestern US during the corn sweat event, we carried out a sensitivity study using the Weather Research and Forecasting (WRF) model v3.9.1 (Skamarock et al., 2008). The model was run on a 36-km parent domain and a 12-km nested domain, covering the relevant areas of the US. The physics parameterizations

23

484   included the WRF Single-Moment (WSM) 6-Class Microphysics (Hong and Lim, 2006), the

485   Kain-Fritsch (KF) subgrid cumulus parameterization (Kain, 2004), the Yonsei University (YSU)

486   planetary boundary layer scheme (Hong et al., 2006), the Noah Land-Surface Model (Ek et al.,

487   2003; Chen and Dudhia, 2001), and the Rapid Radiative Transfer Model (RRTM). Horizontal

488   turbulent diffusion was based on the standard Smagorinsky first-order closure. The initial and

489   lateral boundary conditions were from the 3-hourly NCEP North American Regional Reanalysis

490   (NARR) at 32-km resolution. To reduce the uncertainty associated with lateral boundary

491   condition for the nested domain, we nudged the model in the parent domain toward the

492   reanalysis, but left the nested domain running freely.

493   To diagnose the contribution of evapotranspiration, the model was run from July 19th to July

494   22nd of 2016 with and without evapotranspiration (calculated in the Noah Land-Surface model).

495   The results for July 21st are shown in Figure 9. TCWV is generally lower in the interior of the

496   domain for the run without evapotranspiration (No ET). The higher TCWV in the No ET run

497   near the southern boundary reflects non-linear water vapor transport from the Gulf region.

498   Turning off evapotranspiration not only directly affects the water vapor flux from the surface but

499   also indirectly influences other meteorological variables, such as winds. Thus, there is a

500   difference in the water vapor flux across the domain boundary. The difference between the

501   default and No ET runs in Figure 9 suggests that evapotranspiration contributes about 15 – 25%

502   of the TCWV in the Midwestern US during the corn sweat event. A detailed study incorporating

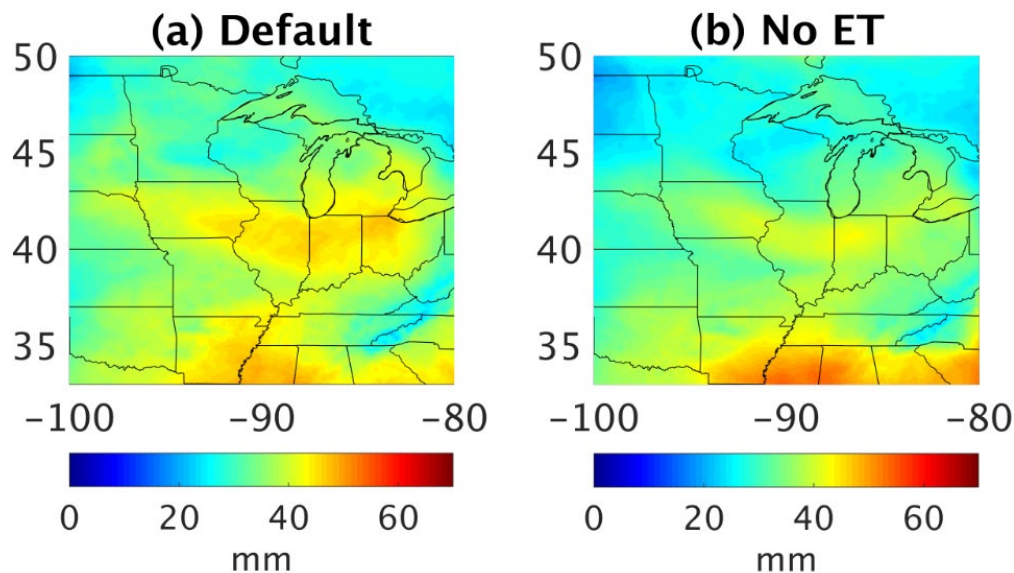503   TCWV data with the WRF model will be carried out in future work.

504

505 **Figure 9.** WRF simulations of TCWV (mm) for Midwestern US on 07/21/2016 for the run (a)
506 with and (b) without evapotranspiration.

507

508 **4.3 Atmospheric River (AR)**

509 **4.3.1 An Intense AR in OMI data**

510   ARs are narrow elongated bands with high TCWV in the atmosphere. With flow rates similar
511 to those of large rivers, ARs are highly important in the global hydrological cycle (Zhu and
512 Newell, 1998). Land-falling ARs can lead to heavy orographic precipitation that affects areas
513 such as the west coast of North America and Europe (Gimeno et al., 2014; Neiman et al., 2008b).

514   The extreme AR of November 6th – 7th, 2006 brought devastating flood to the Pacific
515 Northwest – the region in western North America bounded by the Pacific to the west and the
516 Cascade mountain range to the east. This AR is described in detail in Neiman et al., 2008a. The
517 signature of this AR is captured in the Version 4.0 OMI TCWV data. The left column of Figure
518 10 shows the Level 3 OMI TCWV and its anomaly on November 6th, 2006. The Level 3 data are
519 generated following the same procedure as that used for Figure 8. Although many pixels are
520 missing because of the cloud filtering (cloud top pressure > 750 mb, cloud fraction < 0.15) and
521 other criteria, the leading edge of the AR is noticeable as an elongated band of high TCWV (15+
522 mm above the climatology) extending from Hawaii to Northern California (indicated by arrows
523 in Figure 7(b) and 7(c)). The position of the AR in OMI TCWV agrees well with that in Special
524 Sensor Microwave/Imager (SSM/I) microwave observation (Neiman et al., 2008a).

525   The right column of Figure 10 shows the Level 3 OMI ozone mixing ratio interpolated to 200
526 mb and its anomaly. The OMI ozone data are retrieved using the SAO ozone profile algorithm
527 (Liu et al., 2010; Huang et al., 2017, 2018). The climatology is derived by averaging all monthly
528 Level 3 data for November from 2004 to 2017. The global distribution of ozone at 200 mb shows
529 low mixing ratio in the low latitudes and high mixing ratio in the high latitudes, opposite to the
530 global distribution of TCWV. The anomaly shows a curvilinear band of high ozone that is
531 parallel to the AR in the left column, but is located further to the west. This feature indicates
532 intrusion of ozone rich stratospheric air along the polar front, and is associated with the same
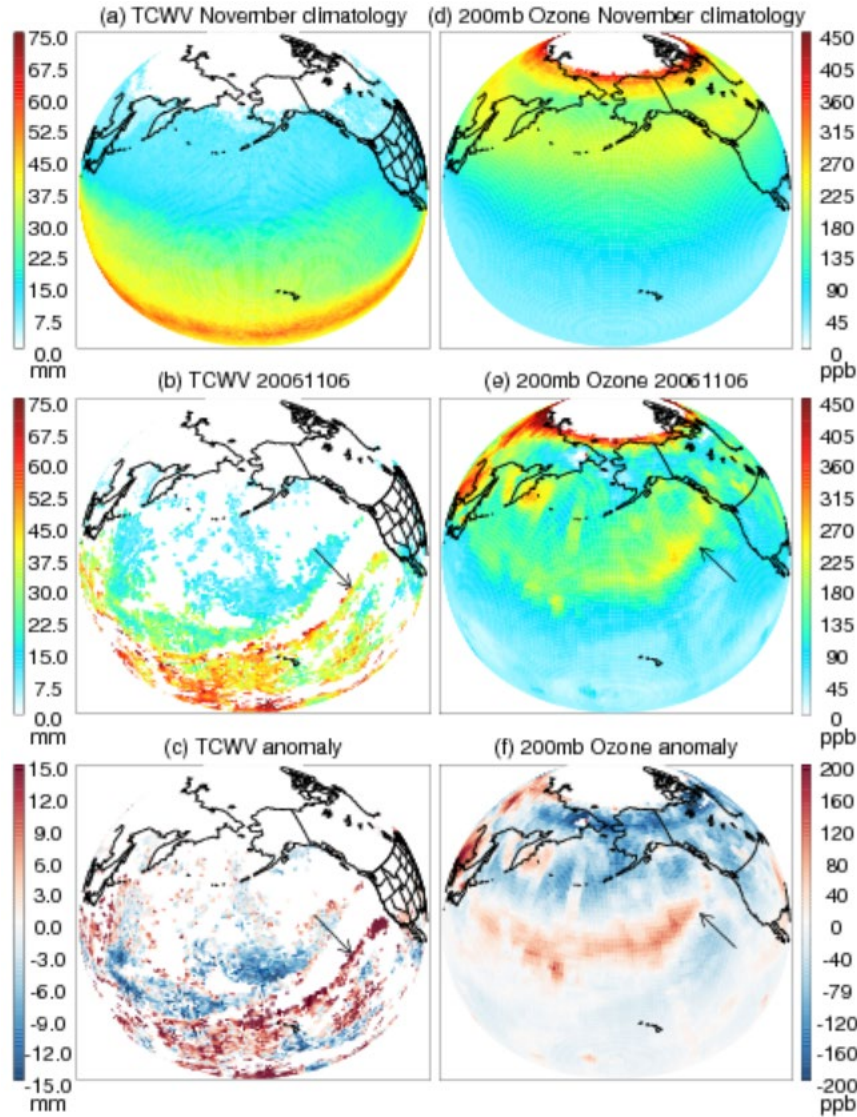533 extra-tropical cyclone as the AR is.

534

Figure 10. The Level 3 (top row) climatology, (middle row) data on November 6th, 2016 and (bottom row) anomaly on November 6th, 2016 with respect to the climatology for (left column) Version 4.0 OMI TCWV (mm, 0.5°×0.5°) and (right column) OMI ozone mixing ratio (ppb, 1°×1°) interpolated to 200 mb.

4.3.2 OMI Data Assimilation for the AR

To evaluate the potential of OMI water vapor data to improve numerical weather forecasts, we conducted a data assimilation experiment from November 2nd to November 8th of 2016 using WRF v3.9.1 and Version 4.0 OMI TCWV. The model was configured with a 27-km (290×270

544   surface grid points with 51 vertical levels), a 9-km (586×586×51 points) and a 3-km

545   (541×526×51) nested domains in a Lambert projection over the relevant portion of the Pacific

546   and North America (Figure 11 top left). The domains are designed for the November 6 AR event

547   and its associated precipitation at landfall. The model has the same physics parameterizations as

548   those used in Section 4.2 except that a more sophisticated double-moment microphysics scheme

549   is used in the 3-km nest for quantifying precipitation. The initial and boundary conditions for the

550   27-km domain were from the 1°×1° NCEP FNL reanalysis. One-way nesting is used for the

551   inner domains. To evaluate the model's skill at simulating the AR and the contribution of OMI

552   TCWV to the quality of the simulation, we did not nudge the run towards the reanalysis, nor

553   assimilate the observed sea surface temperature within the computational domains.

554   The OMI TCWV is assimilated into the model using analytical optimal estimation (Rodgers,

555   2000). This method minimizes the cost function $J(x) = (\mathbf{y} - H\mathbf{x})^T \mathbf{E}^{-1}(\mathbf{y} - H\mathbf{x}) +$

556    $(\mathbf{x} - \mathbf{x}^b)^T \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}^b)$, where x is the true TCWV, x^b is the a priori TCWV (from the model), y

557   is the observed TCWV, H represents the model Jacobian, $\mathbf{B}$ and $\mathbf{E}$ are the error covariance

558   matrices of the a priori and observation. $\mathbf{B}$ is estimated using the 12-hour and 24-hour forecasts

559   using the National Meteorological Center method (Parrish and Derber, 1992). $\mathbf{E}$ is based on the

560   fitting uncertainties of OMI data.

561   The a posteriori analysis ($\hat{\mathbf{x}}$) can be obtained from $\hat{\mathbf{x}} = \mathbf{x}^b + \mathbf{K}(\mathbf{y} - H\mathbf{x})$, where $\mathbf{K} =$

562    $\mathbf{B}H^T(H\mathbf{B}H^T + W^{-1}\mathbf{E})^{-1}$ is the Kalman gain, $W = \frac{(R^2 - r^2)}{(R^2 + r^2)}$ is the Cressman function to weigh the

563   observations based on their Euclidian distance r to the model grids, and R is the influence radius

564   of the observations. We simply assume R to be 1°, 0.5° and 0.25° for the 27-km, 9-km and 3-km

565   domain to get a quick look at the results in this paper and leave a more vigorous quantification of

566   R to future work. The a posteriori TCWV is solved hourly when OMI data are available and is

567   used to initialize the next simulation window.

568   During the assimilation, we adjust the OMI data using the AMF calculated with the modeled

569   water vapor profile ($OMI_{satellite}^{adjusted} = \frac{OMI_{satellite} \times AMF_{satellite}}{AMF_{model}}$) and the scattering weights provided

570   with the Level 2 OMI data. This can reduce the observational error associated with using the

571   monthly mean water vapor profile in the operational OMI product. The standard deviation of the

572   difference between $AMF_{satellite}$ and AMF_{model} is about 20%.
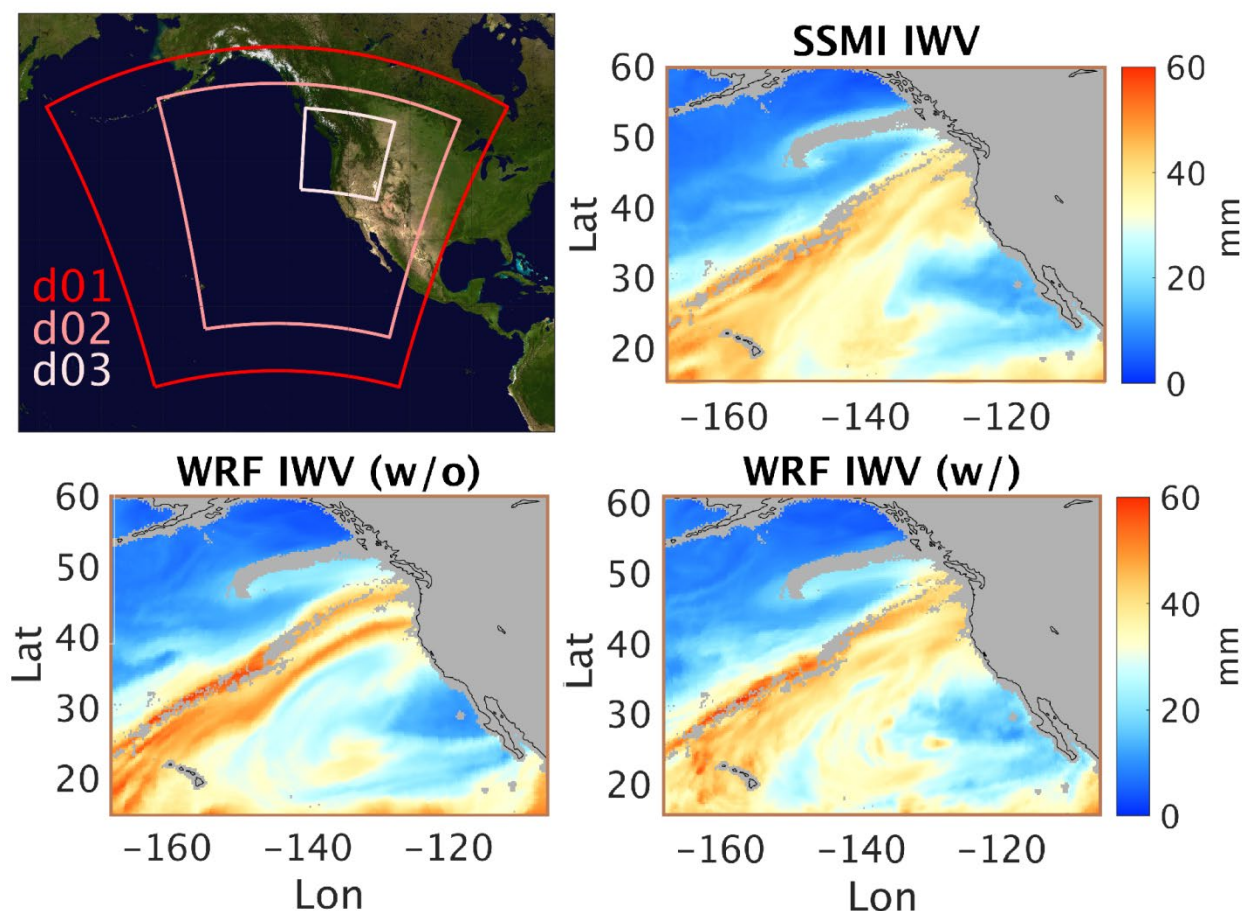
Figure 11. Top left: WRF model domain configuration for the November 2016 AR event. Top right: TCWV observed by SSM/I on November 6th, 2016. Bottom row: TCWV simulated by WRF on November 6th, 2016 (left) without and (right) with OMI data assimilation. Gray color indicates area with no SSM/I data.

Figure 11 shows the zoomed-in views of the AR on November 6th, 2016. The TCWV independently observed by SSM/I is shown in the upper right panel. The lower left and lower right panels show the model results without and with OMI TCWV assimilation. The model without assimilation shows an AR that is split into two parallel filaments making landfall at separate locations on the west coast of North America, where the TCWV is too high compared to the SSM/I observation, especially for the southern filament. As discussed later, this has a significant impact on precipitation (Figure 12). After assimilating OMI TCWV, the modeled

586   TCWV agrees much better with the SSM/I observation. The spurious southern filament

587   disappeared, the overall shape and magnitude of the AR are significantly improved.

588   The location and intensity of precipitation over land are crucial for local flood control and

589   water management, and are closely related to the shape and strength of AR at landfall. The 24-

590   hour accumulated precipitation on November 6 in the 3-km domain is examined in Figure 12.

591   The model output is coarsened to 0.25°×0.25° to match the resolution of the Tropical Rainfall

592   Measuring Mission (TRMM) observation product. The model without OMI data assimilation

593   produces spurious rainfall over the Oregon - California border (box A) as a result of the

594   erroneously strong southern filament of the simulated AR (Figure 11, lower left panel). This

595   artifact was removed after OMI data assimilation, showing better agreement with the

596   corresponding TRMM rainfall observation. The difference in rainfall between the assimilation

597   and observation in the Oregon / Washington area is probably related to both the model error and

598   the data error, as well as the data density and distribution. A detailed error attribution for
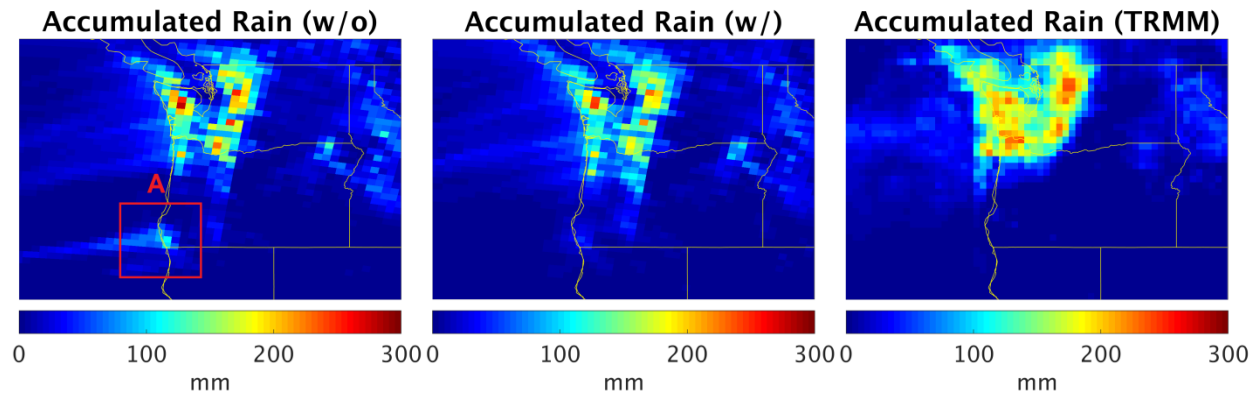
599   precipitation is beyond the scope of this paper.

600

601   **Figure 12.** The simulated rainfall accumulated from 0000 UTC to 2300 UTC (in mm) on

602   November 6, 2006 for the model (left) without and (middle) with OMI TCWV assimilation. The

603   rightmost panel show the accumulated rainfall observed by TRMM for the same time period.

604   Note that the 3-km model result is coarsened to match the resolution of the TRMM product.

605   Box A highlights the erroneously simulated precipitation in the run without OMI data

606   assimilation.

607

608   **5 Summary and Conclusion**

609   The Version 4.0 retrieval algorithm for OMI Total Column Water Vapor (TCWV) is presented

610   in this paper. The algorithm follows the usual two-step approach where Slant Column Density

611   (SCD) is derived from spectral fitting and Vertical Column Density (VCD) is obtained through

612   the ratio of SCD and Air Mass Factor (AMF). In Version 4.0, the spectral fitting no longer

613   considers common mode. The retrieval window (432.0 - 466.5 nm) results from a systematic

614   optimization that reflects trade-offs among several factors, including small fitting RMS, small

615   fitting uncertainty, large fraction of successful retrieval and long retrieval window length. The

616   AMF calculation uses the latest OMI O_2-O_2 cloud product (Veefkind et al., 2016) and monthly

617   variable vertical profiles from the MERRA-2 reanalysis (Gelaro et al., 2017).

618   The Version 4.0 OMI TCWV product is compared against the GPS network data over land

619   and the SSMIS microwave observations over the oceans for 2006. Version 4.0 OMI TCWV has

620   much smaller bias than Version 3.0 and has replaced previous versions on the Aura Validation

621   Data Center website. Version 4.0 OMI TCWV is characterized under different cloud conditions.

622   Under "clear-sky" condition (cloud fraction < 5% and cloud top pressure > 750 mb), the overall

623   mean of OMI-GPS over land is 0.32 mm with a standard deviation of 5.2 mm, and the smallest

624   bias occurs when TCWV is between 10 mm and 20 mm; the overall mean of OMI-SSMIS over

625   the oceans is 0.4 – 1.1 mm with a standard deviation of 6.5 - 6.8 mm, and the smallest bias

626   occurs for TCWV between 20 mm and 30 mm. The correlation coefficient between OMI TCWV

627   and the reference datasets realizes the largest gain when the cloud fraction threshold is increased

628   from 5% to 15%. The regression line appears the best when f = 0.25 is used over land and when f

629   = 0.15 is used over the oceans. But, larger cloud fraction leads to larger bias and scatter. Thus,

630   for most applications, we recommend to consider only OMI data with cloud fraction < 5% to

631   25% and cloud top pressure > 750 mb, in addition to main data quality flag = 0, no row anomaly,

632   fitting RMS < 0.001 and 0<TCWV<75 mm. Relaxing the cloud top pressure threshold has a

633   similar effect as relaxing the cloud fraction threshold. TCWV corresponding to low cloud top

634   pressure (high altitude) should be used with caution due to the degraded accuracy for these

635   clouds in the OMCLDO2 product.

636   As example applications of the Version 4.0 OMI TCWV data across a variety of temporal

637   and spatial scales, this paper examines the climate pattern associated with El Niño / La Niña, the

638   enhanced humidity during a week-long corn sweat event in the Midwest US, and the linear band

639   of high TCWV associated with an intense atmospheric river which made landfall on the west

640   coast of North America. Strong signals are found in OMI TCWV for all three examples. A data
641   assimilation experiment shows that the OMI TCWV data can help improve WRF's skill of
642   simulating the shape and intensity of the AR, as well as the accumulated rainfall near the coast.

643   Further improvement of the product can proceed from both spectral fitting and AMF
644   calculation, such as, water vapor reference spectrum, instrument slit-function and solar irradiance
645   for spectral fitting, aerosol correction and surface bi-directional reflectance for AMF calculation.

646

647   **Data availability**

648   The GPS network data are downloaded from NCAR (rda.ucar.edu/datasets/ds721.1). The SSMIS
649   data used in this paper are downloaded from the Remote Sensing Systems
650   (http://www.remss.com/support/data-shortcut/). The Multivariate ENSO Indices are downloaded
651   from NOAA (https://www.esrl.noaa.gov/psd/enso/mei/table.html). OMI TCWV and ozone
652   profile data are released through the Aura Validation Data Center (https://avdc.gsfc.nasa.gov/).

653

654   **Author contribution**

655   Huiqun Wang optimized the OMI TCWV retrieval window, performed the data validation
656   and tested most of the data application described in this paper. Amir Souri performed the WRF
657   simulations and data assimilation experiment presented in this paper. Gonzalo González Abad
658   developed and maintained the SAO retrieval code and implemented OMI TCWV data production
659   for the Aura Validation Data Center. Xiong Liu developed the OMI ozone profile retrieval and
660   provided the relevant data used in the AR application. Kelly Chance is the PI of the NASA grant,
661   and is responsible for the overall direction and execution of the project. Huiqun Wang prepared
662   and revised the manuscript with contributions from all co-authors. All authors contributed to
663   technical and scientific discussions during this project.

664

665   **Competing interests**

666   The authors declare that they have no conflict of interest.

667

668   **Acknowledgement**

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