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Classification of the global Sentinel-1 SAR vignettes for ocean surface process studies

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Abstract

Spaceborne synthetic aperture radar (SAR) can provide finely-resolved (meters-scale) images of ocean surface roughness day-or-night in nearly all weather conditions. This makes it a unique asset for many geophysical applications. Initially designed for the measurement of directional ocean wave spectra, Sentinel-1 SAR wave mode (WV) vignettes are small 20 km scenes that have been collected globally since 2014. Recent WV data exploration reveals that many important oceanic and atmospheric phenomena are also well captured, but not yet employed by the scientific community. However, expanding applications of this whole massive dataset beyond ocean waves requires a strategy to automatically identify these geophysical phenomena. In this study, we propose to apply the emerging deep learning approach in ocean SAR scenes classification. The training is performed using a hand-curated dataset that describes ten commonly-occurring atmospheric or oceanic processes. Our model evaluation relies on an independent assessment dataset and shows satisfactory and robust classification results. To further illustrate the model performance, regional patterns of rain and sea ice are qualitatively analyzed and found to be very consistent with independent remote sensing datasets. In addition, these high-resolution WV SAR data can resolve fine, sub-km scale, spatial structure of rain events and sea ice that complement other satellite measurements. Overall, such automated SAR vignettes classification may open paths for broader geophysical application of maritime Sentinel-1 acquisitions.

Keywords: Synthetic aperture radar (SAR), Ocean surface phenomena, Sentinel-1 wave mode, Deep learning, Convolutional neural network (CNN), Image classification

1. Introduction

The spaceborne synthetic aperture radar (SAR) is a well-established technique to collect high-resolution sea surface backscatter data during day and night in most weather conditions. Over the ocean, SAR images provide an estimate of the sea surface roughness primarily through backscattering of short waves (Alpers et al., 1981; Hasselmann et al., 1985; Hasselmann and Hasselmann, 1991), where this small-scale (cm) roughness responds to the near-surface ocean winds (Lehner et al., 2000; Winstead et al., 2006; Mouche et al., 2012). In addition, these short waves are also modulated by ocean swell (Heimbach et al., 1998; Lehner et al., 2000; Collard et al., 2009), upper ocean processes (Johannessen et al., 1996; Rascle et al., 2017; Jia et al., 2018), and atmospheric phenomena (Alpers and Brümmer, 1994; Young et al., 2005; Winstead et al., 2006; Li et al., 2007, 2013; Alpers et al., 2016). Beginning with SEASAT in 1978, ocean SAR imagery has been widely used to examine numerous air-sea interaction processes (Meadows et al., 1983; Gerling T W, 1986; Carsey and Holt, 1987; Fu and Holt, 1982; Katsaros and Brown, 1991). Since then, ever-improving SAR data have been obtained by satellite missions that include ERS-1/2, Envisat/ASAR, RADARSAT-1/2, TerraSAR-X, TanDEM-X and Sentinel-1 constellation.

However, global-scale applications of ocean SAR data remain quite limited. This is largely because the wide swath SAR images are not routinely collected over the open ocean. These acquisitions mainly focus on land, Arctic regions, and near the coasts. Thus, most previous ocean SAR data investigations only involve limited regional or single SAR scene case study (Alpers and Brümmer, 1994; Babin et al., 2003; Sikora et al., 2011; Li et al., 2013; Alpers et al., 2016). One exception is the wave mode (WV) dedicated to retrieving ocean wave properties at global scale (Kerbaol et al., 1998; Stopa et al., 2016). The WV has been developed for ERS-1/2 (1991-2003) and Envisat/ASAR (2002-2012), and now introduced to Sentinel-1 (2014-present) and Gaofen-3 (2016-present). It normally collects relative small SAR images (typically 5 to 10 km square) along the orbit with a distance of about 100 km in between. This is sufficient for ocean wave spectrum retrieval and empirically estimation of the total significant wave height (Heimbach et al., 1998; Collard et al., 2009; Stopa and Mouche, 2017), which can be used in wave forecasting. At present, the routine WV measurements are only available from the Sentinel-1 (S-1) A&B (Torres et al., 2012). It was improved upon Envisat and ERS by having finer spatial resolution (4 m), higher signal-to-noise (which reduces speckle noise), larger scene footprint (20 by 20 km), and increased global sampling.

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45 [Wang et al. \(2019\)](#) demonstrated that the S-1 WV dataset has the potential for new studies on
46 air-sea interactions at scales of 0.5-10 km. The primary advantage of the S-1 WV dataset is its
47 ability of measuring high resolution sea surface roughness globally (~120k images per month).
48 However, without an automated means to identify the geophysical features captured by each im-
49 age, the potential would remain untapped. For example, previous studies have relied solely on
50 visual inspection to identify SAR images with wind streaks before performing statistical analy-
51 sis or surface wind direction derivation ([Lehner et al., 2000](#); [Levy, 2001](#); [Mouche et al., 2012](#);
52 [Zhao et al., 2016](#)). Such manual classification approach is impractical for the huge volume of S-1
53 WV data. Similarly, dedicated classic machine learning algorithms have mostly been developed
54 for specific applications such as detection of oil spills and ships. These methods depend on the
55 empirically hand-crafted features, which are usually insufficient to generalize the local variations,
56 shapes and structural patterns of different geophysical phenomena ([Topouzelis and Kitsiou, 2015](#);
57 [Zhang et al., 2016](#)).

58 This study attempts to train a deep convolutional neural network (CNN) to classify the ten
59 prescribed geophysical phenomena seen in WV vignettes. Deep CNN models have been applied
60 with great success in detection, segmentation, and recognition of objects, features, and textures
61 within digital images ([LeCun et al., 2015](#)). They have also been applied to hyperspectral and
62 optical remote sensing imagery ([Zhao and Du, 2016](#); [Li et al., 2017](#); [Hu et al., 2015](#); [Cheng and](#)
63 [Han, 2016](#); [Zhou et al., 2017](#)). However, the primary use of CNN in ocean SAR application has
64 mostly been for target recognition ([Zhang et al., 2016](#); [Zhu et al., 2017](#)). In general, CNN is a
65 multilayer architecture that can be trained to automatically extract the optimal image features and
66 to amplify distinctions between images ([LeCun et al., 2015](#); [Zhang et al., 2016](#)). A practical and
67 effective way to develop a robust CNN for a specific application is to re-train an existing image
68 recognition model. This so-called transfer-learning or fine-tuning strategy has been proven to
69 be more efficient and practical than creating and training a new CNN architecture from scratch
70 ([Yosinski et al., 2014](#); [Zhu et al., 2017](#); [Cheng et al., 2017](#); [Too et al., 2018](#); [Wang et al., 2018a](#)).

71 In this paper, we adapt the Inception-v3 CNN ([Szegedy et al., 2015](#)) to train a model dedicated
72 to the classification of S-1 WV vignettes, called CMwv. The involved datasets are described in sec-
73 tion 2. Section 3 demonstrates the training process of CMwv and illustrates the model performance
74 based on an independent assessment dataset. In section 4, we compare our classification results
75 qualitatively with rain precipitation from Global Precipitation Measurement (GPM) and sea-ice
76 concentration from Special Sensor Microwave Imager (SSM/I). Conclusions follow in section 5.

77 2. Datasets

78 This study uses ocean SAR vignettes from S-1 WV, precipitation data from GPM and sea ice
79 concentration data from SSM/I. To train the CNN architecture, we create training datasets drawn
80 from the labelled TenGeoP-SARwv database (Wang et al., 2018b). In addition, to assess and
81 quantify the performance of CMwv, we build an assessment dataset of 10,000 visually verified
82 images. All datasets are described in the following.

83 2.1. S-1 WV

84 The S-1 mission is a constellation of two (A&B) polar-orbiting, sun-synchronous SAR satel-
85 lites (Torres et al., 2012). They were launched by European Space Agency (ESA) in April of 2014
86 and 2016, respectively. The two satellites share the same orbital plane, which crosses the equator
87 at approximately 0600 or 1800 local time, with a 180° phase difference to provide an effective
88 6-day repeat cycle. The S-1 microwave SAR instruments have a 5.5 cm wavelength (C-band).
89 WV is the default mode over the open ocean unless other imaging mode collections are requested.
90 According to the defined Mission Operation Scenario, there is no WV acquisition in the Arctic
91 Ocean, closed seas (Red, Black, Mediterranean and Caribbean seas) and coastal areas. Figure 1
92 displays the spatial coverage of S-1A WV data acquired in July of 2016. Although only S-1A WV
93 data is used in this study, S-1B images have essentially equivalent characteristics with S-1A. Thus,
94 the combination of S-1A and S-1B will expand sampling in time and space for different geophys-
95 ical phenomena applications. Moreover, the developed classification model and results presented
96 hereafter are also applicable to S-1B.

97 S-1 WV vignettes are acquired in a 'leapfrog' pattern at two alternating center incidence angles
98 of 23° (WV1) and 36.5° (WV2) every 100 km along the flight track. Each vignette has a 20 by 20
99 km footprint with 5 m spatial resolution. The default radar polarization is VV, though some HH
100 images have been acquired. Combining both satellites and WV incidence angles, approximately
101 120,000 vignettes per month are acquired. This study focuses on the VV polarized SAR vignettes
102 as they comprise more than 99% of acquisitions to date. Also, data quality control is carried out
103 by removing data files with the following criteria:

- 104 • **HH polarization:** HH-polarized images are excluded.
- 105 • **Land contamination:** The distance of one vignette center (longitude and latitude) to the
106 nearest coastline is calculated based on the dataset of Distance from Nearest Coastline

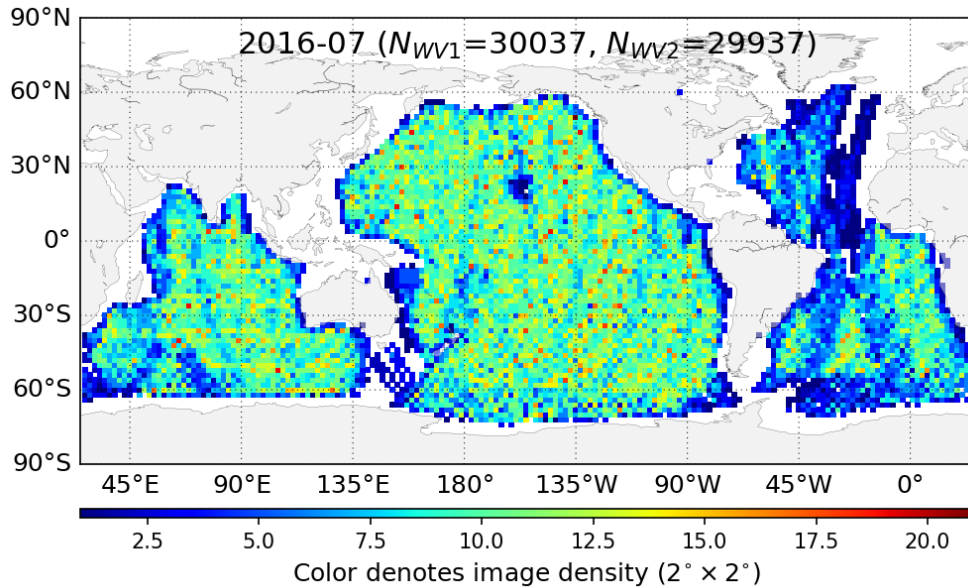


Figure 1: Global distribution of the WV SAR data obtained by S-1A in July of 2016. Color is indicative of the SAR image density in 2° by 2° spatial grid.

107 (DNC¹). We filter out the vignettes if their center is over the land.

- 108 • **Low mean signal intensity:** We filter out the low-quality vignettes by limiting the mean
109 Normalized Radar Cross Section (NRCS) to be larger than -22 dB, which is the Noise Equiv-
110 alent Sigma Zero (Torres et al., 2012).

111 2.2. TenGeoP-SARwv dataset

112 TenGeoP-SARwv is a labelled dataset of more than 37k ocean SAR images corresponding to
113 ten commonly-observed and expertly-defined geophysical phenomena (Wang et al., 2019). These
114 ten choices, though somewhat subjective, were selected and defined after an extensive review of
115 the S-1 WV data and with reference to past ocean SAR studies. This study denotes the classes
116 as pure ocean waves (PureWave), wind streaks (WindStreak), micro-convective cells (WindCell),
117 rain cells (RainCell), biological slicks (BioSlick), sea ice (SeaIce), icebergs (IceBerg), low wind
118 areas (LowWind), atmospheric fronts (AtmFront), and oceanic fronts (OcnFront). Thousands of
119 VV-polarized vignettes for each case were manually selected from the S-1A WV acquisitions
120 in 2016. These vignettes are chosen with the criteria that within one scene, one geophysical

¹The Distance from Nearest Coastline dataset is available at http://oos.soest.hawaii.edu/erddap/info/dist2coast_1deg/index.html

121 phenomenon dominates with its specific signature or pattern. It is worth noticing that PureWave
 122 signatures normally exist in SAR images as background for other classes. Example vignettes of
 123 the ten defined classes are displayed in Figure 2. These visually-identified and tagged SAR scenes,
 124 37560 in total, are provided in formats of Portable Network Graphics (PNG) and Georeferenced
 125 Tagged Image File Format (GeoTIFF). Despite the fact that the GeoTIFF product maintains high
 126 precision of the original data, PNG files are more suitable for visual interpretation and satisfy the
 127 training input requirement for CNN models. Thus, PNG product is the dataset of interest in this
 128 study. It is important to note that the detectability of SAR on these phenomena, especially these
 129 modulations induced by the surface wind, can differ for WV1 versus WV2. Because the complex
 130 response of C-band radar scatter of the sea surface depends primarily on the incidence angle and
 131 the relative angle between the radar and the surface wind direction. Under some atmospheric
 132 conditions such as strong winds (>15 m/s), the backscatter is dominated by sea states (winds and
 133 waves). Consequently, other phenomena except ocean waves can not be well captured.

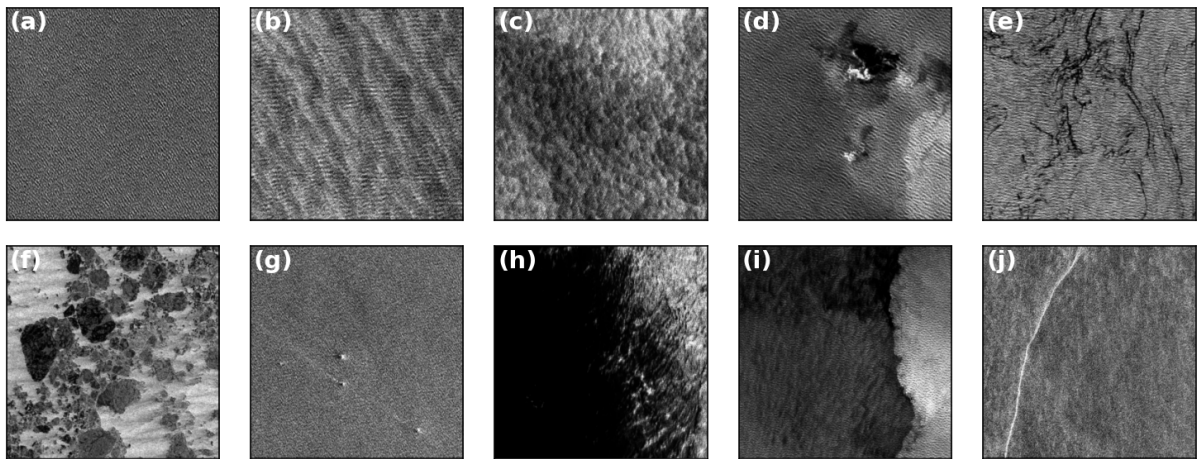


Figure 2: Ten vignette examples of expertly-defined geophysical phenomena. From (a) to (j) are pure ocean waves (PureWave), wind streaks (WindStreak), micro convective cells (WindCell), rain cells (RainCell), biological slicks (BioSlick), sea ice (SeaIce), icebergs (IceBerg), low wind area (LowWind), atmospheric front (AtmFront) and oceanic front (OcnFront).

134 2.3. Assessment dataset

135 S-1 WV SAR vignettes are able to capture a wide range of ocean surface geophysical processes
 136 and the most common ten categories have been included in the TenGeoP-SARwv. To assess and
 137 quantify performance of the developed classification model on the whole WV database, an in-
 138 dependent assessment dataset is thus created. 5000 WV1 and WV2 vignettes respectively were

139 randomly selected from 2016 S-1A acquisitions and classified by visual inspection. A less strict
140 criteria of PureWave was adopted to make this validation dataset representative of the actual WV
141 measurements. We then apply the classification model to each of these scenes. The resulting class
142 identifications were compared to visual results, which is a skill test commonly used in image clas-
143 sification modeling (Zhang et al., 2016; Cheng et al., 2017). For the vignettes that do not belong
144 to any of the ten defined classes, we sort them into a special 'The Other' category (TheOther).
145 These more infrequent phenomena include, but are not limited to, oceanic internal waves (Alpers
146 and Huang, 2011; Jia et al., 2018), atmospheric gravity waves (Chunchuzov et al., 2000; Li et al.,
147 2013), upwelling regions (Jackson et al., 2004), and irregular atmospheric patterns.

148 2.4. Rain precipitation from GPM and IMERG

149 The GPM mission is an international satellite network that provides global estimates of rain-
150 fall and snowfall from space (Hou et al., 2014). A primary instrument is the GPM Core Obser-
151 vatory that was launched in February 2014 by the National Aeronautics and Space Administra-
152 tion (NASA) and the Japan Aerospace and Exploration Agency (JAXA). This Core Observatory
153 carries the first dual-frequency (Ku-/Ka-band) precipitation radar (DPR) and a multichannel mi-
154 crowwave imager (GMI). The Ku-band radar accurately measures moderate to heavy rain rates and
155 the Ka-band radar can measure light rain and snowfall. They provide cross-track swaths of 245
156 km (Ku) and 120 km (Ka) with 5 km resolution. Retrieved precipitation estimates from the swath
157 measurements are available at the NASA data center ([https://pmm.nasa.gov/data-access/
158 downloads/gpm](https://pmm.nasa.gov/data-access/downloads/gpm)). In addition, the Integrated Multi-satellitE Retrievals for GPM (IMERG) is a
159 gridded precipitation product that combines all satellite precipitation measurements. In this study,
160 we collocate GPM level-2 (swath) DPR Ku-only surface rain precipitation data with S-1A WV
161 vignettes acquired from March 2016 to February 2017. Spatial and temporal collocation crite-
162 ria of 35 km and less than 10 mins are used and result in 2588 matched data pairs. The mean
163 precipitation value for DPR measurements averaged across the 35 km square is used. We also
164 use the IMERG 0.1°-monthly product to qualitatively validate the global and seasonal features of
165 CMwv-classified rain events. Results and discussions are given in section 4.1.

166 2.5. Ice concentration from SSM/I

167 Sea ice concentration maps are produced by applying the Artist Sea Ice (ASI) algorithm to
168 the brightness temperatures from Special Sensor Microwave Imager (SSM/I) radiometer (Ezraty
169 et al., 2007). The concentration product has been operational since 1992 with 12.5 km spatial
170 resolution. It is publicly available at <ftp://ftp.ifremer.fr/ifremer/cersat/products/>

171 [gridded/psi-concentration/](#). The seasonal sea ice concentration is computed based on the
172 daily data, and compared with the CMwv-classified sea ice event occurrences (see section 4.2).

173 **3. Automated ocean SAR scene classification**

174 This section describes how the automated classifier for S-1 WV ocean SAR vignettes was
175 developed by re-training the Inception-v3 CNN. The performance of this tool is evaluated and
176 quantified using the independent assessment dataset described in section 2.3.

177 *3.1. Inception-v3 and training strategies*

178 Many successful CNN architectures have shown solid performance in the ImageNet large-
179 Scale Visual Recognition Challenge (ILSVRC) (Russakovsky et al., 2015). In this study, we use
180 the Inception-v3 architecture proposed by Google in 2015 (Szegedy et al., 2015; Szegedy et al.,
181 2016) to demonstrate the potential of deep CNN in identifying and classifying geophysical phe-
182 nomena from ocean SAR scenes. The Inception model was firstly introduced as GoogLeNet or
183 Inception-v1 (Szegedy et al., 2015), a classic deep CNN architecture. The initial Inception ar-
184 chitecture was refined in many ways. A first improvement was introduced in the Inception-v2
185 of batch normalization to accelerate the training process (Szegedy et al., 2016). While later, the
186 Inception-v3 used additional factorization ideas to augment the number of convolutions without
187 increasing the computational cost. It achieves remarkable performance with 94.4% top-5 accuracy
188 on the ILSVRC 2012 classification dataset. We choose Inception-v3 in this study because of its
189 promising performance and easy implementation with the python deep learning library of Keras
190 (<https://keras.io/>). Also, at the time of starting this work, this model represented the good
191 tradeoff between classification performance and huge parameters (Bianco et al., 2018).

192 The Inception-v3 architecture has 48 network layers with more than 23 million trainable
193 weights. These layers are generally divided into feature extraction and classification parts. Weights
194 of the feature extraction part are trained to describe common image characteristics such as curves,
195 edges, gradients and particular patterns. These features are expected to be adopted to the task of
196 ocean SAR vignette classification (Yosinski et al., 2014; Too et al., 2018; Wang et al., 2018a).
197 The last layer of this CNN architecture represents the classification part, which is replaced with
198 a new classification layer in our applications. Note that capability comparison of different CNN
199 architectures may also be of interest, but it is beyond the scope of this work.

200 We examined two training strategies: transfer-learning and fine-tuning. The transfer-learning
201 only trains the final classifier layer, while the fine-tuning adjusts all the layers in the CNN architec-

202 ture. For each input image, Inception-v3 requires the image size to be 299 pixels for both height
 203 and width. Then, 2048 optimal features per image are extracted to construct the final classifier. As
 204 noted above, the sensitivity of SAR to different oceanic or atmospheric phenomena can be differ-
 205 ent for the two WV incidence angles. We therefore create separate training datasets for WV1 and
 206 WV2 (hereafter TDwv1 and TDwv2). To equalize the size of TDwv1 and TDwv2, 320 images per
 207 class are randomly selected from the labelled dataset of TenGeoP-SARwv (Wang et al., 2018b).
 208 For training Inception-v3, the input dataset is randomly split into training and validation subsets
 209 with proportions of 70% and 30%. Training subset is fed into the CNN to learn and extract image
 210 features. The validation subset, by contrast, is used to gauge the CNN model performance at each
 211 epoch (iteration of CNN optimization).

212 3.2. CMwv model

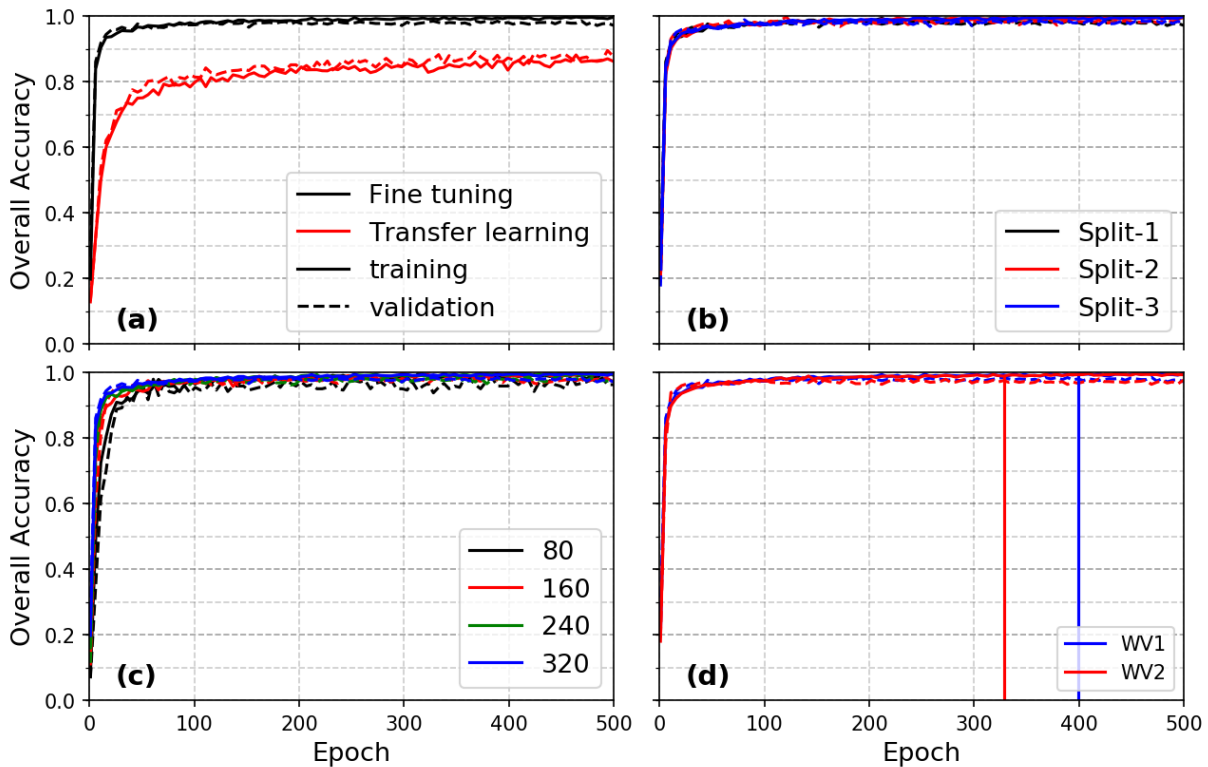


Figure 3: Overall accuracy (OA) in each 5 epochs during the training of inception-v3. The first 500 epochs are shown for (a) comparison of transfer-learning and fine-tuning, (b) experiment of random splitting process, (c) experiment of the training dataset size and (d) the development of CMwv.

213 First, we compare results found for the transfer-learning versus fine-tuning training approaches.
 214 Based on TDwv1, the Overall Accuracy (OA, Stehman (1997)) is calculated within 500 epochs

215 and is displayed in Figure 3 (a). As shown, the OA of both transfer-learning (red lines) and fine-
 216 tuning (black lines) increases rapidly within the first 100 epochs, and then remains stable at around
 217 89% and 97%, respectively. Fine-tuning is more accurate than transfer-learning and is therefore
 218 chosen in this study. Figure 3 (b) displays the sensitivity assessment of the fine-tuning process to
 219 random training inputs. Random shuffling is repeated three times to generate different training and
 220 validation subsets drawn from TDwv1. Result shows no significant effect on OA due to different
 221 data draws. The impact of dataset size is also tested using image input datasets of 80, 160, 240
 222 and 320 samples, respectively. All four models achieve comparable OA, as displayed in Figure 3
 223 (c). The largest training dataset converges most quickly and with the highest and most constant
 224 OA. In this paper, we use 320 images per class to train the final model. Figure 3 (d) shows that OA
 225 improves rapidly with training epochs. The trained CNN weights at epochs 399 and 329 where
 226 OA reaches the maximum (blue and red vertical lines) are adopted in the final CMwv. This model
 227 has a OA of 98.5% and 98.3% for WV1 and WV2, respectively.

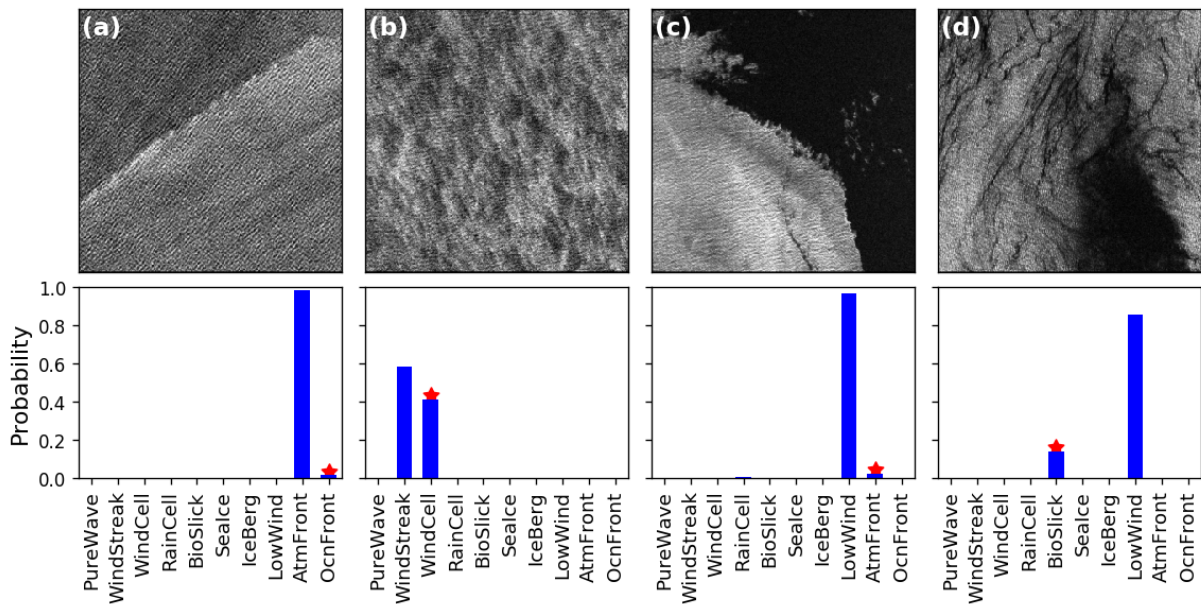


Figure 4: Examples of misclassified WV images from CMwv along with the classification probability of each class. Red stars indicate the class determined visually (manually-labelled).

228 Misclassifications still occur even though the model OA is very high. With visual inspection of
 229 the misclassified images in the validation part, four representative examples with their classifica-
 230 tion probabilities are shown in Figure 4. The red stars indicate the actual class. Ambiguous image
 231 features are one of the reasons leading to misclassification. For example in Figure 4 (a), the linear

232 feature of an oceanic front (OcnFront) looks more like the softer mottled linear features that we
233 ascribed to the atmospheric front (AtmFront) class (Wang et al., 2019). Both cell-shaped features
234 (WindCell) and the linear-shaped features (WindStreak) are visible in Figure 4 (b), also resulting
235 in an ambiguity within this vignette. Superimposition of these two phenomena is captured by the
236 CMwv model with high classification probabilities in both classes. Indeed, the atmospheric coher-
237 ent structures that generate the WindStreak signature often undergo a transition to the convective
238 structures that generate the WindCell signature when the surface buoyancy increases (Atkinson
239 and Wu Zhang, 1996). Another reason responsible for misclassifications is that multiple geophys-
240 ical phenomena can coexist within the same vignette. Low wind area (LowWind) is often asso-
241 ciated with wind gust fronts (AtmFront), as shown in Figure 4 (c). Biological slicks (BioSlick)
242 usually accompany the LowWind (Figure 4 (d)) because they both occur in low wind conditions.
243 Signatures of ocean waves are also clearly seen in the four examples. The PureWave classifica-
244 tion probability for these scenes is nearly zero due to our imposed lowest ranking of ocean waves
245 within these prelabelled events. In other words, the priority of other phenomena in the developed
246 classification model is much higher. This corresponds to the fact that our definition of PureWave
247 is a SAR image that only contains signature of ocean waves without any other geophysical phe-
248 nomena. It is thus expected that adjustment of our model to address multi-labelling with equal
249 weights for these multiple feature SAR images might improve future classification. To this end,
250 the current classification probabilities can be further exploited to get more fuzzy probabilities or
251 refine the training dataset. A thorough labeling strategy allowing the existence of multiple features
252 is also demanded. In particular, wave detection shall facilitate the labeling of its coexistence with
253 other phenomena.

254 3.3. CMwv model assessment

255 To further assess the CMwv performance on the whole WV database, a quantitative figure was
256 obtained through comparison against the independent assessment dataset introduced in Section
257 2.3. Figure 5 provides the normalized confusion matrix. The rows and columns in the matrix indi-
258 cate the truth (manually-labelled) and CMwv prediction, respectively. One image is assigned to be
259 the class of the largest classification probability. As shown, most of the class identification skill re-
260 sults for both WV1 and WV2 cases show accuracy that exceeds 0.8. One exception is PureWave,
261 this class being strongly influenced by IceBerg, AtmFront and OcnFront events. This leads to
262 much lower PureWave classification accuracy of 47% and 39% for WV1 and WV2, respectively.
263 It is likely because signatures of ocean waves are prevalent in most images and we choose a loose

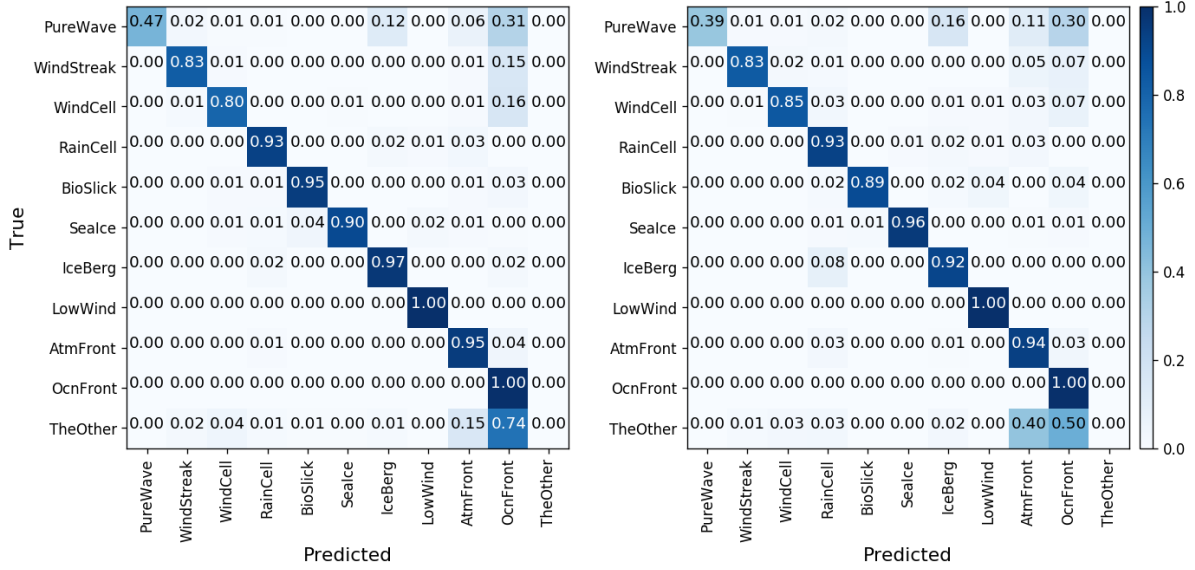


Figure 5: CMwv normalized confusion matrix when the model is applied to the WV1 (left) and WV2 (right) independent verification data subsets.

264 criteria for PureWave class in the assessment dataset. In addition, about 15% of WindStreak and
 265 WindCell images are misclassified as AtmFront and OcnFront, resulting in the relatively lower
 266 classification accuracy. Nearly 90% of the TheOther images are classified into categories of Atm-
 267 Front and OcnFront. Overall, images of PureWave, IceBerg, AtmFront and OcnFront are often
 268 misclassified. To further quantify CMwv performance, recall, precision and F-score parameters
 269 (Sokolova and Lapalme, 2009) are calculated based on the confusion matrix:

$$270 \quad \text{Recall} = \frac{\text{number of correctly classified}}{\text{number of truth}} \quad (1)$$

$$271 \quad \text{Precision} = \frac{\text{number of correctly classified}}{\text{number of classified}} \quad (2)$$

$$272 \quad \text{F-score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (3)$$

273 For given class, recall (also called sensitivity) is equivalent to the classification accuracy discussed
 274 above. Precision (also called positive predictability) indicates the model's internal accuracy or
 275 skill. The F-score takes both recall and precision into account as one comprehensive index for
 276 model performance. Values of these three parameters are all expected to be near one.

277 CMwv recall, precision and F-score results against the assessment dataset are given in Table 1. Results indicate a hierarchy in skill across classes where RainCell, BioSlick, SeaIce and

Table 1: CMwv recall, precision and F-score metrics for each of the 10 geophysical categories when applied to WV1 (upper) and WV2 (lower) vignette detection.

	PureWave	WindStreak	WindCell	RainCell	BioSlick	SeaIce	IceBerg	LowWind	AtmFront	OcnFront
Recall	0.47	0.83	0.80	0.93	0.95	0.90	0.97	1.00	0.95	1.00
	0.39	0.83	0.85	0.93	0.89	0.96	0.92	1.00	0.94	1.00
Precision	1.00	0.77	0.76	0.88	0.88	0.96	0.16	0.87	0.39	0.02
	0.98	0.96	0.94	0.80	0.91	0.96	0.18	0.79	0.38	0.02
F-score	0.64	0.80	0.78	0.90	0.91	0.93	0.27	0.93	0.56	0.04
	0.56	0.89	0.89	0.86	0.90	0.96	0.30	0.88	0.54	0.04

278 LowWind classes show similarly highest levels of recall, precision and F-scores that exceed 85%
279 in any measure, and for both WV1 and WV2 vignettes. A second tier with slightly lower skill is
280 seen for WindStreak and WindCell with WV2 F-scores of nearly 0.9 and 0.8 for WV2 and WV1
281 respectively. The drop in WV1 F-score is due to nearly 20% lower precision in WV1 scene de-
282 tection. This is due to the fact that ocean wave signatures are suppressed at higher incidence and
283 other atmospheric phenomena are more pronounced. Overall, the results indicate robust CMwv
284 model performance for these six phenomena. A next drop in skill is seen for the PureWave class.
285 PureWave detection shows much lower recall levels of 47% and 39% for WV1 and WV2, respec-
286 tively. Inspection found that this is because a large number of PureWave dominated SAR scenes
287 are misclassified as IceBerg (12% and 16%), AtmFront (6% and 11%), and OcnFront (31% and
288 30%), as shown in Figure 5. Yet, high PureWave precision suggests strong confidence when a
289 PureWave detection occurs. The lowest performance tier is seen when CMwv is applied to detect
290 icebergs, atmospheric, and ocean fronts (IceBerg, AtmFront and OcnFront). In these three classes,
291 the model shows poor precision (i.e. an excess of false positives) caused by the misclassification
292 of scenes that should have been ocean waves (PureWave) or more ambiguous events (TheOther).

293 Although time consuming, the visual classification provided by Wang et al. (2019) demon-
294 strated the capabilities of S-1 WV to capture signatures of air-sea interactions. Above results
295 suggest that an adapted deep CNN image recognition model can be trained for automated clas-
296 sification of the S-1 WV VV-polarized SAR vignettes. A brief summation of CMwv skill taken
297 from these results suggests reasonable confidence levels for investigations that focus on six of
298 the prescribed classes (WindStreak, WindCell, RainCell, BioSlick, SeaIce and LowWind), while
299 CMwv refinements would be needed for OcnFront, AtmFront, IceBerg, and PureWave applica-
300 tions. Other deep learning techniques such as pixel-level based classification, object detection and
301 image segmentation (Zhang et al., 2016; Cheng et al., 2017) are expected to efficiently target the

302 localized phenomena (RainCell, IceBerg, AtmFront and OcnFront) within each scene. In addition,
303 it will be beneficial to include the geographic and time information of SAR data in deep learning
304 approaches. Latitude is just one of many possible important and obvious data inputs, helping for
305 example, to limit sea ice and iceberg detection windows to cold waters.

306 **4. Geophysical applications**

307 As a first demonstration, the CMwv model was applied to all S-1A WV VV-polarized acquisi-
308 tions from March 2016 to February 2017. We examine the images classified as rain cells (RainCell)
309 and sea ice (SeaIce) as well as their occurrence in space and time. GPM and IMERG rain precipi-
310 tation and SSM/I sea ice concentration data are used for comparison. Specifically, seasonal varia-
311 tions of these two phenomena are presented and discussed in the four seasons: March-April-May
312 (MAM), June-July-August (JJA), September-October-November (SON) and December-January-
313 February (DJF) from March 2016 to February 2017. There are more than 160k vignettes acquired
314 globally by S-1A in each of these seasons.

315 *4.1. Rain cells*

316 A detected RainCell in the S-1 vignettes has been defined as one or several km-scale circular-
317 or semi-circular-shaped patches that may be either relatively bright or dark (Wang et al., 2019).
318 These patches are typical signature of rain downdraft (Atlas, 1994; Alpers et al., 2016) in the
319 convective rain cells (Houze, 1997). From March 2016 to February 2017, nearly 10% of S-1A
320 images are classified as RainCell. The seasonal mapping of SAR-detected RainCell occurrence
321 (fraction within 2° lat/lon bins) in the left panel of Figure 6 indicates distinct spatial and temporal
322 patterns. We also plot the seasonal maps of monthly averaged IMERG rain rate in the right panel
323 of Figure 6 for comparison. However, it must be noted here that the IMERG product aims at
324 intercalibrating, merging, and interpolating satellite microwave precipitation estimates, together
325 with microwave-calibrated infrared (IR) satellite estimates. This leads to different temporal and
326 coverage resolution between SAR-detected RainCell occurrence and IMERG precipitation.

327 Across the whole tropical ocean (3 basins), SAR-detected rain events are found to be infre-
328 quent right along the equator with a band of strong occurrence north of the Equator. This band
329 is clearly observed throughout the year and with the Inter-Tropical Convergence Zone (ITCZ). In
330 the particular case of the Pacific ocean, strong occurrence of rain cells are also found in the South
331 Pacific Convergence Zone. It is in good agreement with IMERG precipitation seasonal patterns.
332 Significant differences are found in the subtropics between 10° and 30°. In the north hemisphere

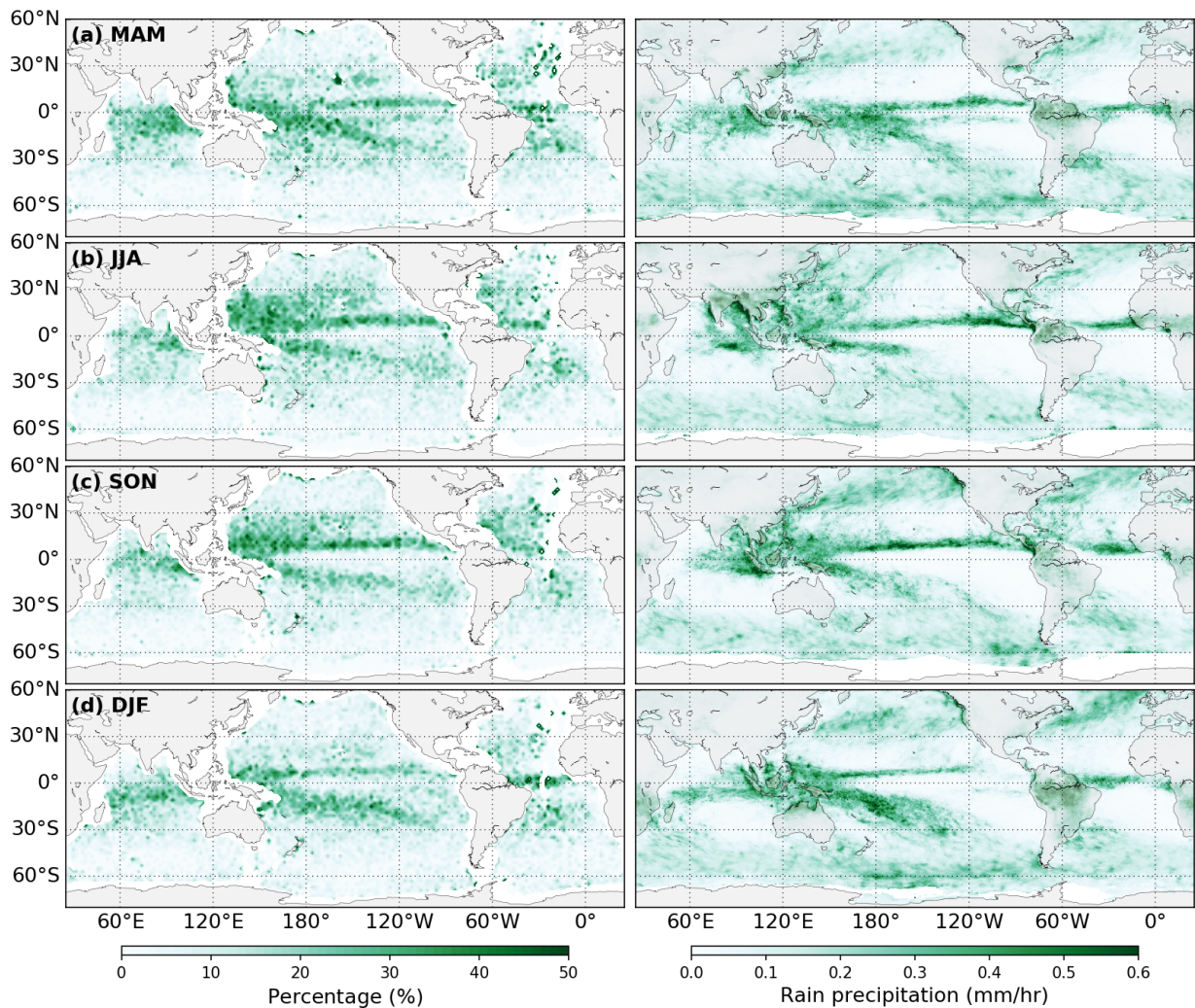


Figure 6: Seasonal comparison of CMWV-detected S-1A rain cells (left) alongside GPM precipitation measurements (right). Rain occurrence percentages are calculated on a 2° by 2° spatial grid based on S-1A WV data from March 2016 to February 2017. The average monthly rain rate in MAM, JJA, SON and DJF are obtained from the IMERG 0.1°-monthly product.

333 (Atlantic and Pacific), SAR-detected RainCell occurrence is high (>10%) whereas the rain precip-
 334 itation from IMERG is low (<0.1 mm/hr). In the south hemisphere, this is also observed in the east
 335 of the south Pacific, in the Atlantic and in the Indian ocean. In the extratropical areas (poleward of
 336 30°N or 30°S), we observe the opposite trend. SAR results present lower occurrence of RainCell
 337 while IMERG measures comparatively higher precipitation rates.

338 Overall, most areas of higher SAR-detected RainCell occurrence are associated with high
 339 IMERG precipitation areas and consistent with the rainfall climatology of previous studies (Kidd,

340 2001; Adler et al., 2003). However, disagreements are found as well. One of the reasons for this
341 is due to the fact that IMEG products measure all types of rainfall and is not limited to rain cells.
342 This certainly explains the agreement observed in the tropical area where the convective cells
343 dominate (Houze, 1997). To further address the difference, a point-by-point collocation between
344 S-1 WV SAR images and GPM level-2 DPR Ku-only surface rain precipitation is conducted. The
345 collocation criteria is within 35 km in space and 10 min in time.

346 In total, there are 2588 matched data pairs with 286 SAR vignettes being classified as RainCell.
347 For 63.4% of the RainCell-classified images, collocated GPM also reports precipitation. In the
348 remaining cases, however, no precipitation is reported by GPM. Figure 7 (a1) and (a2) display
349 two examples of this situation that SAR detects rain events while GPM does not. The upper panel
350 shows the SAR images and the bottom gives the precipitation. The red dashed box, white box
351 and white arrow indicate the collocated area, image box and surface wind vector, respectively.
352 As shown, these two SAR images exhibit clear RainCell signatures, confirming the credibility of
353 RainCell classification results. The precipitation is not resolved by GPM, possibly because they
354 are short-lived and/or weak rain events. For the images that are not classified as RainCell, 23.2%
355 of the collocated GPM reports precipitation. With the visual inspection, we confirmed that most
356 of these images do not have clear RainCell signature as defined in Wang et al. (2019). Two such
357 examples are shown in Figure 7 (b1) and (b2). RainCell signatures in SAR images are primarily
358 caused by modulations of the surface waves due to rainfall, downdraft and also a direct attenuation
359 of the signal by rain drops in the atmosphere (Alpers et al., 2016). However, we recall here that
360 the first order impact on the sea surface roughness as detected by C-band active radar is the local
361 wind. As a result, there is a competition between the ambient wind and possible rain impacts on
362 the small-scale waves. Thus, we suspect that in situation where the wind speed is sufficiently high,
363 the wind impact dominates the backscattering over the rain, yielding SAR scenes with hardly
364 detectable rain signature. Figure 8 further evidences this interpretation. It is the distribution of
365 surface wind speed for the four possible situations (SAR-detected RainCell or not, GPM DPR-
366 measured precipitation or not). As shown, SAR-detected RainCell (blue and orange lines) occurs
367 mostly at intermediate wind speed of 3-10 m/s. By contrast, the wind distribution of the images
368 with non-detected RainCell but precipitation as given by GPM (red line) centers at 12 m/s. This
369 implies that when the backscattering is mainly impacted by the high wind speed, the detectability
370 of rain cell signatures weakens.

371 From these comparisons, we conclude that Deep Learning methods can be used to automat-
372 ically identify SAR images impacted by rain cells. As a matter of fact, the high resolution of

373 SAR may complement the existing rainfall measurements available from space by detecting very
 374 short scale events. For now this potential seems limited to convective rain and is less relevant for
 375 high latitudes where sea state dominates the signature in SAR image, preventing for a reliable rain
 376 detection.

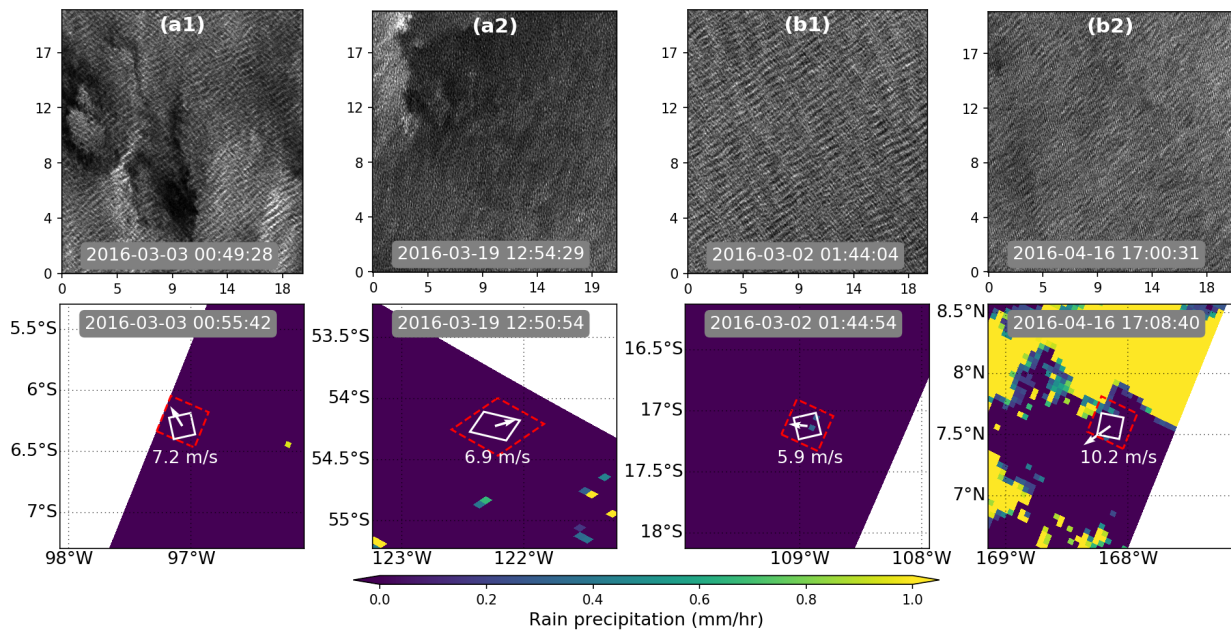


Figure 7: Four cases of point-by-point comparison between classified rain cells and the collocated GPM level-2 DPR Ku-only surface rain precipitation. (a1) and (a2) are cases in which WV detects RainCell and GPM indicates no precipitation. (b1) and (b2) are cases in which WV did not detect RainCell and GPM measured precipitation. Upper panels are WV images, lower panels show the GPM rain rate swath data. In the lower panels, the WV outline is the white box and the collocation region is the red box. The vector indicates the sea surface wind.

377 4.2. Sea Ice Near Antarctica

378 Interactions between sea ice, ocean, and the atmosphere in polar regions significantly impact
 379 global weather and climate systems (Fyke et al., 2018). Changing boundaries between the ocean
 380 and sea ice have dominant effects on marine ecosystem structure around the Antarctic (Tynan,
 381 1998; Nicol et al., 2000). Monitoring of Southern Ocean sea ice has thus been of high interest
 382 among remote sensing and geoscience communities for many years. In this subsection, we assess
 383 sea ice (SeaIce) detected by CMwv near the Antarctica using S-1A WV SAR vignettes from March
 384 2016 to February 2017. Note that our classification model distinguishes all type of SeaIce images
 385 from open ocean water.

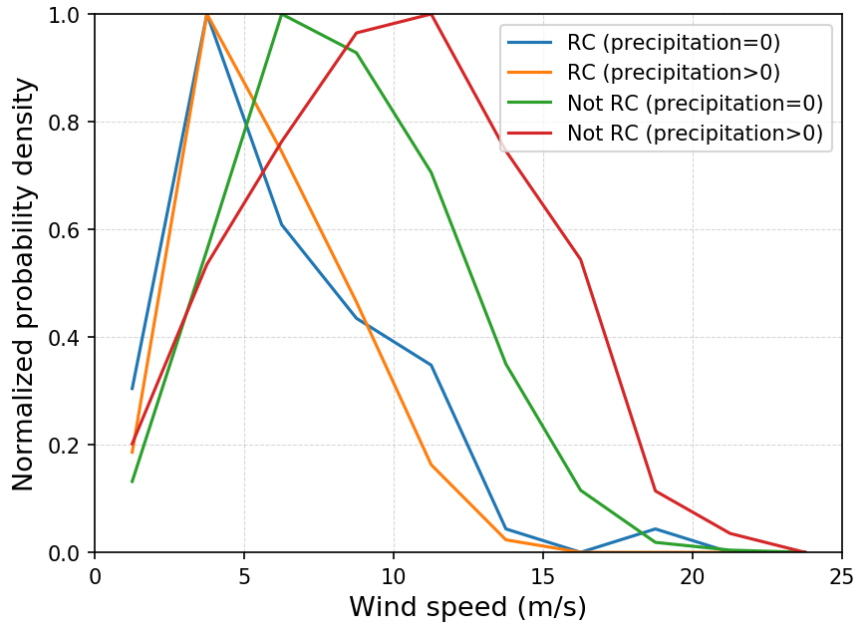


Figure 8: Normalized probability density function of surface wind speed for the point-by-point comparisons with condition of rain cells are detected or not and precipitation is measurable or not.

386 In total, there are nearly 25k vignettes classified as SeaIce. As shown in Figure 9 (a), most S-
 387 1A vignettes indicating SeaIce are distributed across the polar Southern Ocean. While the SeaIce
 388 subset mapping clearly shows a few misclassified cases of small islands, heavy rain and strong
 389 convection phenomena, the otherwise realistic geographic SeaIce distribution appears to confirm
 390 the high classification precision of 0.96 (see Table 1). Although the reason for misclassifications
 391 need further investigation, these misclassified SeaIce images can be easily filtered out according
 392 to the latitudes or SeaIce events occurrence map (see Figure 9 (c)). Figure 9 (b) provides the
 393 number of classified SeaIce SAR vignettes per month. As expected, the number of detected SeaIce
 394 vignettes has a clear seasonal variability, increasing from March to a maximum in October and
 395 subsequently decreasing. This variation is highly consistent with the seasonal cycle of Antarctic
 396 SeaIce extent (Doddrige and Marshall, 2017).

397 S-1A detected SeaIce occurrence is calculated on a 2 by 2 degree grid and shown in Figure
 398 9 (c). It illustrates the seasonal variation view of SeaIce coverage around the Antarctica. The
 399 SeaIce extent is also denoted by the contour lines where occurrence percentage is equal to 10%.
 400 In the austral summer (DJF and MAM), most of the classified SeaIce lies close to the Antarctica
 401 and is poleward of 60°S. It is also clear that the SeaIce extent is non-uniformly distributed along
 402 the Antarctic coasts, with more SeaIce from 0°-60°W, and from 120°W-150°E. Varied SeaIce

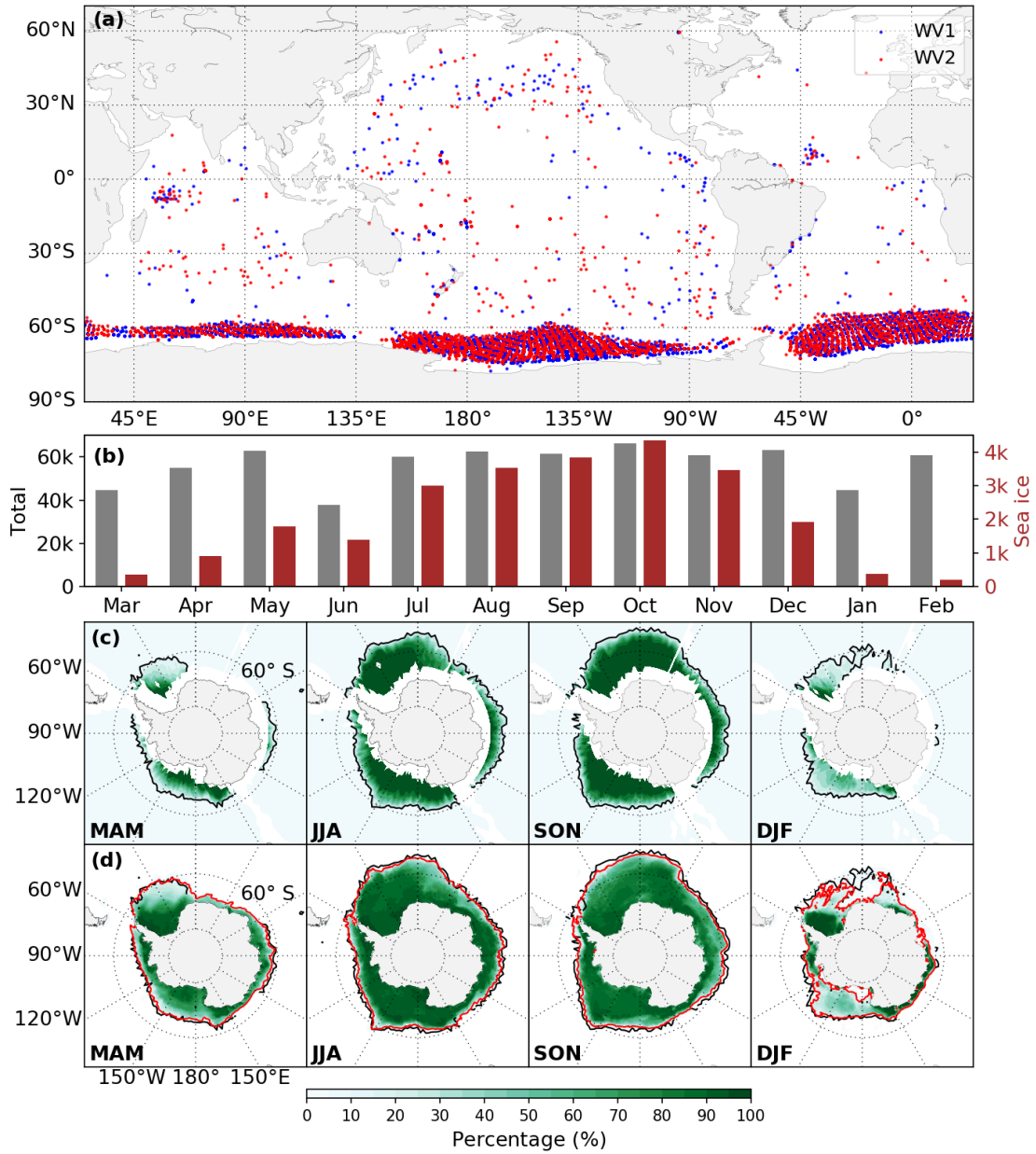


Figure 9: Ocean sea ice around the Antarctica from March 2016 to February 2017. (a) displays the locations of classified sea ice vignettes with blue and red colors indicating WV1 and WV2, respectively. (b) presents the total number of S-1A and sea ice detected vignettes for each month. Sea ice coverage in four seasons derived from the classified SAR vignettes are shown in (c) with color representing the occurrence percentage in 2° boxes. (d) shows the mean sea ice concentration from the SSM/I daily product. Contour lines in (c) and (d) are calculated from the occurrence percentage (black, 10%) and sea ice concentration (red, 10%), denoting the ice-water boundaries.

403 coverage also exists in the Antarctic winter from JJA to SON. As shown in Figure 9 (c), winter
404 period SeaIce significantly expands in comparison to the austral summer. It even spreads north
405 of 60°S between 10°E and 70°W during the summer. It is important to note that there is no WV
406 SAR data acquired very close to the coast of or over Antarctica (Torres et al., 2012). This is
407 the reason for the null/white space around the coastline in these maps. For comparison, seasonal
408 maps of mean SeaIce concentration from the SSM/I daily product are provided in Figure 9 (d).
409 Contour lines of SeaIce edge calculated from both the occurrence percentage (black) and SeaIce
410 concentration (red) are superimposed on these maps. As shown, the patterns seen on the SAR-
411 detected SeaIce largely mirrors these SeaIce concentration maps where both systems collect data.
412 Boundaries between ocean water and SeaIce from SAR and SSM/I data are highly consistent with
413 each other. This agreement is another measure of CMwv credibility as an WV data classification
414 tool.

415 As demonstrated, these high-resolution WV acquisitions of SeaIce are another data catalogue
416 to monitor SeaIce edge boundaries around the Antarctica. In particular, they can benefit the sur-
417 vey of wave-ice interactions. Indeed, a new method has been recently developed to derive the
418 directional wave spectrum in the sea-ice, from which wave heights, periods and directions can be
419 derived (Ardhuin et al., 2015). Stopa et al. (2018) used these extensive information to address
420 the wave forces on sea ice through break-up and rafting, advancing the knowledge of wave-ice
421 dynamics. With respect of the waves and sea ice interactions, the use of sea-ice classification in
422 combination with waves-in-ice algorithm is certainly a perspective.

423 5. Conclusions

424 The S-1 WV SAR vignette classification model (CMwv) has been successfully developed by a
425 SAR-adaptation of the Inception-v3 CNN image recognition architecture. Experimental testing of
426 the training process indicates that fine-tuning is a more effective approach than transfer-learning.
427 The CMwv mode is able to identify and assign detection probabilities to ten geophysical phe-
428 nomena that are pre-defined in a hand-labelled dataset (TenGeoP-SARwv, Wang et al. (2018b)).
429 To evaluate and quantify the performance of CMwv, recall, precision and F-scores are calculated
430 against an independent assessment dataset. Results show that this classification tool works well
431 for classes of WindStreak (wind streaks), WindCell (micro-convective cells), RainCell (rain cells),
432 BioSlick (biological slicks), SeaIce (sea ice) and LowWind (low wind area). However, classifi-
433 cation of PureWave (pure ocean waves) is limited with very high precision, but low recall. Class
434 detections for IceBerg (icebergs), AtmFront (atmospheric fronts) and OcnFront (oceanic fronts)

435 are severely influenced by PureWave and the special category of TheOther. The developed clas-
436 sification model can directly be applied to S-1A&B WV datasets. In the near future, efforts to
437 improve the classification of PureWave, IceBerg, AtmFront and OcnFront are necessary. In addi-
438 tion, the inclusion of new classes corresponding to other geophysical phenomena and the definition
439 of a multi-labelled dataset would likely yield further improvements.

440 Two geophysical applications are demonstrated based on the classification results of S-1A WV
441 vignettes from March 2016 to February 2017. Geophysical maps of classified rain cells and sea
442 ice are qualitatively comparable to precipitation data from GPM and sea ice concentration from
443 SSM/I. Results further verify the credibility of this classification tool. Moreover, once classi-
444 fied, access to the large catalogue of class-specific high-resolution WV vignettes may provide new
445 and more detailed geophysical information to complement existing global ocean satellite mea-
446 surements. The various geophysical phenomena captured within the massive S-1 A&B WV data
447 suggest promise to further advance our understanding of air-sea interactions, particularly at sub-
448 kilometer scales. Application of this CMwv tool to the growing three plus year of S-1 global ocean
449 SAR data archive should allow, for the first time, access to the spatial (global and regional) and
450 temporal (seasonal and inter-annual) statistics of numerous geophysical phenomena. This may, in
451 turn, help to advance certain aspects of atmospheric and climate theory and numerical ocean and
452 weather models.

453 This present work provides a basis to move application of ocean SAR remote sensing beyond
454 the case study stage. It also demonstrates the potential of these global SAR WV mode vignettes for
455 broader geophysical application, augmenting its operational role supporting ocean wave prediction
456 systems. While this study is limited to the S-1 WV SAR acquisitions, the methodology could
457 be applied to any other sub-scene (10-20 km) SAR data products from platforms such as ERS-
458 1/2, Envisat/ASAR, TerraSAR-X, Gaofen-3 and CFOSAT. Similar exploitation of the full WV
459 mode SAR data archive could provide a long-term (nearly 30 years) climatology including data on
460 interannual and seasonal variability at global scale.

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648 List of Figure Captions

- 649 • Figure 1: Global distribution of the WV SAR data obtained by S-1A in July of 2016. Color
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- 651 • Figure 2: Ten vignette examples of expertly-defined geophysical phenomena. From (a) to
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- 656 • Figure 3: Overall accuracy (OA) in each 5 epochs during the training of inception-v3. The
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- 660 • Figure 4: Examples of misclassified WV images from CMwv along with the classifica-
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