

1 **Assessing snow extent data sets over North America to inform and improve trace gas**  
2 **retrievals from solar backscatter**

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10 **Abstract**

11 Accurate representation of surface reflectivity is essential to tropospheric trace gas retrievals  
12 from solar backscatter observations. Surface snow cover presents a significant challenge due to  
13 its variability and thus snow-covered scenes are often omitted from retrieval data sets; however,  
14 the high reflectance of snow is potentially advantageous for trace gas retrievals. We first  
15 examine the implications of surface snow on retrievals from the upcoming TEMPO  
16 geostationary instrument for North America. We use a radiative transfer model to examine how  
17 an increase in surface reflectivity due to snow cover changes the sensitivity of satellite retrievals  
18 to NO<sub>2</sub> in the lower troposphere. We find that a substantial fraction (>50%) of the TEMPO field  
19 of regard can be snow covered in January, and that the average sensitivity to the tropospheric  
20 NO<sub>2</sub> column substantially increases (doubles) when the surface is snow covered.

21 We then evaluate seven existing satellite-derived or reanalysis snow extent products against  
22 ground station observations over North America to assess their capability of informing surface  
23 conditions for TEMPO retrievals. The Interactive Multisensor Snow and Ice Mapping System  
24 (IMS) had the best agreement with ground observations (accuracy of 93%, precision of 87%,  
25 recall of 83%). Multiangle Implementation of Atmospheric Correction (MAIAC) retrievals of  
26 MODIS-observed radiances had high precision (90% for Aqua and Terra), but underestimated  
27 the presence of snow (recall of 74% for Aqua, 75% for Terra). MAIAC generally outperforms  
28 the standard MODIS products (precision of 51%, recall of 43% for Aqua; precision of 69%,

29 recall of 45% for Terra). The Near-real-time Ice and Snow Extent (NISE) product had good  
30 precision (83%) but missed a significant number of snow-covered pixels (recall of 45%). The  
31 Canadian Meteorological Centre (CMC) Daily Snow Depth Analysis Data set had strong  
32 performance metrics (accuracy of 91%, precision of 79%, recall of 82%). We use the  $F$  score,  
33 which balances precision and recall, to determine overall product performance ( $F = 85%$ ,  
34 82(82)%, 81%, 58%, 46(54)% for IMS, MAIAC Aqua(Terra), CMC, NISE, MODIS  
35 Aqua(Terra) respectively) for providing snow cover information for TEMPO retrievals from  
36 solar backscatter observations. We find that using IMS to identify snow cover and enable  
37 inclusion of snow-covered scenes in clear-sky conditions across North America in January can  
38 increase both the number of observations by a factor of 2.1 and the average sensitivity to the  
39 tropospheric  $\text{NO}_2$  column by a factor of 2.7.

40

## 41 **1. Introduction**

42 Satellite observations of solar backscatter are widely used as a source of information on  
43 atmospheric trace gases (Richter and Wagner, 2011). These observations have provided valuable  
44 information on vertical column densities of  $\text{O}_3$ ,  $\text{NO}_2$ ,  $\text{SO}_2$ ,  $\text{CO}$ ,  $\text{HCHO}$ ,  $\text{CH}_4$  and other important  
45 trace gases in the troposphere (Fishman et al., 2008). Satellite observations of trace gases have  
46 been used to assess air quality (Duncan et al., 2014; Martin, 2008) and to gain insight into  
47 atmospheric processes including emissions (Streets et al., 2013), lifetimes (Beirle et al., 2011;  
48 Fioletov et al., 2015; de Foy et al., 2015; Valin et al., 2013), and deposition (Geddes and Martin,  
49 2017; Nowlan et al., 2014). The utility of these observations is dependent on their quality, and  
50 thus ensuring retrieval accuracy is essential.

51 Previous studies have found that retrieved  $\text{NO}_2$  vertical column densities are highly  
52 sensitive to errors in assumed surface reflectance (Boersma et al., 2004; Lamsal et al., 2017;  
53 Martin et al., 2002). Much of this error sensitivity results from observation sensitivity to trace  
54 gases in the lower troposphere. The observation sensitivity is accounted for in the air mass factor  
55 (AMF) conversion of observed line-of-sight [  $\int \sigma(\lambda, z) dz$  ] to vertical column densities.  
56 Uncertainties in surface reflectance are a significant contributor to AMF uncertainty.

57 Existing reflectivity climatologies (e.g. Kleipool et al., 2008; Koelemeijer et al., 2003;  
58 Liang et al., 2002; Herman and Celarier, 1997) do not represent snow cover well, since the  
59 statistical methods to exclude reflective clouds from the climatologies also exclude variable  
60 snow cover; Correspondingly, surface snow may be mistaken for cloud, leading to errors in  
61 cloud fraction and pressure estimates used in trace gas retrievals (Ueyama et al., 2010; Vasilkov et al., 2017). Therefore, snow cover is particularly challenging to retrievals.  
62 Misrepresenting surface snow cover can lead to large errors (20-50%) in retrieved NO<sub>2</sub> columns  
63 over broad regions with seasonal snow cover (Liang et al., 2002). For this reason, observations  
64 over snow are often omitted or flagged as unreliable to avoid potential errors. This  
65 limits the ability of satellite retrieved data sets to offer adequate temporal and spatial sampling in  
66 winter months. Additionally, over highly reflective surfaces such as snow observation sensitivity  
67 to the lower troposphere is larger and has less dependence on *a priori* NO<sub>2</sub> profiles (Lorente et  
68 al., 2000). Thus, omitting snow-covered scenes means omitting the  
69 observations with the greatest sensitivity to the lower troposphere. This could be remedied by  
70 using a product that would allow for snow cover identification to be done with confidence.

72 Several data products provide information on snow extent using surface station  
73 observations, satellite-observed radiances, or visible imagery. Previous evaluations have found it  
74 difficult to determine which of these products is definitively the best, partly due to differences in  
75 resolution. Most products are more consistent during the winter months when persistent, deep  
76 snow is present (Frei et al., 2012; Frei and Lee, 2010). However, disagreements are common  
77 during accumulation and melting seasons, over mountains, and under forest canopies. These  
78 evaluations have largely focused on local or regional snow cover or have included only cloud-  
79 free observations.

80 The upcoming geostationary Tropospheric Emissions: Monitoring of Pollution (TEMPO)  
81 satellite instrument will provide hourly observations of air quality relevant trace gases over  
82 North America at an unprecedented spatial and temporal resolution (Zoogman et al., 2017). As is  
83 the case for all nadir satellite retrievals, the quality of these observations will depend on the  
84 accuracy of the surface reflectance used in the retrieval. As a significant portion of the observed  
85 domain experiences snow cover, an accurate representation of snow cover is needed. Current  
86 plans to deal with snow cover for TEMPO are to rely on external observations.

87           In this work, we examine the importance of accurate snow identification by using a  
88 radiative transport model to evaluate how the vertical sensitivity of a satellite retrieval is  
89 impacted by surface reflectance. We then assess seven snow extent products that are expected to  
90 continue to be operational during the TEMPO mission using in situ observations across North  
91 America with the intent of determining which product is best suited for providing snow cover  
92 information for TEMPO and other future satellite retrievals. Finally, we combine radiative  
93 transfer model results with a snow extent product to show how including snow-covered scenes  
94 improves both the quantity and quality of information in a retrieval data set.

95

## 96 **2. Data and algorithms**

### 97 **2.1. Gridded snow products**

#### 98 **2.1.1. IMS**

99           One of the most widely used sources of snow extent data is the Interactive Multisensor  
100 Snow and Ice Mapping System (IMS). IMS provides daily, near-real-time maps of snow and sea  
101 ice cover in the Northern Hemisphere at 4 km resolution (Helfrich et al., 2007). The maps are  
102 produced by a trained analyst using visible imagery from a collection of geostationary (e.g.  
103 GOES, MeteoSat) and polar orbiting (e.g. AVHRR, MODIS, SAR) satellite instruments, with  
104 additional information from microwave sensors (e.g. DMSP, AMSR, AMSU), surface  
105 observations (e.g. SNOTEL), and models (e.g. SNODAS) (Helfrich et al., 2007). By using  
106 multiple sources of information with different spatial resolution and temporal sampling, IMS can  
107 minimize interference from clouds.

#### 108 **2.1.2. MODIS**

109           A second commonly used snow and ice product is derived from MODIS satellite  
110 observations from the Terra and Aqua satellites (Hall and Riggs, 2007). Terra and Aqua have  
111 sun-synchronous, near-polar orbits with overpass times of 1030 and 1330, respectively. Snow  
112 cover is calculated using a Normalized Difference Snow Index (NDSI), which examines the  
113 difference between observed radiation at visible wavelengths (where snow is highly reflective)  
114 and short infrared wavelengths (where there is little reflection from snow). Observations are

115 made at 500 m spatial resolution and aggregated to produce daily snow cover fractions on a  
116 0.05° resolution grid. Past evaluations of the standard MODIS snow product show good  
117 agreement in cloud-free conditions but often snow is misidentified as cloud (Hall and Riggs,  
118 2007; Yang et al., 2015).

119 The Multiangle Implementation of Atmospheric Correction (MAIAC) algorithm is  
120 another algorithm processing MODIS observations. MAIAC retrievals uses radiances observed  
121 by the MODIS Aqua and Terra satellites to provide atmospheric and surface products including  
122 snow detection on a 1 km grid (Lyapustin et al., 2011a, 2011b, 2012). While the NDSI used by  
123 the standard MODIS product is also used by MAIAC as one of the criteria, the overall snow and  
124 cloud detection in MAIAC are different from the standard MODIS algorithm (Lyapustin et al.,  
125 2008).

### 126 **2.1.3. NISE**

127 The Near-real-time Ice and Snow Extent (NISE) provides daily updated snow cover  
128 extent information on a 25x25 km grid (Nolin et al., 2005). NISE uses microwave measurements  
129 from the Special Sensor Microwave Imager/Sounder (SSM/I) on a sun-synchronous, quasi-polar  
130 orbit to observe how microwave radiation emitted by soil is scattered by snow. Products based  
131 on microwave measurements such as NISE are known to miss wet and thin snow, as wet snow  
132 emits microwave radiation similar to soil, and thin snow does not provide sufficient scattering.

### 133 **2.1.4. CMC**

134 The Canadian Meteorological Centre (CMC) Daily Snow Depth Analysis Data is a  
135 statistical interpolation of snow depth measurements from 8,000 surface sites across Canada and  
136 U.S. interpolated using a snow pack model (Brasnett, 1999). Unlike the aforementioned satellite  
137 products that provide snow extent, CMC provides snow depths. Daily snow maps are produced  
138 at 25 km resolution. As it a reanalysis product, there is a time delay in availability. The CMC  
139 snow depths show good agreement with independent observations over midlatitudes and is  
140 considered an improvement over previous snow depth climatologies (Brown et al., 2003).

## 141 **2.2 Surface observations**

142 These snow identification products are evaluated against surface station observations  
143 from the Global Historical Climatology Network Daily (GHCN-D) database, an amalgamation of  
144 daily climate records from over 80,000 surface stations worldwide (Menne et al., 2012a). Most  
145 observations over Canada and the United States are collected by government organizations  
146 (Environment and Climate Change Canada and NOAA National Climatic Data Center,  
147 respectively) with additional measurements from smaller observation networks. While the focus  
148 of the database is collecting temperature and precipitation measurements, many stations (1,279 in  
149 Canada and 13,932 in the United States in 2015 used here) also offer snow depth measurements.

150 A subset of the surface stations included in GHCN-D may also be used in the CMC  
151 reanalysis. It is difficult to definitively know which stations are used, as CMC does not routinely  
152 archive this information. However, we estimate that only 5% of the GHCN-D stations used here  
153 are located within  $0.1^\circ$  of a possible CMC station, and thus GHCN-D has sufficient independent  
154 information sources to evaluate the CMC product.

### 155 **2.3 Radiative transfer calculations**

156 The sensitivity of satellite observations of  $\text{NO}_2$  to its vertical distribution is calculated  
157 here using the LIDORT radiative transfer model (Spurr, 2002). The model is used to calculate  
158 scattering weights, which quantify the sensitivity of backscattered solar radiation to  $\text{NO}_2$  at  
159 different altitudes (Martin et al., 2002; Palmer et al., 2001). The observation sensitivity to lower  
160 tropospheric  $\text{NO}_2$  is represented by the AMF. AMFs for OMI satellite observations in January  
161 2013 are calculated as a useful analog for future TEMPO observations as both instruments are  
162 spectrometers observing reflected sunlight at UV to visible wavelengths. AMFs are calculated at  
163 440 nm, at the centre of the  $\text{NO}_2$  retrieval window for OMI and TEMPO where  $\text{NO}_2$  has strong  
164 absorption features. Vertical  $\text{NO}_2$  profiles, as well as other trace gas and aerosol profiles needed  
165 for the AMF calculation shown here, are obtained from a simulation of the GEOS-Chem  
166 chemical transport model version 11-01 ([www.geos-chem.org](http://www.geos-chem.org)).

167 Figure 1 shows maps of snow-free and snow-covered reflectances used here. Snow-free  
168 surface reflectance at 470 nm is provided by Nadir BRDF-Adjusted reflectances from the  
169 MODIS CMG Gap-Filled Snow-Free Products (Sun et al., 2017). Reflectivities at 354 nm for  
170 snow-covered scenes are derived from OMI observations as described by Choudhury et al. (2010).  
171 This data set is consistent with previous snow reflectivity (e.g. Moody et al., 2007; Tanskanen

172 and Manninen, 2007) over most land types (Cobb et al., 2010). Snow-covered reflectivity has  
 173 an estimated uncertainty of 10-20% in most regions, with higher uncertainties in regions with  
 174 thin or transient snow. Although the 354 nm wavelength is different than the 440 nm wavelength  
 175 used to calculate AMFs, snow reflectivity has weak spectral dependence in UV-visible  
 176 wavelengths (Lacis and Oinas, 1991). Snow can increase surface reflectance by over a factor of 10 in central North America where short vegetation is readily  
 177 covered by snow.

### 179 3. Methods

180 Here we test daily snow cover products for 2015. Snow products are regridded from their  
 181 native resolutions to a common 4 km grid (similar to the spatial resolution of TEMPO). A grid  
 182 box is considered to be snow covered if any observations within that box are snow covered.  
 183 MAIAC, NISE, and IMS give only a yes or no flag for presence of snow. MODIS products  
 184 provide a pixel snow fraction, and we consider any pixels with nonzero snow fractions as snow  
 185 covered. Any CMC grid box with nonzero snow depth is considered snow covered.

186 GHCN-8 and reanalysis snow data products tested here. If measurements from multiple surface data  
 187 networks exist in the same grid box, the most reliable source is used per the priority order given  
 188 by GHCN-D (Menne et al., 2012b). If observations from multiple surface stations within the  
 189 most reliable network within a grid box disagree on the presence of snow on a given day, that  
 190 day is excluded from the evaluation.

192 We assess the snow data sets using metrics that are commonly used for evaluating binary  
 193 data sets (Rittger et al., 2013). These metrics are based on the possible outcomes for identifying  
 194 snow: true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

195 Accuracy measures the likelihood that a grid box, with snow or without, is correctly classified:

$$\frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

196 Precision is the probability that a region identified as snow covered has snow:

$$\frac{TP}{TP + FP} \quad (2)$$

197 Recall is the likelihood that snow cover is detected when present:

(3)

198 The  $F$  score balances recall (which accounts for false negatives) and precision (which accounts  
199 for false positives) to measure correct classification of snow without the influence of frequent  
200 snow-free periods, and it is therefore the metric which is most relevant for TEMPO:

(4)

#### 201 4. Results

202 We first examine the effect of surface reflectivity on retrieval sensitivity by using the  
203 LIDORT radiative transfer model to calculate  $\text{NO}_2$  AMFs for both snow-free and snow-covered  
204 scenarios using the corresponding snow-free (Sun et al., 2017) or snow-covered (Lacis et al.,  
205 2010) surface reflectance over North America. We calculate AMFs over North America in  
206 January 2013. We assume cloud-free conditions in all AMF calculations, as the impact of surface  
207 reflectance on retrieved cloud fractions is beyond the scope of this paper.

208 Figure 2 shows the sensitivity of backscattered radiation (scattering weights) over snow-  
209 covered and snow-free surfaces for two locations: a midlatitude location (US Midwest:  $42^\circ\text{N}$ ,  
210  $99^\circ\text{W}$ ) with a solar zenith angle of  $60^\circ$  and at a high-latitude location (Northern Canada:  $58^\circ\text{N}$ ,  
211  $76^\circ\text{W}$ ) with a solar zenith angle of  $79^\circ$ . The snow-covered scattering weights are greater than the  
212 snow-free scattering weights throughout the troposphere, by factors of 2.0 (2.7) below 5 km, 2.7  
213 (3.7) below 2 km, and 2.6 (5.3) below 1 km at the mid- (high-) latitude location. This shows that  
214 satellite-observed backscattered radiation in clear-sky conditions is up to 5 times as sensitive to  
215  $\text{NO}_2$  in the boundary layer after accounting for increased reflection by snow, due to the increased  
216 absorption by  $\text{NO}_2$  in the lower troposphere when the surface reflects more sunlight.

217 Figure 3 shows the distribution of AMF values over North America with and without  
218 reflectance from snow. The snow-free AMF distribution is unimodal with a median of 1.2.  
219 Allowing for the presence of snow introduces a second mode with a median of 3.2. Mean AMFs  
220 increase by a factor of 2.0 in the presence of snow, indicating an overall doubling in the  
221 sensitivity to tropospheric  $\text{NO}_2$  over snow-covered surfaces across North America. The impact is  
222 larger over polluted regions, as mean AMFs increase by a factor of 2.2 in regions where  $\text{NO}_2$

223 columns exceed  $1 \times 10^{15}$  molec/cm<sup>2</sup>. Maps of AMF with and without snow cover for January 2013  
224 show that AMF values increase over 69% of the land surface within the TEMPO domain.

225 We next examine the snow datasets to identify the one most suited for the TEMPO  
226 retrieval algorithm. Figure 4 shows the spatial distribution of false positives and false negatives  
227 in the data sets. In all data sets, both false positives and negatives are most frequent over  
228 mountainous regions, particularly in the Rocky Mountain region, consistent with previous  
229 validation studies (Chen et al., 2012, 2014; Frei et al., 2012; Frei and Lee, 2010). These errors  
230 are often attributed to differences in representativeness, as snow cover in mountain regions is  
231 often spatially inhomogeneous, and thus *in situ* measurements may not be representative of the  
232 pixel. A slight increase in the number of false positives in IMS over mid-western and prairie  
233 regions may result from crop regions with high snow-free albedos being mistaken for snow in  
234 visible imagery (Chen et al., 2012; Yang et al., 2015). NISE, MODIS Aqua, and MODIS Terra  
235 have more false negatives overall, especially in the Great Lakes and New England regions. False  
236 positives are less frequent than false negatives in all data sets. IMS and CMC have the lowest  
237 frequency of false negatives. NISE and MAIAC have the lowest frequency of false positives.

238 Figure 5 shows the metrics used to evaluate data set performance. Table 1 summarizes  
239 these results. All data sets have high accuracy numbers, owing largely to a high number of true  
240 negatives during the summer months. MODIS Aqua and Terra have low recall and *F* scores.  
241 When only observations with MODIS cloud fractions less than 20% are used, MODIS has better  
242 agreement with the ground stations (*F* statistic increases from 0.38 to 0.49 at native resolution  
243 for Aqua, 0.43 to 0.63 for Terra), but this reduces the number of usable MODIS observations by  
244 up to 60%. NISE has high precision but low recall, indicating that while areas classified as snow-  
245 covered by NISE are likely correct, many snow-covered regions are missing in the data set. This  
246 is consistent with evaluations by McLinden et al. (2014) and C D 6 m f b (2010). Although  
247 CMC, IMS, and MAIAC products show an increase in frequency of false negatives over the  
248 Rocky Mountains, they retain a high precision in this region due to frequent snow cover. While  
249 MAIAC Aqua and Terra have high accuracy and precision, lower recall values indicate that they  
250 are conservative in identifying the presence of snow. This is possibly a consequence of the  
251 method used for identifying cloud, which may incorrectly classify fresh snowfall as cloud  
252 (Lyapustin et al., 2008). Data sets were also evaluated by season with similar results (Appendix

253 Table A1). All data sets have weaker performance metrics during the spring melt season, which  
254 has been observed in past evaluations (Frei et al., 2012). IMS has the highest  $F$  score in winter  
255 and autumn but is slightly outperformed by MAIAC in spring. Data sets were also evaluated at  
256 their native resolutions and at a common 25 km resolution (Appendix Tables A2-3). Results are  
257 similar at each resolution with two exceptions: MODIS Aqua and Terra products perform better  
258 when regridded from their native  $0.05^\circ$  resolution to a 4 km resolution as it reduces the number  
259 of grid boxes missing observations due to cloud, and MAIAC Aqua and Terra perform better at  
260 their native resolution than at either 4 km or 25 km as degrading the spatial resolution results in a  
261 loss of information.

262 For all data sets, recall is generally low in two regions: along the Pacific coastline where  
263 snow depths are relatively thin and in the south when snow is rare and generally short lived. Thin  
264 snow is likely to be less homogenous across a pixel and more likely to be obscured by forest  
265 canopies or tall grasses, and thus is difficult to observe from satellite imagery. Short-lived snow  
266 in the south is likely to be missed by satellite observations, especially since clouds are often  
267 present. However, as IMS uses multiple observations at multiple times of day in addition to  
268 incorporating ground station data, it is more likely to find snow in these cases than other satellite  
269 products (Hall et al., 2010). Overall, IMS has best agreement with *in situ* observations, with the  
270 highest accuracy, recall, and  $F$  statistic and relatively high precision.

271 While CMC also has strong performance metrics, it is important to consider the  
272 information source used to describe snow extent in each product. Products based on satellite  
273 observations are advantageous when assessing how surface reflectivity affects backscattered  
274 radiation observed from space. For example, thin snow, or snow obscured by tree canopies, may  
275 not affect the observed brightness from space, but would be considered snow-covered by a  
276 product based on surface observations (e.g. CMC). Also, the reflectivity of a snow-covered  
277 surface decreases over time as the snow ages (Warren and Wiscombe, 1980); This effect would  
278 not be captured by snow depth measurements. Additionally, while snow depth has been used as  
279 an indicator of brightness (Arola et al., 2003), it cannot account for snow aging or canopy  
280 effects. IMS is based on visible satellite imagery and thus determines snow extent based on  
281 brightness from space, which is more applicable to satellite retrievals. And while most satellite-  
282 based products rely on observations made at a single overpass time and viewing geometry, IMS

283 has the advantage of incorporating observations from multiple satellites with differing  
284 measurement times and geometries, including both geostationary and low Earth orbits. These  
285 reasons, in addition to a strong agreement with in situ measurements and near-real-time updates,  
286 make IMS best suited for informing TEMPO retrievals.

287 We next examine the effect on both spatial sampling and sensitivity to the lower  
288 troposphere of a retrieval data set if observations with surface snow are included rather than  
289 omitted. We use IMS to identify the presence of snow for OMI observations over North America  
290 in January 2015. We then use LIDORT to calculate AMFs for these observations using the  
291 corresponding snow-free (Sun et al., 2017) or snow-covered surface reflectance and examine the results of either including or omitting snow-covered scenes. Figure 6  
292 shows that including snow-covered scenes results in a significant (factor of 2.1) increase in  
293 observation frequency, particularly in the northern US and Canada. Additionally, including  
294 snow-covered scenes increases the average AMF by a factor of 2.7 in regions with occasional  
295 snow cover. The increase in AMF demonstrates that including snow-covered scenes increases  
296 the quality of information about the tropospheric NO<sub>2</sub> column by increasing the observation  
297 sensitivity to tropospheric NO<sub>2</sub>. As we assume clear-sky conditions, these are likely upper  
298 bounds on potential increases in observation quantity and quality. In practice, the presence of  
299 clouds and errors in cloud retrieval algorithms will likely diminish these impacts.

301

## 302 **5. Conclusion**

303 An accurate representation of snow cover is essential to ensuring satellite retrieval  
304 accuracy, including those from TEMPO. Radiative transfer model calculations indicate that  
305 clear-sky NO<sub>2</sub> retrievals over reflective snow-covered surfaces are more than twice as sensitive  
306 to NO<sub>2</sub> in the boundary layer than over snow-free surfaces. This makes snow an attractive  
307 surface over which to observe tropospheric NO<sub>2</sub>. However, the lack of confidence in snow  
308 identification has previously led many retrieval procedures to omit observations over snow. We  
309 show that increasing this confidence such that these observations could be included not only  
310 improves spatial and temporal sampling but also allows the inclusion of observations with  
311 higher-quality information on the lower troposphere.

312 We evaluated seven snow extent data sets to determine their usefulness for informing  
313 satellite retrievals of trace gas from solar backscatter observations. All products were more likely  
314 to misidentify snow over mountains or where snow cover is thin or short lived. IMS had the best  
315 agreement with *in situ* observations ( $F=0.85$ ), and as a satellite-based, operational, daily updated  
316 product, it is well suited for informing TEMPO satellite retrievals. The low recall value (0.45)  
317 for NISE indicated that a significant number of snow-covered pixels are missed. The standard  
318 MODIS products showed medium precision and low recall owing to cloud contamination. The  
319 MAIAC products had the highest precision (0.90 for both Aqua and Terra) of those tested, but is  
320 conservative in ascribing the presence of snow (recall of 0.74 for Aqua, 0.75 for Terra). CMC  
321 had strong performance metrics ( $F=0.81$ ), but as a reanalysis product based on ground  
322 observations it may not appropriately represent how a surface snow reflectivity would affect  
323 TEMPO-observed radiances.

324 The potential improvements in NO<sub>2</sub> retrieval performance over snow-covered scenes  
325 outlined here were tested for clear-sky conditions. The accuracy of cloud retrieval schemes also  
326 impacts the quality of trace gas retrievals. Many cloud retrieval schemes have difficulty  
327 distinguishing between a bright surface and bright, low-altitude clouds; This may diminish the  
328 impact that improved surface snow reflectance can have on observation frequency and sensitivity  
329 when clouds are present. However, using accurate surface snow cover information may also lead  
330 to corresponding improvements in cloud retrieval accuracy.

331 Future work should investigate snow reflectance products that could be used when snow  
332 is detected. This could potentially include BRDFs that describe reflection at different viewing  
333 angles, as this effect has been shown to have significant impact on retrieved NO<sub>2</sub> columns and  
334 clouds (Lorente et al., 2018; Vasilkov et al., 2017). Accurate knowledge of snow reflectivity is  
335 also needed to improve retrievals over snow. A retrieval algorithm that combines daily snow  
336 detection from IMS with a climatology of snow reflectance has the potential to greatly improve  
337 upon current methodologies.

338

## 339 **6. Data Availability**

	Accuracy	Precision	Recall	F
CMC	0.91	0.79	<b>0.83</b>	0.81
IMS	<b>0.93</b>	0.87	<b>0.83</b>	<b>0.85</b>
MAIAC AQUA	0.91	<b>0.90</b>	0.74	0.82
MAIAC TERRA	0.91	<b>0.90</b>	0.75	0.82
MODIS AQUA	0.76	0.51	0.43	0.46
MODIS TERRA	0.82	0.69	0.45	0.54
NISE	0.84	0.83	0.45	0.58

578 Table 1: Evaluation of daily snow extent data set performance for 2015. GHCN-D surface

579 c V g Y f j U h ] c b g ' U f Y ' i g Y X ' U g ' í h f i h 4 km resolution. The d f c X i Wh  
580 highest value for each metric is shown in bold.

581 **Appendix**

Months	Data set	Accuracy	Precision	Recall	F
DJF	CMC	0.84	0.84	0.89	0.86
	IMS	<b>0.88</b>	0.90	<b>0.88</b>	<b>0.89</b>
	MAIAC AQUA	0.84	<b>0.93</b>	0.80	0.86
	MAIAC TERRA	0.84	0.92	0.80	0.86
	MODIS AQUA	0.58	0.84	0.34	0.48
	MODIS TERRA	0.60	0.88	0.37	0.52
	NISE	0.63	0.90	0.41	0.57
MAM	CMC	0.90	0.63	0.57	0.59
	IMS	<b>0.93</b>	0.74	<b>0.67</b>	0.70
	MAIAC AQUA	<b>0.93</b>	<b>0.81</b>	0.62	<b>0.71</b>
	MAIAC TERRA	<b>0.93</b>	<b>0.81</b>	0.63	<b>0.71</b>
	MODIS AQUA	0.86	0.43	0.39	0.41
	MODIS TERRA	0.89	0.62	0.40	0.49
	NISE	0.90	0.71	0.34	0.46
SON	CMC	0.91	0.73	<b>0.81</b>	0.76
	IMS	<b>0.92</b>	0.82	0.74	<b>0.78</b>
	MAIAC AQUA	0.91	<b>0.86</b>	0.60	0.71
	MAIAC TERRA	0.90	0.85	0.61	0.71
	MODIS AQUA	0.82	0.51	0.36	0.42
	MODIS TERRA	0.86	0.71	0.39	0.51
	NISE	0.85	0.85	0.25	0.39

582 Table A1: Evaluation of daily snow extent data set performance by season for 2015. GHCN-D

583 g i f Z U W Y ' c V g Y f j U h ] c b g ' U f Y ' i g Y X ' U g ' 4 km resolution. The highest value for each metric/season is shown in bold.  
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	Resolution	Accuracy	Precision	Recall	F
CMC	25 km	0.92	0.81	0.81	0.81
IMS	4 km	<b>0.93</b>	0.87	<b>0.83</b>	<b>0.85</b>
MAIAC AQUA	1 km	0.91	<b>0.91</b>	0.71	0.80
MAIAC TERRA	1 km	0.91	0.90	0.71	0.80
MODIS AQUA	0.05°	0.77	0.50	0.30	0.37
MODIS TERRA	0.05°	0.81	0.65	0.32	0.43
NISE	25 km	0.85	0.87	0.37	0.51

587 Table A2: Evaluation of daily snow extent data set performance for 2015. GHCN-D surface

588 The highest value for each metric is shown in bold.

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	Accuracy	Precision	Recall	F
CMC	0.92	0.81	0.81	0.81
IMS	<b>0.93</b>	0.84	<b>0.85</b>	<b>0.84</b>
MAIAC AQUA	0.87	0.69	0.73	0.71
MAIAC TERRA	0.88	0.68	0.73	0.71
MODIS AQUA	0.78	0.50	0.41	0.45
MODIS TERRA	0.83	0.68	0.43	0.53
NISE	0.85	<b>0.87</b>	0.37	0.52

590 Table A3: Evaluation of daily snow extent data set performance for 2015. GHCN-D surface

591 The highest value for each metric is shown in bold.

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