

1 **Aeolus winds improve Arctic weather prediction**

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6 **Key Points:**

- 7 • Operational wind products are a key component of skillful numerical weather prediction
- 8 in the Arctic.
- 9 • Augmenting operational winds with Aeolus winds could enhance the forecasts of winds
- 10 and temperature fields by 14-18%.
- 11 • Aeolus wind improvements are most pronounced on strong wind days.

12 **Abstract**

13 It has been proven that assimilating winds from the Aeolus global Doppler wind lidar would
14 enhance the predictive skill of weather forecast models. In this study, we use a series of
15 Observing System Experiments to examine how operational winds and Aeolus winds impact
16 Environment and Climate Change Canada’s global forecast system over the data-sparse Arctic
17 region. Aeolus winds improve the tropospheric wind and temperature forecasts by about 0.7 to
18 0.9% of error reduction (a 15-20% effect compared to the impact of operational wind products),
19 while having little impact on the specific humidity field. In particular, Aeolus winds have an
20 impact on forecasts of strong wind days on the wind and temperature fields that is double the
21 impact of the forecasts of less intense wind days and provides a disproportionate improvement to
22 forecasts on these days compared to other operational wind measurements. These findings
23 suggest significant potential for global doppler wind lidar observations to enhance severe-
24 weather prediction in polar regions.

25 **Plain Language Summary**

26 Wind observations are necessary to produce accurate weather forecasts. Aeolus is a new satellite
27 that provides the first global wind profile measurements and it has a proven positive impact on
28 forecasts. In this study, we investigate the impact of a large set of wind observations, including
29 Aeolus winds, on Arctic weather forecasts using Canada’s main forecast. We can calculate how
30 these wind observations improve the forecast throughout the atmosphere, and find that Aeolus
31 winds further improve the forecast in the lower atmosphere. Furthermore, our findings highlight
32 the heightened significance of wind observations in ensuring precise forecasts of strong wind
33 days. The difference is about double the improvement on the forecast of less intense wind days.
34 This suggests that future doppler wind lidar programs following from Aeolus could significantly

35 benefit forecast skill in data-sparse regions like the Arctic and Antarctic, which are of growing
36 societal, political, and economic interest.

37 **1 Introduction**

38 Arctic weather forecasts produced by operational numerical weather prediction (NWP)
39 models present unique challenges (Bauer et al., 2016; Jung et al., 2016; Gascard et al., 2017).
40 The Arctic presents unique logistical and environmental challenges that hinder real-time data
41 collection and the maintenance of observation equipment (Randriamampianina et al., 2019;
42 Lawrence et al., 2019; James et al., 2020; Joe et al., 2020; Chou et al., 2020). Furthermore, the
43 Arctic's unique geography and rapidly changing climate contribute to unpredictable and extreme
44 weather events (Cohen et al. 2014; Francis et al., 2017; Lawrence et al., 2019; Eikeland et al.,
45 2022). Nevertheless, improving Arctic forecasts remains imperative for the safety of residents
46 and travellers in the region. Furthermore with melting sea ice opening up new opportunities, the
47 Arctic is gaining increasing importance for shipping and industry (Gascard et al., 2017; Eicken,
48 2013; Inoue et al., 2015). Finally, given implications of Arctic change for sea level rise and
49 altered weather patterns, accurate forecasts promises to improve our understanding of and ability
50 to adapt to climate change (Cohen et al. 2014; Jung et al., 2014; Overland et al. 2015; Francis et
51 al., 2017; Laroche and Poan, 2021).

52 An essential element in producing reliable forecasts is the initialization of NWP systems
53 with precise and timely observational data (Inoue et al., 2015; Randriamampianina et al., 2021).
54 These observations allow estimation of the present atmospheric state, enabling the NWP system
55 to establish the initial conditions necessary for accurate forecasts. Wind is a fundamental
56 component of atmospheric dynamics, influencing the movement of air masses, the formation and
57 evolution of weather systems, and the transport and advection of heat, moisture, and other

58 atmospheric constituents (Baker et al., 1995; Graham et al., 2000; Naakka et al., 2019). Thus,
59 wind observations play a pivotal role in NWP initialization, even after accounting for the balance
60 that constrains winds given pressure and temperature measurements (Horányi et al., 2014;
61 Naakka et al., 2019; James et al., 2020).

62 Observations of altitude-resolved winds are available through aircraft reports (AMDAR;
63 Dai et al., 2014; James et al., 2020), radiosondes (Durre et al., 2018; Carminati et al., 2019; Rani
64 et al., 2021), and wind profiling technologies (e.g., Doppler radar and lidar; Augustine and
65 Zipser, 1987; Rogers et al., 1993; Liu et al., 2020). However, these observations are often
66 sporadic and notably scarce, particularly over vast bodies of water like oceans and the polar
67 regions. Passive space-based observations offer an alternative, with Atmospheric Motion Vectors
68 (AMVs) estimating wind speed and direction based on cloud and water vapor movements
69 (Velden et al., 2017; Mizyak et al., 2016). Additionally, space-based scatterometers provide
70 surface winds over the ocean. Despite the advantages of AMVs in offering wind information
71 across multiple tropospheric layers through multispectral water vapor remote sensing (Velden et
72 al., 1997; Bormann and Thépaut, 2004; Le Marshall et al., 2008), they lack precision in altitude
73 assignment and are limited to a few levels, hindering their representation of small-scale vertical
74 wind profile structures. Conversely, spaceborne scatterometers focus only on near-surface ocean
75 winds, with their accuracy highly dependent upon surface weather conditions (Chiara et al.,
76 2017; Young et al., 2017).

77 The Aeolus mission, featuring the first spaceborne Doppler Wind Lidar (DWL), provides
78 the first-ever global horizontal line-of-sight (HLOS) wind profile measurements. Studies have
79 demonstrated that assimilating Aeolus HLOS winds into NWP systems significantly enhances
80 forecast accuracy. Examples of operational forecast systems include those of ECMWF (Rennie

81 et al., 2021), NCMRWF (George et al., 2021), DWD (Martin et al., 2023), NOAA (Garrett et al.,
82 2022), Météo-France (Pourret et al., 2022), and Environment and Climate Change Canada
83 (ECCC; Laroche and St-James, 2022). Most of the improvements were found in the tropical
84 troposphere to lower stratosphere. Notably, Aeolus winds have also demonstrated a beneficial
85 impact on forecasts in data-sparse regions such as the Southern Hemisphere extra-tropics and the
86 Arctic (Mile et al., 2022; Chou and Kushner, 2023; Zuo and Hasager, 2023).

87 Despite the good coverage that polar-orbiting satellites provide over the Arctic, more
88 than 90% of the assimilated observations over the Arctic are microwave and infrared radiances
89 (Lawrence et al., 2019; Randriamampianina et al., 2021). As previously discussed, wind
90 observations from conventional surface and aircraft measurements are extremely sparse in this
91 region. Hence, it is important to assess the impact of existing wind observations and any
92 additional wind observations over the Arctic to compare and determine their impact on NWP
93 model performance over the Arctic.

94 In this study, we extend the work of Chou and Kushner (2023) and evaluate the impact of
95 operational winds and Aeolus winds on the global forecast system of ECCC with a focus on the
96 Arctic. Chou and Kushner (2023) used a series of Observing System Experiments (OSE), in
97 which all operational winds or Aeolus winds are withheld in the assimilation and the forecasts
98 are verified against the fifth-generation European Centre for Medium-Range Weather Forecasts
99 (ECMWF) atmospheric reanalysis (ERA5, Hersbach et al., 2023). The integration of operational
100 winds significantly enhanced tropospheric wind forecasts, particularly in tropical regions,
101 resulting in an impressive 8% reduction in forecast error. Further augmenting these assimilations
102 with Aeolus winds contributed an additional 0.7-0.9% improvement or about 10% of the impact
103 of operational winds. Notably, Aeolus winds also proved beneficial in regions with limited data,

104 such as the Arctic and the extra-tropical Southern Hemisphere, demonstrating a reduction in
105 forecast errors ranging from 0.5% to 0.9%. While operational winds contribute significantly to
106 forecast improvement, unexpected occurrences such as the COVID-19 pandemic can disturb
107 aircraft measurements, resulting in less precise forecasts during such periods (James et al., 2020).
108 This circumstance, and the need to quantify Doppler wind lidar profiles' impact in isolation from
109 other wind-observation systems, prompts the addition of this study's OSE labeled "CNTRL–
110 wind+Aeolus" (refer to Section 2 for the experimental setup). This new OSE aims to specifically
111 assess the isolated impact of Aeolus winds in the Arctic without the influence of other wind
112 products.

113 Our investigation encompasses an assessment of the overall improvements in Arctic
114 forecasts resulting from the assimilation of different sets of wind observations, as well as an
115 exploration of the influence of wind observations on the forecasts related to enhanced kinetic
116 energy and intense Integrated Vapor Transport (IVT). Henceforth, "disturbed" atmospheric state
117 is used to describe days with strong winds or intense vapor transport. These two metrics were
118 selected because of their large societal and economic impacts. Enhanced kinetic energy is
119 commonly used as a severe-weather indicator, e.g. for severe storms, tornadoes, hurricanes, and
120 typhoons (Palmén, 1958; DeMego and Bosart, 1982; Misra et al., 2013; Bass et al., 2017) and as
121 an indirect indicator of extreme rainfall and flooding events (Brodie and Rosewell, 2007; Chang
122 et al., 2017; Kim et al., 2022). Energetic systems can also transport substantial moisture from
123 moisture sources, which can lead to weather-related water damage (Hills, 1978; Jiang, 2003;
124 Chen et al., 2012; Martinez et al., 2019; Olaguera et al., 2021). Recent research suggests that
125 ongoing climate changes are likely modifying IVT patterns, influencing the frequency and

126 intensity of future extreme weather events (Radic et al., 2015; Mattingly et al., 2016; Gershunov
127 et al., 2017; Tan et al., 2019).

128 This paper is organized as follows: Section 2 outlines the experimental setup, including
129 details on the ECCC global forecast system and OSE. In Section 3, we present impact scores by
130 comparing forecasts to ERA5 and define strong wind and strong vapor transport events. Section
131 4 unveils our results on the impact of wind observations on forecasts over the Arctic and on
132 atmospheric events in the region. Finally, Section 5 offers a discussion of the main conclusions
133 derived from this study.

134 **2 Experimental Setup**

135 OSEs are used to evaluate and assess the impact of observational data on NWP models
136 by adding or removing a set of observations that are assimilated into the NWP model (Bouttier
137 and Kelly, 2001; Laroche and Poan, 2021; Laroche and St-James, 2022). In this study, we use an
138 extension of the series of OSEs used in Chou and Kushner (2023) to examine the impact of the
139 operational wind observations and of Aeolus HLOS winds on the Arctic forecasts of the
140 Canadian Global Deterministic Prediction System (GDPS). The OSEs cover two seasons: from
141 July 1 to September 30 2019 (summer 2019) and from December 1 2019 to March 31 2020
142 (winter 2020). The atmospheric component of the forecast system is the latest version of the
143 operational Global Environmental Multiscale (GEM) model implemented at ECCC in 2019
144 (McTaggart-Cowan et al., 2019) and the ocean component of the forecast system is the NEMO
145 ocean model (Smith et al., 2018). The model uses approximately 15 km horizontal grid spacing
146 and 84 vertical levels. The data assimilation scheme is the operational four-dimensional
147 ensemble-variational (4D-EnVar) (Buehner et al., 2015) system, with a 6-h assimilation window
148 which includes over 13 million observations assimilated daily. Two forecasts were generated

149 daily (at 00 and 12 UTC). To minimize the computational cost, a coarser horizontal grid
150 resolution of 39 km is employed and some aspects of the GEM physics are simplified.
151 Implications of the use of this coarse resolution will be discussed in Section 5. Further details
152 and justification on this simplified GDPS version are provided in Laroche and St-James (2022)
153 and Chou and Kushner (2023). To examine the impact of wind observations, four experiments
154 are carried out:

- 155 1. CNTRL, an experiment with all operational observations.
- 156 2. CNTRL–winds (i.e., “control-minus-winds”), an experiment with all operational
157 observations except the operational wind observations. Operational winds include wind
158 measurements from AMDAR, AMVs, radiosondes, surface stations, surface buoys, wind
159 profilers, and scatterometry. This assesses the impact of all operational wind products on
160 NWP skill.
- 161 3. CNTRL–wind+ Aeolus (i.e., “control-minus-winds-plus-Aeolus”), an experiment with all
162 operational observations and Aeolus HLOS winds (both Rayleigh-clear and Mie-cloudy
163 winds) but without the operational wind observations. The winds used are from the
164 second reprocessed product, the Level-2B11 product. This tests the impact of Aeolus
165 winds in isolation from the other wind products and provides an assessment of NWP
166 performance if traditional wind observations were halted (such as the reduction in
167 AMDAR flights during Covid 19) but Aeolus was assimilated.
- 168 4. CNTRL+ Aeolus (i.e., “control plus Aeolus”), an experiment that adds the Aeolus HLOS
169 winds (both Rayleigh-clear and Mie-cloudy winds) to the CNTRL experiment. This tests
170 the impact of Aeolus winds on top of the other wind products and provides an assessment
171 of NWP performance if Aeolus winds were operationally assimilated.

172 Chou and Kushner (2023) used OSEs 1, 2, and 4. The current study is the first to use OSE 3 to
173 test the effect of Aeolus wind impacts separately from other wind products.

174 To evaluate the impact of the wind observations, we compare the forecast root-mean-
175 square error (RMSE) between the experiments. The mathematical expression of the forecast
176 impact scores will be discussed in Section 3. Henceforth, the expression “impact of operational
177 winds” (IOW) refers to the normalized change in the forecast scores from the CNTRL compared
178 to the CNTRL-winds (i.e., error of CNTRL-winds minus error of CNTRL, which is therefore
179 positive for improvement), the expression “impact of Aeolus winds” (IAW) refers to the change
180 in the forecast scores from the CNTRL-winds+Aeolus compared to the CNTRL-winds (i.e.,
181 error of CNTRL-winds minus error of CNTRL-winds+Aeolus, which is therefore, again,
182 positive for improvement), and the expression “impact of Aeolus on top of operational winds”
183 (IAOW) refers to the change from the CNTRL+Aeolus compared to the CNTRL (i.e., error of
184 CNTRL minus error of CNTRL+Aeolus, so, again, positive for improvement).

185 **3 Method**

186 We verify the forecasts from OSEs described in Section 2, against ERA5 from ECMWF
187 (Hersbach et al., 2023). ERA5 is based on a four-dimensional variational (4DVar) data
188 assimilation scheme using Cycle 41r2 of the Integrated Forecast System (IFS). We use the
189 hourly winds, temperature, and specific humidity at 00 and 12 UTC. The data are gridded on a
190 regular latitude-longitude grid of 0.25° , but linearly interpolated onto grid of 0.5° to match the
191 coarser resolution of the OSEs, and only the OSEs’ 16 pressure levels are selected (10, 20, 30,
192 50, 70, 100, 150, 200, 250, 300, 400, 500, 700, 850, 925, and 1000 hPa).

193 The impact of wind observations is defined as the normalized change (percentage
194 change) in the forecast RMSE between the experiments over the Arctic. The steps to calculate
195 the forecast RMSE are as follows:

- 196 1. Calculate the cosine-weighted mean-square-error (MSE) between the forecasts from
197 OSEs and the verification field from ERA5, over the Arctic (70° to 90°N), for each
198 forecast hour (two forecasts daily for a total of seven months). The MSE for a scalar field
199 x (i.e., temperature, specific humidity, and IVT) is

$$200 \quad MSE = \frac{\sum_i w_i (x_f - x_v)_i^2}{\sum_i w_i} \quad (1)$$

202 and the MSE for a vector field \vec{v} (i.e., vector wind and wind shear) is

$$203 \quad MSE_{vector} = \frac{\sum_i w_i \|\vec{v}_f - \vec{v}_v\|_i^2}{\sum_i w_i} \quad (2)$$

205 The index i indicates a grid point along a latitude band, the subscript f indicates the
206 forecast, and the subscript v indicates the verification field. The weight $w_i = \cos \theta_i$,
207 where θ_i is the latitude at location i .

- 208 2. The weighted MSEs are averaged over the seven months covering the available Aeolus
209 observation products.
- 210 3. The square-root of the averaged weighted MSEs is the RMSE at each pressure level.
- 211 4. The normalized change in scores represents the percentage change of the RMSE between
212 a pair of OSEs from Step 3.

213 5. The tropospheric impact score is the averaged scores from Step 4 from the four pressure
214 levels: 850 hPa, 500 hPa, 250 hPa, and 100 hPa.

215 As introduced in Section 2, the impact of operational winds (IOW) is the percentage
216 difference of forecast RMSE between CNTRL and CNTRL-winds; the impact of Aeolus winds
217 (IAW) is the percentage difference of CNTRL-winds+Aeolus and CNTRL-winds; the impact of
218 Aeolus on top of operational winds (IAOW) is the percentage difference of CNTRL+Aeolus and
219 CNTRL.

220 Chou and Kushner (2023) show that adding Aeolus winds into data assimilation, which
221 are the first global wind profile measurements, can improve the forecasts of the vertical structure
222 of the wind field. We carry out this analysis in this study and will investigate the impact of wind
223 observations on Arctic weather events on the tropospheric wind vector, temperature, wind shear
224 (thermal-wind) vector (defined as the vector wind difference between 250 hPa and 850 hPa),
225 specific humidity, and IVT. Analysis of specific humidity was included to help interpret the
226 results of the IVT analysis.

227 For the second part of the paper (Section 4.2), we will discuss the impact of wind
228 observations over the Arctic when the atmosphere is disturbed (i.e., strong kinetic energy or
229 intense IVT). In preliminary work, we have investigated the impact of wind observations on
230 localized events, such as strong wind events at radiosonde stations over the Arctic and forecasts
231 along Aeolus swaths. This analysis is not shown in this study because, due to the short period of
232 the Aeolus mission and the coarse resolution of the OSE forecasts, there were not many
233 individual local events to average over, and we found that the OSEs had limited ability to resolve
234 smaller-scale atmospheric features associated with severe Arctic weather such as polar lows.
235 Instead, to investigate the impact of wind observations on predictability of extreme Arctic

236 weather events, we focus on days in which the atmosphere is strongly disturbed over the entire
 237 Arctic. In particular, we examine the impact of wind observations on the forecasts of “strong”
 238 500-hPa Kinetic Energy (KE500) days vs. “normal” KE500 days, and of strong IVT days vs.
 239 normal IVT days over the Arctic. The KE500 ($m^2 s^{-2}$) is

$$240 \quad KE500 = \frac{1}{2}(u^2 + v^2)$$

241 (3)

242 where u and v are the 500-hPa zonal and meridional wind components, respectively. The IVT
 243 ($kgm^{-1}s^{-1}$) is

$$244 \quad IVT = \sqrt{\left(\frac{1}{g} \int_{1000}^{300} qu dp\right)^2 + \left(\frac{1}{g} \int_{1000}^{300} qv dp\right)^2}$$

245 (4)

246 where g is the gravitational acceleration, q is the specific humidity, u and v are the zonal and
 247 meridional winds, and the product of the specific humidity and the winds is integrated over 1000,
 248 925, 850, 700, 500, 400, and 300 hPa (Cordeira and Ralph, 2020; Reynolds et al., 2022).

249 We define the strong KE500 days and strong IVT days in a similar way. First, we define
 250 the threshold at each grid point as the 90th percentile of the local KE500 or the local IVT for the
 251 summer season and the winter season separately. We record the number of grid points poleward
 252 of 70°N that exceed this threshold and take the top 25% of this number for both seasons
 253 combined to get “strong weather-event days” with more disturbed atmospheric conditions. Trial
 254 and error suggests that this provides sufficient sampling to assess the impact of wind
 255 observations on the forecasts (Section 4.2).

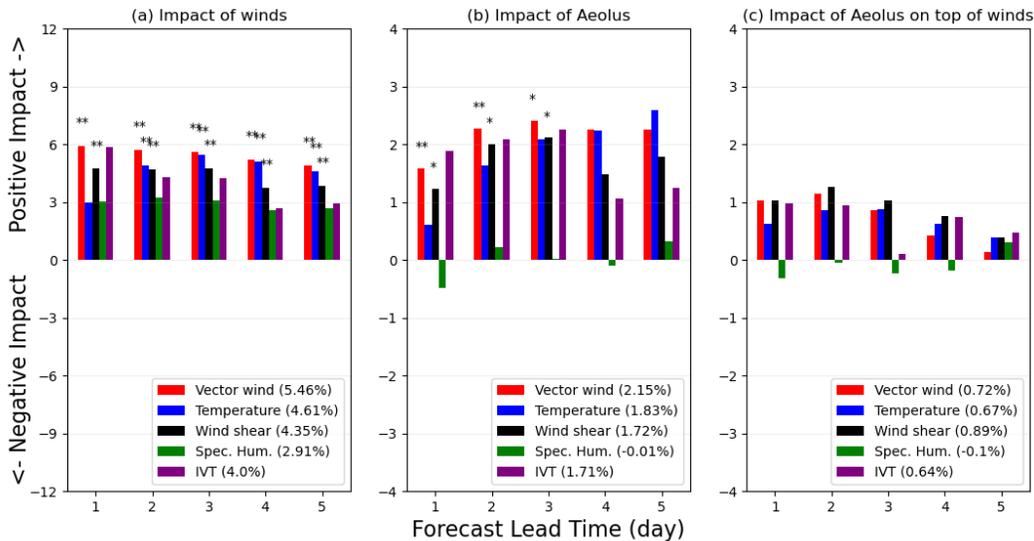
256 **4 Results**

257 4.1 Impact of operational winds and Aeolus winds over the Arctic

258 Figure 1 shows the impact of operational winds (IOW), Aeolus winds (IAW), and Aeolus
259 winds on top of operational winds (IAOW) on the tropospheric forecast RMSE over the Arctic.
260 Note that the y-axis extends from -12 to 12% for the IOW (panel a) and from -4 to 4% for the
261 IAW and IAOW (Figure 1b,c). As expected, operational wind observations notably enhance the
262 forecasts of wind fields (vector wind and wind shear) and the temperature field, which provides a
263 context for assessing the impacts of Aeolus (Chou and Kushner, 2023). Averaged scores for
264 these three fields over five days demonstrate an improvement of approximately 5%. Replacing
265 operational winds by Aeolus winds, IAW (Figure 1b), consistently delivers a positive impact of
266 about 2%, constituting roughly 40% of the improvement achieved with all operational winds. It
267 is noteworthy that Aeolus, despite being a single-satellite measurement system, contributes
268 meaningfully to forecast enhancement.

269 Considering all operational winds, as reflected in the IAOW in Figure 1c, Aeolus winds
270 further enhance the wind and temperature fields throughout the five-day forecast lead time by
271 0.7% and 0.9%, respectively, representing 14% to 18% of the overall improvement obtained with
272 all operational winds. While this positive IAOW is relatively modest compared to improvements
273 found by Aeolus for other models (e.g., Garrett et al., 2022; Rennie et al., 2021), it aligns with
274 previous findings in OSEs conducted with the ECCO GDPS (Laroche and St-James, 2022; Chou
275 and Kushner, 2023). The reasons for this modest impact are elaborated on in Chou and Kushner
276 (2023). Despite the relatively small contribution, the impact of Aeolus winds on top of
277 operational winds is noteworthy, particularly considering that Aeolus observations for this period
278 constitute less than 1% of all operational wind observations. Notably, operational winds,

279 inclusive of measurements from various ground-based instruments, radiosondes, and satellites,
 280 account for roughly 10% of all operational observations over the Arctic in the ECCC GDPS. The
 281 lack of significance when assimilating Aeolus winds on top of operational winds might arise
 282 from the simplification and relatively coarse resolution of the ECCC model version used in this
 283 work to reduce computational cost, systematic model issues beyond this simplification, or
 284 assimilation system deficiencies, as discussed in Chou and Kushner (2023). Importantly, the
 285 IAW remains significant, reaching at least 90% confidence level, particularly in the wind fields
 286 for the first three days of the lead time.



287
 288 Figure 1: Normalized change in RMS forecast error between (a) CNTRL–winds and CNTRL (IOW), (b) CNTRL–
 289 winds and CNTRL–winds+Aeolus (IAW), and (c) CNTRL and CNTRL+Aeolus (IAOW), compared to ERA5 in the
 290 troposphere for vector wind (red), temperature (blue), wind shear (black), specific humidity (green), and integrated
 291 vapor transport (IVT) (purple) in the troposphere (850-100hPa layer) for 5-day forecasts over the Arctic. Positive
 292 impact means a reduction in the forecast error. The impacts that are significant at 95% confident level are marked
 293 with double asterisk (**) and impacts that are significant at 90% confident level are marked with single asterisk (*).
 294 The significance is tested using a t-test for the null hypothesis that the pair of experiments have identical cosine-

295 weighted RMSE from all four layers. The averaged impact over the five forecast lead time days is shown in the
296 brackets.

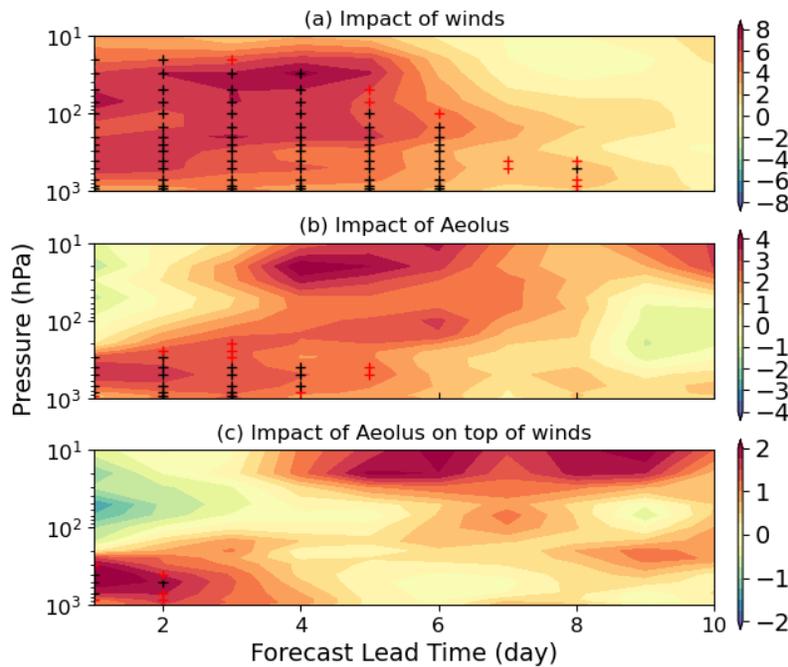
297 Both operational winds and Aeolus winds show minimal to no impact on the specific
298 humidity field, despite enhancements in other fields. The averaged IOW in Figure 1a over a five-
299 day forecast lead time is approximately 3%, which is about half of the impact observed in the
300 vector wind field. The IAW in Figure 1b and the IAOW in Figure 1c on the specific humidity
301 field lack consistency throughout the forecast lead time. Consequently, the impact on the IVT,
302 encompassing both wind and specific humidity information, falls between the impact on the
303 wind fields and the specific humidity field. The averaged scores for the IVT are 4.0, 1.7, and
304 0.6% for the IOW, IAW, and IAOW, respectively.

305 Figure 2 provides a view of the spatial structure of the impact of wind observations on the
306 vector wind field by breaking down the pressure-level and forecast lead time dependence (up to
307 day 10). The tropospheric impacts observed in the first five days of the forecast lead time align
308 with the findings depicted in Figure 1. Note that the color scale is compressed by factors of two
309 when transitioning from the IOW in Figure 2a to the IAW in Figure 2b, and to the IAOW in
310 Figure 2c. This demonstrates, consistently with Figure 1, that IAW contributes to about half of
311 the improvement obtained by all operational winds. In the case of tropospheric IAOW, the
312 enhancements from Aeolus winds on top of operational winds exceed 25% of the improvement
313 obtained with all operational winds in short-range forecasts and are slightly less than 20% in
314 short- to medium-range forecasts.

315 Conversely, Figure 2 reveals a degradation in forecast skills when assimilating Aeolus in
316 the stratosphere. As previously discussed in Chou and Kushner (2023), this issue may arise from

317 the simplification of the ECCO model version used to reduce computational costs, systematic
318 model issues beyond this simplification, or deficiencies in the assimilation system.

319 Overall, Figure 2 underscores the potential of Aeolus to enhance medium- to long-range
320 forecasts, particularly in the upper atmosphere beyond day 4. The IAW accounts for more than
321 50% of the improvements from operational winds, and more than 25% for the IAOW. This
322 stratospheric improvement in long-range forecasts over the Arctic is primarily attributed to the
323 signal during the winter season, characterized by an anomalously strong Arctic stratospheric
324 polar vortex in 2019-2020 (Chou and Kushner, 2023; Lawrence et al., 2020).



325

326 Figure 2: Normalized change in RMS forecast error as a function of pressure level between (a) CNTRL–winds and
327 CNTRL, (b) CNTRL–winds and CNTRL–winds+Aeolus, and (c) CNTRL and CNTRL+Aeolus, for wind vector for
328 10-day forecasts over the Arctic. Positive impact means a reduction in the forecast error. The impacts that are
329 significant at 95% confident level are marked with black plus sign and impacts that are significant at 90% confident

330 level are marked with red plus sign. The scores with respect to ERA5 data are interpolated onto the 16 pressure
331 levels of the OSEs.

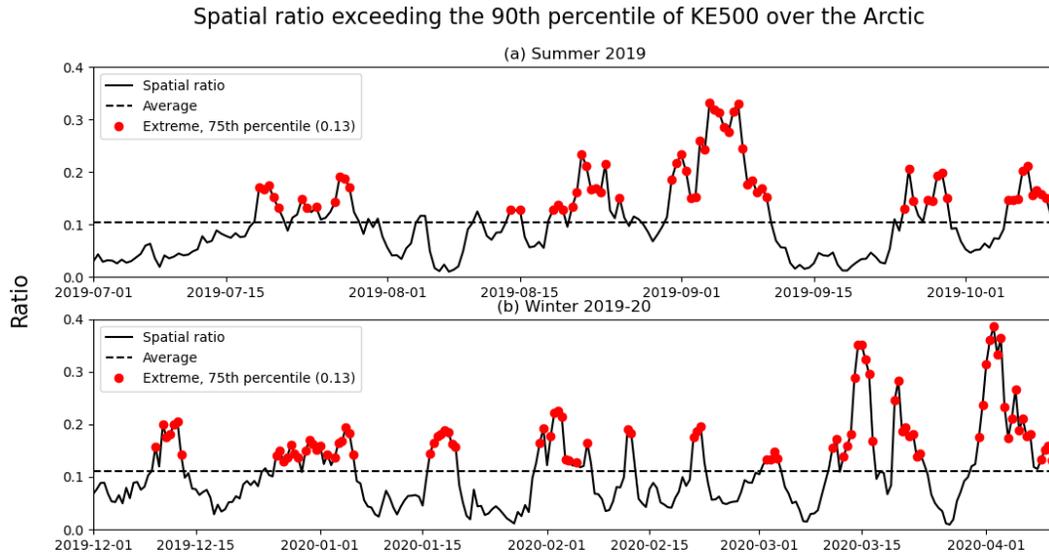
332 Despite previous challenges in attributing improvements in the Arctic forecast to
333 localized regions, some regional insight can be gained by including all forecasts and dividing the
334 Arctic into quadrants. We repeat the pan-Arctic analysis for four Arctic quadrants and investigate
335 the IOW, IAW, and IAOW on the wind and temperature fields over each quadrant (SFigures 1 to
336 3 respectively). This shows that over the Arctic, Russian-Pacific-Northern Canada sector
337 forecasts ($90^{\circ}\text{E} - 180^{\circ}\text{E}$ and $180^{\circ}\text{E} - 270^{\circ}\text{E}$) are most improved and sensitive to the wind
338 observations; the IOW on the vector wind field are 5.7% and 6.7%, compared to 4.6% and 5.0%
339 over the other two quadrants and similar results are found when Aeolus winds are assimilated.
340 The IAW and IAOW on the vector wind field are around 2.7 and 0.8% respectively over the
341 quadrants between 90° and 270°E , which are about 40 and 13% of the IOW, but the impacts are
342 only around 1.6 and 0.6% over the other two quadrants, which are 33 and 12% compared to
343 IOW. The reason why this region's forecasts are more sensitive to wind observations remains
344 unclear, but it is consistent when different sets of wind observations are assimilated into the
345 forecast model. There are many aspects that can lead to this difference; for example, the
346 proportion of land, ocean, and snow/ice, number of observations over the region, and the physics
347 used for the region in the model. However, such investigations are beyond the scope of this
348 paper.

349

350 4.2 Impact of wind observations on strong wind and vapor transport events over the Arctic

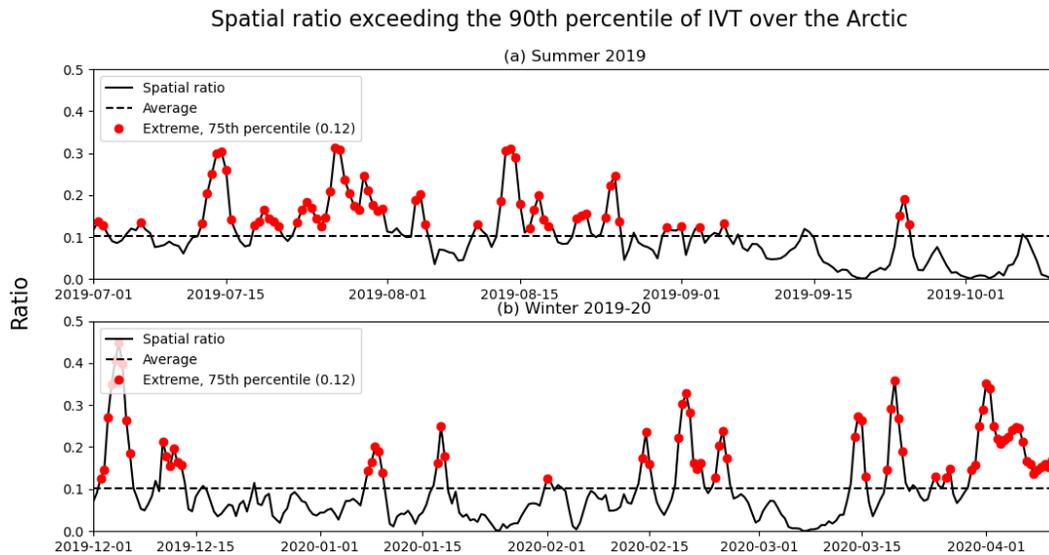
351 We are interested in whether wind observations would improve the forecasts of severe
352 weather events and how much in advance the forecasts would show an improvement. More

353 specifically, this subsection presents the impact of wind observations on strong wind events and
354 water vapor transport events over the Arctic. The proportions of the Arctic that exceed the
355 KE500 and IVT thresholds (90th percentile of the field of the season) are recorded at each
356 forecast hour and the time-series of this spatial coverage ratio are shown in Figures 3 and 4,
357 respectively. The days that are defined as more energized or in a more disturbed atmospheric
358 state are the top 25% (red dots) of this spatial coverage ratio during the entire period of analysis.
359 For these events at and above the 75th percentile, the forecasts that are defined as strong KE500
360 occur when at least 13% of the Arctic points exceed the thresholds of the field, and the forecasts
361 that are defined as strong IVT occur when at least 12% of the Arctic exceed the threshold of the
362 field. Strong KE500 forecasts do not necessarily overlap with the forecasts that have strong IVT.
363 For example, before mid-July 2019, there are around eight forecasts that experienced strong IVT,
364 but none of the forecasts during this period are defined as strong KE500 forecasts. Also, at the
365 end of December 2019 and in early January 2020, most of the forecasts show an energetic, strong
366 KE500, atmosphere, but the IVT over the Arctic during this period is relatively weak. By
367 grouping the forecasts using the top 25%, we get sufficient forecasts (around 100 forecasts) to
368 compare and to investigate the impact of wind observations on disturbed atmospheric states.



369

370 Figure 3: The time-series (solid black line) during (a) summer 2019 and (b) winter 2019-20 of the spatial coverage
 371 ratio that exceeds the 90th percentile of the 500-hPa Kinetic Energy of the season over the Arctic. The time-averaged
 372 of the spatial ratio of the season is shown as the dashed black line. The strong KE500 days (red dots) are defined as
 373 when the spatial ratio exceeds the 75th percentile of the two seasons combined. The threshold of the spatial ratio (the
 374 75th percentile) is indicated in the legend for the extreme days.

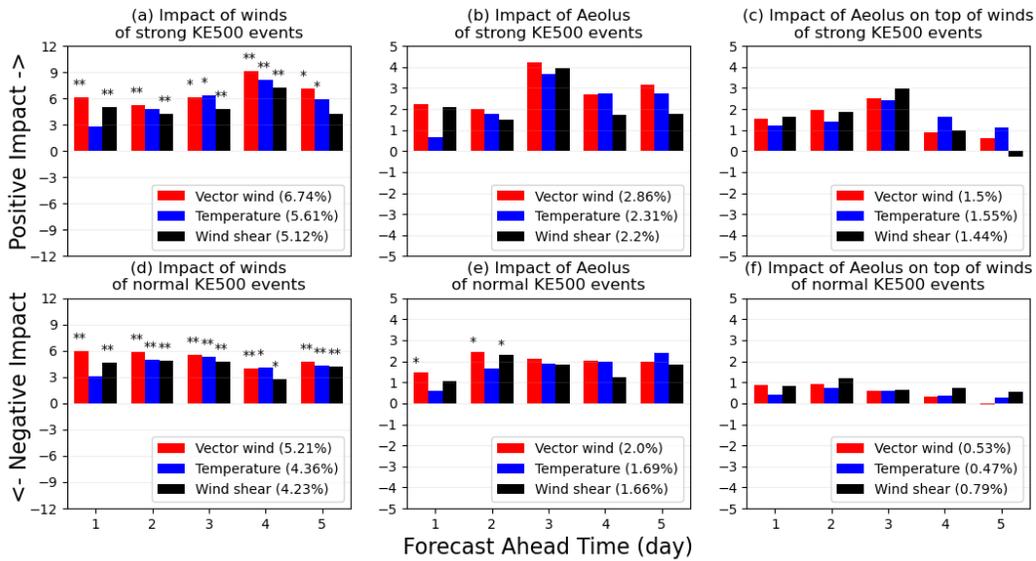


375

376 Figure 4: Similar to Figure 3, but for the spatial coverage ratio that exceeds the 90th percentile of the IVT over the
377 Arctic.

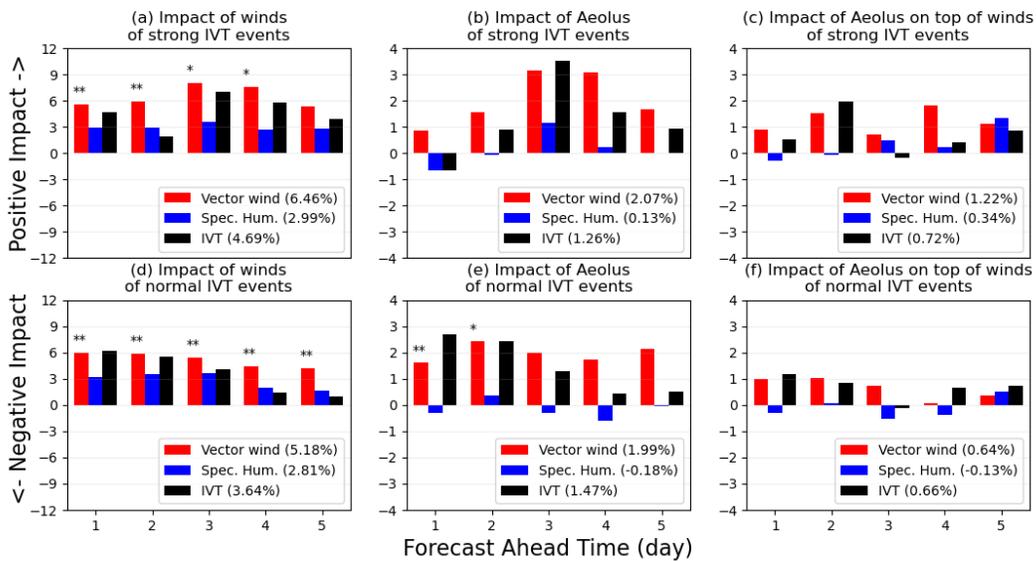
378 We use the same approach, outlined in Section 3, to find the normalized change in the
379 forecast RMSE between a pair of experiments, but we composite tropospheric forecast skill
380 impacts conditioned on strong (Figure 5a,b,c) and normal (Figure 5d,e,f) Arctic KE500, and on
381 strong (Figure 6a,b,c) and normal (Figure 6d,e,f) Arctic IVT. Note that the x-axis is showing the
382 forecast “ahead” time, instead of the forecast lead time as shown in Figures 1 and 2. The forecast
383 ahead time represents the number of days prior to the identified disturbed atmospheric day, as
384 measured with KE500 or IVT. For instance, if there is a strong wind event on July 15th, then the
385 scores show the impact of wind observations on forecasts of July 15th that were made prior to the
386 event. If the score for forecasts of two-day ahead time is 2%, then it means that the forecast
387 RMSE with two-day lead time that was made on July 13th is reduced by 2% when wind
388 observations are assimilated.

389 The wind observations consistently provide more positive impact on forecasts of strong
390 KE500 on wind and temperature fields. For example, the IOW on forecasts of normal KE500 is
391 around 4.6% and it increases to around 5.8% when conditioned on forecasts of strong KE500.
392 Consistent findings are noted with the assimilation of Aeolus winds. The impact scores show an
393 increase from 1.8 to 2.4% when operational winds are replaced by Aeolus winds, when
394 conditioned on normal (Figure 5e) and strong (Figure 5b) KE500 days. Specifically, the IAOW
395 for forecasts of strong KE500 is nearly triple the impact scores observed when conditioned on
396 normal KE500 days. The averaged scores over the five forecast lead times rise from 0.6 to 1.5%.



397

398 Figure 5: Normalized change in RMS forecast error for IOW (left column), IAW (middle column), and IAOW (right
 399 column) for vector winds, temperature and wind shear, as a function of “Forecast Ahead Time” (see text), for strong
 400 KE500 forecasts only (top row) and normal KE500 forecasts only (bottom row). Note that the scale of the y-axis
 401 extends from -5 to 5% for panels b, c, e, and f. Significance testing as in Figure 1. Strong KE500 events are defined
 402 in Figure 3; the remaining KE500 events are identified as “normal”.



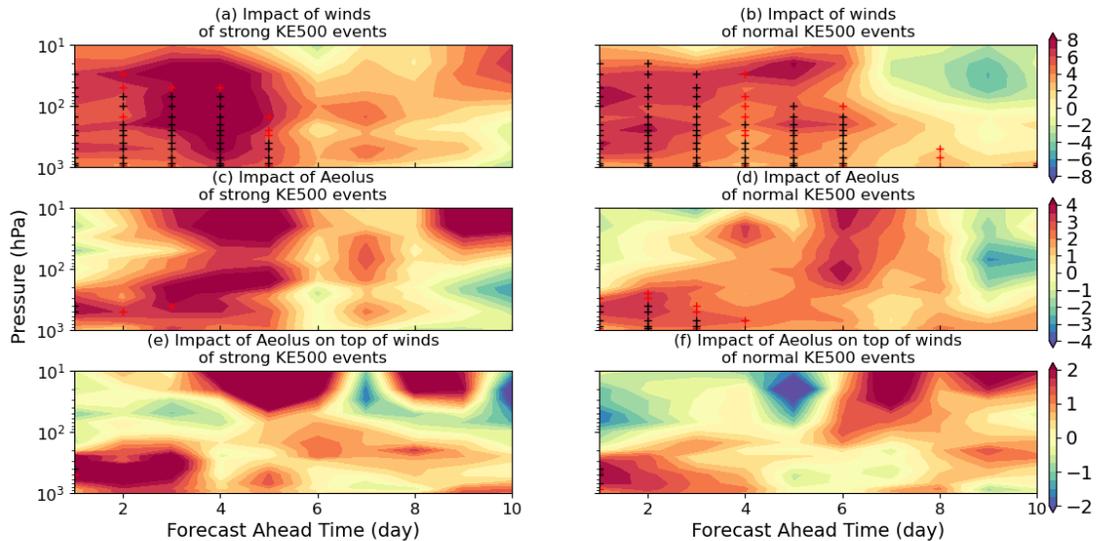
403

404 Figure 6: Similar to Figure 5, but for vector winds, specific humidity, and IVT, for strong and normal IVT events
405 defined in Figure 4.

406 Greater impacts are also seen when conditioned on forecasts of strong IVT (Figure
407 6a,b,c) compared to forecasts of normal IVT (Figure 6d,e,f). The IOW on the wind field
408 increases by approximately 1.3% when conditioned on strong IVT and by 1.0% for the IVT field.
409 Conversely, the averaged IAW over five days shows little to no difference when conditioned on
410 forecasts of strong IVT days (Figure 6b,e). The impact scores averaged over the five forecast
411 lead times on the wind and IVT fields exhibit no more than a 0.2% difference. If Aeolus winds
412 are assimilated on top of operational winds, the IAOW would approximately double the impact
413 scores for the wind field when conditioned on forecasts of strong IVT (Figure 6c). Generally,
414 Aeolus winds (Figure 6b,c,e,f) demonstrate little to no consistent impact on the specific humidity
415 field.

416 The results from Figure 5 encourage us to investigate the profiles of impact of wind
417 observations conditioned on strong (Figure 7a,c,e) and normal (Figure 7b,d,f) Arctic KE500 with
418 a longer forecast ahead time. Profiles of impact conditioned on strong and normal Arctic IVT are
419 shown in the supplementary information (SFigure 6). The operational winds reduce the forecast
420 RMSE by more than 8% throughout the atmosphere with 3 to 5 days of lead time before strong
421 KE500 days (Figure 7a), whereas they only reduce the forecast RMSE by about 4% for normal
422 KE500 (Figure 7b). When operational winds are replaced by Aeolus winds, the IAW on forecasts
423 of strong KE500 with a lead time of 3 to 5 days (Figure 7c) accounts for approximately 50% of
424 the improvement obtained with all operational winds. Consistently with our findings above, the
425 IAW is about 40% of the IOW and the IAW impact on strong KE500 days is greater than on
426 normal KE500 days (Figures 7c-d), and IAOW is about 25% of the IOW, with extended lower

427 tropospheric impacts four or more days ahead being evident for the strong KE500 days, which is
428 not as evident for the normal KE500 days (Figures 7e-f).



429
430 Figure 7: Normalized change in RMS forecast error as a function of pressure level for IOW (top row), IAW (middle
431 row) and IAOW (bottom row), for wind vector errors up to 10 forecast days ahead. Positive impact means a
432 reduction in the forecast error. The left column shows the impact of the added wind observations respectively of the
433 strong KE500 days only defined in Figure 3 and column two shows the impact of the non-strong KE500 days only.
434 Significance testing as in Figure 2.

435 5 Conclusions

436 The Arctic has fewer weather observation stations and limited data sources due to its low
437 population density, limited accessibility, and harsh environment. However, the Arctic's
438 distinctive geography, increasing economic activity, global geopolitical importance, and rapidly
439 evolving climate changes necessitate advances in weather modeling and forecasting. Precise
440 weather predictions in the Arctic are crucial for the safety of individuals and navigation in the
441 area, and a deeper comprehension of Arctic weather has the potential to improve global climate
442 models.

443 To better understand the role of wind observations in the weather forecasts over the
444 Arctic, we have assessed the impact of operational winds (IOW), Aeolus winds (IAW), and
445 Aeolus winds on top of operational winds (IAOW) on the ECCO global forecast system over the
446 Arctic during July to September 2019 and December 2019 to March 2020. The analysis covers
447 both the difference between disturbed atmospheric conditions (high versus normal KE500 and
448 IVT days) and surveys different Arctic sectors for improvements. This extends Chou and
449 Kushner (2023) who examined the general scale dependence and global distribution of IOW and
450 IAOW. The IAOW has been enabled by the new experiment without the operational winds but
451 with the Aeolus winds (CNTRL_winds+Aeolus), which allows us to study the impact of Aeolus
452 winds as if it were, hypothetically, the only source of wind observations.

453 As anticipated, operational winds significantly enhance Arctic forecasts, reducing
454 forecast RMSE by approximately 5%, particularly in the wind and temperature fields. This
455 improvement is even greater for disturbed atmospheric conditions, as measured by high KE500
456 and IVT values. This highlights how wind observations become even more important during
457 extreme atmospheric states where simple dynamical balances that couple mass and circulation
458 break down. Despite Aeolus winds representing less than 1% of operational wind observations,
459 substituting operational winds with Aeolus winds in the assimilation process results in an
460 observed 2% reduction in errors, equivalent to approximately 40% of the improvement achieved
461 by operational winds. This improvement extends to the additional forecast improvements seen on
462 strong KE500 and IVT days. Thus, despite being derived from a single satellite, Aeolus winds
463 can match nearly half of the forecast enhancement realized by operational winds, which
464 incorporate wind measurements from multiple ground-based instruments, radiosondes, and
465 satellites. This suggests that Doppler wind lidar systems have the potential to strongly

466 complement conventional wind observations. This was already seen when Aeolus data was
467 shown, during the COVID-19 pandemic, to be capable of compensating for the disruption of
468 AMDAR aircraft wind measurements and consequent forecast degradation (James et al., 2020).
469 Altogether, assimilating Aeolus winds on top of operational winds (IAOW) yields an additional
470 0.8% reduction in errors, constituting around 16% of the overall improvement obtained with all
471 operational winds.

472 While wind observations exhibit positive outcomes for mass-related fields like
473 temperature, operational winds only contribute approximately half of the impact on the specific
474 humidity field compared to the temperature field. Additionally, both the IAW and IAOW show
475 little to no influence on the specific humidity field over the Arctic. This suggests that wind
476 observations have limited efficacy in improving the specific humidity field.

477 As noted, Aeolus not only improves overall forecasts over the Arctic but also improves
478 predictions for specific days characterized by strong winds and enhanced water vapor transport,
479 which are associated with extreme weather events. In particular, the IAOW further reveals a two
480 to threefold increase in impact scores (ranging from 0.5 to 1.5% for strong KE500 and 0.6 to
481 1.2% for intense IVT) on the wind field when forecasts are conditioned on a disturbed
482 atmosphere, as opposed to normal days. While these results are found consistently in our
483 diagnostics, their statistical significance is marginal and, we expect, will depend strongly on the
484 smaller scale phenomena associated with extreme wind and IVT events. We thus strongly
485 recommend conducting longer periods of OSEs at a higher resolution or with the use of a limited
486 area regional forecast model.

487 The results also provide a compelling rationale for ECCO and other modelling centres to
488 consider the operational assimilation of Aeolus winds. In particular, results have demonstrated

489 enhancements in forecast skill over data-sparse regions such as the Canadian Arctic, and for
490 forecasts of intense wind events linked to extreme weather patterns, which can have large health,
491 societal, and economic impacts. Notably, several European weather forecast centers, including
492 ECMWF, DWD, Météo-France, and UK Met Office, have already embraced assimilation of
493 Aeolus (Rennie et al., 2021; Pourret et al., 2022; Kiriakidis et al., 2023). Therefore, we
494 recommend that weather forecast centers consider assimilating global wind profile measurements
495 from the potential Aeolus follow-on mission, Aeolus-2, scheduled for launch in 2030 (Heliere et
496 al., 2023).

497

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502

503 **Data availability**

504 The OSEs' MSE verified against ERA5 can be downloaded from the Borealis
505 (<https://doi.org/10.5683/SP3/C0XY1B>). The ERA5 data can be downloaded from the Copernicus
506 Climate Change Service (C3S) Climate Data Store
507 (<https://doi.org/10.24381/cds.bd0915c6>, Hersbach et al., 2023).

508

509

510 **References**

- 511 Augustine, J. A., & Zipser, E. J. (1987). The Use of Wind Profilers in a Mesoscale
512 Experiment. *Bulletin of the American Meteorological Society*, 68(1), 4-
513 17. [https://doi.org/10.1175/1520-0477\(1987\)068<0004:TUOWPI>2.0.CO;2](https://doi.org/10.1175/1520-0477(1987)068<0004:TUOWPI>2.0.CO;2)
- 514 Baker, W. E., Emmitt, G. D., Robertson, F., Atlas, R. M., Molinari, J. E., Bowdle, D. A., Paegle,
515 J., Hardesty, R. M., Menzies, R. T., Krishnamurti, T. N., Brown, R. A., Post, M. J.,
516 Anderson, J. R., Lorenc, A. C., & McElroy, J. (1995). Lidar-Measured Winds from
517 Space: A Key Component for Weather and Climate Prediction. *Bulletin of the American*
518 *Meteorological Society*, 76(6), 869-888. [https://doi.org/10.1175/1520-
519 0477\(1995\)076<0869:LMWFSA>2.0.CO;2](https://doi.org/10.1175/1520-0477(1995)076<0869:LMWFSA>2.0.CO;2)
- 520 Bass, B., Irza, J.N., Proft, J. *et al.* (2017). Fidelity of the integrated kinetic energy factor as an
521 indicator of storm surge impacts. *Nat Hazards* **85**, 575–595.
522 <https://doi.org/10.1007/s11069-016-2587-3>
- 523 Bauer, P., Magnusson, L., Thépaut, J.-N. and Hamill, T.M. (2016), Aspects of ECMWF model
524 performance in polar areas. *Q.J.R. Meteorol. Soc.*, 142: 583-596.
525 <https://doi.org/10.1002/qj.2449>
- 526 Bormann, N., & Thépaut, J.-N. (2004). Impact of MODIS polar winds in ECMWF's 4D-VAR
527 data assimilation system. *Monthly Weather Review*, 132, 929–940.
- 528 Bouttier, F. and Kelly, G. (2001), Observing-system experiments in the ECMWF 4D-Var data
529 assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 127: 1469-
530 1488. <https://doi.org/10.1002/qj.49712757419>

531 Brodie, I. and Rosewell, C. (2007). Theoretical relationships between rainfall intensity and
532 kinetic energy variants associated with stormwater particle washoff. *Journal of*
533 *Hydrology*, Volume 340, Issues 1–2, 2007, Pages 40-47, ISSN 0022-1694.
534 <https://doi.org/10.1016/j.jhydrol.2007.03.019>

535 Buehner, M., McTaggart-Cowan, R., Beaulne, A., Charette, C., Garand, L., Heilliette, S.,
536 Lapalme, E., Laroche, S., Macpherson, S. R., Morneau, J., & Zadra, A. (2015).
537 Implementation of Deterministic Weather Forecasting Systems Based on Ensemble–
538 Variational Data Assimilation at Environment Canada. Part I: The Global
539 System. *Monthly Weather Review*, 143(7), 2532-2559. [https://doi.org/10.1175/MWR-D-](https://doi.org/10.1175/MWR-D-14-00354.1)
540 [14-00354.1](https://doi.org/10.1175/MWR-D-14-00354.1)

541 Carminati, F., A. Migliorini, S., Ingleby, B., Bell, W., Lawrence, H., Newman, S., Hocking, J., &
542 Smith, A. (2019). Using reference radiosondes to characterise NWP model uncertainty
543 for improved satellite calibration and validation. *Atmospheric Measurement*
544 *Techniques*, 12(1), 83-106.

545 Chang, J.-M., Chen, H., Jou, J.-D., Tsou, N.-C., and Lin, G.-W. (2017). Characteristics of
546 rainfall intensity, duration, and kinetic energy for landslide triggering in Taiwan.
547 *Engineering Geology*, Volume 231, Pages 81-87, ISSN 0013-7952.
548 <https://doi.org/10.1016/j.enggeo.2017.10.006>

549 Chen, C.-S., Lin, Y.-L., Zeng, H.-T., Chen, C.-Y., and Liu, C.-L. (2012). Orographic effects on
550 heavy rainfall events over northeastern Taiwan during the northeasterly monsoon season.
551 *Atmospheric Research*, Volume 122, 2013, Pages 310-335, ISSN 0169-8095.
552 <https://doi.org/10.1016/j.atmosres.2012.10.008>

553 Chiara, G. D., Bonavita, M., & English, S. J. (2017). Improving the Assimilation of
554 Scatterometer Wind Observations in Global NWP. *IEEE Journal of Selected Topics in*
555 *Applied Earth Observations and Remote Sensing*, 10(5), 2415-2423.
556 <https://doi.org/10.1109/JSTARS.2017.2691011>

557 Chou, C.-C. & Kushner, P.J. (2023) Scale-dependent impact of *Aeolus* winds on a global forecast
558 system. *Quarterly Journal of the Royal Meteorological Society*, 1–15.
559 <https://doi.org/10.1002/qj.4601>

560 Chou, C.-C., Kushner, P. J., Laroche, S., Mariani, Z., Rodriguez, P., Melo, S., and
561 Fletcher, C. G.: Validation of the Aeolus Level-2B wind product over Northern Canada
562 and the Arctic, *Atmos. Meas. Tech.*, 15, 4443–4461, [https://doi.org/10.5194/amt-15-](https://doi.org/10.5194/amt-15-4443-2022)
563 [4443-2022](https://doi.org/10.5194/amt-15-4443-2022)

564 Cohen, J., Screen, J., Furtado, J. *et al.* (2014). Recent Arctic amplification and extreme mid-
565 latitude weather. *Nature Geosci* **7**, 627–637. <https://doi.org/10.1038/ngeo2234>

566 Cordeira, J. M., & Ralph, F. M. (2021). A Summary of GFS Ensemble Integrated Water Vapor
567 Transport Forecasts and Skill along the U.S. West Coast during Water Years 2017–
568 20. *Weather and Forecasting*, 36(2), 361-377. <https://doi.org/10.1175/WAF-D-20-0121.1>

569 Dai, C., Wang, Q., Kalogiros, J. A., Lenschow, D. H., Gao, Z., & Zhou, M. (2014). Determining
570 boundary-layer height from aircraft measurements. *Boundary-layer meteorology*, 152,
571 277-302.

572 DiMego, G. J., & Bosart, L. F. (1982). The Transformation of Tropical Storm Agnes into an
573 Extratropical Cyclone. Part II: Moisture, Vorticity and Kinetic Energy Budgets. *Monthly*

574 *Weather Review*, 110(5), 412-433. <https://doi.org/10.1175/1520->
575 [0493\(1982\)110<0412:TTOTSA>2.0.CO;2](https://doi.org/10.1175/1520-0493(1982)110<0412:TTOTSA>2.0.CO;2)

576 Durre, I., Yin, X., Vose, R. S., Applequist, S., & Arnfield, J. (2018). Enhancing the Data
577 Coverage in the Integrated Global Radiosonde Archive. *Journal of Atmospheric and*
578 *Oceanic Technology*, 35(9), 1753-1770. <https://doi.org/10.1175/JTECH-D-17-0223.1>

579 Eicken, H. (2013). Arctic sea ice needs better forecasts. *Nature*, 497(7450), 431-433.

580 Eikeland, O. F., Hovem, F. D., Olsen, T. E., Chiesa, M., Bianchi, F. M. (2022). Probabilistic
581 forecasts of wind power generation in regions with complex topography using deep
582 learning methods: An Arctic case. *Energy Conversion and Management: X*, Volume 15,
583 2022, 100239, ISSN 2590-1745. <https://doi.org/10.1016/j.ecmx.2022.100239>

584 Francis, J.A., Vavrus, S.J. and Cohen, J. (2017), Amplified Arctic warming and mid-latitude
585 weather: new perspectives on emerging connections. *WIREs Clim Change*, 8: e474.
586 <https://doi.org/10.1002/wcc.474>

587 Garrett, K., Liu, H., Ide, K., Hoffman, R.N. & Lukens, K.E. (2022). Optimization and impact
588 assessment of Aeolus HLOS wind assimilation in NOAA's global forecast
589 system. *Quarterly Journal of the Royal Meteorological Society*, 148(747), 2703–2716.
590 <https://doi.org/10.1002/qj.4331>

591 Gascard, J.C., Riemann-Campe, K., Gerdes, R. *et al.* (2017). Future sea ice conditions and
592 weather forecasts in the Arctic: Implications for Arctic shipping. *Ambio* **46** (Suppl 3),
593 355–367. <https://doi.org/10.1007/s13280-017-0951-5>

594 George, G., Halloran, G., Kumar, S., Rani, S. I., Bushair, M.T., Jangid, B. P., George, J. P., and
595 Maycock, A. (2021). Impact of Aeolus Horizontal Line of Sight Wind Observations in a

596 Global NWP System” *Atmospheric Research* 261 (October): 105742.
597 <https://doi.org/10.1016/j.atmosres.2021.105742>

598 Gershunov, A., Shulgina, T., Ralph, F. M., Lavers, D. A., and Rutz, J. J. (2017), Assessing the
599 climate-scale variability of atmospheric rivers affecting western North
600 America, *Geophysical Research Letter.*, 44, 7900–7908, doi:[10.1002/2017GL074175](https://doi.org/10.1002/2017GL074175).

601 Graham, R.J., Anderson, S.R. and Bader, M.J. (2000), The relative utility of current observation
602 systems to global-scale NWP forecasts. *Quarterly Journal of the Royal Meteorological*
603 *Society*, 126: 2435-2460. <https://doi.org/10.1002/qj.49712656805>

604 Heliere, A., Wernham, D., Mason, G., De Villele, G., Corselle, B., Lecrenier, O., Belhadj, T.,
605 Bravetti, P., Arnaud, S., Bon, D., Lingot, P., Foulon, R., Marchais, D., Olivier, M.,
606 D'Ottavi, A., Verzegnassi, F., Mondello, A., Coppola, F., Landi, G., Hoffmann, H.-D.,
607 Esser, D., Prieto, L.P., Wührer, C., Rivers, C., Bell, R. (2023). Status of Aeolus-2 mission
608 pre-development activities. Proc. SPIE 12777, *International Conference on Space Optics*
609 — ICSO 2022, 1277709. <https://doi.org/10.1117/12.2688794>

610 Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J.,
611 Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., Thépaut,
612 J.-N. (2023). ERA5 hourly data on pressure levels from 1940 to present. Copernicus
613 Climate Change Service (C3S) Climate Data Store (CDS).
614 <https://doi.org/10.24381/cds.bd0915c6>

615 Hills, R. C. (1979). The Structure of the Inter-Tropical Convergence Zone in Equatorial Africa and Its
616 Relationship to East African Rainfall. *Transactions of the Institute of British*
617 *Geographers*, 4(3), 329–352. <https://doi.org/10.2307/622055>

618 Horányi, A., Cardinali, C., Rennie, M. and Isaksen, L. (2015), The assimilation of horizontal
619 line-of-sight wind information into the ECMWF data assimilation and forecasting
620 system. Part I: The assessment of wind impact. *Quarterly Journal of the Royal
621 Meteorological Society*, 141: 1223-1232. <https://doi.org/10.1002/qj.2430>

622 Inoue, J., Yamazaki, A., Ono, J., Dethloff, K., Maturilli, M., Neuber, R., ... & Yamaguchi, H.
623 (2015). Additional Arctic observations improve weather and sea-ice forecasts for the
624 Northern Sea Route. *Scientific Reports*, 5(1), 16868.

625 James, E. P., Benjamin, S. G., & Jamison, B. D. (2020). Commercial-Aircraft-Based
626 Observations for NWP: Global Coverage, Data Impacts, and COVID-19. *Journal of
627 Applied Meteorology and Climatology*, 59(11), 1809-1825.
628 <https://doi.org/10.1175/JAMC-D-20-0010.1>

629 Jiang, Q. (2003). Moist dynamics and orographic precipitation. *Tellus A: Dynamic Meteorology
630 and Oceanography*, 55:4, 301-316, DOI: [10.3402/tellusa.v55i4.14577](https://doi.org/10.3402/tellusa.v55i4.14577)

631 Joe, P., Melo, S., Burrows, W. R., Casati, B., Crawford, R. W., Deghan, A., Gascon, G., Mariani,
632 Z., Milbrandt, J., & Strawbridge, K. (2020). The Canadian Arctic Weather Science
633 Project: Introduction to the Iqaluit Site. *Bulletin of the American Meteorological
634 Society*, 101(2), E109-E128. <https://doi.org/10.1175/BAMS-D-18-0291.1>

635 Jung, T., Kasper, M. A., Semmler, T., & Serrar, S. (2014). Arctic influence on subseasonal
636 midlatitude prediction. *Geophysical Research Letters*, 41(10), 3676-3680.

637 Jung, T., Gordon, N. D., Bauer, P., Bromwich, D. H., Chevallier, M., Day, J. J., Dawson, J.,
638 Doblas-Reyes, F., Fairall, C., Goessling, H. F., Holland, M., Inoue, J., Iversen, T., Klebe,
639 S., Lemke, P., Losch, M., Makshtas, A., Mills, B., Nurmi, P., Perovich, D., Reid, P.,

640 Renfrew, I. A., Smith, G., Svensson, G., Tolstykh, M., & Yang, Q. (2016). Advancing
641 Polar Prediction Capabilities on Daily to Seasonal Time Scales. *Bulletin of the American*
642 *Meteorological Society*, 97(9), 1631-1647. <https://doi.org/10.1175/BAMS-D-14-00246.1>

643 Kim, G., Kim, J. & Cha, DH. (2022) Added value of high-resolution regional climate model in
644 simulating precipitation based on the changes in kinetic energy. *Geosci. Lett.* **9**, 38.
645 <https://doi.org/10.1186/s40562-022-00247-6>

646 Kiriakidis, P., Gkikas, A., Papangelis, G., Christoudias, T., Kushta, J., Proestakis, E., Kampouri,
647 A., Marinou, E., Drakaki, E., Benedetti, A., Rennie, M., Retscher, C., Straume, A. G.,
648 Dandocsi, A., Sciare, J., and Amiridis, V. (2023). The impact of using assimilated Aeolus
649 wind data on regional WRF-Chem dust simulations. *Atmos. Chem. Phys.*, 23, 4391–4417.
650 <https://doi.org/10.5194/acp-23-4391-2023>

651 Laroche, S. & Poan, E.D. (2021). Impact of the Arctic observing systems on the ECCO global
652 weather forecasts. *Quarterly Journal of the Royal Meteorological*
653 *Society*, 148(742), 252–271. <https://doi.org/10.1002/qj.4203>

654 Laroche, S. & St-James, J. (2022) Impact of the Aeolus Level-2B horizontal line-of-sight winds
655 in the Environment and Climate Change Canada global forecast system. *Quarterly*
656 *Journal of the Royal Meteorological Society*, 148(745), 2047–2062.
657 <https://doi.org/10.1002/qj.4300>

658 Lawrence, H, Bormann, N, Sandu, I, Day, J, Farnan, J, Bauer, P. (2019). Use and impact of
659 Arctic observations in the ECMWF Numerical Weather Prediction system. *Quarterly*
660 *Journal of the Royal Meteorological Society*, 145: 3432–3454.
661 <https://doi.org/10.1002/qj.3628>

662 Lawrence, Z. D., Perlwitz, J., Butler, A. H., Manney, G. L., Newman, P. A., Lee, S. H., & Nash,
663 E. R. (2020). The remarkably strong Arctic stratospheric polar vortex of winter 2020:
664 Links to record-breaking Arctic Oscillation and ozone loss. *Journal of Geophysical*
665 *Research: Atmospheres*, 125, e2020JD033271. <https://doi.org/10.1029/2020JD033271>

666 Le Marshall, J., Jung, J., Zapotocny, T., Redder, C., Dunn, M., Daniels, J., & Riishojgaard, L. P.
667 (2008). Impact of MODIS atmospheric motion vectors on a global NWP system.
668 *Australian Meteorological Magazine*, 57, 45–51.

669 Liu, B., Guo, J., Gong, W., Shi, L., Zhang, Y., & Ma, Y. (2020). Characteristics and performance
670 of wind profiles as observed by the radar wind profiler network of China. *Atmospheric*
671 *Measurement Techniques*, 13(8), 4589-4600.

672 Martinez, C., Goddard, L., Kushnir, Y. *et al.* (2019). Seasonal climatology and dynamical
673 mechanisms of rainfall in the Caribbean. *Clim Dyn* **53**, 825–846.
674 <https://doi.org/10.1007/s00382-019-04616-4>

675 Martin, A., Weissmann, M., and Cress, A. (2023). Investigation of links between dynamical
676 scenarios and particularly high impact of Aeolus on numerical weather prediction (NWP)
677 forecasts. *Weather Climate Dynamics*, 4, 249–264. [https://doi.org/10.5194/wcd-4-249-](https://doi.org/10.5194/wcd-4-249-2023)
678 [2023](https://doi.org/10.5194/wcd-4-249-2023)

679 Mattingly, K. S., Ramseyer, C. A., Rosen, J. J., Mote, T. L., and Muthyala, R. (2016), Increasing
680 water vapor transport to the Greenland Ice Sheet revealed using self-organizing
681 maps. *Geophys. Res. Lett.*, 43, 9250–9258. <https://doi.org/10.1002/2016GL070424>

682 McTaggart-Cowan, R., Vaillancourt, P. A., Zadra, A., Chamberland, S., Charron, M., Corvec, S.,
683 *et al.* (2019). Modernization of atmospheric physics parameterization in Canadian

684 NWP. *Journal of Advances in Modeling Earth Systems*, 11, 3593–3635.
685 <https://doi.org/10.1029/2019MS001781>

686 Mile, M., Azad, R., & Marseille, G.-J. (2022). Assimilation of Aeolus Rayleigh-clear winds
687 using a footprint operator in AROME-Arctic mesoscale model. *Geophysical Research*
688 *Letters*, 49, e2021GL097615. <https://doi.org/10.1029/2021GL097615>

689 Misra, V., DiNapoli, S., & Powell, M. (2013). The Track Integrated Kinetic Energy of Atlantic
690 Tropical Cyclones. *Monthly Weather Review*, 141(7), 2383-2389.
691 <https://doi.org/10.1175/MWR-D-12-00349.1>

692 Mizyak, V. G., Shlyaeva, A. V., & Tolstykh, M. A. (2016). Using satellite-derived Atmospheric
693 Motion Vector (AMV) observations in the ensemble data assimilation system. *Russian*
694 *Meteorology and Hydrology*, 41, 439-446. <https://doi.org/10.3103/S1068373916060091>

695 Naakka, T., Nygård, T., Tjernström, M., Vihma, T., Pirazzini, R., & Brooks, I. M. (2019). The
696 impact of radiosounding observations on numerical weather prediction analyses in the
697 Arctic. *Geophysical Research Letters*, 46, 8527–8535.
698 <https://doi.org/10.1029/2019GL083332>

699 Olaguera, L.M.P., Caballar, M.E., De Mata, J.C. *et al.* (2021). Synoptic conditions and potential
700 causes of the extreme heavy rainfall event of January 2009 over Mindanao Island,
701 Philippines. *Nat Hazards* **109**, 2601–2620. <https://doi.org/10.1007/s11069-021-04934-z>

702 Overland, J., Francis, J. A., Hall, R., Hanna, E., Kim, S., & Vihma, T. (2015). The Melting
703 Arctic and Midlatitude Weather Patterns: Are They Connected?. *Journal of*
704 *Climate*, 28(20), 7917-7932. <https://doi.org/10.1175/JCLI-D-14-00822.1>

705 Palmén, E. (1958), Vertical Circulation and Release of Kinetic Energy during the Development
706 of Hurricane Hazel into an Extratropical Storm. *Tellus*, 10: 1-23.
707 <https://doi.org/10.1111/j.2153-3490.1958.tb01982.x>

708 Pourret, V., Šavli, M., Mahfouf, J.-F., Raspaud, D., Doerenbecher, A., Bénichou, H., et al.
709 (2022) Operational assimilation of Aeolus winds in the Météo-France global NWP model
710 ARPEGE. *Quarterly Journal of the Royal Meteorological Society*, 148(747), 2652–2671.
711 <https://doi.org/10.1002/qj.4329>

712 Radić, V., Cannon, A. J., Menounos, B., and Gi, N. (2015), Future changes in autumn
713 atmospheric river events in British Columbia, Canada, as projected by CMIP5 global
714 climate models. *J. Geophys. Res. Atmos.*, 120, 9279–9302.
715 <https://doi.org/10.1002/2015JD023279>

716 Randriamampianina, R., Bormann, N., Køltzow, M. A., Lawrence, H., Sandu, I., & Wang, Z. Q.
717 (2021). Relative impact of observations on a regional Arctic numerical weather
718 prediction system. *Quarterly Journal of the Royal Meteorological Society*, 147(737),
719 2212-2232.

720 Randriamampianina, R., Schyberg, H., & Mile, M. (2019). Observing System Experiments with
721 an Arctic Mesoscale Numerical Weather Prediction Model. *Remote Sensing*, 11(8), 981.
722 <https://doi.org/10.3390/rs11080981>

723 Rani, S. I., Sharma, P., George, J. P., & Das Gupta, M. (2021). Assimilation of individual
724 components of radiosonde winds: An investigation to assess the impact of single-
725 component winds from space-borne measurements on NWP. *Journal of Earth System*
726 *Science*, 130(2), 89.

727 Rennie, M.P., Isaksen, L., Weiler, F., de Kloe, J., Kanitz, T. & Reitebuch, O. (2021). The impact
728 of Aeolus wind retrievals on ECMWF global weather forecasts. *Quarterly Journal of the*
729 *Royal Meteorological Society*, 147(740), 3555–3586. <https://doi.org/10.1002/qj.4142>

730 Reynolds, C. A., Crawford, W., Huang, A., Barton, N., Janiga, M. A., McLay, J., Flatau, M.,
731 Frolov, S., & Rowley, C. (2022). Analysis of Integrated Vapor Transport Biases. *Monthly*
732 *Weather Review*, 150(5), 1097-1113. <https://doi.org/10.1175/MWR-D-21-0198.1>

733 Smith, G. C., Bélanger, J., Roy, F., Pellerin, P., Ritchie, H., Onu, K., Roch, M., Zadra, A., Colan,
734 D. S., Winter, B., Fontecilla, J., & Deacu, D. (2018). Impact of Coupling with an Ice–
735 Ocean Model on Global Medium-Range NWP Forecast Skill. *Monthly Weather*
736 *Review*, 146(4), 1157-1180. <https://doi.org/10.1175/MWR-D-17-0157.1>

737 Tan, X., Gan, T.Y., & Chen, Y.D. (2019). Synoptic moisture pathways associated with mean and
738 extreme precipitation over Canada for summer and fall. *Clim Dyn* **52**, 2959–2979.
739 <https://doi.org/10.1007/s00382-018-4300-6>

740 Velden, C. S., Hayden, C. M., Nieman, S. J., Menzel, W. P., Wanzong, S., & Goerss, J. S.
741 (1997). Upper-tropospheric winds derived from geostationary satellite water vapor
742 observations. *Bulletin of the American Meteorological Society*, 78, 173–195.
743 [https://doi.org/10.1175/1520-0477\(1997\)078,0173:UTWDFG.2.0.CO;2](https://doi.org/10.1175/1520-0477(1997)078<0173:UTWDFG.2.0.CO;2)

744 Velden, C., Lewis, W. E., Bresky, W., Stettner, D., Daniels, J., & Wanzong, S. (2017).
745 Assimilation of High-Resolution Satellite-Derived Atmospheric Motion Vectors: Impact
746 on HWRP Forecasts of Tropical Cyclone Track and Intensity. *Monthly Weather Review*,
747 145, 1107-1125. <https://doi.org/10.1175/MWR-D-16-0229.1>

748 Young, I. R., Sanina, E., & Babanin, A. V. (2017). Calibration and Cross Validation of a Global
749 Wind and Wave Database of Altimeter, Radiometer, and Scatterometer Measurements.
750 *Journal of Atmospheric and Oceanic Technology*, 34, 1285-1306.

751 Zuo, H. and Hasager, C. B. (2023). The impact of Aeolus winds on near-surface wind forecasts
752 over tropical ocean and high-latitude regions. *Atmospheric Measurement Technique*, 16,
753 3901-3913. <https://doi.org/10.5194/amt-16-3901-2023>