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The Microwave Climate Data Center Repository

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Abstract: Since 1979, Remote Sensing Systems has been providing a global community of researchers and decision makers 5 with inter-calibrated microwave measurements and geophysical retrievals derived from passive and active spaceborne 6 sensors. These datasets, from 35 microwave sensors covering a time period of 40 years, have been consolidated at the Mi-7 crowave Climate Data Center repository. The geophysical retrievals include: sea-surface temperature, near-surface ocean 8 wind speed and direction, columnar atmospheric water vapor, columnar cloud liquid water, sea-surface rain rate, sea-9 surface salinity, and atmospheric temperature profiles. Consistent calibration procedures and retrieval methods have been 10 applied during the data processing to ensure these datasets are suitable for climate research. All of the geophysical retrievals 11 relate to the air-sea boundary layer and are classified as essential climate variables by the Global Climate Observing System. 12 In this paper, we give an overview of the microwave sensors, the inter-calibration methods, the retrieval algorithms, and 13 the air-sea essential climate variable datasets housed at the Microwave Climate Data Center. 14

Keywords: Microwave Climate Data Center; Remote Sensing; Air-Sea Essential Climate Variables; Sensor Inter-Calibration; 15 Radiative Transfer Model; Maximum Likelihood Estimator; Validation 16

Background and Summary

In the electromagnetic spectrum, microwave (MW) frequencies range from approximately 0.3 to 300 GHz (wavelengths 18 between one millimeter and one meter). This MW radiation, whether emitted passively by various sources including the 19 Sun and Earth or actively by radar that sends out pulses of radiation, interacts in unique ways with the Earth's surface and 20 atmosphere¹. Instruments designed to measure radiation at MW frequencies onboard Earth-orbiting satellites are used to 21 retrieve geophysical quantities that are crucial for understanding the world's weather and climate. In this regard, Remote 22 Sensing Systems (RSS) has focused on a specific area of research and data production: passive and active MW observations 23 of the world's oceans. Using frequently updated retrieval algorithms, RSS translates the MW radiation observed by satellites 24 into climate-quality data. These datasets are publicly available and hosted by the RSS Microwave Climate Data Center 25 (MCDC) repository at https://www.remss.com. 26

MCDC Datasets include: sea-surface temperature, near-surface ocean wind speed and direction, columnar atmospheric 28 water vapor, columnar cloud liquid water, sea-surface rain rate, sea-surface salinity, and atmospheric temperature profiles. 29 All of these climate datasets are considered air-sea (AS) variables and are classified as essential climate variables (ECVs) by 30 the Global Climate Observing System (GCOS)². Most of these global geophysical datasets, hereafter referred to as AS-ECVs, 31 extend from 1987 to the present day. 32

While there are many ways to observe AS-ECVs over the ocean, using spaceborne MW sensors to do so provides distinct 33 advantages over other forms of measurement. First, the atmosphere is relatively transparent at many MW frequencies. This 34 allows spaceborne MW sensors to observe the surface of the Earth even in areas of heavy cloud cover or high columnar 35 water vapor. Around 22 and 60 GHz, the atmosphere becomes opaque to MW radiation; nonetheless, these MW frequencies 36 can be used for measuring geophysical qualities of the intervening atmosphere. Secondly, MW sensors do not require solar 37 illumination to observe the Earth's surface and atmosphere, and therefore they can take measurements at any time of the 38 day making them well-suited for observing diurnal cycles in AS-ECVs. Infrared (IR) imagers can similarly take snapshots 39 of clouds throughout the day; however, they can only image the tops of clouds. Third, polar orbiting MW sensors are able 40 to view wide swaths of the Earth over the course of a single day and can provide global coverage every few days. This is in 41 contrast to airborne, ship, or other ground-based measurements which can only provide information at a single point or 42 within a relatively small area³. 43

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Despite the advantages of MW remote sensing, there are two primary limitations to using spaceborne MW instruments to 44 measure AS-ECVs over the world's oceans. First, the presence of heavy rain interferes with MW radiation at higher fre-45 quencies (>~12 GHz) because rain drops attenuate and scatter MW signals while also creating splash effects that are difficult 46 to disentangle from the AS-ECV signals of interest^{4,5}. Second, MW sensors have a relatively coarse spatial resolution as 47 compared to higher frequency bands of radiation, such as visible and IR. To increase the spatial resolution, the MW fre-48 quency must be increased or a larger antenna needs to be used¹³. Unfortunately, some AS-ECVs, such as salinity, are only 49 sensitive at the lower frequencies (1.4 GHz). Given these limitations, RSS uses MW satellite sensors to retrieve AS-ECVs in 50 ocean areas that are generally free of heavy rain and assumes that the AS-ECVs are relatively constant at kilometer scales. 51 However, there are several exceptions to this, which are discussed in greater detail in this paper. 52

RSS has 40+ years of experience in generating and refining the MCDC AS-ECV products from MW sensors. As a result, RSS has developed a reputation for providing precisely calibrated AS-ECVs that can be used for the most demanding climatetrend analyses. This trust is based on the high-degree of consistency in all aspects of data production, starting with sensor inter-calibration, continuing through to the advanced radiative transfer models and geophysical model functions in the RSS retrieval algorithms, and ending with rigorous validation analyses. The goal of this paper is to provide the community with a detailed description of the generation and current status of AS-ECV datasets hosted by the RSS MCDC repository. 58



Figure 1 MCDC Microwave Sensor Collection. Microwave sensors with their mission timelines that are used in constructing the MCDC AS-ECV data records.

Methods

MW Sensor Inventory

The MCDC AS-ECV sensor inventory currently includes 62 35 MW sensors covering a time period of 40 years. Meas-63 urements from these sensors have been inter-calibrated 64 and processed using consistent data processing tech-65 niques for: (1) resampling, (2) geolocation, and (3) AS-66 ECV retrievals. Figure 1 shows the mission timelines for 67 the sensors, and Tables 1–3 provide the instrument char-68 acteristics. The following additional sensors will be 69 added in the near future: CIMR, COWVR, MWI/WSF-70 M, AMSR-3, MWI/Metop-SG, SCA, and MWS/Metop-71 SG. 72

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There are three basic types of sensors:

- 1. The conical scanning MW imager (Table 1)
- 2. The cross-track scanning MW sounder (Table 2)

3. The scatterometer (both conical scanning and fixed cross-track) (Table 3)

The MW imagers and sounders are radiometers that ob-78 serve the upwelling brightness temperature (T_B) that is 79 passively emitted from the Earth. The scatterometers are 80 active radars that transmit power to the Earth and then 81 measure the received power, reporting the normalized 82 radar cross-section (σ_0). Both radiometer and scatterom-83 eter MW sensors fly in polar orbits with varying degrees 84 of inclination. The trajectory of a slightly inclined near-85 polar orbit is nearly north-south, with the satellite pass-86 ing near the Earth poles each orbit. At the equator, the 87 near-polar orbiters are sun-synchronous and cross the 88 equator at the same local mean solar time with ascend-89 ing and descending orbit segments having local 90 equatorial crossing times that are approximately 12 hours apart. The local equator crossing time slowly drifted for some of 91 the early sensors, for which orbit maintenance was not done. These near-polar orbiters roughly orbit the Earth 14 times a 92 day, every 90 minutes. On the other hand, a highly inclined orbit ground trajectory does not reach the North and South 93 poles, but rather, covers a smaller latitude band (e.g., 40°S to 40°N for TMI and 60°S to 60°N for GMI) than near-polar 94 orbiters. Sensors in inclined orbits view the Earth at different times of the day, precessing through the entire diurnal cycle 95 and providing greater coverage at lower latitudes. Depending on the swath width of the sensor, it takes two to four days 96 for the sensor to provide full longitudinal coverage. 97



Figure 2 Inputs to Observed Microwave Brightness Temperature (T_B). The arrows show the various components that contribute to the observed T_A and top-of-the-at-mosphere T_B .

addition, at the 1.4 GHz frequency required for the salinity algorithm, the ionosphere rotates the polarization vector of the radiation traveling through it due to the Faraday effect⁶. Polarization rotation also needs to be considered for fully polarimetric imagers like WindSat, although its higher frequencies are less affected by the rotation. To remove the ionosphere effects from the observed top-of-the-atmosphere T_B, an ancillary dataset of total electron content (TEC) is used to correct the T_B as it passes through the ionosphere. Figure 2 shows how these spurious contamination sources contribute to the overall T_A and top-of-the-atmosphere T_B observation.

$$\begin{pmatrix} T_{B,\nu} \\ T_{B,h} \end{pmatrix} = \mathbf{A}^{-1} \begin{pmatrix} T'_{A,\nu} \\ T'_{A,h} \end{pmatrix} = \frac{1}{\det(\mathbf{A})} \begin{pmatrix} 1 - \chi_{h\nu} & -\chi_{h\nu} \\ -\chi_{\nu h} & 1 - \chi_{\nu h} \end{pmatrix} \begin{pmatrix} T'_{A,\nu} \\ T'_{A,h} \end{pmatrix}$$
(1)

$$T'_{A,p} = \frac{T''_{A,p} - E_{refl,p}T_{refl}}{\left(1 - E_{refl,p}\right)} \quad p = v, h \text{ polarization}$$
(2)

$$T_{A,p}^{\prime\prime} = \frac{T_{A,p} - (1 - \eta_p)T_c}{\eta_p} \quad p = v, h \text{ polarization}$$
(3)

$$\det(\mathbf{A}) = (1 - \chi_{vh})(1 - \chi_{hv}) - \chi_{vh}\chi_{hv}$$
(4)

MW Sensor Inter-Calibration

According to the National Research Council, a climate data record (CDR) is defined as "a time series of measurements of 127 sufficient length, consistency, and continuity to determine climate variability and climate change". In order for the data 128

The MW imager and sounder retrieval algorithms re-98 quire the top-of-the-atmosphere TBS calculated from 99 the observed antenna temperature (TA) for each MW 100 polarization and frequency (Equation 1; Table 4). The 101 TA is converted to top-of-the-atmosphere TB by re-102 moving cold space spillover onto the sensor field of 103 view and polarization contamination from orthogo-104 nal polarizations, i.e., cross-polarization (Equations 105 1-4; Table 4). Equation (2) accounts for the additional 106 radiative input from an emissive reflector in the case 107 of SSMI/S, TMI, and SMAP sensors. Before applying 108 the retrieval algorithm, extraneous sources of radia-109 tion contributing to observed T_A (and, subsequently, 110 observed top-of-the-atmosphere T_B) must be identi-111 fied. In most AS-ECV retrievals, these sources include 112 land or sea ice within the antenna field of view as well 113 as radio frequency interference (RFI). For the salinity 114 retrievals, additional extraneous radiation sources 115 116

include cosmic MW background, sun, moon, and galaxy, either viewed directly through the antenna or through the reflection from the ocean surface. In

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products to reach the consistency required to build a climate-quality dataset, covering two to four decades, the basic measurements (T_B or σ_0) need to be precisely inter-calibrated. Given the 35 MW sensors in the MCDC inventory, inter-calibration has been a major component of the work done at RSS.

RSS performed the first MW imager inter-calibration in 1990 when the second SSM/I went into operation. Since then, there 132 have been many generations of calibration procedures^{8,9,10,11,12}. Currently, 14 MW imagers, excluding one of the SSMIS', have 133 been inter-calibrated to GMI which provides the most accurate measurements with a T_B <u>absolute</u> accuracy of 0.25 K and a 134 T_A <u>absolute</u> accuracy of 0.1 K valid from cold ocean temperatures to the hot rainforest¹². Moreover, GMI is in an inclined 135 orbit and provides coincident collocations with other sensors, essentially eliminating errors related to diurnal variations. 136

The MW sounder T_{BS} are a self-consistent dataset and are not inter-calibrated with the imagers because the 50–60 GHz observations taken by the sounders are fundamentally different than the T_B measurements taken by the imagers. MW sounders are inter-calibrated by comparing co-orbiting satellite measurements of top of the atmosphere T_{BS} from MSU and AMSU. Moreover, the difference between MSU and AMSU measurements are averaged and then subtracted from the AMSU data so that co-orbiting MSU and AMSU T_{BS} match one another¹³. In addition, the MW sounder inter-calibration 141 solves for differences in the earth incidence angle (EIA), diurnal drift, and weighting functions between MSU and AMSU^{14,15}.

Buoy wind speeds (< 15 m/s) and dropsondes (\geq 15 m/s) are the ultimate calibration standard for scatterometer wind speed retrievals. WindSat wind speeds have been validated against buoys and dropsondes in rain-free conditions, and now Wind-Sat serves as a consistent reference for scatterometer wind retrievals. Adjustments are made to the σ_0 measurements to obtain agreement between the imager and scatterometer wind speed retrievals. For scatterometer wind direction retrievals, the National Center for Environmental Prediction (NCEP) Global Data Assimilation System (GDAS) was used as the calibration standard. Direct comparisons between contemporaneous scatterometers are also used in the inter-calibration procedure¹⁶.

MW Imager AS-ECV Retrieval Algorithm

The sev	ven AS-ECVs that are retrieved by the MW imager algorithm are:	151
1.	Sea-surface temperature	152
2.	Ocean wind speed at 10 m above surface	153
3.	Ocean wind direction at 10 m above surface	154
4.	Columnar atmospheric water vapor above the ocean	155

- 5. Columnar cloud liquid water above the ocean
- 6. Sea-surface rain rate
- 7. Sea-surface salinity

The retrieval algorithm for the MW imagers is based on a radiative transfer model (RTM) for the earth and attenuating 159 atmosphere, which is common to all of the imagers. The RTM is also called the forward model because it provides top-of-160 the-atmosphere T_{BS} for a given earth scene when AS-ECVs are used as inputs (Equations 5–10; Table 4). The essential ele-161 ments of the RTM are surface temperature (Ts) and emissivity (E), as well as atmospheric profiles of pressure (P), tempera-162 ture (T), water vapor (ρ_V), and cloud liquid water (ρ_L). The emissivity is a function of surface temperature, sea-surface 163 salinity (S), wind speed (W), and wind direction relative to the azimuthal look (φ). The rain rate is a function of the RTM-164 derived cloud liquid water and the rain column height, which in turn is linearly related to RTM-derived sea-surface tem-165 perature; generally speaking, rain occurs when the cloud liquid water value exceeds a threshold of 0.18 kg/m². In the sea-166 surface salinity retrieval, there is only one frequency available (1.4 GHz); therefore, the RTM requires several ancillary 167 datasets to retrieve emissivity and top-of-the-atmosphere TB, including sea-surface temperature, wind speed and direction, 168atmospheric profiles, and rain rate¹⁷. The RTM is described in greater detail in the literature^{18,19,20,21} and provided for cases 169 in which the atmospheric scattering by liquid water droplets is neglected^{22,23,24}. 170

$$T_B = T_{BU} + \tau(0, H) [ET_S + (1 - E)(T_{BD} + \tau(0, H)T_C)] + \tau(0, H)T_{B,scat}$$
(5)

$$T_{B,scat} = \Omega(1-E)[T_{BD} + \tau(0,H)T_C - T_C]$$
(6)

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$$T_{BU} = \sec\theta \int_0^H \alpha(h)T(h)\tau(h,H)dh, \ T_{BD} = \sec\theta \int_0^H \alpha(h)T(h)\tau(0,h)dh$$
(7)

$$\tau(h_1, h_2) = \exp\left(-\sec\theta \int_{h_1}^{h_2} \alpha(h)dh\right)$$
(8)

$$\alpha(h) = \alpha_D(T(h), P(h)) + \alpha_V(T(h), P(h), \rho_V(h)) + \alpha_L(\varepsilon_L, \rho_L(h))$$
(9)

$$E = E_0(\theta, S, T_S) + \Delta E_W(\theta, W, T_S) + \Delta E_{\varphi}(\theta, W, \varphi)$$
(10)

The retrieval algorithm is an approximate inversion of the forward model. It provides estimates of the AS-ECVs for a given 171 set of top-of-the-atmosphere T_B observations taken over a range of frequencies and polarizations. The retrieval algorithm 172 uses multiple non-linear regressions in order to find the AS-ECVs^{18,25}. The regression coefficients are derived from a training 173 set of simulated TBS from the RTM using Monte Carlo combinations of AS-ECVS representative of all-possible global con-174 ditions. To deal with a possible non-linear dependence between the TB and AS-ECV, a two-stage linear regression is used 175 (Equations 11–13, using two AS-ECVs as an example; Table 4). The first stage (m_{1i}) is valid for global conditions and pro-176 vides a first-guess for the AS-ECVs. Given this first guess, a second-stage regression (m_{2i}) is selected based on the specific 177 environment found by the first stage. 178

$$m_{1j} = a_{0j} + \sum_{i=1}^{n M W chan} a_{ij} t_i + b_{ij} t_i^2$$
(11)

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$$m_{2j} = \sum_{k=k_0}^{k_0+1} \sum_{l=l_0}^{l_0+1} w_{k-k_0,l-l_0} \left(c_{0jkl} + \sum_{i=1}^{nMWchan} c_{ijkl} t_i \right)$$
(12)

$$t_i = T_{Bi} - 150$$
 for all but 24 GHz, $t_i = -\ln(290 - T_{Bi})$ for 24 GHz (13)

An exception to the retrieval algorithm regression approach is used in the wind vector retrieval (wind speed and wind 179 direction). In this case, the MW imager needs to be fully polarimetric and a classical "chi-squared" Maximum Likelihood 180 Estimator (MLE) is used that minimizes the differences between the observed T_B and RTM-computed T_B . The wind direction 181 algorithms generally, but not always, provide multiple solutions (ambiguities) for wind directions. The final step in the wind direction retrieval is an ambiguity selection that chooses the wind vector that is consistent with nearby values²⁶. 183

MW Sounder Atmospheric Temperature Retrieval Algorithm

The retrieval algorithm for the MW sounders finds the temperature for five atmospheric layers²⁷:

- 1. Temperature of the Lower Troposphere (TLT)
 - 2. Temperature of the Total Troposphere (TTT)
 - 3. Temperature of the Middle Troposphere (TMT)
- 4. Temperature of the Troposphere and Stratosphere (TTS)
 - 5. Temperature of the Lower Stratosphere (TLS)

The atmospheric temperature products are provided globally over ocean, land, and ice. This is in contrast to the other 191 MCDC data products which are only provided over the global ocean. The sounding channels used in the retrieval are in 192 the 50-60 GHz part of the MW spectrum. Since molecular oxygen in the atmosphere strongly absorbs and emits MW radi-193 ation in this range, the T_B at these frequencies represents the vertically-averaged air temperature over a select layer of the 194 atmosphere. The extent and vertical location of the layer depends on the EIA and frequency of the observation. Equation 195 (14) relates the observed T_B to the sum of the small surface contribution (first term) and the vertically-averaged atmospheric 196 contribution (second term) (Table 4)¹³. The surface contribution to the T_B depends on the zenith optical depth (z) for an 197 atmospheric layer, which is the integration of the atmospheric absorption coefficient (κ) (Equation 15; Table 4). Weighting 198 functions in the second term are used to separate the T_B contributions from various layers in the atmosphere; they are a 199

function of the height above sea level and depend on the observation frequency and the EIA (Equation 16; Table 4). For 200 three of the channels (TMT, TTS, and TLS) we report the T_B for a limited set of near-nadir views, with each off-nadir T_B 201 referred to nadir using adjustments calculated from the RTM for climatological atmospheric profiles. TTT is constructed 202 from a weighted combination of TMT and TLS to reduce the stratospheric contribution²⁸. TLT is constructed using a linear 203 combination of measurements at different views to move the weighting function closer to the surface^{14,15}. 204

$$T_B = ET_S \exp(-z(0,\infty)\sec\theta) + \int_0^{\infty} F(h)T(h)dh$$
(14)

$$z(h_1, h_2) = \int_{h_2}^{h_1} \kappa(h) dh$$
 (15)

$$F(h) = \kappa(h) \sec \theta \exp(-z(h, \infty) \sec \theta) + \kappa(h) \sec \theta \exp(-z(0, h) \sec \theta)(1 - E)\exp(-z(0, \infty) \sec \theta)$$
(16)

MW Scatterometer Wind Vector Retrieval Algorithm

In low wind conditions, the smooth ocean surface reflects most of the microwave energy away from the scatterometer and 206 there is very little backscatter returned to the sensor. However, wind-induced ocean surface roughness increases scatter in 207 every direction off of the capillary waves. The amount of backscatter depends on surface wind speed (W) and wind direc-208 tion relative to the azimuthal look (φ)³. The retrieval algorithm for the MW scatterometers measures the ocean wind vector 209 (wind speed and wind direction) 10 meters above the ocean surface. The retrieval algorithm is based upon a geophysical 210 model function (GMF) that relates σ_0 to wind speed and direction^{23,29,30}. The GMF is an expanded Fourier series of even 211 harmonics in the relative wind direction (Equation 17, keeping harmonics up to the second order; Table 4). The coefficients 212 for the fifth order polynomial of wind speed for each of the harmonic functions in the wind direction are tuned using wind 213 speed measurements from WindSat and wind directions from NCEP that are both matched up with the scatterometer σ_0 . 214 Similar to the wind vector retrieval algorithm for fully polarimetric MW imagers, the scatterometer wind vector retrieval 215 algorithm employs a classical "chi-squared" MLE that minimizes the differences between the observed σ_0 and the GMF σ_0 . 216 The MLE is then followed by an ambiguity selection algorithm²⁶. 217

$$\sigma_o = \sum_{i=1}^{5} d_{0,i} W^i + \cos \varphi \sum_{i=1}^{5} d_{1,i} W^i + \cos(2\varphi) \sum_{i=1}^{5} d_{2,i} W^i$$
(17)

Data Records

The AS-ECVs hosted by the MCDC are used by the scientific community to study climate change, as well as by commercial 220 and operational agencies for a variety of purposes, including weather operations, renewable energy, and shipping logistics. 221 The MCDC AS-ECV datasets are freely available from the RSS website via both HTTP (https://data.remss.com/) and FTP 222 file transfer protocols. Table 5 provides key specifications of individual AS-ECV datasets, the majority of which are on an 223 Earth-centered grid at regular 0.25-degree latitude/longitude intervals with a daily or composite (3-day, weekly, 8-day, 224 monthly) temporal resolution. Although the AS-ECVs are released on a 0.25-degree sampling grid, it is important to note 225 that their inherent resolution in kilometers depends on the sensor (Tables 1-3). In addition to the individual AS-ECV da-226 tasets, intercalibrated top-of-the-atmosphere TBs from MW imagers are freely available upon request. The following sub-227 sections describe individual AS-ECV datasets as well as merged AS-ECV CDRs. 228

Sea-Surface Temperature

Sea-surface temperature (SST) is a measure of the temperature (°C) of the skin layer of the ocean (~20 µm-depths measured by IR imagers), sub-skin layer of the ocean (~1 mm-depths measured by MW imagers), and foundation ocean (0.5–1.5 mdepths). SST measurements are used to observe changes in global climate, monitor decadal climate variability including the El Niño Southern Oscillation (ENSO), and forecast tropical cyclones. SSTs are important boundary (input) conditions for atmosphere-only models and have been used to train coupled ocean-atmosphere climate models so that their outputs match observations³¹. Beyond climate modeling and seasonal forecasting, SST observations are useful for predicting coral bleaching, tracking pollution, and commercial fishery and tourism industries. The MCDC provides sub-skin SSTs from MW 236

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imagers with low frequency channels (6–11 GHz) that are sensitive to ocean temperatures at these depths. The MCDC also produces an optimally interpolated (OI) foundation SST, which merges observations from multiple sensors^{32,33,34} and reas input, while the other employs both MW imagers *and* IR imagers that measure skin SST. MCDC SSTs range from -3 to 35°C.

Ocean Wind Speed and Wind Vectors over Ocean and Land

The MCDC repository of wind speed (m/s) and wind vectors (wind speed and direction in degrees) represent near-surface 243 conditions (10 meters above the ocean surface). The wind direction is provided in the wind vector azimuth convention, i.e., 244 the direction points along mass flow with 0 degrees referring to wind blowing towards the Northern direction (the degrees 245 increase in the clockwise direction). On short timescales (daily to weekly), winds are used for predicting and monitoring 246 tropical cyclones. On longer timescales (seasonal to interannual), winds can provide insight into climate variability, includ-247 ing monsoon intensity and changes in rain patterns (e.g., due to ENSO), which can greatly affect global populations in 248 various parts of the world via flooding or droughts^{37,38}. The MCDC provides scalar ocean wind speeds from MW imagers 249 both in non-rainy conditions and rainy conditions (Tropical Cyclone (TC) winds and All-Weather winds^{39,40,41}) (Figure 3). 250 In addition, the MCDC distributes ocean wind vectors from fully polarimetric MW imagers, MW scatterometers as well as 251 the Cross-Calibrated Multi-Platform (CCMP) wind vector analysis product^{42,43}. Note that the MCDC supplies two wind 252 speed products, one from low frequency MW imager observations (11-37 GHz) and the second from medium frequency 253 MW imager observations (19–37 GHz). MCDC wind speeds range from 0 to 70 m/s and wind directions range from 0 to 350 254 degrees. 255



Figure 3 MCDC Tropical Cyclone (TC) Winds. Subplots show wind speeds in hurricanes and tropical cyclones for AMSR-E (a), AMSR-2 (b, d), and SMAP (c).

Columnar Cloud Liquid Water over Ocean

Columnar cloud liquid water is a measure of the depth of liquid water in mm contained in a cloud for a vertical column of 282 the atmosphere (any ice and snow present in the cloud are not included in this measurement). Cloud liquid water is also 283 often reported as the mass of liquid water per mass or volume of air (g/kg or g/m³). Cloud liquid water plays a substantial 284

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Columnar Atmospheric Water Vapor over Ocean

Columnar atmospheric water vapor is the amount 257 of gaseous water present in a column of air extend-258 ing from the Earth's surface to the top of the atmos-259phere. Columnar water vapor is reported in units of 260 kg/m² (the vertically-integrated mass of water va-261 por), which can then be converted to mm when di-262 vided by the density of water. Atmospheric water 263 vapor is essential for cloud formation and latent 264 heat transport, both of which contribute to tropical 265 and extratropical storms. In addition, evidence sug-266 gests that increased atmospheric moisture will en-267 hance the intensity of atmospheric rivers, which will 268 lead to substantially longer and wider atmospheric 269 rivers than the ones observed today^{44,45}. Water vapor 270 also plays an important role in the climate due to its 271 potency as a greenhouse gas and water vapor posi-272 tive feedback loop. This water vapor feedback plus 273 the temperature lapse rate feedback, 1.30 W m⁻² °C⁻¹ 274 in total, will increase the total climate feedback 275 warming by 50%^{46,47}. The MCDC provides measure-276 ments of water vapor over the ocean calculated from 277 the 22 GHz band of MW imagers, which is near the 278 peak of one of the water vapor absorption frequen-279 cies; values range from 0 to 120 mm. 280

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role not only in the global water cycle, but also in how atmospheric radiation is absorbed, scattered, and reemitted: clouds 285 can have competing effects on the climate, some of which cool the earth by reflecting visible light while others warm the 286 earth by absorbing IR radiation⁴⁸. The MCDC supplies cloud liquid water measurements above the ocean calculated from 287 a range of MW imager frequencies (19-37 GHz); values range from 0 to 1.8 mm. 288

Sea-Surface Rain Rate

Sea-surface rain rate is a measure of the average rain rate at the ocean surface in mm/hr. Rain from atmospheric rivers and 290 monsoons supplies fresh water to the world's population centers^{49,50,51}. Over recent decades there has been a narrowing and 291 strengthening of rain in the Inter-Tropical Convergence Zone (ITCZ), a belt of rainfall that shifts north and south, providing 292 monsoonal rain⁵². Accurate measurements of rain improve characterization of droughts, landslides, floods, and severe 293 storms, which have enormous impacts on society. The MCDC provides sea-surface rain rates calculated from a range of 294 MW imager frequencies (19–37 GHz); values range from 0 to 25 mm/hr. 295

Sea-Surface Salinity

Sea-surface salinity (SSS) is a measure of how salty the ocean is in its uppermost layer (~1 cm). It is expressed in terms of 297 Practical Salinity Units (psu), which are approximately equivalent to parts per thousand. Satellite measurements of SSS are 298 important for studying the global water cycle (e.g., areas of precipitation and evaporation), oceanic currents and transport, 299 and river discharge53. The MCDC provides SSS retrievals from the 1.4 GHz frequency characteristic of the SMAP MW im-300 ager at two resolutions: 40 km and 70 km; values range from 0 to 45 psu. The 70 km SSS product should be used for most 301 scientific purposes as the noise associated with the SSS retrievals is greatly reduced when compared to the 40 km product 302 303

RSS SMAP Sea-Surface Salinity 8-Day Average Centered on 06/15/2018



Figure 4 MCDC Sea-Surface Salinity (SSS). SSS from SMAP is averaged over eight days centered on June 15, 2018.

(Figure 4).

Atmospheric Temperature Profiles over Ocean and Land

Satellite measurements of atmospheric temperature are critical for train-305 ing and verifying atmosphere-ocean coupled general circulation models 306 (GCMs) to predict future changes to the climate⁵⁴. According to the Inter-307 governmental Panel on Climate Change (IPCC), under high greenhouse 308 gas emissions scenarios the lower troposphere global average tempera-309 tures are predicted to increase by 1.5 °C relative to pre-industrial levels 310 by 2030 to 2052⁵⁵. The MCDC at RSS provides temperature measurements 311 for five layers of the atmosphere over ocean and land: Temperature 312 Lower Troposphere (TLT), Temperature Total Troposphere (TTT), Tem-313 perature Middle Troposphere (TMT), Temperature Troposphere Strato-314 sphere (TTS), and Temperature Lower Stratosphere (TLS)²⁷. Atmospheric 315 temperatures are calculated from the 50-60 GHz channels of MW sound-316 ers; values range from approximately 80 to 310 K depending on the at-317 mospheric layer. 318

AS-ECV CDRs

RSS has combined select AS-ECV data from multiple MW imagers into a 320 single CDR on a 2.5-degree, global grid for each month from 1987 to pre-321 sent: wind speed, columnar atmospheric water vapor, columnar cloud 322

liquid water, and sea-surface rain rate. During sensor overlap periods, the CDR AS-ECV is determined by averaging the 323 multi-sensor retrievals together into a single gridded map. The CDR additionally includes sea-surface temperature from 324 Reynolds Optimal Interpolation (OI) because the MCDC MW sea-surface temperature record does not extend back to 1987. 325 The CDR was created for trend analysis; for example, Figure 5 shows trend maps of the AS-ECVs from this CDR. A second-326 ary available CDR contains tropospheric and stratospheric temperatures derived from MW sounders, MSU and AMSU, 327 spanning 1979 to present. Figure 6 shows the long-term trends from this CDR: tropospheric temperatures have increased 328 by 0.213 K per decade and stratospheric temperatures have decreased by -0.210 K per decade. The data for the MW imager 329 AS-ECV CDR is located at: https://www.remss.com/climate/Air-Sea-Essential-Climate-Variables/. The data for the MW 330 sounder AS-ECV CDR is located at: https://images.remss.com/msu/msu_time_series.html. 331

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Figure 5 MCDC AS-ECV CDR Trend Maps. Trend maps of monthly MCDC MW imager AS-ECV CDRs for July 1987 to December 2020: sea-surface temperature (SST) (a), wind speed (b), columnar atmospheric water vapor (c), columnar cloud liquid water (d), sea-surface rain rate (e). Monthly values are de-seasonalized to account for monthly variation, i.e., the average monthly value over the entire period for January, February, etc. is subtracted from the observed monthly value before the trend is calculated.



Technical Validation

A majority of work completed at 334 RSS revolves around the 335 validation of the MCDC datasets. 336 The following sub-sections 337 provide examples of the technical 338 validation of individual AS-ECV 339 datasets. 340

Sea-Surface Temperature

The average bias between MCDC 342 MW sub-skin SSTs from TMI and 343 moored buoys is -0.08°C and the 344 standard deviation of the bias is 345 0.57°C for all collocations from 346 1998 to 200156. To mitigate the ef-347 fect of diurnal warming on the 348 bias, SST measurements with cor-349 responding wind speeds less than 350 6 m/s and between 10 am and 6 pm 351 were excluded from the above sta-352 tistics. In addition, all retrievals 353 within 25 km of a non-zero rain re-354 trieval were excluded from the 355 bias statistics because undetected 356 rain can cause a warm bias in the 357 MW SSTs. Similar to the TMI vali-358 dation study, the MCDC MW sub-359 skin SSTs from AMSR-E (AMSR-2) 360 collocated with moored and drift-361 ing buoys, ships, and Coastal-Ma-362 rine Automated Network in situ 363 SSTs spanning 2002 to 2011 (2012 364 to 2014) exhibited a bias of -0.05°C 365 (-0.04°C) and standard deviation 366 of 0.48°C (0.55°C)57,58. 367

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Ocean Wind Speed and Wind Vectors 369 over Ocean and Land 370

On a global scale, wind speeds between 0–15 m/s from MCDC MW 372 imagers and scatterometers agree 373 with buoy measurements with an 374 error of about 1–1.5 m/s^{59,60,61,62}. For 375 higher wind speeds, between 15– 376 25 m/s, accurate in situ measure- 377



ments from buoys are difficult to obtain because the wind-measuring devices (anemometers) on buoys are impacted by buoy tilting, high sea state, and wave-sheltering^{63,64,65}. However, when compared to anemometers mounted high on oil 379

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platforms in the North Sea (and therefore not subject to the same ocean effects as buoys) imager and scatterometer wind 380 measurements between 15–25 m/s perform well⁶⁶. Specifically, WindSat exhibited a -0.5 m/s bias and 2.5 m/s standard de-381 viation of the bias at wind speeds of 22 m/s. While the scalar wind speed signal responds with a linear emissivity that does 382 not saturate at extreme winds ~70 m/s^{22,67,68}, the backscatter signal of wind vector measurements saturates at wind speeds 383 above 35–40 m/s making it difficult to tell the exact wind magnitude^{69,70,71}. For MW imagers and scatterometers it is chal-384 lenging to validate wind speeds above 25–30 m/s because there is a scarcity of data to use as ground truth. That being said, 385 wind information from dropsondes and Stepped-Frequency Microwave Radiometers (SFMRs) on board hurricane-pene-386 trating aircrafts have shown that SMAP can accurately measure wind speeds of up to 70 m/s in tropical cyclones^{67,72}. Note 387 that since the TC winds algorithms are trained in TC conditions, they become less accurate in areas where sea-surface 388 temperatures are < 20 °C and wind speed is < 10 m/s. In these conditions, the All-Weather winds product should be used. 389 CCMP should not be used to measure high winds (> 25 m/s) associated with tropical cyclones because the background 390 model winds used in CCMP consistently underestimate winds relative to satellite observations at higher wind speeds, and 391 in some cases tropical cyclones are too spatially-small for the background models to pick up. 392

Columnar Atmospheric Water Vapor over Ocean

The MCDC water vapor retrievals agree with water vapor measurements from GPS ground stations located on small islands 394 across the globe with mean differences of less than 1 mm between the two⁷³. The MCDC water vapor retrievals display a 395 global trend of approximately 1.5% increase per decade74. This tracks well with the water vapor increase relative to the 396 increase in global temperature as predicted by the Clausius-Clapeyron equation (~7% increase in water vapor per degree 397 of warming)75,76,77. Unfortunately, water vapor is not retrieved in areas of moderate to high rain rate (> 5–10 mm/hr). This 398 can result in a systematic "non-rainy" negative bias in globally-averaged water vapor. Indeed, the MCDC average water 399 vapor retrievals have a small "non-rainy" bias (-0.35-0.15 mm relative to GPS stations)⁷⁴. In the presence of light rain (0-5 400 mm/hr), RSS is able to retrieve water vapor; however, in this case there is a large positive bias in AMSR-E water vapor 401 measurements (up to 2 mm at rain rates of \geq 2 mm/hr)⁷³. Another issue relates to wind speed: almost every MCDC sensor 402 shows a roughly linear decrease in its water vapor bias relative to GPS stations as wind speed increases⁷³. This is potentially 403 due to small errors in the ocean surface model used in the RTM. 404

Columnar Cloud Liquid Water over Ocean

It is difficult to check the accuracy of MCDC columnar cloud liquid water retrievals against in situ sources because meas-406 urements of cloud liquid water over the oceans are sparse and cloud coverage can vary significantly over the large area that 407 the satellite observes. Provided these difficulties, cloud liquid water is validated with probability distribution functions 408 (PDFs) of cloud liquid water for different ranges of sea-surface temperature, wind speed, and atmospheric water vapor. 409 The PDFs have a distinctive shape where the peak of the PDFs is near a cloud liquid water value of 0.025 mm with a half-410 peak at 0.000 mm. The steeply-sloped left sides correspond to clear-sky conditions when there is little to no cloud liquid 411 water. If the left side half-peak of the stratified PDFs are aligned, it indicates minimal errors in the cloud liquid water 412 measurement, and therefore, minimal contamination or crosstalk from SST, wind speed, or water vapor. Conversely, if the 413 clear-sky portions of the PDFs are not aligned then signals from one of the other geophysical variables in a given scene may 414 be causing an erroneous cloud water signal when there is none. This analysis suggests that the systemic cloud liquid water 415 root-mean-square error is: +/- 0.005 mm¹⁹. Another source of error could be related to the cloud liquid water vs rain thresh-416 old value. In the MCDC algorithm, a cloud is assumed to be raining if the cloud liquid water value is greater than 0.180 mm 417 (i.e., the rain threshold, Lnain, is equal to 0.180). It is possible that cloud liquid water may end up being over- (under-) esti-418 mated if clouds are precipitating below (above) the threshold of 0.180 mm. However, this threshold was shown to be rea-419 sonable78. 420

Sea-Surface Rain Rate

The MCDC sea-surface rain rate average bias is 4 mm/yr, or approximately $5x10^{-4}$ mm/hr, for all measurements of rain rate422from TMI compared to the Pacific Marine Environmental Laboratory (PMEL) tropical buoys located between 25°S and 21°N423across the years 1997–2011¹¹. For the retrieval of rain rate, we use the columnar cloud liquid water as a proxy for rain; for424values of cloud liquid water below 0.18 mm, the rain is assumed to be zero⁷⁸. Unaccounted for variations this threshold may425produce spurious trends in the rain calculation.426

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Sea-Surface Salinity

In non-raining scenes and SSTs > 5 °C, the MCDC 70 km SMAP SSS data product has a -0.01 psu bias and a 0.14–0.15 psu 428 standard deviation of the bias when compared to drifting ARGO buoys¹ (a global array of over 3000 floats) and the Hybrid 429 Coordinate Ocean Model (HYCOM)79,80,81. In high rain, the ARGO data are not a reliable validation source. This is because 430 the stratification of the upper ocean layer caused by rain results in a sampling mismatch error between the satellite sensor 431 observation, which is within a few centimeters of the surface, and the in-situ observation, which is taken at a depth of 1–5 432 m⁸². In addition, the MCDC salinity retrievals degrade in cold water, as the 1.4 GHz L-band surface emission loses sensitiv-433 ity at low SSTs. Other reasons for possible degradation include proximity of the retrieval to land or sea ice and the presence 434 of sun glint or high wind speeds. The effect of the sea ice edge on SSS retrievals has been largely mitigated by a sea ice flag 435 developed by RSS⁸³. 436

Atmospheric Temperature Profiles over Ocean and Land

The MCDC TLT dataset shows greater trends in warming (0.21-0.25 K/decade) as compared to radiosonde datasets (0.18-438 0.20 K/decade)¹⁵. The University of Alabama-Huntsville (UAH) TLT trends are also smaller than the MCDC TLT trends 439 (0.124 vs 0.174 K/decade for near-global regions and 0.121 vs 0.147 K/decade for tropical regions)¹⁵. In addition, MCDC TLT 440 is validated with total column water vapor, which is highly correlated with atmospheric temperature over the tropical 441 oceans. In contrast to the radiosonde and UAH TLT biases, the MCDC TLT trend ratio (8%/K) implies slightly less warming 442 than the expected water vapor trend ratio (6.2%/K)¹⁵. Overall, the MCDC TLT exhibited global errors of ±0.044 K and trop-443 ical errors of ±0.034 K in a Monte Carlo analysis that systematically incorporated 400 combinations of errors in TLT⁸⁴. 444

Code Availability

The Radiative Transfer Model code that is used to generate the regressions for the microwave imager retrievals of MCDC 446 AS-ECVs is available upon request from: https://www.remss.com/rtm/. Coefficients for the microwave imager retrieval 447 regressions and scatterometer GMF are available upon request. Weighting functions for the microwave sounder retrievals 448 of atmospheric temperatures are available at: https://data.remss.com/msu/weighting_functions/. In addition, the code for 449 the diurnal warming model used to compute foundation sea-surface temperature is available on the RSS website: 450 https://www.remss.com/research/. 451

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¹ The buoy data were collected and made freely available by the International ARGO Program and the national programs that contribute to it; the ARGO Program is part of the Global Ocean Observing System.

Tables

Table 1. Inputs: MW conical scanning imagers used to generate AS-ECV data. SSM/I=Special Sensor Microwave Imager. SSMIS=SSMI467Sounder. DMSP=Defense Meteorological Satellite Program. TMI=Tropical Rainfall Measuring Mission (TRMM) Microwave Imager.468GMI=Global Precipitation Measurement (GPM) Microwave Imager. AMSR-E & AMSR-2=Advanced Microwave Scanning Radiometers.469GCOM-W1=Global Change Observation Mission. SMAP=Soil Moisture Active Passive.470

Sensor Name	Satellites	Time Period (years)	Ascending Local Equatorial Time ¹	Frequencies (GHz)	Mean Footprint Resolu- tion (km)²	Swath Width (km)
SSM/I ⁸⁵	DMSP F08 F10–11 F13–15	1987– Present	06:00 (F08), 17:00–22:00 Near-Polar Orbit	19.35 V H 22.24 V 37.00 V H 85.50 V H	56 45 32.5 14	1400
SSMIS ⁸⁵	DMSP F16–18	2003– Present	16:30–18:30 Near-Polar Orbit	19.35 V H 22.24 V 37.00 V H 91.35 V H	56 45 32.5 14	1700
TMI ⁸⁶	TRMM	1997–2015	Variable Inclined Orbit: 40°S to 40°N	10.70 V H 19.35 V 21.30 V H 37.00 V H 85.50 V H	57.5 28 23.5 14 7	758.5
GMI ⁸⁷	GPM	2014– Present	Variable Inclined Orbit: 60°S to 60°N	10.65 V H 18.70 V H 23.80 V 36.64 V H 89.00 V H	25.5 14.5 13 12 5.5	930
AMSR-E ⁸⁸	Aqua	2002–2011	13:30 Near-Polar Orbit	6.925 V H 10.65 V H 18.70 V H 23.80 V H 36.50 V H 89.00 V H	59 40 21.5 25 11 5	1445
AMSR-2 ⁸⁸	GCOM-W1	2012– Present	13:30 Near-Polar Orbit	6.925 V H 7.300 V H 10.65 V H 18.70 V H 23.80 V H 36.50 V H 89.00 V H	48.5 48.5 33 18 15 9.5 4	1450
WindSat ⁸⁹	Coriolis	2003–2020	18:10 Near-Polar Orbit	6.800 V H 10.70 V H ³ 18.70 V H ³ 23.80 V H 37.00 V H ³	55 31.5 21.5 25 10.5	950
SMAP ⁶	SMAP	2015– Present	18:00 Near-Polar Orbit	1.410 V H U	43	1000

¹ Information was obtained from: https://www.remss.com/support/crossing-times/. ² Information was obtained from: https://www.remss.com/missions/. ³Fully polarimetric channels.

Table 2. Inputs: MW cross-track scanning sounders used to generate AS-ECV data. MSU=Microwave Sounding Unit. AMSU=Advanced473Microwave Sounding Unit. FOV=Sensor Field of View.474

Sensor Name	Satellites	Time Period (years)	Ascending Local Equatorial Time ¹	Frequencies (GHz)	Mean Footprint Resolution (km)	Swath Width (km)
MSU ¹³	Tiros-N, NOAA-06–12, 14	1978– 2005	13:30–20:30 Near-Polar Orbit	4 channels: 50.30–57.95 Vx2, Hx2	110	~ 640 (central 5 FOVs)
AMSU-A ¹³	NOAA-15, 18–19, MetOp-A, -B, Aqua	1998– Present	13:30–22:00 Near-Polar Orbit	11 channels: 52.80–57.29 Vx2, Hx9	48	~ 660 (central 12 FOVs)

¹ Information was obtained from: https://www.remss.com/support/crossing-times/.

Table 3. Inputs: MW scatterometers used to generate AS-ECV data. SeaWinds is a conical scanning "pencil beam" scatterometer, whileASCAT is a cross-track chirping "fan beam" scatterometer. ASCAT=Advanced Scatterometer.

Sensor Name	Satellites	Time Period (years)	Ascending Local Equatorial Time ¹	Frequencies (GHz)	Mean Footprint Resolution (km)	Swath Width (km)
Sea- Winds ⁹⁰	Quickbird (<i>QuikSCAT</i>) ADEOS-2/ MIDORI-2 (<i>SeaWinds</i>)	1999–2009 (QuikSCAT) 2002–2003 (SeaWinds)	06:00 (QuikSCAT) 22:30 (SeaWinds) Near-Polar Orbit	13.40 V H	44.5 (V) 39 (H)	1800
ASCAT ⁹¹	MetOp -A, -B, -C	2007– Present	21:30 Near-Polar Orbit	5.255 V	25 & 50	500 x2

¹ Information was obtained from: https://www.remss.com/support/crossing-times/.

Table 4.	Variable	definitions	for	Equations	(1)	through	(17).
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Variable Name	Definition				
T _B	Top-of-the-atmosphere T ^B (K) for a given MW frequency and polarization.				
T _A	Top-of-the-ionosphere $T_A(K)$ for a given MW frequency and polarization.				
24	The coefficients of fractional power coming from the orthogonal polarization (cross-polarization				
X	coupling).				
E _{refl}	Emissivity of the main sensor reflector.				
T _{refl}	Temperature (K) of the main sensor reflector.				
η	The fraction of received power coming from cold space (spillover).				
T _C	Temperature (~2.7 K) of the cosmic microwave background radiation (cold space).				
Е	Sea-surface emissivity for a given MW frequency and polarization.				
Ts	Surface temperature (K).				
T _{BU} , T _{BD}	Upwelling and downwelling atmospheric T_B (K).				
τ	The total transmissivity through the atmosphere.				
T _{B,scat}	$T_{B}(K)$ adjustment that accounts for scattering as opposed to reflections from sea surface.				
Ω	Empirical factor term.				
ЪH	Height (h; km) above Earth' surface and height (H; km) at which the atmospheric absorption is				
11, 11	zero.				
θ	Angle between the satellite viewing direction and the zenith of the Earth's geoid at boresight				
0	(EIA; degrees).				
Т	Air temperature (K).				
α	Atmospheric absorption coefficient for a given MW frequency and polarization.				
$\alpha_{\rm D}, \alpha_{\rm V}, \alpha_{\rm L}$	The three components of atmospheric absorption: dry air, water vapor, liquid cloud water.				
ε _L	Dielectric constant of pure (cloud) water which depends on the temperature of the medium.				
$ ho_V$, $ ho_L$	Water vapor density and cloud liquid water density (kg/m ³).				
Р	Dry air pressure (kPa).				
$E_0, \Delta E_w, \Delta E_\omega$	Emissivity of the specular ocean surface, isotropic wind-induced emissivity, four Stokes parame-				
υ, νι, φ	ters of the wind direction signal.				
S	Sea-surface salinity (psu).				
W	Wind speed (m/s).				
φ	Wind direction relative to azimuthal look (degrees).				
m _{1j} , m _{2j}	Measurement of AS-ECV for 1 st stage regression and 2 nd stage regression.				
j, k, l	AS-ECV sea-surface temperature or wind speed index (j), sea-surface temperature 1st stage re-				
,, , ,	gression integer value index (k), wind speed 1 st stage regression integer value index (l).				
a, b, c	Coefficients for AS-ECV non-linear and linear regressions.				
W	Linear combination of AS-ECV measurements from 1 st stage regression.				
Z	Zenith optical depth (km).				
F	Weighting function for atmospheric layers.				
к	Atmospheric absorption coefficient.				
σ_o	The normalized radar cross-section (radar backscatter).				
d_0, d_1, d_2	Coefficients of radar backscatter 5^{th} order polynomials.				

		Spatial Temporal			Data	
Variable	Sensors	Range Grid		Range	Resolution	Format
Sea-Surface Temperature	TMI, GMI, AMSR-E, AMSR- 2, WindSat	40°S to 40°N (<2002-06-01) Global Ocean (>=2002-06-01)	0.25°	1997– Present	Daily¹, 3-Day, Weekly, Monthly	netCDF4, bytemap
OI Sea-Surface Temperature (MW)	TMI, GMI, AMSR-E, AMSR- 2, WindSat	40°S to 40°N (<2002-06-01) Global Ocean (>=2002-06-01)	0.25°	1998– Present	L4 Daily	netCDF4, bytemap
OI Sea-Surface Temperature (MW + IR)	TMI, GMI, AMSR-E, AMSR- 2, WindSat, MODIS-Terra, MODIS-Aqua, VIIRS-NPP, VIIRS-N20	Global Ocean	0.09°	2002– Present	L4 Daily	netCDF4, bytemap
Ocean Wind Speed	SSM/I, SSMIS, TMI, GMI, AMSR-E, AMSR-2, SMAP	Global Ocean	0.25°	1987– Present	Daily¹, 3-Day, Weekly, Monthly	netCDF4, bytemap
Ocean Wind Vector ²	WindSat, QuikScat, Sea- Winds, ASCAT	Global Ocean	0.25°	1999– Present	Daily ¹ , 3-Day, Weekly, Monthly	bytemap
Ocean TC/ All-Weather Wind Speed	AMSR-E (only TC), AMSR-2, WindSat, SMAP	TC: Tropical Ocean ³ All-Weather: Global Ocean	0.25°	2002– Present	Daily	netCDF4, bytemap
CCMP Ocean Wind Vector ²	MCDC Wind Vector, Quik- SCAT, ASCAT, Moored Buoys, ERA-Interim	Global Land Global Ocean	0.25°	1988– Present	6-Hourly	netCDF4
Columnar Atmospheric Water Vapor	SSM/I, SSMIS, TMI, GMI, AMSR-E, AMSR-2, WindSat	Global Ocean	0.25°	1987– Present	Daily ¹ , 3-Day, Weekly, Monthly	netCDF4, bytemap
Columnar Cloud Liquid Water	SSM/I, SSMIS, TMI, GMI, AMSR-E, AMSR-2, WindSat	Global Ocean	0.25°	1987– Present	Daily ¹ , 3-Day, Weekly, Monthly	netCDF4, bytemap
Sea-Surface Rain Rate	SSM/I, SSMIS, TMI, GMI, AMSR-E, AMSR-2, WindSat	Global Ocean	0.25°	1987– Present	Daily ¹ , 3-Day, Weekly, Monthly	netCDF4, bytemap
Sea-Surface Salinity	SMAP (40 km & 70 km)	Global Ocean	0.25°	2015– Present	L2 Swath, 8-Day, Monthly	netCDF4
Atmospheric Temperature Profiles	MSU, AMSU	Global Land Global Ocean	2.5°	1978/1987 (TTS)– Present	Monthly	netCDF4, bytemap

Table 5. Outputs: Data available at the MCDC. Most products are L(evel) 3 unless specified as L2 or L4. Spatial "Grid" is the spatial511sampling in lat/lon degrees. OI=Optimally Interpolated; TC=Tropical Cyclone; CCMP=Cross-Calibrated Multi-Platform.512

¹Indicates that the daily products include both ascending and descending orbits. ²Direction+Speed. ³SST>20°C; Winds>10 m/s.

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