

Abstract

Surface crevasses on the Greenland Ice Sheet deliver significant volumes of meltwater to the englacial and subglacial environment, but the topic has received little attention compared to supraglacial lake and moulin drainage. Here, we explore relationships between crevasse hydrology and the surface stress regime at a fast-flowing, marine-terminating sector of the Greenland ice sheet. Regional-scale observations of surface water, crevasses, and stress were made across a 3,000 km² region using satellite data. Contemporaneous high spatio-temporal resolution observations were obtained from uncrewed aerial vehicle surveys on Store Glacier using a supervised classifier and feature-tracked velocities. While previous studies have identified crevasses using von Mises stress thresholds, we find these are insufficient for predicting crevasse hydrology. We found that dry crevasse fields, where no ponded meltwater was observed through the entire melt season, were more likely to exist in tensile mean stress regimes, which we interpret to be due to meltwater draining continuously into the englacial system. Conversely, wet crevasse fields, hosting ponded meltwater, were more likely to exist in compressive mean stress regimes, which we interpret to be a result of closed englacial conduits. We show that these ponded crevasses drain through episodic rapid drainage events (i.e. hydrofracture). Mean stress regime can therefore inform spatially heterogeneous styles of meltwater delivery through crevasses to the bed of ice sheets, with distinct consequences for basal processes such as subglacial drainage efficiency and cryo-hydrologic warming. Thus, we recommend simple guidelines for improving the representation of crevasse hydrology in regional hydrological models.

1 Introduction

Surface crevasses are open fractures in glaciers and ice sheets, ranging in width from millimetres to tens of metres. As a visible expression of glacier stress regimes, the size and orientation of crevasses are closely linked to glacier dynamics, associated with extensional flow and deformation of ice through compression or shear along margins (Colgan et al., 2016). Motivations for detecting crevasses and understanding their formation include morphological insights into glacier flow (E. Phillips et al., 2013; Dell et al., 2019), the development of fracturing criteria for supraglacial lake drainage (Das et al., 2008; Arnold et al., 2014) and ice calving (Benn et al., 2017; Todd et al., 2019), and quantifying the dynamic influence of water transmitted to the bed of glaciers (McGrath et al., 2011; Koziol & Arnold, 2018).

In regions of high advection, such as fast-flowing outlet glaciers of the Greenland Ice Sheet (GrIS), crevasses form in upstream zones where extensional tensile stress regimes favour crevasse opening, and then advect downstream into regions where compressive stress regimes result in crevasse closure, forming healed crevasses. The fracture process is generally understood in terms of simple 1-D numerical models, such as the ‘zero stress’ model in which crevasses penetrate to the depth at which ice creep closure (due to ice overburden pressure) equals tensile stress (Nye, 1957), or the linear elastic fracture mechanics (LEFM) approach, which further accounts for factors such as stress concentrations at fracture tips, fracture toughness, geometry, and water level (van der Veen, 1998; Krawczynski et al., 2009). There is a growing recognition of the need to understand more complex multidimensional and mixed-mode crevasse formation (Colgan et al., 2016), but transferring mechanical understanding to higher dimensions is nontrivial (van der Veen, 1999; Colgan et al., 2016). As such, many studies that predict crevasse presence in real-world scenarios use simpler methods such as basic thresholds of first principal strain or von Mises Stress (Poinar et al., 2015; Clason et al., 2015; Koziol et al., 2017; Williamson, Willis, et al., 2018), which have been identified from observational studies to be suitable predictors of crevasse presence (Vaughan, 1993; Hambrey & Müller, 1978; Harper et al., 1998; van der Veen, 1998).

65 Crevassing is an important mechanism to transfer water to the bed of the GrIS and
66 water itself drives the propagation of crevasses via hydrofracture (Weertman, 1973; R. B. Al-
67 ley et al., 2005; van der Veen, 2007; Krawczynski et al., 2009). Once full-depth hydrofrac-
68 ture has occurred, water flow forms an efficient route for continued meltwater delivery
69 to the bed in the form of moulins. To date, this meltwater pathway to the bed has largely
70 been focussed on supraglacial lake drainage (Banwell et al., 2016; Hoffman et al., 2018;
71 Christoffersen et al., 2018). Crevasse hydrology has been included in only a few recent
72 numerical modelling studies (e.g. Clason et al., 2015; Koziol et al., 2017; Koziol & Arnold,
73 2018)), but is understood to capture as much as half of seasonal surface runoff (McGrath
74 et al., 2011; Koziol et al., 2017). Despite the apparent importance of crevasse hydrology,
75 there are few studies of the transfer of water to the bed of ice masses through crevasse
76 fields, and the limited number of studies that do exist describe variable - and often con-
77 tradictory - processes. Some studies observe discrete drainage of crevasses (Lampkin et
78 al., 2013; Cavanagh et al., 2017), which appear to result from episodic full-depth hydrofrac-
79 ture and display similarities to supraglacial lake drainages. In contrast, other studies con-
80 ceptualise crevasse fields as continuously, but inefficiently, transmitting a low water flux
81 to the subglacial system without the need for full-depth hydrofracture (Colgan et al., 2011;
82 McGrath et al., 2011). However, no studies have attempted to account for this spectrum
83 of observations and the assumptions surrounding crevasse hydrology, nor attempted to
84 explain where and why these types of drainage occur. Given this lack of information, pre-
85 vious modelling studies have assumed that crevasse drainage occurs in a uniform man-
86 ner, and use existing thresholds intended to predict crevasse presence to instead predict
87 crevasse hydrology (Clason et al., 2015; Everett et al., 2016; Koziol et al., 2017). To date,
88 no observational studies exist to guide such choices.

89 This study aims to better understand crevasse hydrological behaviour by relating
90 the presence of crevasses and water to stress regimes in the ablation zone of the GrIS
91 at two different spatial scales. The first utilises large-scale, satellite-derived data to ex-
92 amine crevasses in a ~ 3000 km² sector of west Greenland, including five major marine-
93 terminating outlet glaciers. The second uses high-resolution photogrammetric datasets
94 collected by uncrewed aerial vehicles (UAVs) to closely examine crevasses in a 7 km² area
95 of fast glacier flow within this sector, allowing us to validate large-scale data and record
96 processes occurring at the scale of individual crevasses. Our goal is to understand how
97 glacier dynamics relate to the spectrum of observed crevasse hydrology, and thereby de-
98 velop guidelines to allow hydrological models to account for the heterogeneity of crevasse
99 hydrological behaviour.

100 2 Methods

101 2.1 Study area

102 We assess satellite-derived data over a ~ 3000 km² sector of the western GrIS (Fig-
103 ure 1), extending ~ 90 km from Sermeq Kujalleq (Danish/English: Store Glacier; 70.4°N
104 50.6°W) in the south to Perlerfiup Sermia (71.0°N, -50.9°W) in the north. Within this
105 large-scale region of interest (the ‘satellite ROI’), we use UAV surveys and Structure-
106 from-Motion with Multi-View Stereo (SfM-MVS) photogrammetry to assess, at high res-
107 olution, a crevasse field in the Store Glacier drainage basin, 25 km from the calving front
108 (the ‘UAV ROI’). The UAV ROI is 1.5 km wide and 5 km long, and was chosen based
109 on its coverage of an initiating crevasse field, ranging from areas with no visible crevasses
110 to areas with crevasses greater than 50 m wide.

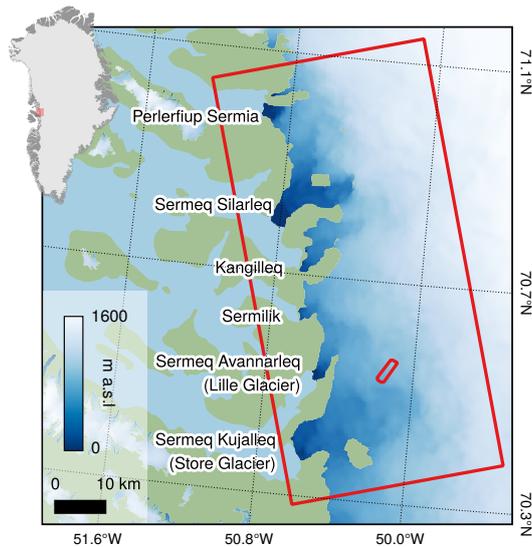


Figure 1. Map of study region. Small red box outline indicates the extent of UAV surveys. Large red box outlines the extent of satellite image analysis. Marine-terminating outlet glaciers are labelled, with the Danish/English name in brackets where applicable. Surface elevation shown in colour is from ArcticDEM v3 (Porter et al., 2018).

111 2.2 Satellite data

112 2.2.1 Crevasse classification

113 A binary crevasse mask (Figure 2) of the satellite ROI was produced from Arctic-
 114 DEM v3 mosaic data at 2 m resolution (Porter et al., 2018). Crevasse identification from
 115 digital elevation models can be approached in a variety of ways (Florinsky & Bliakharskii,
 116 2019), but we use a simple method identifying crevasses from the residuals between the
 117 original and a smoothed elevation model. As a result, we limit our analysis to the outer
 118 40 km of the ablation zone (Figure 1), where snow-filled crevasses are rare, in order to
 119 reduce the number of false negatives in the final dataset. We performed these operations
 120 in Google Earth Engine (GEE; Gorelick et al., 2017), which allows for efficient compu-
 121 tation and rapid evaluation over a large study area. We first cropped the ArcticDEM
 122 to the GIMP ice mask (Howat et al., 2014), before smoothing the elevation model by con-
 123 volving the raster with a circular kernel of 50 m radius. Residuals greater than 1 m be-
 124 tween the smoothed and raw elevation values were identified as crevasses. To compare
 125 with stress estimates, the 2 m dataset was aggregated into grid cells to match the res-
 126 olution (200 m) and projection (NSIDC sea ice polar stereographic north) of the veloc-
 127 ity grid. Aggregated values ranged from 0–1, representing the fraction of grid cell area
 128 classified as crevasses.

129 Because relict crevasses can advect through a variety of stress regimes (Mottram
 130 & Benn, 2009), we further identified crevasse initiation zones. We manually identified
 131 the upstream boundary between crevasse fields and bare ice from the 2 m crevasse dataset.
 132 Then, we used a 200 m buffer to identify pixels in the 200 m dataset that should be clas-
 133 sified as being in crevasse initiation zones.

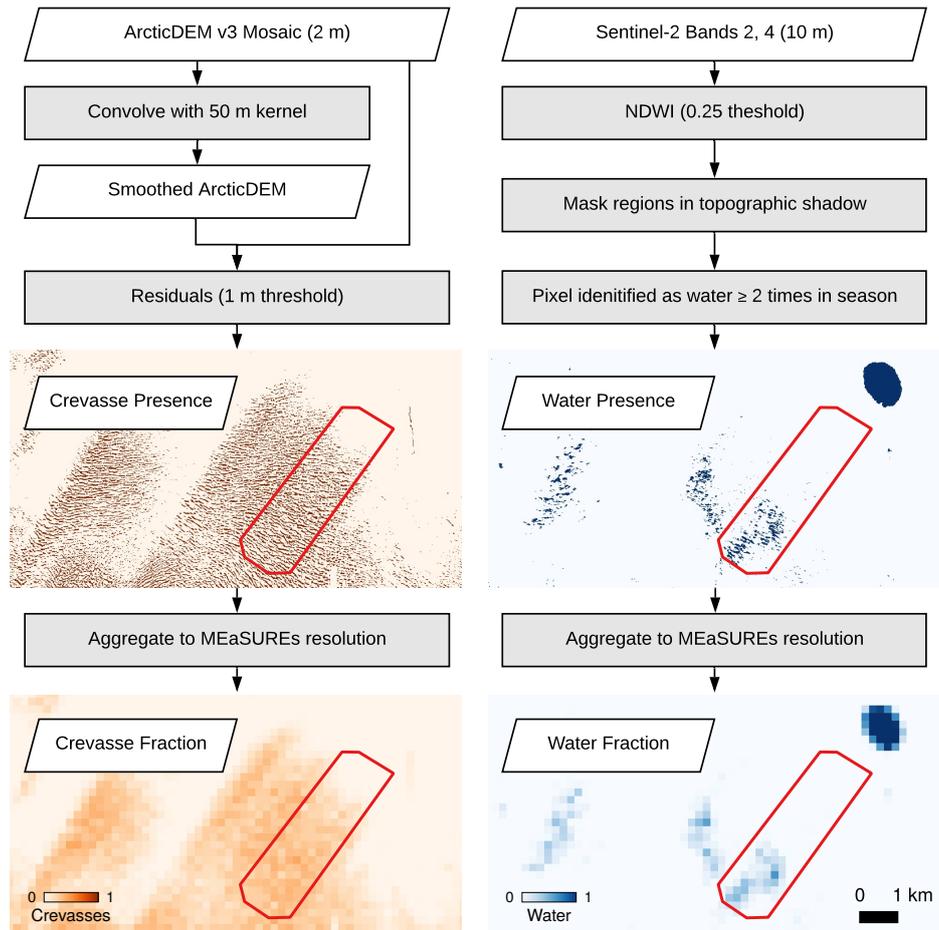


Figure 2. Flow diagram visualising the production of crevasse fraction data from ArcticDEM (left) and water fraction data from Sentinel-2 optical imagery (right). Red box outlined in maps marks the extent of the UAV ROI.

134

2.2.2 Water classification

135

136

137

138

139

140

141

142

143

144

145

146

147

148

149

150

151

152

153

154

155

We produced a binary map of water presence across the satellite ROI through the 2018 melt season (Figure 2) using Sentinel-2 imagery in GEE. The ablation season of 2018 was chosen for analysis to match the timing of the UAV surveys on Store Glacier. We first identified all Sentinel-2 scenes with $< 40\%$ cloud cover and $< 70^\circ$ solar zenith angle between May-October 2018, selecting a total of 360 images. We clipped the images to the GIMP ice mask (Howat et al., 2014) and converted digital number values to top of atmosphere (TOA) reflectance. TOA reflectance values have been shown to be suitable for identifying surface water in Greenland with Landsat 8 OLI imagery (Pope, 2016), and have been used for surface water classification in Sentinel-2 data (Williamson, Banwell, et al., 2018). We then calculate the normalised difference water index (NDWI) from bands 2 (blue) and 4 (red) for all images: following Williamson, Banwell, et al. (2018) for the Store Glacier region, we use an NDWI threshold of 0.25 to create binary water classification maps for each Sentinel-2 image. In order to avoid false positive identification of shaded regions, we mask areas in topographic shadow with the GEE hillShadow function, using the ArcticDEM for topography and the solar zenith angle from Sentinel-2 image metadata. Finally, we sum the image stack to count the number of times through the 2018 melt season that a pixel was identified as water. In order to reduce the chance of false positive classification (e.g. cloud shadow, ephemeral slush zones at the beginning of the melt season) we classify as water any pixel that was identified as water in ≥ 2 images through the melt season. As for crevasse maps, we aggregate this data onto the velocity grid with a unit of fractional coverage of water within each grid cell.

156

2.2.3 Stress classification

157

158

159

160

161

162

163

164

165

166

167

168

169

170

Although some previous studies have used strain rate thresholds to predict crevasse location (Poinar et al., 2015; Williamson, Willis, et al., 2018), we follow the recommendations of Colgan et al. (2016) to use estimated stress thresholds as a robust and generalisable criterion across glaciers of widely varying thermal regimes. Studies exploring relationships between crevassing, hydrology, and surface dynamics have used a multitude of 2-D stress measures. In order to test this variation, we calculate: (i) the first and second principal stresses (σ_1 and σ_2 as applied by Poinar et al. (2015) and Williamson, Willis, et al. (2018)); (ii) the longitudinal stress (σ_l ; as used by Clason et al. 2015); and (iii) the von Mises yield stress (σ_v ; as used by Clason et al., 2015; Koziol et al., 2017; Everett et al., 2016). We were also motivated to test further measures of stress, as σ_1 , σ_2 , and σ_l consider stress in only one axis, whilst σ_v considers only the deviatoric component of the stress tensor. Hence, we calculated the mean stress (σ_m , also referred to as the hydrostatic stress), and the signed von Mises Stress (σ_{sv}). Both of these measures account for the normal components of the stress tensor.

171

172

173

174

175

Stresses were estimated using surface strain derived from MEaSURES (Making Earth System Data Records for Use in Research Environments) gridded GrIS velocity data for 2018 (Joughin et al., 2010), with Glen’s flow law as the constitutive equation following Clason et al. (2015). We first calculated the surface strain rate tensor $\dot{\epsilon}_{ij}$ from the horizontal components of velocity u and v (in grid directions x and y):

176

$$\dot{\epsilon}_{ij} = \begin{bmatrix} \frac{\delta u}{\delta x} & \frac{1}{2}(\frac{\delta v}{\delta x} + \frac{\delta u}{\delta y}) \\ \frac{1}{2}(\frac{\delta v}{\delta x} + \frac{\delta u}{\delta y}) & \frac{\delta v}{\delta y} \end{bmatrix} = \begin{bmatrix} \dot{\epsilon}_x & \dot{\epsilon}_{xy} \\ \dot{\epsilon}_{xy} & \dot{\epsilon}_y \end{bmatrix} \quad (1)$$

177

178

179

We approximated the derivatives using the finite difference of the velocity field (K. E. Alley et al., 2018). We calculated longitudinal strain rate ($\dot{\epsilon}_l$) by resolving strain-rate components relative to the local flow direction according to Bindschadler et al. (1996):

180

$$\dot{\epsilon}_l = \dot{\epsilon}_x \cos^2 \alpha + 2\dot{\epsilon}_{xy} \sin \alpha + \dot{\epsilon}_y \sin^2 \alpha \quad (2)$$

181 where α is the flow angle defined anti-clockwise from the x axis. Stresses approx-
 182 imated from strain rates following Nye (1957):

$$183 \quad \sigma_{ij} = B\dot{\epsilon}_e^{(1-n)/n}\dot{\epsilon}_{ij} \quad (3)$$

184 Where $\dot{\epsilon}_e$ is effective strain, calculated following Cuffey and Paterson (2010):

$$185 \quad \dot{\epsilon}_e = \sqrt{\frac{1}{2}[\dot{\epsilon}_{xx} + \dot{\epsilon}_{yy}] + \dot{\epsilon}_{xy}} \quad (4)$$

186 and n is the flow law exponent with value 3. B is a viscosity parameter, which we
 187 follow Clason et al. (2015) in assigning a value of 324 kPa a^{1/3} (based on an assumed
 188 ice temperature of -5 °C).

189 The first principal stress (σ_1) was calculated as the highest eigenvalue of the stress
 190 tensor σ_{ij} , and second principal stress (σ_2) as the lowest eigenvalue (Jouvet et al., 2017).

191 We calculate the von Mises yield criterion (σ_v) according to Vaughan (1993):

$$192 \quad \sigma_v = \sqrt{(\sigma_1\sigma_1) + (\sigma_2\sigma_2) - (\sigma_1\sigma_2)} \quad (5)$$

193 We calculate the mean stress (σ_m) as follows:

$$194 \quad \sigma_m = \frac{1}{2}[\sigma_1 + \sigma_2] \quad (6)$$

195 Finally, the signed von Mises stress (σ_{sv}) is a simple modification of the von Mises
 196 stress, calculated as the magnitude of σ_v with the sign of σ_m :

$$197 \quad \sigma_{sv} = \text{sgn}(\sigma_m) \cdot \sigma_v \quad (7)$$

198 **2.3 UAV data**

199 **2.3.1 UAV photogrammetry and velocity**

200 We acquired aerial imagery across a 13-day period in July 2018 (Table S1) utilis-
 201 ing a custom-built, fixed-wing UAV with 2.1 m wing span. Imagery was collected using
 202 a Sony *alpha6000* 24 MP camera with a fixed 16-mm lens, processed using Structure-
 203 from-Motion with Multi-View Stereo (SfM-MVS) photogrammetry, and used to derive
 204 velocity fields within the UAV ROI as described by Chudley, Christoffersen, Doyle, Abel-
 205 lan, and Snooke (2019). In brief, photogrammetry was performed using AgiSoft Metashape
 206 v.1.4.3 software, and geolocated by using an on-board L1 carrier-phase GPS unit (post-
 207 processed against an on-ice ground station) to locate the position of aerial photos. Out-
 208 puts from the photogrammetric process were 0.15 m resolution orthophotos and 0.2 m
 209 DEMs. Horizontal velocity fields were derived by feature-tracking topographic hillshades
 210 using OpenPIV (Taylor et al., 2010). Stress fields were derived as outlined in Section 2.2.3,
 211 with a 5 x 5 pixel median-filter on the input velocity fields introduced as an additional
 212 preprocessing step to reduce noise.

213 **2.3.2 Surface classification**

214 To date, UAV-based crevasse detection has been based on DEM-based topographic
 215 analysis (Ryan et al., 2015; Florinsky & Bliakharskii, 2019). Whilst these methods have
 216 been shown to be useful from a hazard assessment perspective (Florinsky & Bliakharskii,

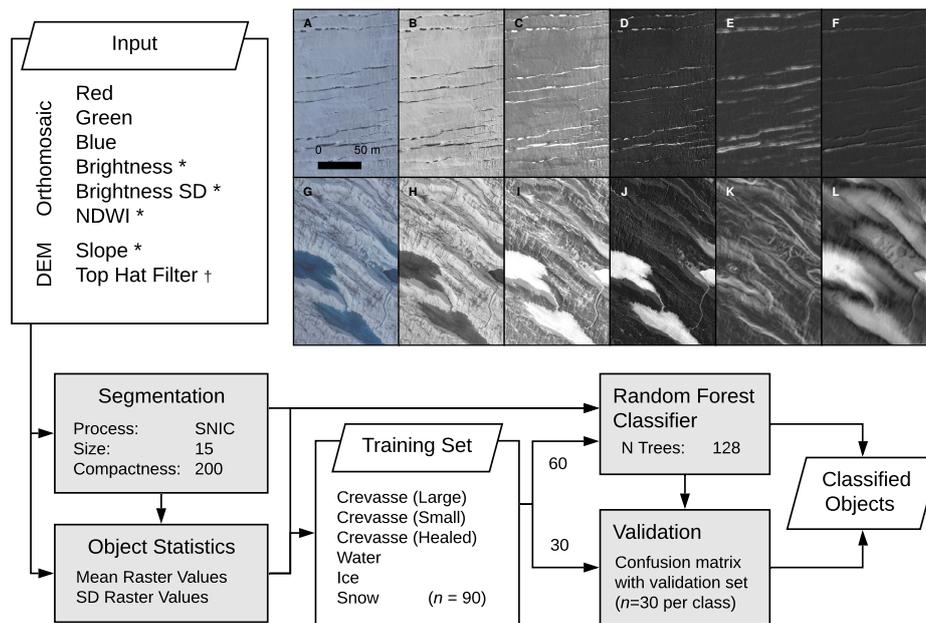


Figure 3. Flowchart of method used to classify UAV imagery. Variables appended with an asterisk were calculated from input data within GEE, while those appended with a cross were calculated separately in Matlab. Inset shows examples of OBIA input data for regions dominated by small (a-f) and (g-l) large crevasses. (a and g) RGB orthophotos. (b and h) Brightness. (c and i) Standard deviation of RGB values. (d and j) NDWI. (e and k) Slope, with hillshade overlaid. (f and l) Black-top-hat filtered DEM, with hillshade overlaid.

217 2019), DEM-based methods alone cannot be used to identify features such as water-filled
218 or healed crevasses, and crevasse detection is sensitive to threshold choice and ultimately
219 the resolution of the DEM (Jones et al., 2018; Florinsky & Bliakharskii, 2019). To take
220 advantage of the high spatial resolution and multi-dimensional outputs of UAV surveys,
221 we used a combination of object-based image analysis (OBIA) and supervised classifi-
222 cation. OBIA is based not on the numerical characteristics of individual pixels but of
223 objects (i.e. groups of meaningfully similar pixels segmented based upon spectral homo-
224 geneity) (Blaschke, 2010)). This has been used successfully in a glaciological context by
225 Kraaijenbrink et al. (2016, 2018) for mapping cliff/pond systems and emissivity on a debris-
226 covered glacier. We again used GEE to perform the full segmentation and supervised
227 classification workflow (Figure 3).

228 We identified a number of variables that could be used as inputs for a supervised
229 classification algorithm to identify crevasse field surface features. This included: the red,
230 blue, and green values of the orthophoto (Figure 3a;g); the ‘brightness’ (mean RGB val-
231 ues; Fig 3b;h) as per Kraaijenbrink et al. (2016); the standard deviation of the RGB val-
232 ues, which appeared to highlight water, small crevasses, and healed crevasses (Figure 3c;i);
233 the NDWI, from blue and red pixel values (Figure 3d;j); the DEM slope, which effectively
234 highlighted small crevasses on the order of a few metres (Figure 3e;k); and DEM values
235 black-top-hat filtered with a 30 m structuring element (Kodde et al., 2007), which were
236 useful in identifying large crevasses on the order of tens of metres (Figure 3f;l). A black
237 top-hat filter morphologically closes the glacier surface at scales smaller than the struc-
238 turing element, before subtracting the closed surface from the original data. This pro-
239 cess was performed in Matlab prior to ingestion into GEE.

240 We performed image segmentation using Simple Non-Iterative Clustering (SNIC)
241 (Achanta & Susstrunk, 2017), a computationally efficient implementation of superpixel-
242 based clustering. Rather than segmenting an image into semantically-meaningful objects,
243 superpixel-based segmentation simplifies the image into small, uniform, and compact clus-
244 ters of similar pixels (‘superpixels’), with a focus on boundary adherence. The variables
245 described above are used as the input to the segmentation algorithm. We manually se-
246 lected a seed spacing of 15 pixels (2.25 m) and a high compactness factor of 200. This
247 resulted in superpixels small enough to display strong boundary adherence to small and
248 healed crevasses at the scale of metres, whilst still clearly delineating the margins of larger
249 features such as water bodies. As an input to the supervised classification, we calculated
250 the average and standard deviation of values in each superpixel from the variables de-
251 scribed above, as well as the perimeter-to-area ratio of the superpixel, and normalised
252 the results.

253 We adopted a supervised classification approach to surface classification (Kraaijenbrink
254 et al., 2016, 2018; Ryan et al., 2018) by training a random forest classifier in GEE. In
255 order to reduce the amount of redundant information used to train the random forest
256 classifier, we performed a non-parametric mutual information (MI) test on our training
257 data as a proxy for the predictive power of each input variable. Rejecting input variables
258 beneath the median MI value (Figure S1) did not notably reduce the accuracy of the out-
259 put data (Figure S2). Therefore, we used only the nine most significant variables as in-
260 put to the random forest classifier. We constructed training datasets of 90 points each
261 for six distinct surface types: bare ice, snow, healed crevasses, ‘small’ crevasses, ‘large’
262 crevasses, and water. We separated ‘small’ and ‘large’ crevasses (those with a diameter
263 of metres vs. tens of metres) into two training datasets as they displayed distinctly dif-
264 ferent values for properties such as brightness, slope, and the top hat filtered DEM (Fig-
265 ure 3). We trained the random forest classifier on two-thirds of the dataset (60 points
266 per classification) and retained one-third (30 points per classification) for validation. Out-
267 put classification performed well visually (Figure S3) and validation data showed that
268 a $> 95\%$ accuracy was observed for all surface types (Figure S2), apart from for snow
269 and bare ice, which for our purposes was not important. Although we identified six sur-

270 face types, for this analysis we were only interested in three distinctions: crevasses (com-
 271 bining ‘small’ and ‘large’ crevasses), ice (combining bare ice, snow, and healed crevasses),
 272 and water.

273 3 Results

274 3.1 Satellite results

275 From ArcticDEM elevation, Sentinel-2 optical imagery, and MEaSURES surface ve-
 276 locity (Figure 4a), we created maps of crevasse fraction values (Figure 4b), water frac-
 277 tion values (Figure 4c), and stress estimates (Figure 4d–i) respectively.

278 Despite an intuitive relationship between first principal stress (σ_1) (Figure 4d; 5a)
 279 and crevasse formation, the measure is not a good predictor of crevasse state, i.e. whether
 280 a crevasse is initiating, dry, or wet. An analysis of the distribution of stresses shows that
 281 although all crevasse types occur at higher values of σ_1 than non-crevassed regions (Fig-
 282 ure 6a), the three states display similar median values (wet 47 kPa; dry 48 kPa; initiat-
 283 ing 50 kPa), suggesting that σ_1 alone is not a strong control on crevasse hydrology. In
 284 contrast, second principal stress (σ_2 ; Figure 4e) displays a clearer relationship with crevasse
 285 state, with crevasses initiating in areas of highest σ_2 and ponding in areas of lowest σ_2
 286 (Figure 5b). Initiating crevasses have the highest median σ_2 (-13 kPa) and are the most
 287 common crevasse state in regions of positive σ_2 (Figure 6b). In contrast, wet crevasses
 288 have the lowest median σ_2 (-58 kPa), and dry crevasses are intermediate between the two
 289 (-38 kPa). Longitudinal stress (σ_l ; Figure 4f), is more successful at distinguishing crevasse
 290 state (Fig 5C; median wet 6 kPa; dry 18 kPa; initiating 33 kPa) than σ_1 , but not as suc-
 291 cessful as σ_2 as it displays a narrower spread of median values, and dry and wet crevasse
 292 states display very similar distributions (Figure 4c). The effective performance of σ_2 , and
 293 less effective performance of σ_1 and σ_l , suggest that structural controls on crevasse hy-
 294 drology are distinct from those traditionally understood to control crevasse formation.

295 Stress criteria that encompass both σ_1 and σ_2 provide further insights into crevasse
 296 hydrology. Von Mises (σ_v ; Figure 4g; 5d) has different median values for crevasse states
 297 (wet 88 kPa, dry 67 kPa, initiating 57 kPa), but with a counter-intuitive relationship given
 298 that the highest stresses appear to be the most likely to be water-filled. Additionally,
 299 dry and wet crevasses display a strong positive skew (Figure 6d), making it difficult to
 300 differentiate the two based on a single threshold. In contrast, σ_m values (Figure 4h; 5e)
 301 capture a distribution for each of the crevasse states: crevasse initiation is most likely
 302 to occur at the highest σ_m values (median +20 kPa), whilst water-filled crevasses are the
 303 only surface type to occur with a median negative σ_m (-4 kPa). Qualitative assessment
 304 (Figure 4e) shows that saturated crevasse zones align with regions of negative σ_m and
 305 crevasse initiation zones align with strongly positive σ_m . However, σ_m is still not con-
 306 venient for predicting crevasse state as the distributions of crevasse states display high
 307 overlap (Figure 6e) such that simple thresholding based on σ_m alone would not delin-
 308 eate crevasse state successfully.

309 In order to combine the relative strengths of σ_v and σ_m approaches, we use σ_{sv} which
 310 is derived as the magnitude of σ_v but with the sign of σ_m (Figure 4i). This measure al-
 311 lows for a more refined differentiation for whether a stress regime is compressive or ex-
 312 tensional. Crevasse initiation zones display a particularly narrow distribution (Figure
 313 6f) almost exclusively in positive σ_{sv} regimes (median +57 kPa). Wet and dry crevasses
 314 can also be differentiated, even though these data exhibit a similarly skewed distribu-
 315 tion in σ_v . When σ_{sv} is highly compressional (i.e., less than -50 kPa), wet crevasses are
 316 more likely than dry crevasses; above this value, the probability of crevasse state is ap-
 317 proximately equal. Conversely, dry crevasses are more likely than wet crevasses to ex-
 318 ist in extensional σ_{sv} regimes from low to high stress (up to 120 kPa). In very high pos-

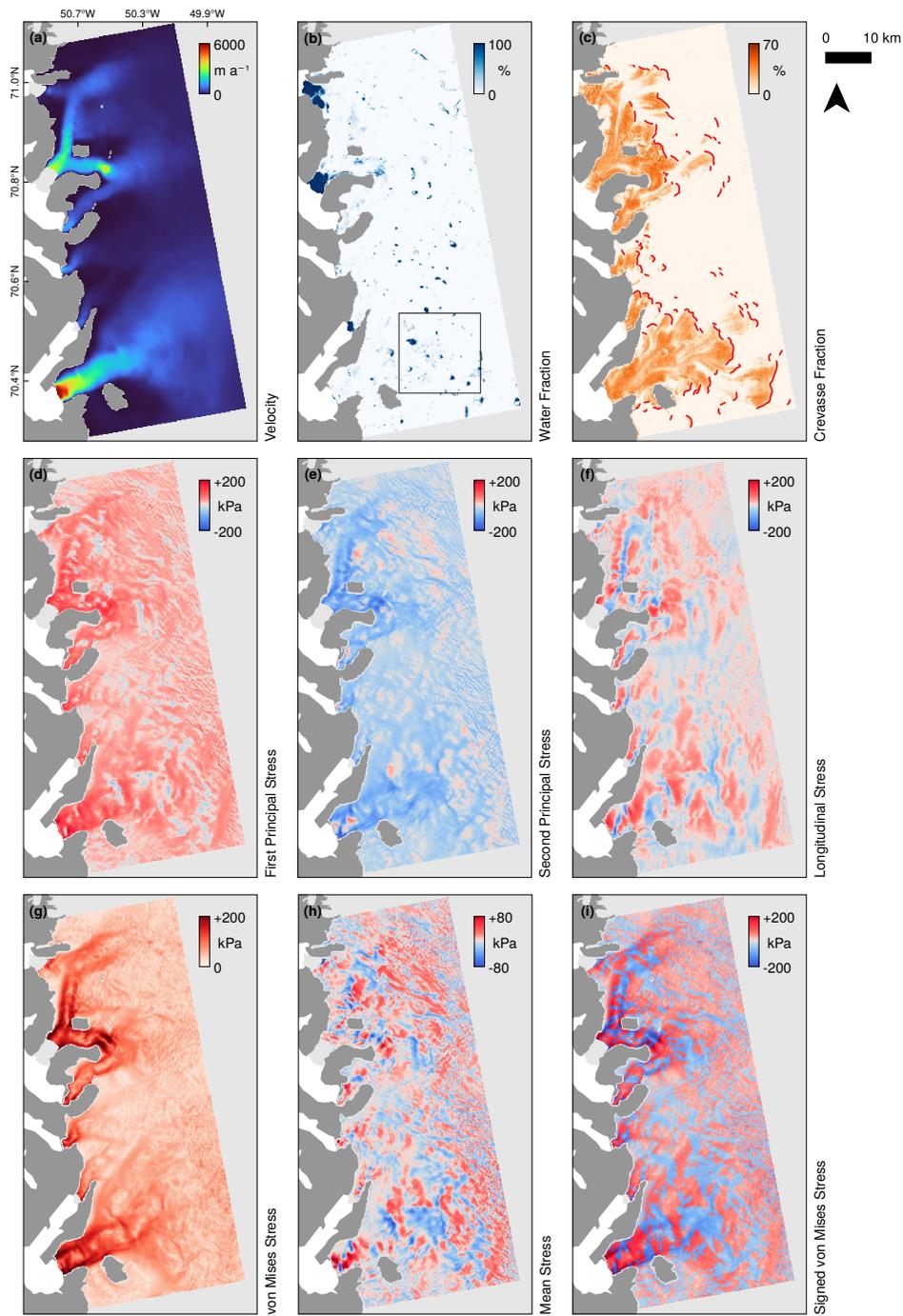


Figure 4. (a) Map of MEASUREs 2018 velocity data over the study region; (b) observed 2018 water fraction; (c) observed crevasse coverage, with manually identified crevasse initiation zones marked in red; (d) first principal stress, (e) second principal stress, (f) longitudinal stress; (g) von Mises Stress, (h) mean stress, and (i) signed von Mises Stress. Black box in (b) shows the location of Figure 5.

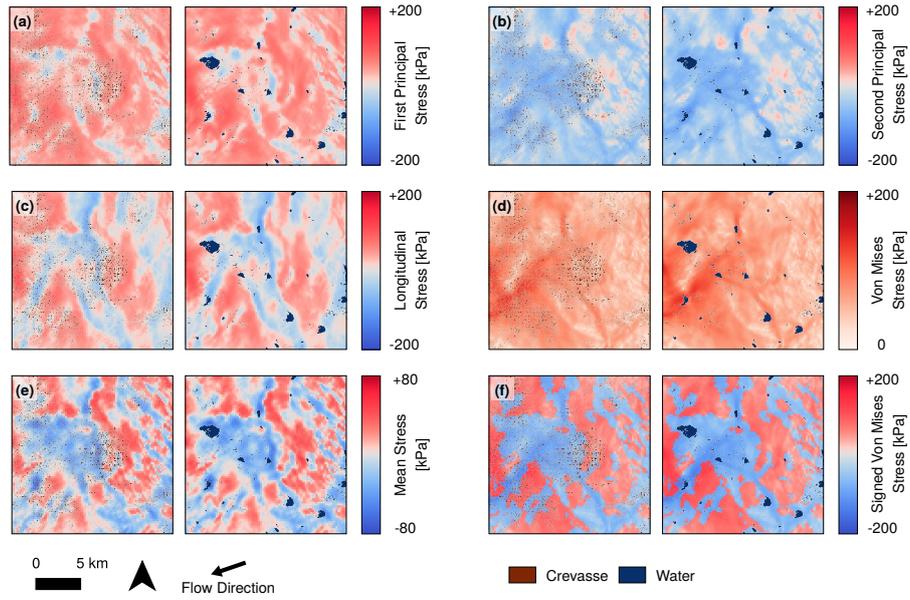


Figure 5. Close-up of stress fields overlaid with observed crevasses (left) and water (right): (a) first principal stress, (b) second principal stress, (c) longitudinal stress; (d) von Mises Stress, (e) mean stress, and (f) signed von Mises Stress.

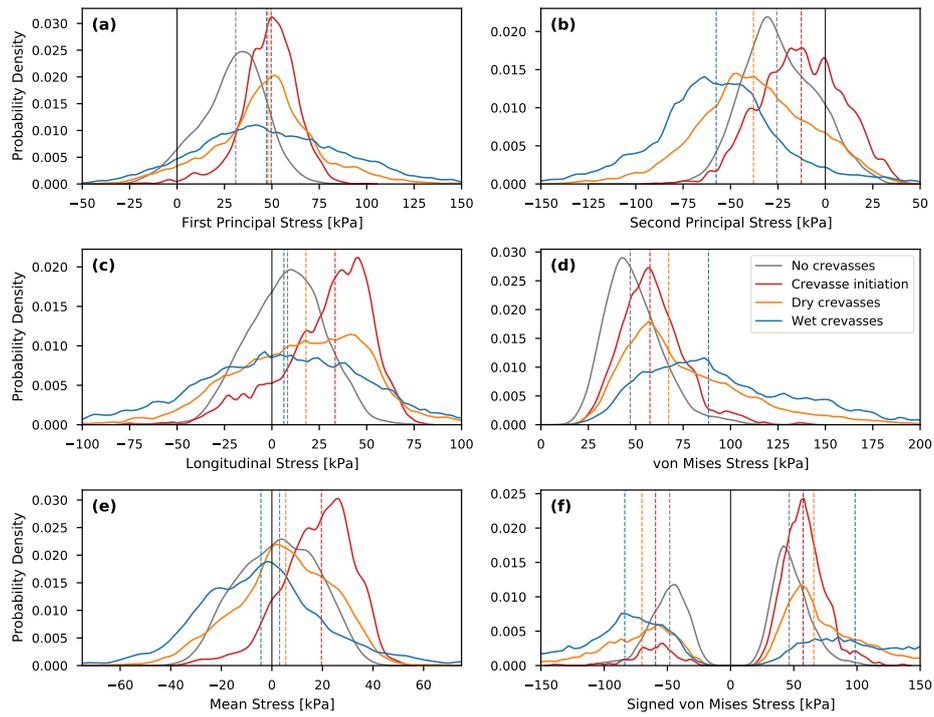


Figure 6. Kernel density estimate distribution plots of different surface classifications for (a) first principal stress, (b) second principal stress, (c) longitudinal stress, (d) von Mises stress, (e) mean stress, and (f) signed von Mises Stress. Median values for different surface classifications are shown as dashed vertical lines. A crevassed grid cell is defined by $> 1\%$ crevasse fraction, and a wet crevassed grid cell is a crevassed grid cell with any water observed ($> 0\%$).

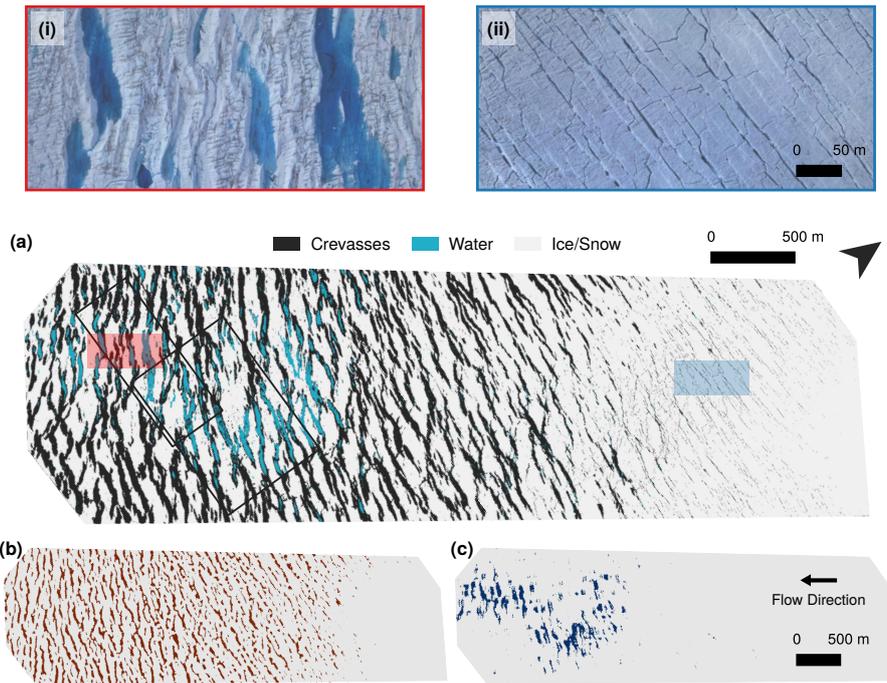


Figure 7. Output of (a) UAV random forest classification, with insets (shaded in red and blue) showing (i) an area with large (50-60 m) crevasses, and (ii) small (2-3 m) crevasses. Satellite-derived data, shown for comparison, include (b) ArcticDEM-derived crevasse classification, and (c) Sentinel-2 derived water classification. Black boxes in (a) mark extents of Figure 9.

319 itive σ_{sv} regimes (greater than 120 kPa), wet crevasses are once again more likely to exist.
 320

321 3.2 UAV results

322 3.2.1 Analysis and comparison to satellite data

323 UAV surface classification (Figure 7a), based on high resolution orthophotos (0.15
 324 m) and DEMs (0.2 m), was able to differentiate crevasses, water, and ice surfaces to a
 325 level of accuracy exceeding 90% (Figure S2). This suggests that the UAV SfM-MVS is
 326 highly suitable as ground verification for the coarser satellite-derived data, especially given
 327 the logistical difficulties of ground-based verification within hazardous crevasse fields. Com-
 328 parison with satellite-derived crevasse classification (Figure 7b) and water classification
 329 (Figure 7c) shows that the datasets agree closely in terms of the distribution of surface
 330 features. Manual comparison between the two datasets suggests the cutoff width below
 331 which crevasses are unable to be identified from ArcticDEM v3 data is approximately
 332 10 m, corresponding to 5 pixels. Although this means the satellite data do not capture
 333 the smallest crevasse fields, the resolvable size of a crevasse is approximately equal to the
 334 resolution of the Sentinel-2 bands used for NDWI calculation (10 m), which gives con-
 335 fidence that the two datasets are comparable. While our ArcticDEM mosaic is derived
 336 from multitemporal data (individual tiles across the study area range from 2009-2017),
 337 crevasse sizes and patterning observed in 2018 UAV surveys were consistent with the 2009-
 338 2017 ArcticDEM (Figure 7a cf. 6b). This suggests that, even though individual crevasses

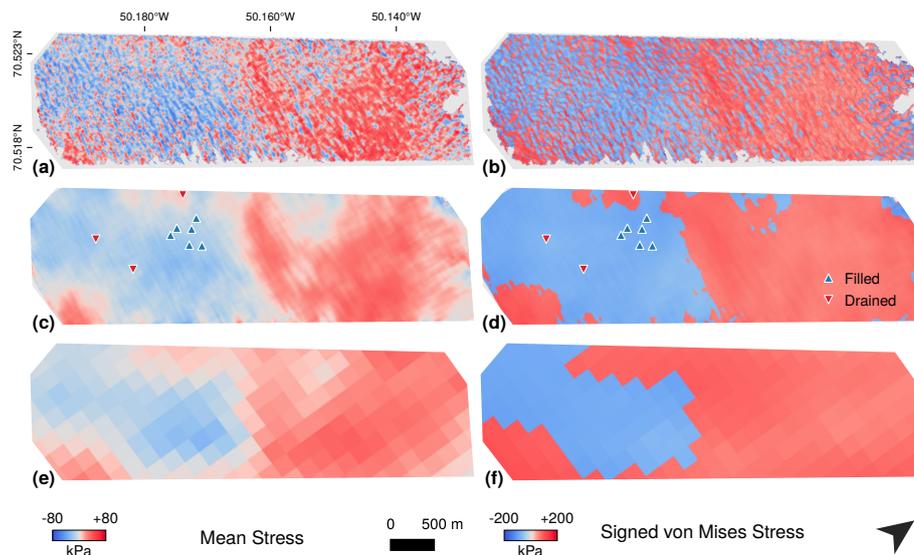


Figure 8. UAV-derived stress outputs for mean stress (left column) and signed von Mises stress (right column). (a–b) shows raw output, (c–d) shows 200 m mean average, and (e–f) shows MEaSUREs-derived output for comparison. Triangles in (c–d) show the locations of crevasse systems that were observed to fill (blue) or drain (red) across the UAV survey period.

339 advect, interannual variation in crevasse fields is relatively small, and that the assumption
 340 that 2009–2017 crevasse distribution can be compared to 2018 surface water distribution
 341 is valid. Sentinel-2 water and UAV-derived water also agree (Figure 7a cf. 6c).
 342 Individual water-filled crevasses are able to be co-located between the satellite and UAV
 343 datasets. Sentinel-2 data additionally identifies additional crevasses that are water-filled
 344 across the span of the season yet not filled on the date of the UAV survey.

345 Stress components evaluated from UAV velocity data, including σ_m (Figure 8a) and
 346 σ_{sv} (Figure 8b), reveal a highly heterogeneous stress regime, where changes can be seen
 347 even between neighbouring crevasses. However, in general, an extensional regime dom-
 348 inates in the northeast (right-hand side of Figures 6 and 7) and a compressive regime
 349 in the southwest. As with satellite-derived data, there are clear relationships between
 350 the nature of the positive/negative mean stress regime and that of crevasse initiation and
 351 water distribution. Crevasses tend to initiate - or at least become identifiable in the decime-
 352 tre resolution data - in the upstream kilometre of the study zone (Figure 7a). In the next
 353 kilometre down-glacier, crevasses open from < 3 m wide to full size (~ 10 – 60 m wide)
 354 by the centre of the study zone (Figure 7a insets). Crevasse initiation and opening is co-
 355 incident with a zone of highly positive mean stress, consistent with satellite-derived ob-
 356 servations (Section 3.1). In the southwestern sector of the study zone, crevasse size re-
 357 mains relatively stable, but crevasses transition from dry to water-filled in the down-glacier
 358 direction (Figure 7a). This region of water-filled crevasses is seen where the mean stress
 359 regime is negative (Figure 8a–b), which is again consistent with satellite datasets.

360 The stress regime as estimated from UAV-derived velocity fields is highly variable
 361 on the scale of tens of metres, making it difficult to compare to the stress regime esti-
 362 mated from MEaSUREs data. To address this, we apply a 31 pixel (198.4 m) mean fil-
 363 ter across the UAV stress fields (Figure 8c–d) to approximate the 200 m resolution of
 364 the MEaSUREs stress field (Figure 8e–f). The results show that the UAV and MEaSUREs
 365 data are in close general agreement, despite the different spatial resolution (6.4 m vs 200

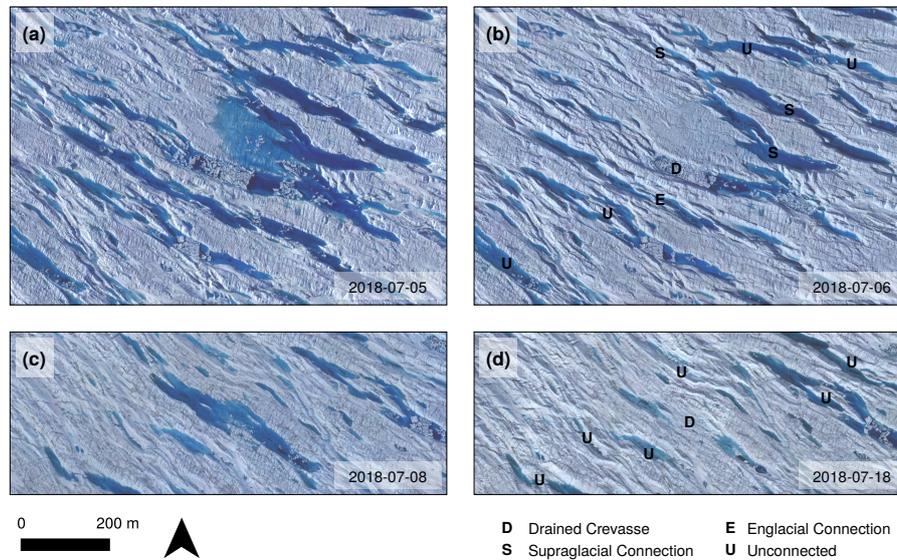


Figure 9. Examples of crevasse drainage when (a–b) a draining crevasse is supraglacially and/or englacially connected to adjacent crevasses and (c–d) when no connections are present. Interpretations are marked where crevasses underwent direct drainage (D), drained via supraglacial connection to a draining crevasse (S), drained via englacial connection to a draining crevasse (E), or remained unconnected to a draining system (U).

366 m) and timescales over which velocity was captured (10 days vs 1 year composite). This
 367 reveals that crevasse fields exhibit high local variability in surface stresses (on the scale
 368 of 10s of metres) that cannot be captured by satellite observations. For instance, in the
 369 southwestern sector of the study zone, there are many localised areas of positive stress,
 370 despite the fact that MEaSURES data is consistently negative. This suggests that one
 371 source of uncertainty in the satellite analysis is the degree to which localised variabil-
 372 ity occurs within its 200 m grid cells.

373 *3.2.2 Water routing in ponded crevasse fields*

374 Satellite-derived analysis (Section 3.1) identified regions of wet crevasses in com-
 375 pressive mean stress regimes, but did not provide information as to whether or how wa-
 376 ter is routed to the bed in these areas. Over the 13-day period in July 2018 over which
 377 repeat UAV surveys were undertaken (Table S1), three crevasse systems in the UAV ROI
 378 were observed to drain, and six underwent significant filling. The locations of these events
 379 are correlated with mean stress regime (Figure 8c–d). For instance, crevasse water fill-
 380 ing was observed in a region that had recently advected from a net extensional into a
 381 net compressive zone. Elsewhere, crevasse drainage was observed in a region that had
 382 recently advected from a net compressive area (where $\sigma_m < 0$) into a net extensional area
 383 ($\sigma_m > 0$), and also in locations where the 200 m-resolution stresses were observed to be
 384 negative but local stresses displayed high heterogeneity (cf. Figure 8a–b; c–d). This sug-
 385 gests that, in general, crevasses fill with water when advecting into a negative mean stress
 386 regime, and display a higher propensity to drain when advecting into a region of pos-
 387 itive mean stresses.

388 Closer analysis of these draining crevasses revealed two key observations regard-
 389 ing water routing. First, there was little evidence to suggest that surface water was routed

for significant distances between crevasses in crevasse fields. Where supraglacial streams existed, connecting larger crevasses, they were easily identified in the imagery (Figure S4a), but this is not common across the survey zone. In one case, a crevasse system that was overflowing with water (Figure 9a) formed local supraglacial networks, and upon one crevasse draining, water levels across the entire network dropped (Figure 9b). This event appeared to result in the formation of incised channels in the days following drainage (Figure S4b–c). It was less common for adjacent crevasses to drain when no surface routing was visible (Figure 9b), and indeed individual crevasses were able to drain without affecting water levels in the surrounding crevasses at all (Figure 9c–d). This suggests that supraglacial and englacial hydrological connections between crevasses may be rare. Second, crevasse drainages appear to be rapid. Of the three drainages we identified, two represent crevasses that were stable or filling in sequential imagery prior to drainage, before losing a majority of water between two adjacent images (e.g. Figure 9c–d). One crevasse system lost a substantial volume of water in less than 24 hours (Figure 9a–b), and water levels continued to drop for the rest of the survey period (Figure S4b–c). This suggests that either a moulin had formed, and that water therefore continued to drain into the subglacial system, or that small open fractures continued to transfer water inefficiently into the englacial system.

4 Discussion

4.1 Relationships between surface stress and observed crevasse hydrology

Our findings show that stress measures previously used to predict water drainage through crevasses - including the first principal stress (Poinar et al., 2015; Williamson, Willis, et al., 2018), longitudinal stress (Clason et al., 2015), and von Mises stress (Koziol et al., 2017; Everett et al., 2016) – are not good at estimating the hydrological state of crevasses. Longitudinal stress (σ_l) is effective at predicting where crevasses initiate, which aligns with the assertion that crevasses can be considered as Mode I fractures that open up perpendicular to the direction of flow when stress in this direction exceeds a certain threshold. However, the fact that both first principal stress (σ_1) and σ_l are poor at predicting crevasse hydrology, whilst second principal stress (σ_2) performs better, suggests that the full range of normal stress, and not only the stress acting in the direction of flow, affect the ability of water to drain englacially. The von Mises (σ_v) criterion, which accounts for only the deviatoric stress, does not clearly distinguish crevasse hydrological state compared to alternative measures which incorporate the full first invariant stress (e.g. mean stress). Additionally, σ_v displays an inverse relationship to hydrology, whereby higher σ_v values are more likely to see water ponding occur (Figure 6d). This is counter-intuitive when considering σ_v as a planform equivalent to a σ_{xx} in an LEFM framework, where high positive σ_{xx} values (tensile stress) are associated with greater fracture propagation (van der Veen, 1998). We suggest this is because the von Mises stress does not differentiate between a compressive or extensional stress regime. In contrast, stress measures that account for the magnitude and direction of the full first invariant stress (i.e. mean stress, σ_m , and signed von Mises stress, σ_{sv}) were better at predicting surface crevasse hydrology. Surface crevasses that were identified to be water-filled through the 2018 ablation season were more likely to exist in regions where mean surface stress was negative (i.e. compressive). In contrast, surface crevasses where no water was observed were more likely to exist in positive (i.e. extensional) mean stress regimes. To explain this link, we interpret that in negative mean stress regimes, hydrological pathways between the surface and active englacial system will likely be subject to enhanced closure. This will be the case regardless of the stress acting in the direction perpendicular to crevasse orientation (Section 4.2.1).

There has been limited consideration of the role of the full first invariant stress in crevasse hydrology, with most studies focussed on first principal or longitudinal stress.

442 A few studies have considered the role of σ_2 in crevasse formation (Hambrey & Müller,
 443 1978; Cuffey & Paterson, 2010), and indirectly in studies of Mode II (van der Veen, 1999)
 444 and Mode III (Colgan et al., 2016) shear in mixed-mode crevasse formation. Whilst LEFM
 445 modelling can, in theory, be extrapolated to two or even three dimensions (van der Veen,
 446 1999), this is nontrivial (Colgan et al., 2016). As a result, studies modelling water trans-
 447 mission to the bed have tended to extrapolate from 1-D LEFM models by directly re-
 448 placing the σ_{xx} stress term with pre-existing measures that have been recommended for
 449 crevasse formation - in particular, the von Mises stress, following Vaughan (1993). Our
 450 work suggests that this can be improved upon, and that accounting for crevasse hydrolog-
 451 ogy requires a more complete consideration of stresses, i.e. both surface-parallel prin-
 452 cipal stresses.

453 4.2 Crevasse drainage mechanisms

454 4.2.1 Wet crevasses

455 A number of drainage processes could be consistent with observations of water-filled
 456 crevasses. For instance, water-filled crevasses in compressive regions can be part of an
 457 active supraglacial network, with water being routed to a moulin elsewhere in the sys-
 458 tem (Poinar, 2015). However, the UAV data presented here suggests that, where crevasses
 459 are large, significant hydrological connections between them are rare and of limited spa-
 460 tial extent (Figure 9b,d). Even where hydrological connections exist, they appear to form
 461 as a consequence, rather than a cause, of drainage events (Figure S4b–c). If channels do
 462 not exist in many cases, the drainage of water in ponded crevasse systems cannot, for
 463 the most part, be caused by water being routed to moulins via supraglacial networks.

464 Given that we found little direct evidence for hydrological connections, we consider
 465 hydrofracture to the subglacial environment to be the most likely mechanism by which
 466 water-filled crevasses drain (Weertman, 1973; Boon & Sharp, 2003; van der Veen, 2007;
 467 Krawczynski et al., 2009). In negative mean stress regimes, we assume that englacial con-
 468 nections undergo what Irvine-Fynn et al. (2011) described as ‘pinch-off’, whereby crevasse
 469 closure or ice creep can isolate the ponded crevasse from the englacial drainage system.
 470 In an environment where ablation is ongoing, this will result in the filling of surface crevasses,
 471 allowing hydrofracture to occur when water depth reaches a critical level. This would
 472 be consistent with the rapid and heterogenous crevasse drainages observed in UAV data,
 473 and align with the numerous observations of hydrofracture occurring during rapid lake
 474 drainages (Das et al., 2008; Doyle et al., 2013; Stevens et al., 2015; Chudley, Christof-
 475 fersen, Doyle, Bougamont, et al., 2019).

476 The state of a subglacial drainage system and subsequent ice dynamic response is
 477 known to be affected by the variability (Schoof, 2010) and distribution (Banwell et al.,
 478 2016) of meltwater inputs. Our evidence indicates that episodic crevasse drainage events
 479 should be expected to deliver distinct, isolated pulses of meltwater to the bed in the same
 480 fashion as - but likely smaller than - rapid lake drainages. The full hydrological conse-
 481 quences of rapid lake drainages are explored in detail elsewhere (e.g. Nienow et al., 2017)),
 482 but it is apparent that similar principles can be applied to crevasse drainages. For in-
 483 stance, studies focussing on draining crevasse systems at the shear margin of Jakobshavn
 484 Isbrae have established that water delivery is of sufficient volume to overwhelm the ca-
 485 pacity of the subglacial system (Lampkin et al., 2013), increasing ice mass flux across
 486 the shear margin and enhancing glacier discharge (Cavanagh et al., 2017; Lampkin et
 487 al., 2018). However, there may be several features of crevasse drainages that are distinct
 488 from better-studied lake drainage events. After hydrofracture, ongoing meltwater deliv-
 489 ery via the newly open moulin is an important hydrological component of lake drainages
 490 (Koziol et al., 2017; Hoffman et al., 2018) but, given the smaller catchments that indi-
 491 vidual crevasses have, this effect is likely less important in crevasse drainage scenarios.
 492 Unlike lakes, it appears to be relatively common that crevasse systems can drain mul-

493 tiple times through a single ablation season (Cavanagh et al., 2017). However, the net
 494 effect of this has yet to be properly considered.

495 **4.2.2 Dry crevasses**

496 As water is never observed to pond in the crevasses we classify as ‘dry’, surface melt-
 497 water produced within the crevasse catchment must either (i) drain via moulins to the
 498 glacier bed, or (ii) drain less efficiently into the englacial system, but still rapidly enough
 499 that water is never collecting at a rate sufficient to fill the crevasse. We argue that the
 500 second interpretation is more likely. Whilst it seems unlikely that discharge rates are suf-
 501 ficient to maintain open moulins, positive mean stress regimes may mean that, unlike
 502 in compressive environments, creep closure does not close narrow hydrological pathways
 503 to the englacial system. This is consistent with the view of crevasse systems on temper-
 504 ate valley glaciers as continually, albeit inefficiently, hydraulically connected to englacial
 505 and/or subglacial drainage systems through a linked network of small fractures (Fountain
 506 et al., 2005).

507 This conceptual model of inefficient, continuous crevasse drainage has previously
 508 been applied to the Greenland Ice Sheet by Colgan et al. (2011) and McGrath et al. (2011).
 509 Both studies assumed that water reaches the bed, albeit slower than through moulins.
 510 Colgan et al. (2011) suggested the difference may be 200-fold between the two types of
 511 surface-to-bed connection (~ 1 hour for a 1 m^2 moulin vs. ~ 12 hours for a 0.1 m wide
 512 crevasse), whilst McGrath et al. (2011) suggested that crevasses may slow englacial drainage
 513 to such an extent that a diurnal cycle of meltwater input can be damped to a quasi-steady-
 514 state discharge on the timescale of hours-days. This sustained inefficient delivery of melt-
 515 water to the glacier bed through crevasses would be less likely to overwhelm the trans-
 516 mission capacity of the subglacial system. Therefore, they argue that regions of the bed
 517 subject to continuous inefficient delivery are less likely to exhibit enhanced basal slid-
 518 ing compared to regions experiencing episodic, efficient meltwater pulses.

519 There is no direct evidence, however, that water draining inefficiently through crevasses
 520 is able to reach the bed of the Greenland Ice Sheet. Another likelihood is that much of
 521 this water does not make it to the bed, and instead freezes englacially. This has conse-
 522 quences for the thermal structure of glaciers, as it has been argued that widespread, in-
 523 efficient meltwater delivery through open crevasses would facilitate cryo-hydrologic warm-
 524 ing relative to regions fed by discrete moulins (Colgan et al., 2011). This is because a
 525 dense spacing of hydrological pathways increases the volume of ice warmed by the la-
 526 tent heat release of englacial freezing, and hence can act to enhance ice velocity via de-
 527 formation (T. Phillips et al., 2010; Lüthi et al., 2015). In contrast, episodically-draining,
 528 water-filled crevasses may focus cryo-hydrologic warming into the upper few hundred me-
 529 tres of the ice column (Poinar, 2015), and open moulins provide little latent heat to the
 530 surrounding ice (Lüthi et al., 2015). As such, it is likely that crevasses that drain con-
 531 tinuously into the ice sheet may act to enhance latent heat delivery relative to other hy-
 532 drological pathways. Colgan et al. (2011) concluded that increased crevasse coverage on
 533 an accelerating ice sheet would increase the area of the bed experiencing enhanced cryo-
 534 hydrologic warming. Based on the findings presented here, it might be expected that an
 535 accelerating ice sheet would result in a transition of some crevasse regions from episodic
 536 to continuous drainage if the mean stress were to become positive (extensional). If this
 537 is the case, some areas of the bed could experience a transition to enhanced cryo-hydrologic
 538 warming, even in regions where crevasse fields already existed.

539 **4.3 Implications for large-scale ice sheet modelling**

540 Neither of the two states of crevasse drainage described above is new, with both
 541 episodic full-depth hydrofracture and continuous englacial drainage having numerous ex-
 542 amples of observations and model implementations in literature focusing on the Green-

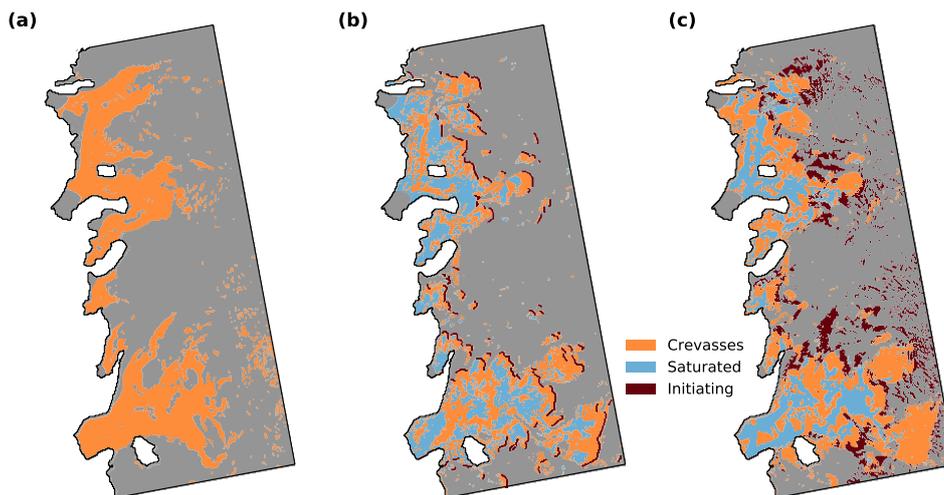


Figure 10. Comparisons of methods of using stress thresholds to identify crevassing. (a) Predicted distribution of crevassing using a von Mises yield threshold of 67.5 kPa. (b) Observed distribution of crevasse-filled pixels (crevasse fraction $> 1\%$), crevasse-filled pixels where water is observed, and manually identified crevasse initiation zones. (c) Predicted location of water-filled crevasses and crevasse initiation zones based on signed von Mises thresholds.

543 land Ice Sheet. Nevertheless, in the past, regional models of ice sheet hydrology and dy-
 544 namics have rarely included crevasse drainage (Arnold et al., 2014; Banwell et al., 2013,
 545 2016). Recent 2-D regional hydrological models have begun to include the process, but
 546 have yet to account for heterogeneous drainage styles. Clason et al. (2015) incorporated
 547 crevasse drainage in a manner similar to the episodic hydrofracture described above. They
 548 identified crevassed regions based on a σ_v threshold, which were then allowed to fill and
 549 hydrofracture according to an LEFM model (van der Veen, 2007). Once a crevasse fractured
 550 to the full ice thickness, a moulin formed and water was transferred continuously
 551 to the bed. More recently, Koziol et al. (2017) based their model on the principle of con-
 552 tinuously draining crevasses, whereby meltwater produced at the surface of crevasse fields
 553 (again identified according to a σ_v threshold) drained immediately without requiring hy-
 554 drofracture. This water was assumed to reach the bed of the ice sheet without freezing
 555 englacially. These two studies, reflecting a paucity of observations, assumed that all crevasse
 556 drainage falls into one of the end-members of crevasse hydrology observed and described
 557 herein.

558 Given the above, we are able to use the findings of this study to provide recommen-
 559 dations as to how future studies may be able to account for a wider diversity of crevasse
 560 hydrology whilst keeping inputs and classifications as simple as possible. We compare
 561 our results to the common method of crevasse field prediction via a qualitatively iden-
 562 tified von Mises stress threshold. A threshold yield strength of 67.5 kPa was determined
 563 to result in the best visual match between predicted (Figure 10a) and observed (Figure
 564 10b) crevasse fields. This method provides a reasonable first-order estimate but is (i) poor
 565 at predicting marginal cases including zones of false negative results in regions of relict
 566 crevasses, and (ii) cannot distinguish between zones of episodic and continuous drainage
 567 as identified in this study. Accepting that zero stress models cannot account for relict
 568 crevasse advection (Mottram & Benn, 2009), we retain the use of our own direct obser-
 569 vations rather than using stress thresholds to predict crevasse location (Figure 10c). This
 570 is achievable for future studies as the method we use is simple and relies only on Arc-
 571 ticDEM data. Then, based upon the stress distribution of surface types (Figure 6f) and

572 visual matching with observed distribution (Figure 10b), we prescribe that water-filled
 573 crevasses exist in MEaSURES grid cells where σ_{sv} is less than -65 kPa or greater than
 574 +140 kPa (Figure 10c). On a pixel-by-pixel level, these thresholds are able to predict
 575 the presence or absence of water in 63% of crevassed grid cells correctly. Visual compar-
 576 ison shows that this thresholding technique provides a good match with broad trends
 577 in crevasse ponding. This includes the diagonal band of ponding across the tongue of Store
 578 Glacier, a bias of ponding towards the shear margins of the northern tributary of Per-
 579 lerfiup Sermia, and even some of the specific localised patterns further upstream into the
 580 drainage basin at Store Glacier. This suggests that simple thresholding such as this could
 581 be used as input to regional hydrological models to investigate the seasonal and long-
 582 term effects of spatial heterogeneity in crevasse hydrology on the subglacial dynamics
 583 of the ice sheet (see, for example, Poinar et al., 2019).

584 In another example of implementing signed Von Mises stress as an improved simple
 585 stress threshold, we use the distribution of stresses in manually identified crevasse
 586 initiation zones (Figure 4e) to prescribe a yield criterion of +55 kPa for crevasse initi-
 587 ation (Figure 10c). This falls within the 30-90 kPa bounds predicted by (van der Veen,
 588 1998), but is lower than the 67.5 kPa we prescribed for von Mises stress alone, as well
 589 as those thresholds used by other studies (e.g. Clason et al., 2015; Koziol et al., 2017).
 590 By using a directional measure of stress, a relatively low critical yield criterion can be
 591 prescribed without enhancing regions of false positive identification in compressive stress
 592 regimes. Initiation zones are clustered where anticipated, at the upstream margins of crevasse
 593 fields, which gives us confidence in this threshold. There also exist scattered initiation
 594 zones at the farthest inland regions of the study area, where crevasses are not observed
 595 in our ArcticDEM-derived dataset. However, examination of higher-resolution Sentinel-
 596 2 data reveals that there are visible crevasse features here, not identified within the study
 597 due to either being too small to appear in ArcticDEM data or snow-filled.

598 The regional observations presented in this study utilise bulk analysis of annual ve-
 599 locity and seasonal water presence to identify potential links between crevasse hydrolog-
 600 y and stress regime. Future work should explore opportunities to better define this re-
 601 lationship using time-series datasets. For example, the proliferation of remote sensing
 602 platforms has allowed for the production of ice velocity datasets at extremely high tem-
 603 poral resolutions (e.g. Minchew et al., 2017), as well as the ability to track the filling and
 604 drainage of individual hydrological systems on the surface of ice sheets (Williamson, Ban-
 605 well, et al., 2018). These advances highlight the possibility of being able to relate the
 606 behaviour and drainage of crevasses with time-variable stress regimes induced by short-
 607 term instabilities in ice dynamics - as has been previously proposed from a modelling per-
 608 spective for supraglacial lake drainage events (Christoffersen et al., 2018) - and hence
 609 provide new insights into the relationship between crevasses and the delivery of melt-
 610 water to the bed of ice sheets.

611 5 Conclusions

612 In order to be able to model and predict the response of GrIS dynamics to increas-
 613 ing runoff, it is necessary to understand where and how water is transferred to the bed
 614 of the ice sheet. Our results indicate that surface stresses, and in particular the mean
 615 normal stress, determines whether crevasses drain episodically via hydrofracture, influ-
 616 encing basal sliding, or drain inefficiently into the englacial system, enhancing cryo-hydrologic
 617 warming via refreezing. Our observations suggest that crevasse drainage state exists on
 618 a spectrum that is controlled by spatially heterogeneous surface stress. We find that these
 619 behaviours cannot be distinguished based upon the yield criterion previously used to pre-
 620 dict crevasse distribution, suggesting that controls on crevasse hydrology are distinct from
 621 controls on crevasse initiation. Simple thresholds obtained from visual analysis remain,
 622 however, a suitable approach to predict the first-order distribution of crevasse hydrolog-
 623 ical state. Hence, we can recommend mean stress thresholds as a simple and practical

624 method for improving the representation of crevasse hydrology in regional hydrological
 625 models, which is necessary to be able to accurately model the spatially variable impact
 626 of seasonal ice sheet hydrology on the thermal regime and ice dynamic behaviour of the
 627 Greenland Ice Sheet.

628 Acknowledgments

629 This research was funded by the European Research Council as part of the RESPON-
 630 DER project under the European Union’s Horizon 2020 research and innovation program
 631 (Grant 683043). TRC and RL were supported by a Natural Environment Research Coun-
 632 cil Doctoral Training Partnership Studentship (Grant NE/L002507/1). We are very grate-
 633 ful to Ann Andreasen and the Uummannaq Polar Institute for their kind hospitality; to
 634 Sean Peters for his assistance with UAV launches; and to Neil Arnold for useful method-
 635 ological discussions.

636 MEaSURES annual velocity mosaics are available from the National Snow and Ice
 637 Data Centre (<https://doi.org/10.5067/0BXC75U7540>). Sentinel-2 and ArcticDEM
 638 v3 data were made available for processing via Google Earth Engine. Data produced in
 639 this study will be made available via the UK Polar Data Centre (UK PDC) alongside
 640 the final publication of this manuscript.

641 The authors declare no financial conflict of interest.

642 References

- 643 Achanta, R., & Susstrunk, S. (2017). Superpixels and polygons using simple non-
 644 iterative clustering. In *Proceedings of the IEEE Conference on Computer Vi-*
 645 *sion and Pattern Recognition* (pp. 4651–4660). doi: 10.1109/CVPR.2017.520
- 646 Alley, K. E., Scambos, T. A., Anderson, R. S., Rajaram, H., Pope, A., & Haran,
 647 T. M. (2018). Continent-wide estimates of Antarctic strain rates from Land-
 648 sat 8-derived velocity grids. *Journal of Glaciology*, *64*(244), 321–332. doi:
 649 10.1017/jog.2018.23
- 650 Alley, R. B., Dupont, T. K., Parizek, B. R., & Anandakrishnan, S. (2005). Access of
 651 surface meltwater to beds of sub-freezing glaciers: Preliminary insights. *Annals*
 652 *of Glaciology*, *40*, 8–14. doi: 10.3189/172756405781813483
- 653 Arnold, N. S., Banwell, A. F., & Willis, I. C. (2014). High-resolution modelling of
 654 the seasonal evolution of surface water storage on the Greenland Ice Sheet.
 655 *The Cryosphere*, *8*(4), 1149–1160. doi: 10.5194/tc-8-1149-2014
- 656 Banwell, A. F., Hewitt, I., Willis, I., & Arnold, N. (2016). Moulin density controls
 657 drainage development beneath the Greenland ice sheet. *J. Geophys. Res. Earth*
 658 *Surf.*, 2015JF003801. doi: 10.1002/2015JF003801
- 659 Banwell, A. F., Willis, I. C., & Arnold, N. S. (2013). Modeling subglacial water rout-
 660 ing at Paakitsoq, W Greenland. *J. Geophys. Res. Earth Surf.*, *118*(3), 1282–
 661 1295. doi: 10.1002/jgrf.20093
- 662 Benn, D. I., Åström, J., Zwinger, T., Todd, J., Nick, F. M., Cook, S., . . . Luckman,
 663 A. (2017). Melt-under-cutting and buoyancy-driven calving from tidewater
 664 glaciers: New insights from discrete element and continuum model simulations.
 665 *Journal of Glaciology*, *63*(240), 691–702. doi: 10.1017/jog.2017.41
- 666 Bindschadler, R., Vornberger, P., Blankenship, D., Scambos, T., & Jacobel,
 667 R. (1996). Surface velocity and mass balance of Ice Streams D and E,
 668 West Antarctica. *Journal of Glaciology*, *42*(142), 461–475. doi: 10.3189/
 669 S0022143000003452
- 670 Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal*
 671 *of Photogrammetry and Remote Sensing*, *65*(1), 2–16. doi: 10.1016/j.isprsjprs
 672 .2009.06.004

- 673 Boon, S., & Sharp, M. (2003). The role of hydrologically-driven ice fracture in
674 drainage system evolution on an Arctic glacier. *Geophysical Research Letters*,
675 *30*(18). doi: 10.1029/2003GL018034
- 676 Cavanagh, J. P., Lampkin, D. J., & Moon, T. (2017). Seasonal Variability in Re-
677 gional Ice Flow Due to Meltwater Injection Into the Shear Margins of Jakob-
678 shavn Isbræ. *Journal of Geophysical Research: Earth Surface*, *122*(12), 2488–
679 2505. doi: 10.1002/2016JF004187
- 680 Christoffersen, P., Bougamont, M., Hubbard, A., Doyle, S. H., Grigsby, S., & Pet-
681 tersson, R. (2018). Cascading lake drainage on the Greenland Ice Sheet
682 triggered by tensile shock and fracture. *Nature Communications*, *9*(1), 1064.
683 doi: 10.1038/s41467-018-03420-8
- 684 Chudley, T. R., Christoffersen, P., Doyle, S. H., Abellan, A., & Snooke, N. (2019).
685 High-accuracy UAV photogrammetry of ice sheet dynamics with no ground
686 control. *The Cryosphere*, *13*(3), 955–968. doi: 10.5194/tc-13-955-2019
- 687 Chudley, T. R., Christoffersen, P., Doyle, S. H., Bougamont, M., Schoonman, C. M.,
688 Hubbard, B., & James, M. R. (2019). Supraglacial lake drainage at a fast-
689 flowing greenlandic outlet glacier. *Proceedings of the National Academy of*
690 *Sciences*, *116*(51), 25468–25477. doi: 10.1073/pnas.1913685116
- 691 Clason, C. C., Mair, D. W. F., Nienow, P. W., Bartholomew, I. D., Sole, A., Palmer,
692 S., & Schwanghart, W. (2015). Modelling the transfer of supraglacial melt-
693 water to the bed of Leverett Glacier, Southwest Greenland. *The Cryosphere*,
694 *9*(1), 123–138. doi: 10.5194/tc-9-123-2015
- 695 Colgan, W., Rajaram, H., Abdalati, W., McCutchan, C., Mottram, R., Moussavi,
696 M. S., & Grigsby, S. (2016). Glacier crevasses: Observations, models, and
697 mass balance implications. *Reviews of Geophysics*, *54*(1), 119–161. doi:
698 10.1002/2015RG000504
- 699 Colgan, W., Steffen, K., McLamb, W. S., Abdalati, W., Rajaram, H., Motyka,
700 R., . . . Anderson, R. (2011). An increase in crevasse extent, West Green-
701 land: Hydrologic implications. *Geophysical Research Letters*, *38*(18). doi:
702 10.1029/2011GL048491
- 703 Cuffey, K. M., & Paterson, W. S. B. (2010). *The physics of glaciers*. Academic
704 Press. doi: 10.1016/C2009-0-14802-X
- 705 Das, S. B., Joughin, I., Behn, M. D., Howat, I. M., King, M. A., Lizarralde, D., &
706 Bhatia, M. P. (2008). Fracture Propagation to the Base of the Greenland Ice
707 Sheet During Supraglacial Lake Drainage. *Science*, *320*(5877), 778–781. doi:
708 10.1126/science.1153360
- 709 Dell, R., Carr, R., Phillips, E., & Russell, A. J. (2019). Response of glacier flow and
710 structure to proglacial lake development and climate at Fjallsjökull, south-east
711 Iceland. *Journal of Glaciology*, 1–16. doi: 10.1017/jog.2019.18
- 712 Doyle, S. H., Hubbard, A. L., Dow, C. F., Jones, G. A., Fitzpatrick, A., Gusmeroli,
713 A., . . . Box, J. E. (2013). Ice tectonic deformation during the rapid in situ
714 drainage of a supraglacial lake on the Greenland Ice Sheet. *The Cryosphere*,
715 *7*(1), 129–140. doi: 10.5194/tc-7-129-2013
- 716 Everett, A., Murray, T., Selmes, N., Rutt, I. C., Luckman, A., James, T. D., . . .
717 Reeve, D. E. (2016). Annual down-glacier drainage of lakes and water-filled
718 crevasses at Helheim Glacier, southeast Greenland. *Journal of Geophysical*
719 *Research: Earth Surface*, *121*(10), 1819–1833. doi: 10.1002/2016JF003831
- 720 Florinsky, I. V., & Bliakharskii, D. P. (2019). Detection of crevasses by geomorpho-
721 metric treatment of data from unmanned aerial surveys. *Remote Sensing Let-*
722 *ters*, *10*(4), 323–332. doi: 10.1080/2150704X.2018.1552809
- 723 Fountain, A. G., Jacobel, R. W., Schlichting, R., & Jansson, P. (2005). Fractures
724 as the main pathways of water flow in temperate glaciers. *Nature*, *433*(7026),
725 618–621. doi: 10.1038/nature03296
- 726 Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R.
727 (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone.

- 728 *Remote sensing of Environment*, 202, 18–27. doi: 10.1016/j.rse.2017.06.031
- 729 Hambrey, M. J., & Müller, F. (1978). Structures and ice deformation in the
730 white glacier, Axel Heiberg Island, Northwest Territories, Canada. *Journal*
731 *of Glaciology*, 20(82), 41–66. doi: 10.3189/S0022143000021213
- 732 Harper, J. T., Humphrey, N. F., & Pfeffer, W. T. (1998). Crevasse patterns and
733 the strain-rate tensor: A high-resolution comparison. *Journal of Glaciology*,
734 44(146), 68–76. doi: 10.3189/S0022143000002367
- 735 Hoffman, M. J., Perego, M., Andrews, L. C., Price, S. F., Neumann, T. A., John-
736 son, J. V., ... Lüthi, M. P. (2018). Widespread Moulin Formation During
737 Supraglacial Lake Drainages in Greenland. *Geophys. Res. Lett.*, 2017GL075659.
738 doi: 10.1002/2017GL075659
- 739 Howat, I. M., Negrete, A., & Smith, B. E. (2014). The Greenland Ice Mapping
740 Project (GIMP) land classification and surface elevation data sets. *The*
741 *Cryosphere*, 8(4), 1509–1518. doi: 10.5194/tc-8-1509-2014
- 742 Irvine-Fynn, T. D., Hodson, A. J., Moorman, B. J., Vatne, G., & Hubbard, A. L.
743 (2011). Polythermal glacier hydrology: A review. *Reviews of Geophysics*,
744 49(4). doi: 10.1029/2010RG000350
- 745 Jones, C., Ryan, J., Holt, T., & Hubbard, A. (2018). Structural glaciology of Isun-
746 guata Sermia, West Greenland. *Journal of Maps*, 14(2), 517–527. doi: 10
747 .1080/17445647.2018.1507952
- 748 Joughin, I., Smith, B. E., Howat, I. M., Scambos, T., & Moon, T. (2010). Green-
749 land flow variability from ice-sheet-wide velocity mapping. *Journal of Glaciol-*
750 *ogy*, 56(197), 415–430. doi: 10.3189/002214310792447734
- 751 Jouvét, G., Weidmann, Y., Seguinot, J., Funk, M., Abe, T., Sakakibara, D., ...
752 Sugiyama, S. (2017). Initiation of a major calving event on the Bowdoin
753 Glacier captured by UAV photogrammetry. *The Cryosphere*, 11(2), 911–921.
754 doi: 10.5194/tc-11-911-2017
- 755 Kodde, M., Pfeifer, N., Gorte, B., Geist, T., & Höfle, B. (2007). Automatic
756 glacier surface analysis from airborne laser scanning. *International Archives*
757 *of the Photogrammetry, Remote Sensing and Spatial Information Sciences*,
758 36(3/W52), 221–226.
- 759 Koziol, C. P., & Arnold, N. (2018). Modelling seasonal meltwater forcing of
760 the velocity of land-terminating margins of the Greenland Ice Sheet. *The*
761 *Cryosphere*, 12(3), 971–991. doi: 10.5194/tc-12-971-2018
- 762 Koziol, C. P., Arnold, N., Pope, A., & Colgan, W. (2017). Quantifying supraglacial
763 meltwater pathways in the Paakitsoq region, West Greenland. *Journal of*
764 *Glaciology*, 1–13. doi: 10.1017/jog.2017.5
- 765 Kraaijenbrink, P. D. A., Shea, J. M., Litt, M., Steiner, J. F., Treichler, D., Koch,
766 I., & Immerzeel, W. W. (2018). Mapping Surface Temperatures on a Debris-
767 Covered Glacier with an Unmanned Aerial Vehicle. *Front. Earth Sci.*, 6. doi:
768 10.3389/feart.2018.00064
- 769 Kraaijenbrink, P. D. A., Shea, J. M., Pellicciotti, F., de Jong, S. M., & Immerzeel,
770 W. W. (2016). Object-based analysis of unmanned aerial vehicle imagery
771 to map and characterise surface features on a debris-covered glacier. *Remote*
772 *Sensing of Environment*, 186, 581–595. doi: 10.1016/j.rse.2016.09.013
- 773 Krawczynski, M. J., Behn, M. D., Das, S. B., & Joughin, I. (2009). Constraints on
774 the lake volume required for hydro-fracture through ice sheets. *Geophysical Re-*
775 *search Letters*, 36(10). doi: 10.1029/2008GL036765
- 776 Lampkin, D. J., Amador, N., Parizek, B. R., Farness, K., & Jezek, K. (2013).
777 Drainage from water-filled crevasses along the margins of Jakobshavn Isbræ: A
778 potential catalyst for catchment expansion. *Journal of Geophysical Research:*
779 *Earth Surface*, 118(2), 795–813. doi: 10.1002/jgrf.20039
- 780 Lampkin, D. J., Parizek, B., Larour, E. Y., Seroussi, H., Joseph, C., & Cavanagh,
781 J. P. (2018). Toward Improved Understanding of Changes in Greenland Outlet
782 Glacier Shear Margin Dynamics in a Warming Climate. *Frontiers in Earth*

- 783 *Science*, 6. doi: 10.3389/feart.2018.00156
- 784 Lüthi, M. P., Ryser, C., Andrews, L. C., Catania, G. A., Funk, M., & Hawley,
785 R. L. (2015). Heat sources within the Greenland Ice Sheet: Dissipation,
786 temperate paleo-firn and cryo-hydrologic warming. *The Cryosphere*. doi:
787 10.5194/tc-9-245-2015
- 788 McGrath, D., Colgan, W., Steffen, K., Lauffenburger, P., & Balog, J. (2011). As-
789 ssuming the summer water budget of a moulin basin in the Sermeq Avannarleq
790 ablation region, Greenland ice sheet. *Journal of Glaciology*, 57(205), 954–964.
791 doi: 10.3189/002214311798043735
- 792 Minchew, B. M., Simons, M., Riel, B., & Milillo, P. (2017). Tidally induced varia-
793 tions in vertical and horizontal motion on Rutford Ice Stream, West Antarc-
794 tica, inferred from remotely sensed observations. *J. Geophys. Res. Earth Surf.*,
795 122(1), 2016JF003971. doi: 10.1002/2016JF003971
- 796 Mottram, R. H., & Benn, D. I. (2009). Testing crevasse-depth models: A field study
797 at Breiðamerkurjökull, Iceland. *Journal of Glaciology*, 55(192), 746–752. doi:
798 10.3189/002214309789470905
- 799 Nienow, P. W., Sole, A. J., Slater, D. A., & Cowton, T. R. (2017). Recent Advances
800 in Our Understanding of the Role of Meltwater in the Greenland Ice Sheet
801 System. *Curr Clim Change Rep*, 1–15. doi: 10.1007/s40641-017-0083-9
- 802 Nye, J. F. (1957). The distribution of stress and velocity in glaciers and ice-sheets.
803 *Proceedings of the Royal Society of London. Series A. Mathematical and Physi-
804 cal Sciences*, 239(1216), 113–133. doi: 10.1098/rspa.1957.0026
- 805 Phillips, E., Finlayson, A., & Jones, L. (2013). Fracturing, block faulting, and
806 moulin development associated with progressive collapse and retreat of a mar-
807 itime glacier: Falljökull, SE Iceland. *J. Geophys. Res. Earth Surf.*, 118(3),
808 1545–1561. doi: 10.1002/jgrf.20116
- 809 Phillips, T., Rajaram, H., & Steffen, K. (2010). Cryo-hydrologic warming: A poten-
810 tial mechanism for rapid thermal response of ice sheets. *Geophysical Research
811 Letters*, 37(20). doi: 10.1029/2010GL044397
- 812 Poinar, K. (2015). *The influence of meltwater on the thermal structure and flow of
813 the Greenland Ice Sheet* (Thesis).
- 814 Poinar, K., Dow, C. F., & Andrews, L. C. (2019). Long-Term Support of an Active
815 Subglacial Hydrologic System in Southeast Greenland by Firn Aquifers. *Geo-
816 physical Research Letters*, 46(9), 4772–4781. doi: 10.1029/2019GL082786
- 817 Poinar, K., Joughin, I., Das, S. B., Behn, M. D., Lenaerts, J. T. M., & van den
818 Broeke, M. R. (2015). Limits to future expansion of surface-melt-enhanced
819 ice flow into the interior of western Greenland. *Geophys. Res. Lett.*, 42(6),
820 2015GL063192. doi: 10.1002/2015GL063192
- 821 Pope, A. (2016). Reproducibly estimating and evaluating supraglacial lake depth
822 with Landsat 8 and other multispectral sensors. *Earth and Space Science*,
823 3(4), 176–188. doi: 10.1002/2015EA000125
- 824 Porter, C., Morin, P., Howat, I., Noh, M.-J., Bates, B., Peterman, K., ... Bojesen,
825 M. (2018). *ArcticDEM*. Harvard Dataverse. doi: 10.7910/DVN/OHHUKH
- 826 Ryan, J. C., Hubbard, A., Stibal, M., Irvine-Fynn, T. D., Cook, J., Smith, L. C.,
827 ... Box, J. (2018). Dark zone of the Greenland Ice Sheet controlled by dis-
828 tributed biologically-active impurities. *Nature Communications*, 9(1), 1065.
829 doi: 10.1038/s41467-018-03353-2
- 830 Ryan, J. C., Hubbard, A. L., Box, J. E., Todd, J., Christoffersen, P., Carr, J. R., ...
831 Snooke, N. (2015). UAV photogrammetry and structure from motion to assess
832 calving dynamics at Store Glacier, a large outlet draining the Greenland ice
833 sheet. *The Cryosphere*, 9(1), 1–11. doi: 10.5194/tc-9-1-2015
- 834 Schoof, C. (2010). Ice-sheet acceleration driven by melt supply variability. *Nature*,
835 468(7325), 803–806. doi: 10.1038/nature09618
- 836 Stevens, L. A., Behn, M. D., McGuire, J. J., Das, S. B., Joughin, I., Herring,
837 T., ... King, M. A. (2015). Greenland supraglacial lake drainages trig-

- 838 gered by hydrologically induced basal slip. *Nature*, 522(7554), 73–76. doi:
839 10.1038/nature14480
- 840 Taylor, Z. J., Gurka, R., Kopp, G. A., & Liberzon, A. (2010). Long-Duration
841 Time-Resolved PIV to Study Unsteady Aerodynamics. *IEEE Transac-*
842 *tions on Instrumentation and Measurement*, 59(12), 3262–3269. doi:
843 10.1109/TIM.2010.2047149
- 844 Todd, J., Christoffersen, P., Zwinger, T., Råback, P., & Benn, D. I. (2019).
845 Sensitivity of a calving glacier to ice–ocean interactions under climate
846 change: New insights from a 3-D full-Stokes model. *The Cryosphere*. doi:
847 10.5194/tc-13-1681-2019
- 848 van der Veen, C. J. (1998). Fracture mechanics approach to penetration of surface
849 crevasses on glaciers. *Cold Regions Science and Technology*, 27(1), 31–47. doi:
850 10.1016/S0165-232X(97)00022-0
- 851 van der Veen, C. J. (1999). Crevasses on glaciers. *Polar Geography*, 23(3), 213–245.
852 doi: 10.1080/10889379909377677
- 853 van der Veen, C. J. (2007). Fracture propagation as means of rapidly transferring
854 surface meltwater to the base of glaciers. *Geophysical Research Letters*, 34(1).
855 doi: 10.1029/2006GL028385
- 856 Vaughan, D. G. (1993). Relating the occurrence of crevasses to surface strain rates.
857 *Journal of Glaciology*, 39(132), 255–266. doi: 10.3189/S0022143000015926
- 858 Weertman, J. (1973). Can a water-filled crevasse reach the bottom surface of a
859 glacier. *IASH Publ*, 95, 139–145.
- 860 Williamson, A. G., Banwell, A. F., Willis, I. C., & Arnold, N. S. (2018). Dual-
861 satellite (Sentinel-2 and Landsat 8) remote sensing of supraglacial lakes in
862 Greenland. *The Cryosphere*, 12(9), 3045–3065. doi: [https://doi.org/10.5194/
863 tc-12-3045-2018](https://doi.org/10.5194/tc-12-3045-2018)
- 864 Williamson, A. G., Willis, I. C., Arnold, N. S., & Banwell, A. F. (2018). Controls
865 on rapid supraglacial lake drainage in West Greenland: An Exploratory Data
866 Analysis approach. *Journal of Glaciology*, 1–19. doi: 10.1017/jog.2018.8