

1 Using remote sensing to assess peatland resilience by estimating soil surface moisture and  
2 drought recovery

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14 Abstract

15 Peatland areas provide a range of ecosystem services, including biodiversity, carbon  
16 storage, clean water, and flood mitigation, but many areas of peatland in the UK have been  
17 degraded through human land use including drainage. Here, we explore whether remote  
18 sensing can be used to monitor peatland resilience to drought. We take resilience to mean  
19 the rate at which a system recovers from perturbation; here measured literally as a recovery  
20 timescale of a soil surface moisture proxy from drought lowering. Our objectives were (1) to  
21 assess the reliability of Sentinel-1 Synthetic Aperture Radar (SAR) backscatter as a proxy  
22 for water table depth (WTD); (2) to develop a method using SAR to estimate below-ground  
23 (hydrological) resilience of peatlands; (3) to apply the developed method to different sites  
24 and consider the links between resilience and land management. Our inferences of WTD  
25 from Sentinel-1 SAR data gave results with an average Pearson's correlation of 0.77 when

26 compared to measured WTD values. The 2018 summer drought was used to assess  
27 resilience across three different UK peatland areas (Dartmoor, the Peak District, and the  
28 Flow Country) by considering the timescale of the soil moisture proxy recovery. Results  
29 show clear areas of lower resilience within all three study sites, which often correspond to  
30 areas of high drainage and may be particularly vulnerable to increasing drought  
31 severity/events under climate change. This method is applicable to monitoring peatland  
32 resilience elsewhere over larger scales, and could be used to target restoration work  
33 towards the most vulnerable areas.

34 Key words: Blanket bog, SAR, Sentinel-1, hydrology, water table dynamics

### 35 1.Introduction

36 There is widespread interest in the resilience, or otherwise, of ecosystems subject to global  
37 changes, especially climate change (Côté & Darling, 2010). However, despite theoretical  
38 progress, there is a paucity of work quantifying the resilience of different real-world  
39 ecosystems (Pimm et al., 2019). This is a critical gap, because if we cannot quantitatively  
40 measure resilience we cannot tell which ecosystems are losing resilience, and we cannot tell  
41 whether efforts to increase the resilience of particular systems are having the desired effect  
42 or not. In order to understand resilience it is important to understand the ecosystem  
43 response to stressors, but also the response to management techniques used to manage  
44 vulnerability (Chambers et al., 2019). The definition of what is meant by resilience can vary  
45 across disciplines (Müller et al., 2016); in this study we define resilience as the rate at which  
46 a system recovers from perturbation (Chambers et al., 2019; Pimm, 1984; Swindles et al.,  
47 2016). This definition of resilience is more easily quantified than definitions of resilience  
48 which relate to ecosystem stability over longer timescales, but there is assumed to be a  
49 correlation between the two (Hillebrand & Kunze, 2020; Müller et al., 2016; Zelnik et al.,  
50 2018). In this study we consider the recovery of water levels following a drought event, an  
51 example of a pulse-disturbance, as this is a clearly defined event with a recovery rate that is

52 relatively easy to monitor, and which may give some insights regarding ecosystem stability  
53 over the longer term.

54 Here we take peatlands as a target ecosystem for monitoring resilience. Peatland  
55 environments are valuable in terms of the many ecosystem services they provide, including  
56 carbon storage (Gorham, 1991), biodiversity (Minayeva et al., 2017), and water purification  
57 (Wallage et al., 2006). However, these landscapes are vulnerable to both climate change  
58 and human land use pressures (Clark et al., 2010; Gallego-Sala et al., 2010; JNCC, 2011).  
59 Given their function as large stores of carbon, there is particular interest in how peatlands  
60 will respond to climate change, and how resilient they will be in the face of climatic pressures  
61 such as increasing droughts (Page & Baird, 2016). Positive feedbacks include a change in  
62 vegetation species towards a community which prefers dryer conditions, and changes in the  
63 specific yield of peat causing greater WTD fluctuations (Sherwood et al., 2013; Waddington  
64 et al., 2015). Compound disturbances, such as the interactions of drainage, fire, and  
65 drought, can cause positive feedbacks to dominate, tipping the peatland over a threshold  
66 and into an alternative state (Sherwood et al., 2013; Swindles et al., 2016). These compound  
67 disturbances are more likely to occur under climate change (Sherwood et al., 2013; Swindles  
68 et al., 2019).

69 Hydrology is considered a key factor in peatland resilience, as high and stable water levels  
70 are associated with healthy peatlands, whilst sustained and/or frequent drought can cause  
71 degradation and long-term damage (Kettridge & Waddington, 2014; Sherwood et al., 2013;  
72 Swindles et al., 2016; Waddington et al., 2015). Some studies have assessed long-term  
73 peatland resilience through paleoecology methods (Lamentowicz et al., 2019; Łuców et al.,  
74 2020; Swindles et al., 2016, 2019), whilst others have considered shorter-term resilience  
75 through field studies (Holden et al., 2011; Sherwood et al., 2013). Peatlands are generally  
76 remarkably resilient over long timescales due to the range of negative feedbacks that can  
77 counteract the effects of perturbations to the system. Negative feedbacks include increased  
78 surface resistance, altered peat deformation and decomposition characteristics during

79 drought events, which act to bring the water table closer to the surface following a drop in  
80 Water Table Depth (WTD), and changes in *Sphagnum* species and behaviour (Kettridge &  
81 Waddington, 2014; Page & Baird, 2016; Waddington et al., 2015). An increase in the  
82 severity or frequency of droughts due to climate change could, however, cause negative  
83 feedback systems to lose their effectiveness (Lowe et al., 2018).

84 Using remote sensing to assess ecosystem resilience is a fast-growing area of research, as  
85 such data can cover large areas over long timescales, with increasingly fine spatial  
86 resolution and frequent repeat measurements (e.g. Díaz-Delgado et al., 2002; Li et al., 2014;  
87 Washington-Allen et al., 2008). Data collected from satellites are particularly useful in  
88 monitoring remote environments where repeat field visits would be difficult and expensive.  
89 Remote sensing can provide large scale assessments of spatial variation in resilience, which  
90 are the most useful for management decisions (Chambers et al., 2019). However, many  
91 remote sensing measures of resilience rely on optical data which can only be obtained under  
92 clear sky conditions, and can only detect surface changes (Li et al., 2014). For example,  
93 several existing efforts have focused on terrestrial vegetation using the normalised  
94 difference vegetation index (NDVI) to monitor the response rate to known perturbations, e.g.  
95 fires (Díaz-Delgado et al., 2002), or utilising the inverse relationship between temporal  
96 autocorrelation and resilience (Verbesselt et al., 2016). Synthetic Aperture Radar (SAR) is  
97 different because it can penetrate below the surface into the top few centimetres of the soil,  
98 thereby giving information that would not be available from optical data. Here we explore  
99 whether we can use remote sensing derived information to monitor a below-ground  
100 (hydrological) measure of ecosystem resilience. SAR backscatter can be used to estimate  
101 surface moisture in soils, and has been shown to correlate with WTD time series in  
102 peatlands and wetlands (Bechtold et al., 2018; Kasischke et al., 2009; Millard & Richardson,  
103 2018; Schlaffer et al., 2016). SAR also has the advantage over optical data that it can  
104 penetrate through cloud, which is a great benefit in the wet climates where peatlands thrive  
105 (Babaeian et al., 2019).

106 The SAR sensor carried on the two Sentinel-1 satellites has great potential for monitoring  
107 soil moisture fluctuations due to its frequent return interval, particularly at high latitudes  
108 where many peatlands are located, and high spatial resolution (down to 10 m). Not many  
109 studies have yet considered the performance of Sentinel-1 SAR due to the relatively recent  
110 launch of the paired satellites (April 2014 and April 2016) and therefore the short time series  
111 of available images (Asmuß et al., 2019; Huang et al., 2018).

112 SAR cannot be used to directly compare soil moisture across different sites, as the  
113 relationship between SAR backscatter and soil moisture is inconsistent and affected by other  
114 factors such as surface topography and vegetation structure (Bechtold et al., 2018; Millard &  
115 Richardson, 2018). To counteract this, we developed a method that compares a site against  
116 itself, indicating how far above or below average a site is for the time of year, and therefore  
117 how long a site takes to recover to its usual moisture level after a drought perturbation. We  
118 use the developed method to compare the effects of the extreme 2018 spring/summer  
119 drought and heat event (Bastos et al., 2020) to previous and subsequent years. As SAR  
120 backscatter functionally estimates soil moisture by penetrating the top few centimetres below  
121 the soil surface, but we validated the method using more easily available WTD datasets, the  
122 resulting estimates are referred to throughout as a soil surface moisture proxy (this is  
123 discussed further in Section 4.1.1.).

124 Our study therefore makes significant steps forward in several areas. First, we consider the  
125 abilities of SAR in general and Sentinel-1 in particular to estimate a soil moisture proxy and  
126 WTD dynamics in peatland sites, focusing on sites in Great Britain as a contrast to sites in  
127 Germany already considered by Asmuß et al. (2019). Secondly, we develop a method to use  
128 SAR estimates of the soil moisture proxy to assess peatland resilience to drought, taking  
129 advantage of the unique abilities of SAR to measure below-ground changes, and minimising  
130 the effect of confounding factors such as surface topography. We use this method to  
131 consider three example peatland sites in Great Britain, focusing on areas where compound

132 disturbances are likely to have decreased resilience. Finally, we discuss the wider  
133 implications for peatland monitoring globally.

## 134 2. Materials and Methods

### 135 2.1. Study sites

136 This work focuses on the Flow Country in Northern Scotland, the Peak District in the centre  
137 of Britain, and Dartmoor in the South-West of England (see Figure 1). These three study  
138 sites include a range of blanket bog conditions which characterise peatlands across Britain.  
139 The Flow Country is one of the largest expanses of blanket bog in the world, with large parts  
140 in good condition with no evidence of human activity. Some areas however were drained  
141 and planted for commercial forestry in the 1980s, many of which are now undergoing  
142 restoration. Areas of the Peak District peatland have, in contrast, been exposed to different  
143 combinations of drainage, managed burns, grazing, and pollution as they are close to  
144 several urban centres. Dartmoor is a smaller area of upland peat which has experienced  
145 drainage, grazing, peat cutting and erosion.

#### 146 2.1.1. Water Table Depth (WTD) data

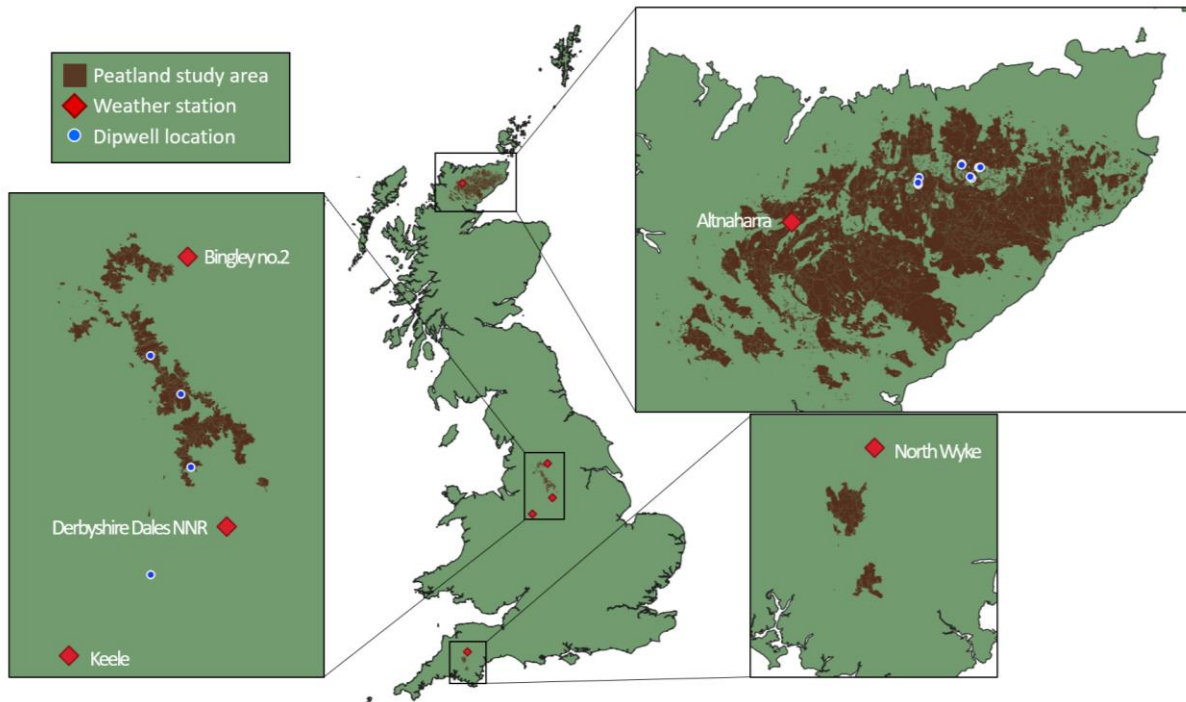
147 Two peatland WTD datasets were selected to validate the SAR data. The first, from sites  
148 across the Forsinard Flows RSPB reserve within the Flow Country, contains nine time series  
149 of WTD dynamics from peatland areas undergoing restoration or slope-matched control  
150 blanket bog areas. Water tables across the Forsinard Flows reserve were monitored using  
151 dipwells. The dipwells comprised auger holes cased with 32 mm polyvinyl chloride (PVC)  
152 pipe, with 4 rows lengthwise of 2 mm holes at 5 cm intervals and sealed at the bottom with a  
153 32 mm PVC plug. Dipwells were installed to 1 m below surface. Each dipwell was equipped  
154 with an Odyssey capacitance probe (1 m), with the logger body encased in a 30-40 cm  
155 section of 40 mm PVC piping secured to the 32 mm dipwell using a reducing coupler. This  
156 additional section ensured that the logger placement did not significantly reduce the internal  
157 volume of the dipwell. The height of the dipwell relative to the peat surface was measured

158 using 3 manual measurements to mm precision at the start of the monitoring period and  
159 checked at subsequent data download site visits. Water level data were captured at 30 min  
160 intervals, and for the purpose of the present work, calculated as daily averages to match the  
161 remotely sensed data. Each of the time series from the Forsinard Flows reserve dataset  
162 used in this study is an average of the data series from at least 3 dipwells within 30 m of  
163 each other across a site. A central point was used as the reference for downloading  
164 Sentinel-1 data.

165 The second dataset, from the Moors for the Future partnership, comprises four time series  
166 from individual dipwells across the Peak District, using daily averages of hourly  
167 observations. The dipwells consisted of a 110 cm PVC pipe sunk to 1 m below the surface,  
168 with holes drilled through the sides to allow water movement. In each dipwell a HOBO water  
169 level logger was suspended on a wire. At each site a second pressure logger was  
170 suspended in a PVC pipe above the surface, with holes drilled to allow movement of air, and  
171 the results used to calibrate the water pressure readings.

172 We were unable to access a WTD dataset covering Dartmoor, but the SAR backscatter  
173 method is calibrated to the Forsinard Flows reserve and Moors for the Future partnership  
174 datasets combined to minimise the effect of local variations.

175 The location and site descriptions for all selected time series are given in Table I, and the  
176 dipwell locations are shown in Figure 1.



177

178 *Figure 1 – Locations of the three peatland study areas, weather stations used in SAR*  
 179 *backscatter processing, and dipwell locations used to give WTD time series. MftF\_R is*  
 180 *located on peatland outside of the selected study area.*

181 *Table I – WTD time series used in this study. Locations for the sites comprising the*  
 182 *Forsinard Flows reserve dataset (ID beginning with F) are central point locations*  
 183 *representing the averaged dipwells. Locations with ID beginning with MftF are from the*  
 184 *Moors for the Future partnership dataset. Most of the Forsinard Flows reserve sites (except*  
 185 *F\_CON) were previously planted for commercial forestry, and are currently undergoing*  
 186 *restoration starting with tree felling.*

<b>ID</b>	<b>Location (WGS84)</b>	<b>Site description</b>	<b>Measurements time period</b>
F_CON	58.3719, -3.9639	Near-natural bog	20/07/2017 – 10/07/2018
F_CL_FTW	58.3853, -3.9612	Felled-to-waste in 2005-6	20/07/2017 – 10/07/2018



F_CL_BCFB	58.3756, -3.9647	Felled-to-waste in 2005-6, brash-crushing and furrow-blocking 2015-16	20/07/2017 – 10/07/2018
F_L_BCFB	58.3875, -3.7601	Felled-to-waste in 2005-6, brash-crushing and furrow-blocking 2017-18	20/07/2017 – 11/07/2018
F_L_FTW	58.3904, -3.7658	Felled-to-waste in 2005-6	18/07/2017 – 25/01/2018
F_R_BCFB	58.4093, -3.7344	Felled-to-waste 2010-11, brash-crushing and furrow-blocking 2014-15	18/07/2017 – 11/07/2018
F_R_FTW	58.4099, -3.7279	Felled-to-waste 2010-11	19/07/2017 – 11/07/2018
F_T_BCFB	58.4152, -3.7995	Felled-to-waste in 1998, brash-crushing and furrow-blocking in 2015-16	21/03/2017 – 12/07/2018
F_T_FTW	58.4135, -3.7998	Felled-to-waste in 1998	22/03/2017 – 12/07/2018
MftF_E	53.3826, -1.8554	Highly degraded with past gullies	09/12/2015 – 19/05/2018
MftF_H	53.5314, -1.8892	<i>Eriophorum vaginatum</i> dominated blanket bog, with <i>Sphagnum</i> present in small patches	11/09/2015 – 10/01/2018
MftF_M	53.6098, -1.9934	<i>Molinia</i> dominated blanket bog with some <i>Sphagnum</i> .	09/10/2015 – 01/08/2018

MftF_R	53.1636, -1.9925	Small but relatively intact area of bog. <i>Eriophorum vaginatum</i> dominated with <i>Sphagnum</i> . This area of bog is in a small dip between two drier slopes dominated (pre-fire) by dwarf shrubs. Fire in August 2018	13/10/2016 – 25/10/2018
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187

188 2.2. Synthetic Aperture Radar (SAR) data

189 Sentinel-1 GRD (Ground Range Detected) Interferometric Wide Swath data (spatial  
190 resolution of 10 by 10 m), were selected using Google Earth Engine (GEE) (Gorelick et al.,  
191 2017). GEE performs thermal noise removal, radiometric calibration, and terrain correction  
192 using a Digital Elevation Model on Sentinel-1 data, and completes the conversion from  
193 intensity to backscatter coefficient (in decibels, dB). Only images with VV polarisation on a  
194 descending pass were used to maintain consistency of imagery.

195 For comparison with the WTD datasets, the backscatter values of each image were  
196 averaged over a circular area of radius 50 m around the point of interest, to reduce speckle  
197 (interference) effects.

198 Processing detailed in sections 2.2.1., 2.2.2., and 2.2.3. was completed for each time series  
199 using R (R Core Team, 2017).

200 2.2.1. Weather filtering

201 Days with high rainfall (>20 mm) or frozen soil (<2°C) were removed following Bechtold *et al.*  
202 (2018), although due to data availability we used soil temperatures at 10 cm depth instead of  
203 5 cm. MIDAS CEDA (Met Office, 2012) datasets from the nearest weather station with  
204 appropriate records were used. The station used for the Forsinard Flows reserve dataset

205 was Altnaharra, and the Derbyshire Dales NNR weather station for the Moors for the Future  
206 partnership dataset (see Figure 1).

### 207 2.2.2. Angle correction

208 We found a negative correlation between incidence angle and SAR backscatter. This was  
209 corrected for by creating an individual linear model describing this relationship for each site,  
210 and subtracting this model from the dataset. This correction improved the correlations by an  
211 average of 8.6%. Previous studies have found more complicated correction systems give  
212 limited improvements in results in wetland environments, and so these were not considered  
213 here (Asmuß et al., 2019; Bechtold et al., 2018; Schlaffer et al., 2016).

### 214 2.2.3. Sine curve

215 We found that subtracting a sine curve from the SAR time series for each site improved the  
216 correlation with WTD data by a further 48.5% on average. The sine curve was fitted using  
217 both the Forsinard Flows reserve and Moors for the Future partnership datasets, and was  
218 described by the equation:

$$219 \quad Y = \sin ( 0.0173 \times ( \text{DoY} - 80 ) )$$

220 Where DoY is Day of Year. This sine curve is a proxy for annual vegetation growth, which  
221 can obscure the moisture content backscatter signal. Growing vegetation increases SAR  
222 backscatter (Baghdadi et al., 2009), and the sine curve therefore simulates the increase and  
223 decrease in backscatter with the growth and senescence of peatland vegetation.

224 Both the SAR backscatter data and the WTD data for each site were smoothed using the  
225 ksmooth function in R, with a bandwidth of 10. Figure 3 presents the SAR datasets resulting  
226 from the steps described in Section 2.2. in comparison to the WTD datasets.

### 227 2.3. Modelling spatial resilience

228 GEE was used to select and process the Sentinel-1 datasets as described in this section  
229 (see Figure 2). Peatland areas of interest were determined using the EDINA 2015 land cover  
230 map (Rowland et al., 2017, see Figure 1).

231 The SAR data was obtained following the same procedure as described in Section 2.2,  
232 filtered for weather conditions as described in section 2.2.1, and corrected for incidence  
233 angle as described in section 2.2.2. The sine curve determined in section 2.2.3. was then  
234 subtracted. Weather data from Altnaharra weather station was used for the Flow Country,  
235 North Wyke for Dartmoor, and Bingley no.2 for the Peak District (as the Derbyshire Dales  
236 NNR weather station was not operational after October 2018). Soil temperature data was not  
237 available from Bingley no.2 for 2019, so data from the Keele weather station was used to fill  
238 in (see Figure 1).

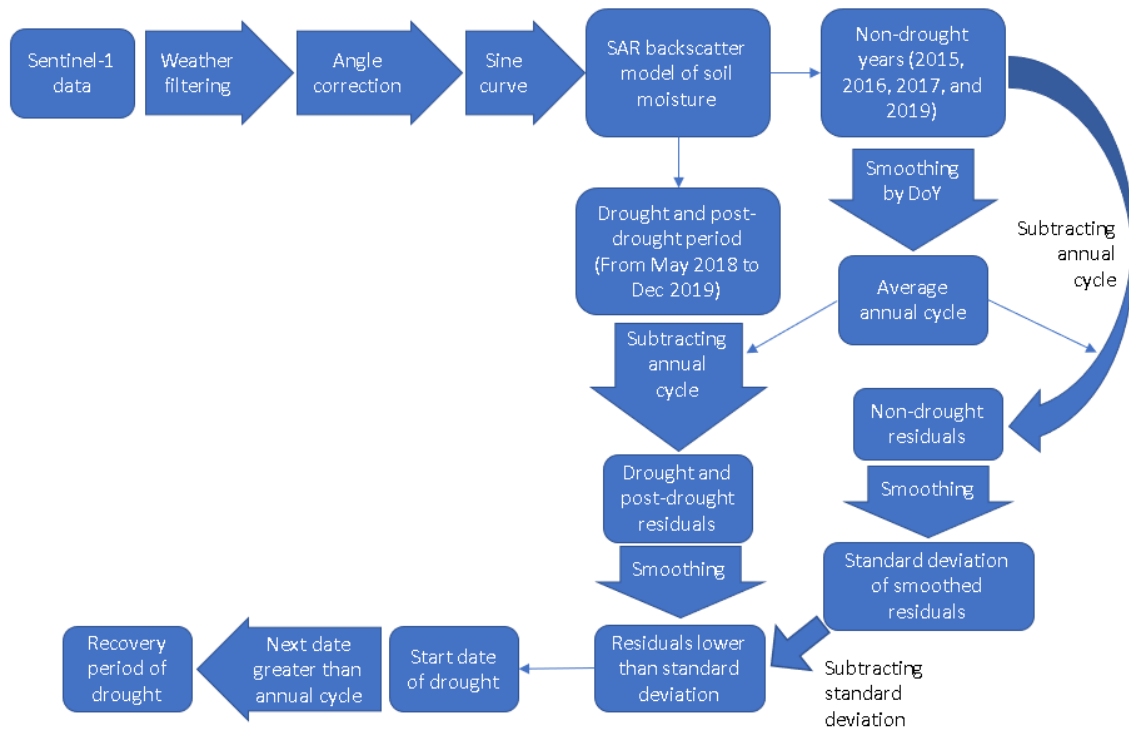
239 Sentinel-1 tiles covering the area of interest were selected using a central point rather than  
240 the entire site polygon, due to the computational limitations of GEE. This means that some of  
241 the outlying parts of the study areas have a lower frequency of data points than the central  
242 areas.

243 The 2018 drought was used as a study period, and the non-drought years were separated  
244 for creation of an average seasonal cycle. The non-drought years with available Sentinel-1  
245 data (2015 to 2017, and 2019) were used to create an annual average cycle of the soil  
246 moisture proxy using the mean of DoY values within 20 days of each date. This average  
247 seasonal cycle was subtracted from both the non-drought years and the drought-affected  
248 and post-drought period (May 2018 to Dec 2019) to give the residuals. The residuals  
249 therefore show whether a date was drier or wetter than the average for that DoY over the  
250 non-drought time period. The residuals of May, July, September, and November 2018 were  
251 averaged for presentation in Section 3.2 (see Figure 4). Using 2019 data as part of the  
252 annual cycle calculation leads to some overlap between the pre-drought and drought-  
253 affected data series. This is not ideal, but without the 2019 data included there were not  
254 enough DoY data points due to the recent launch dates of the Sentinel-1 satellites. Weather

255 and WTD fluctuations in previous years will also have impacted the annual cycle, and using  
256 the maximum data available minimises seasonal anomalies.

257 The residuals of both the non-drought years and the drought period were smoothed using  
258 the average of values within 20 days of each image to minimise the effect of outliers in the  
259 data series whilst retaining the trends. The standard deviation of the smoothed residuals of  
260 the non-drought period was calculated, and used to detect the starting point of the 2018  
261 drought at each pixel. The drought start point was considered to be the first instance after 1<sup>st</sup>  
262 May 2018 (to avoid anomalies earlier in the year that were not considered part of the study  
263 drought) when the residuals fell below the standard deviation of the smoothed non-drought  
264 period residuals. The next point when the smoothed residual was greater than the average  
265 annual cycle was then found, and the time difference between these two points was  
266 calculated to give the length of the drought recovery period at each pixel. If a value greater  
267 than the average annual cycle had not been reached after 500 days a value of 500 was  
268 assigned.

269 Results from this method cannot be assumed to be reliable over burnt peatland areas (see  
270 Section 4.1 for discussion). Some areas of the Peak District site are regularly burnt, and we  
271 have therefore ignored these areas in our analysis (see Figure 8).



272

273 *Figure 2 – Flow chart showing the process used to calculate the recovery period.*

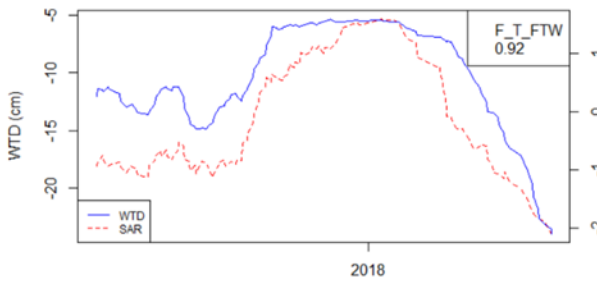
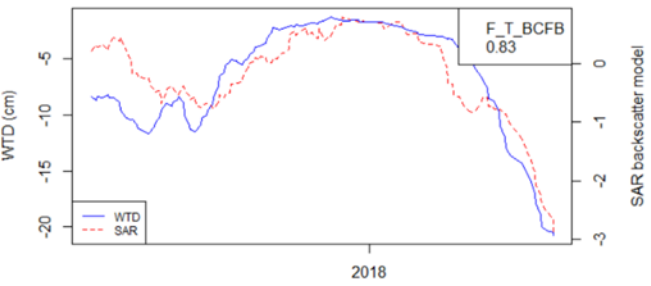
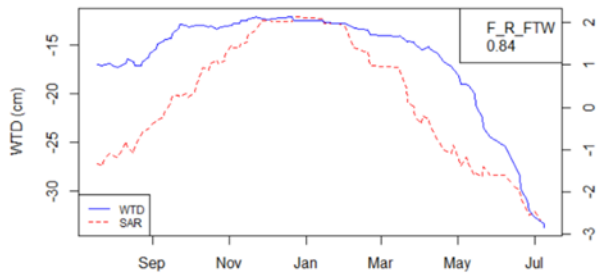
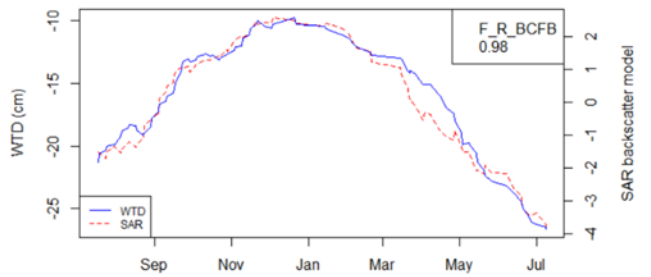
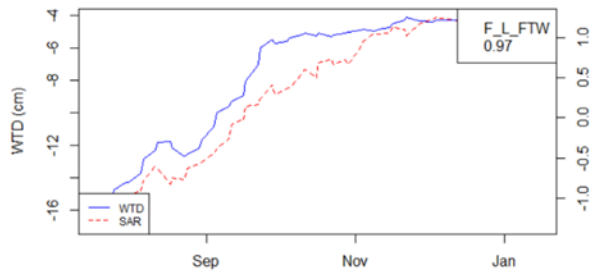
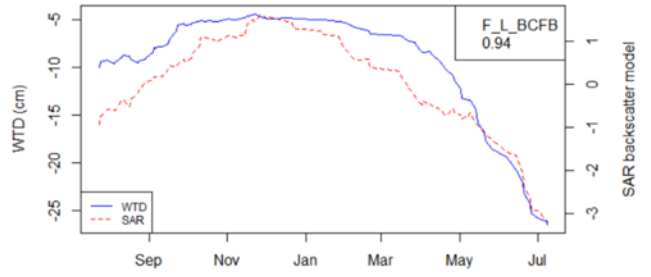
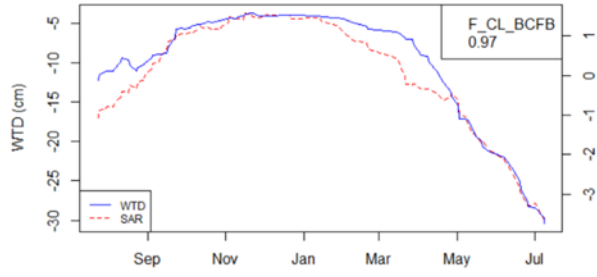
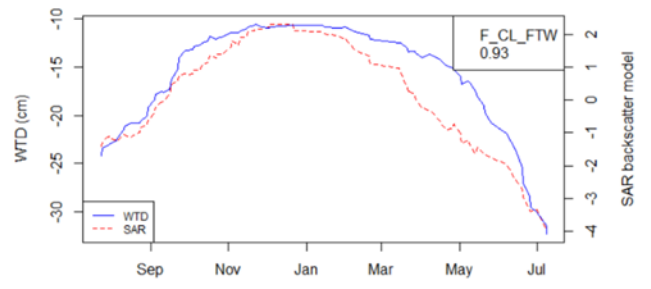
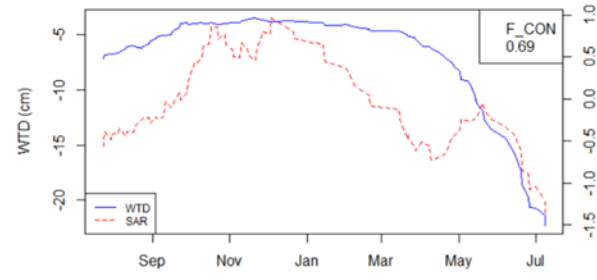
274 **3. Results**

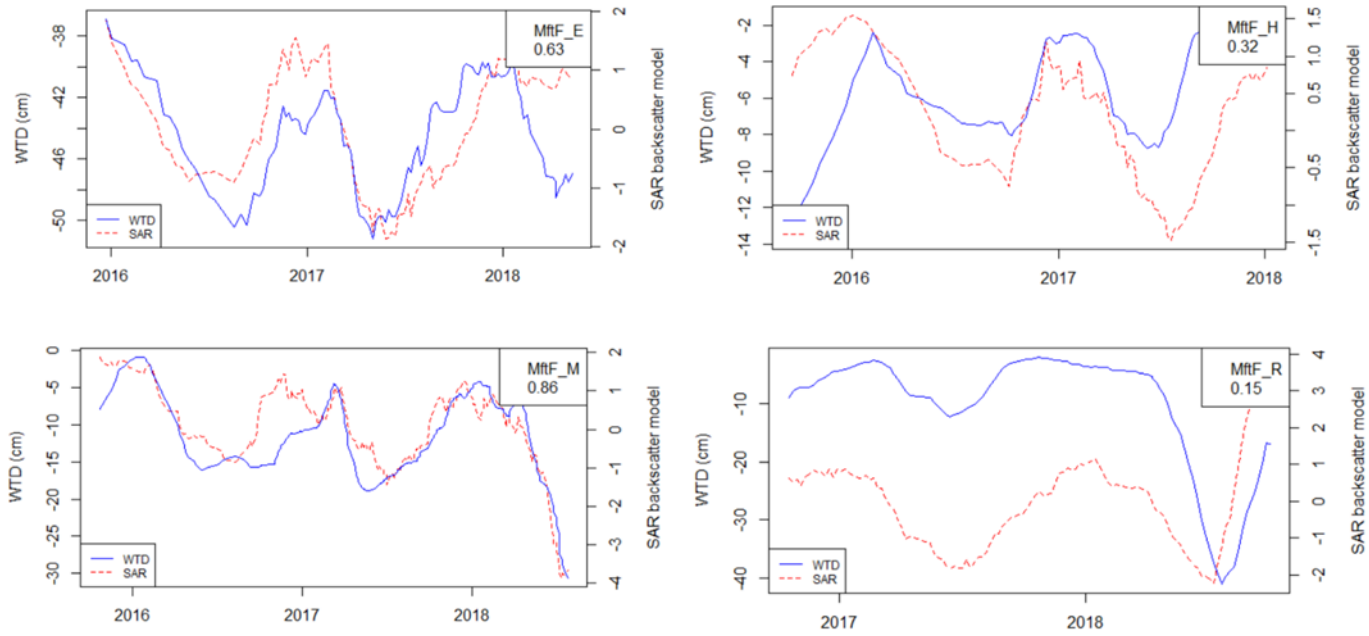
275 **3.1. SAR method**

276 The average Pearson's correlation between the smoothed WTD dynamics and the smoothed  
 277 SAR based method was  $0.77 \pm 0.26$  (see Figure 3).

278 Despite strong correlations for many of the sites, the relationship between WTD and the  
 279 SAR-based method is not consistent across the selected areas. Some sites, notably  
 280 F\_R\_BCFB and F\_R\_FTW, have higher SAR values in general than the other sites. The  
 281 MftF\_E site has much lower WTD values than the other sites, whilst F\_CON and MftF\_H  
 282 have high WTD values across the whole period.

283

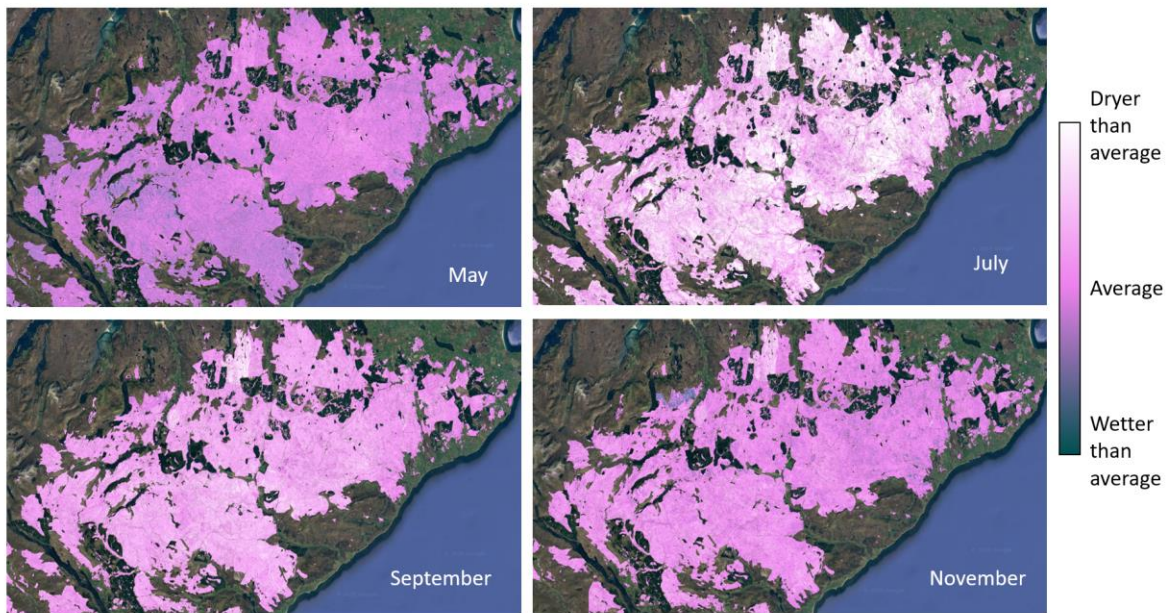




285

286 *Figure 3 – Smoothed WTD (left-hand axes) and smoothed SAR backscatter (right hand*  
 287 *axes) for all sites. All axes are varied to fit the data. Pearson’s correlation values are given*  
 288 *with the name of the site in the top right corner of each graph.*

289 3.2. Peatland resilience



290



291 *Figure 4 – SAR-based model residuals showing the Flow Country during the 2018 drought*  
292 *period, May to November.*

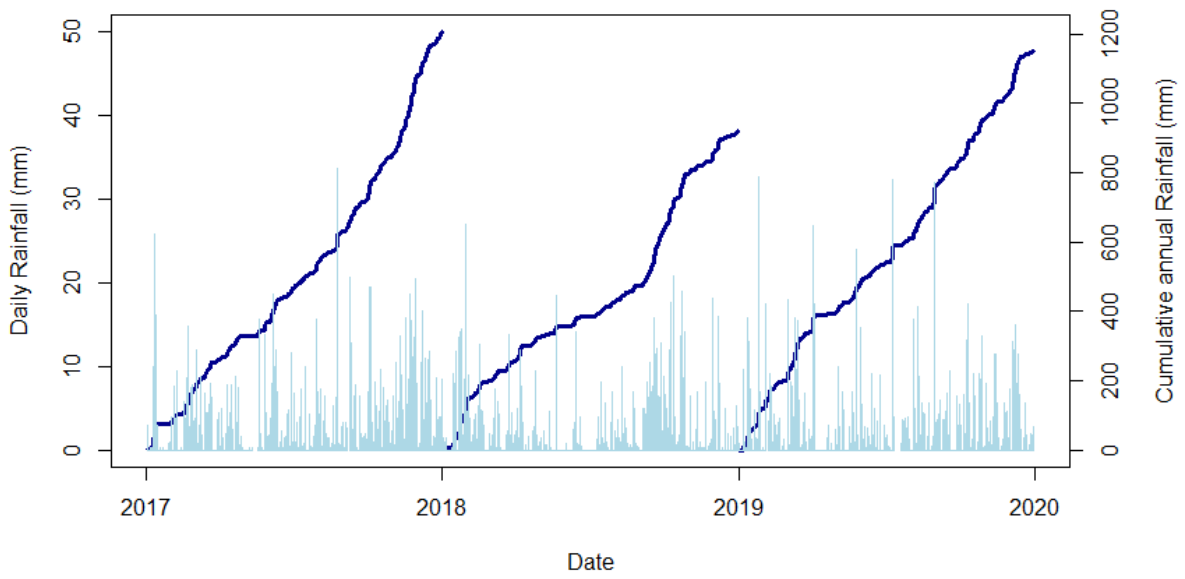
293 Figure 4 shows the progression of the 2018 drought in the Flow Country peatland area. The  
294 site was noticeably drier than previous years in July, and some areas were still drier than  
295 average in September and November.

296 Figure 5 shows daily and cumulative annual rainfall totals for weather stations in the vicinity  
297 of the selected peatland areas. Rainfall for the Flow Country (Figure 5A) was lower in 2018  
298 than either the preceding or following year. Dartmoor (Figure 5B), however, shows similar  
299 rainfall totals for all three years, although the 2018 drought is evident as a plateau in the  
300 cumulative data. The Peak District (Figure 5C) has similar totals in 2017 and 2018, but  
301 noticeably more rain in 2019.

302 Figures 6, 7, and 8 show the length of the recovery period from the 2018 drought in the Flow  
303 Country, Dartmoor, and the Peak District respectively. The selected larger-scale sections in  
304 these figures show areas of particular interest. Some, such as 6A, 7B, and 8A, show areas  
305 that were affected by wildfire in 2018 or 2019. Other areas were selected because they show  
306 noticeably longer recovery times than surrounding areas; some of these also have evidence  
307 of drainage ditches, such as 6B and C, and others are known to have experienced gullying,  
308 such as 8B and C.

A

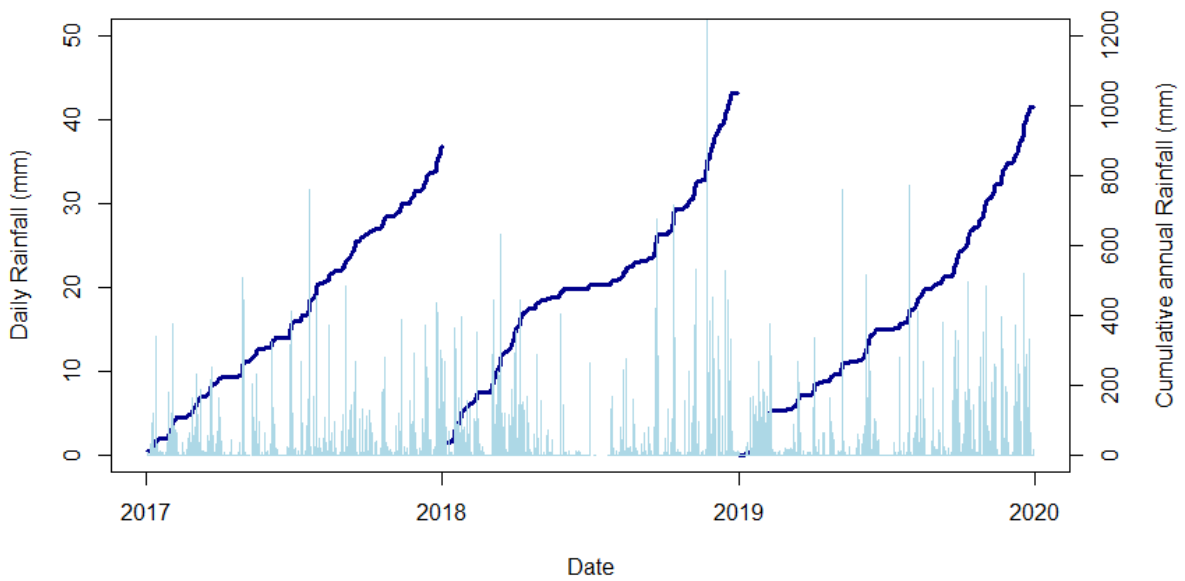
### Flow Country



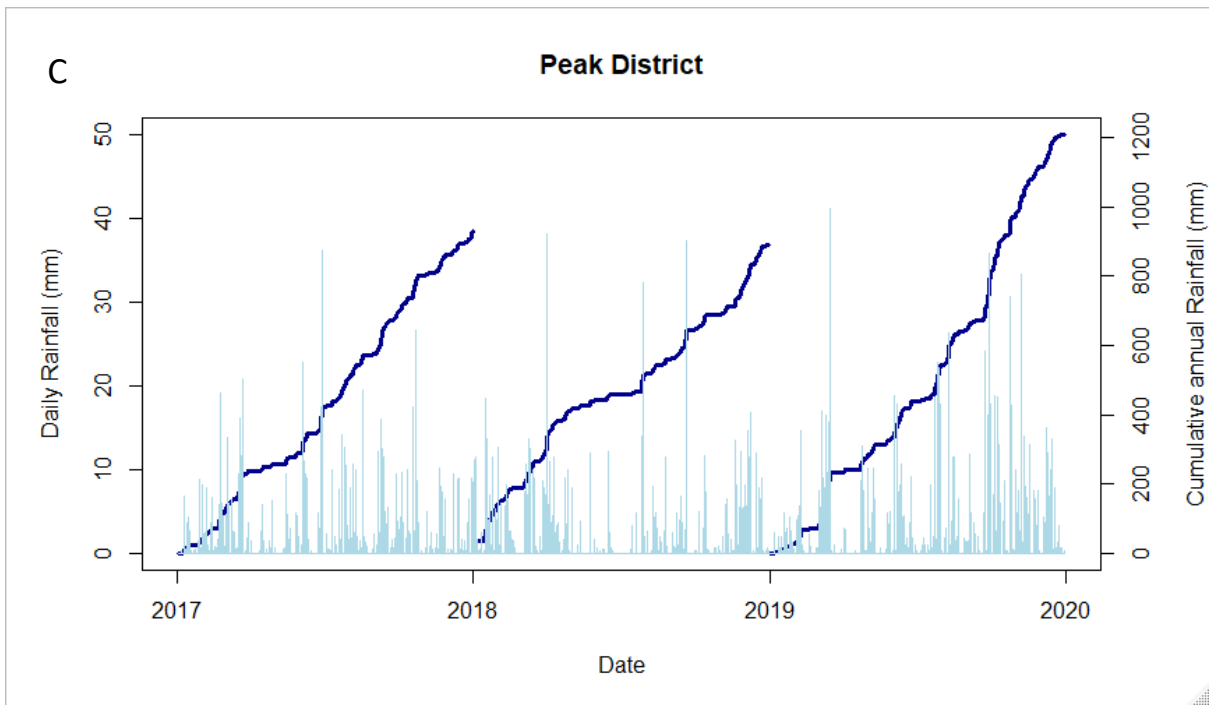
309

B

### Dartmoor



310



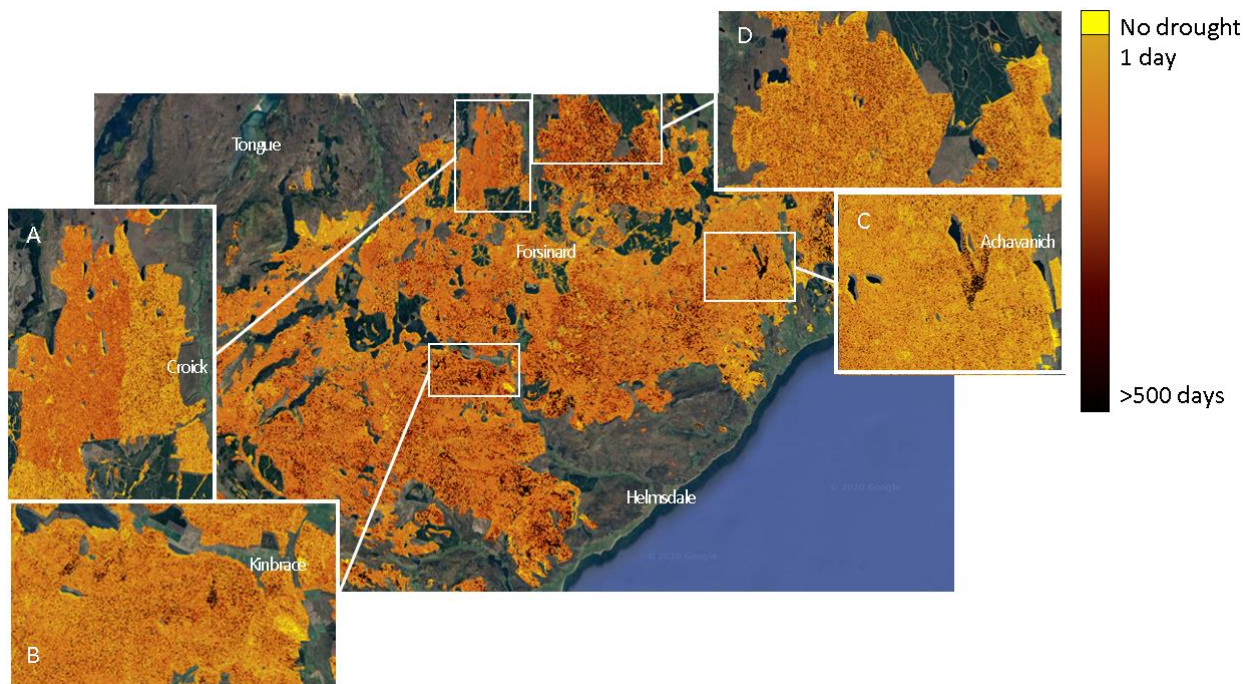
311

312 *Figure 5 – Rainfall at weather stations in the vicinity of the three selected peatland areas.*

313 *Figure A shows rainfall data from the Altnaharra station, B from North Wyke, and C from*

314 *Bingley no2.*

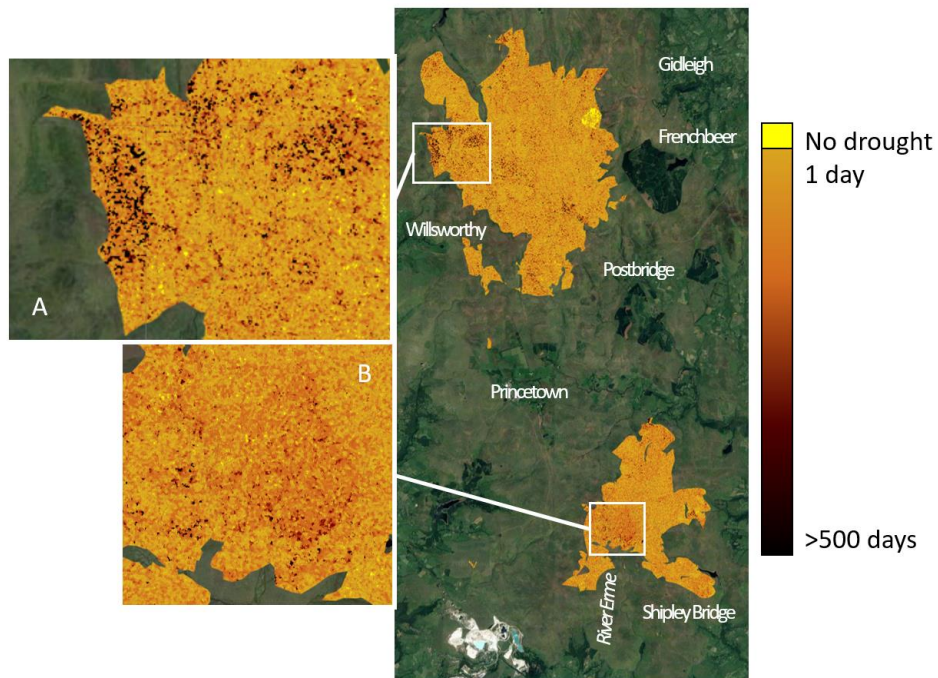
315



316

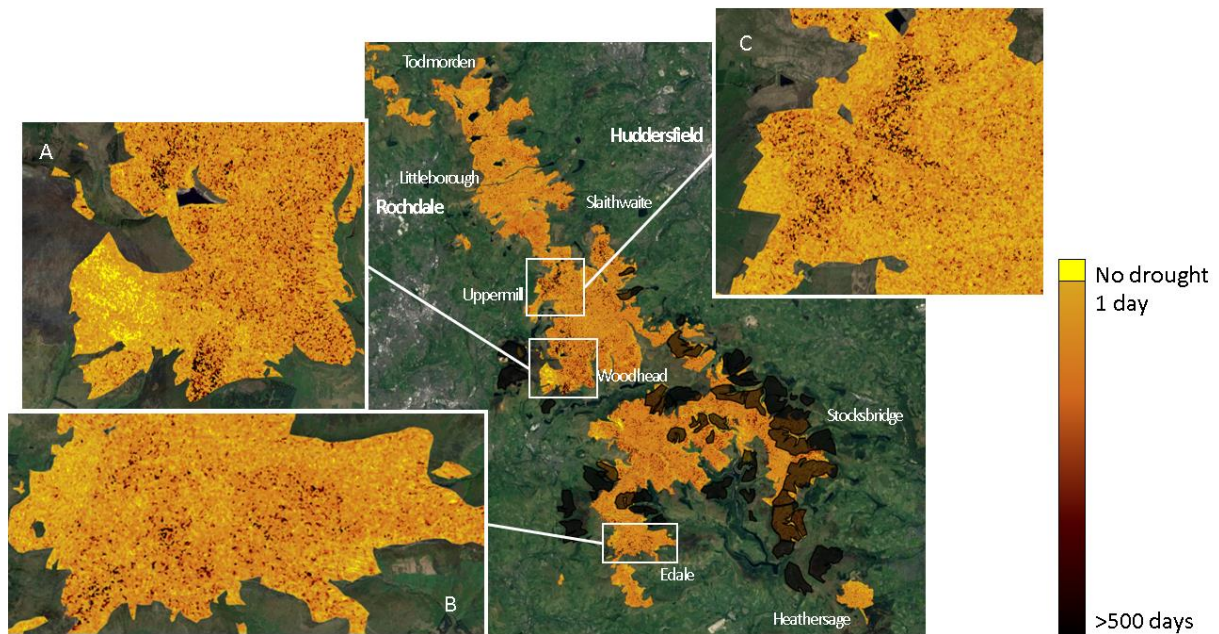
317 *Figure 6 - Length of drought recovery period for the peatland area of the Flow Country. 6A*  
 318 *shows the area affected by the Melvich wildfire in May 2019. 6B has a lot of drainage, both*  
 319 *natural watercourses and some man-made channels, and 6C has visible drains. 6D shows*  
 320 *an area of generally low resilience, although the reasons for this are unclear.*

321



322

323 *Figure 7 - Length of drought recovery period for the peatland area of Dartmoor. 7A shows an*  
 324 *area to the East of Lydford village, which is detected as being less resilient than the*  
 325 *surrounding area. 7B shows an area near the source of the River Erme which burnt in a*  
 326 *wildfire in April 2019.*



327

328 *Figure 8 - Length of drought recovery period for the peatland areas of the Peak District.*  
 329 *Areas with prescribed burn management have been visually identified and are shown as*  
 330 *semi-transparent black polygons; the results should not be considered reliable in these*  
 331 *areas. 8A was affected by the Saddleworth wildfire in June 2018. 8B shows the Kinder Scout*  
 332 *area, which has extensive gullying, but also much restoration work done over the previous*  
 333 *decade (Alderson et al., 2019). 8C also has extensive gullying and had gully-blocking and*  
 334 *revegetation work done in 2016*

#### 335 4. Discussion

##### 336 4.1. Using SAR to estimate WTD

337 As Bechtold *et al.* (2018) found, SAR backscatter can give reasonable agreement with  
 338 temporal variation in WTD, but cannot reliably detect spatial differences. This is particularly  
 339 noticeable for sites F\_R\_FTW and F\_R\_BCFB, both of which have large micro-topographical  
 340 variations due to a relic furrow and ridge system. This micro-topography increases the SAR  
 341 backscatter values, giving a higher y-axis intersect than other Forsinard Flows reserve sites.  
 342 The lack of detectable spatial difference is also evident at site MftF\_E, which has a low  
 343 average WTD but similar SAR backscatter values compared to the other Moors for the



344 Future partnership sites. The method used in this study, which compares anomalies in  
345 residuals to the average seasonal cycle of each pixel, allows useful comparisons between  
346 areas to be made despite the SAR backscatter data being affected by topography and other  
347 factors, as temporal variation in peatland surface roughness is slow compared to soil  
348 moisture fluctuations (Millard & Richardson, 2018). Similar to Bechtold *et al.* (2018) we found  
349 that the most natural site in the Forsinard Flows reserve dataset (F\_CON) had the least  
350 agreement with the SAR data, and the most natural Moors for the Future partnership site  
351 (MftF\_H) also had a relatively low correlation. This may be due to the natural sites being  
352 saturated with only minimal fluctuation in WTD for much of the year, or due to the presence  
353 of pools (see Section 4.1.1.).

#### 354 4.1.1. Limitations of using SAR to estimate WTD

355 Some peatland sites have areas of open water in the form of pools, which have a different  
356 relationship with SAR compared to soil moisture and so could disrupt the signal (Kasischke  
357 *et al.*, 2009; Schlaffer *et al.*, 2016). Several studies have considered the effect of inundation  
358 on SAR backscatter (Kasischke *et al.*, 2009; Schlaffer *et al.*, 2016), and have found that  
359 standing water generally reduces the backscatter signal by providing a reflective surface  
360 (Bartsch *et al.*, 2012). The peatland sites considered in this study are unlikely to experience  
361 complete inundation due to their elevation and topography, but there is standing water  
362 present in pools across the Forsinard Flows reserve in the most natural sites, and during  
363 winter months in some of the restored sites in the former planting furrows, which may affect  
364 the average signal. Many of the pools dried up or at least reduced significantly in size during  
365 the peak of the drought, and the resulting fluctuation in SAR backscatter may have affected  
366 the recovery estimates.

367 The results from site MftF\_R suggest that fires on peatland can affect the SAR signal in  
368 ways which are not yet fully understood. At this site there was a fire in August 2018, and  
369 there is a corresponding increase in SAR backscatter following this event. Due to the limited  
370 WTD data available from burnt peatland sites, we cannot at this stage say with certainty

371 whether the post-fire changes in WTD shown using our method are reliable, or whether the  
372 SAR data is picking up signals from other changes such as vegetation loss. Zhou *et al.*  
373 (2019), for example, found that burnt tundra sites had higher backscatter, in line with our  
374 results from the MftF\_R site. This means that our method should not be applied to sites  
375 which are regularly burnt to encourage heather (*Calluna vulgaris*) growth. Some studies  
376 have found that WTD is closer to the surface after fire (Clay *et al.*, 2009), whilst others show  
377 that it is deeper (Holden *et al.*, 2015). Brown *et al.* (2015) suggest that this disparity may be  
378 due to the dominant species on the peatland, with feather moss increasing hydrophobicity  
379 and therefore limiting evaporation after fire (Kettridge *et al.*, 2014).

380 It is important to consider that WTD is an indirect proxy for soil surface moisture, and the  
381 accuracy of the model could perhaps be improved if compared against direct measurements  
382 of soil moisture, which are unfortunately rarely available (and often inaccurate in very wet  
383 peatland soils). It is difficult to calculate soil surface moisture from WTD due to the specific  
384 yield, the amount of water needed to raise the water table by a given amount in a given peat  
385 volume, which varies across peat types due to the porosity. Where peat is highly  
386 decomposed, the porosity and therefore the specific yield is low, leading to large WTD  
387 fluctuations (Price, 1996). Capillary processes in *Sphagnum* can also affect the relationship  
388 between soil surface moisture and WTD, as can aspect, slope, and vegetation. The WTD  
389 datasets used for the method development in this study were mostly only available up to the  
390 middle of the 2018 drought, and did not cover the full recovery period. Future work in this  
391 area could consider how extreme droughts such as the 2018 event affect the relationship  
392 between WTD and soil moisture. It may also be the case that the depth of SAR penetration  
393 into the peat is affected by local variations in bulk density, and so the relationship between  
394 SAR and soil moisture might also be variable depending on the depth at which soil moisture  
395 is measured.

396 The effects of drainage on WTD may be very localised (Holden et al., 2011) and the speckle  
397 (interference) inherent in SAR data may mask these small-scale variations, particularly when  
398 using SAR data with a coarse spatial resolution.

#### 399 4.2. Peatland resilience

400 Locations where the drought persisted for longer periods of time are understood to be less  
401 resilient than areas which recovered faster. These areas may be most vulnerable to the  
402 future effects of climate change, notably increasing drought and heatwave events and  
403 severities. This method may also be useful as a way of locating areas which could benefit  
404 most from peatland restoration, especially where areas of lower resilience correlate with  
405 visible drains on the peat surface.

406 Many of the areas which are shown to be least resilient in the Flow Country and the Peak  
407 District have evidence of high drainage, both natural and due to human land management  
408 (see Figures 6 and 8).

409 Both areas highlighted on Dartmoor (Figures 7A and B) have evidence of peatland cuttings,  
410 gullies and erosion (Carless et al., 2019), but not noticeably more so than other areas of  
411 Dartmoor. Figure 7B, near the source of the River Erme, was affected by wildfire in 2019  
412 (see Section 4.2.1.), whilst the reasons for the longer recovery times seen in Figure 7A may  
413 be due to its peatland-edge location. The area to the left of Figure 7A that shows longer  
414 drought recovery is an area of high moorland with steep slopes to either side, which may  
415 increase drainage. The peat is also potentially thinner there than in the centre of the peat  
416 area.

417 Figures 8B and C show areas which are known to have had extensive gullying, but are now  
418 being restored through gully-blocking. Gullying is a form of peatland erosion which can be  
419 initiated through the removal of stabilising surface vegetation by fire, pollution, or  
420 overgrazing (Evans & Warburton, 2007). Other areas of low resilience may also be affected



421 by erosion, due to management decisions or other factors, that is not visible from satellite  
422 imagery.

423 The area of the Peak District shown in Figure 8C was subject to gully blocking in 2016, and  
424 shows a drop in the SAR backscatter signal at around the same time. This may be due to  
425 the sudden increase in standing water within the blocked gullies causing a decrease in  
426 backscatter due to the reflective surface. The model shows slow recovery in this area, which  
427 may be exaggerated due to the seasonal cycle being calculated from both pre- and post-  
428 restoration SAR data. The recovery is likely also slow in this area because there would not  
429 have been time for the restoration works to be fully effective in recovering peatland function  
430 and reversing lower resilience before the 2018 drought. Kinder Scout (Figure 8B), which was  
431 badly degraded but had earlier restoration work done (Alderson et al., 2019), shows slow  
432 recovery but is not dramatically different from surrounding areas. It may be the case that  
433 more recently restored areas have lower resilience because they are not yet in a stable  
434 state, and without maintenance and monitoring could again start to degrade. This  
435 corresponds with Holden et al. (2011) who found that the hydrology of a peatland area with  
436 blocked drains had results between those of a natural and a drained site for several  
437 hydrological indicators. Their drain-blocked site had been under restoration for 6-7 years, but  
438 the hydrological processes had not yet fully recovered.

439 Previous studies have found evidence that peatlands become less resilient as compound  
440 disturbances increase positive feedbacks (Sherwood et al., 2013; Swindles et al., 2016).  
441 Areas which are affected by a combination of anthropogenic disturbances such as drainage  
442 and peat cutting, and natural disturbances such as droughts and fires, are likely to be less  
443 resilient than areas which have only been subject to one form of disturbance. Our findings  
444 show that areas which have been subject to drainage, and areas with severe erosion in the  
445 form of gullying, had lower resilience to drought than areas with less evidence of  
446 disturbance. This supports the concept of compound disturbances leading to lower  
447 resilience.

448 Increases in the frequency and magnitude of pulse-disturbances can lead to increased  
449 variability in ecosystem functions, particularly where resilience is low, and thereby lower  
450 stability over the longer term (Zelnik et al., 2018). An increase in drought severity and  
451 frequency due to climate change could therefore lead to greater variability in water levels in  
452 areas where resilience is low, as the time taken for recovery may become longer than the  
453 intervals between drought events. This could lead to a less stable ecosystem and potentially  
454 a shift towards an alternative state (Worrall et al., 2006).

#### 455 4.2.1. Limitations in monitoring peatland resilience through drought recovery

456 Differing recovery timescales are in part due to varying weather conditions and precipitation.  
457 Hence, the three peatland areas considered in this study cannot be directly compared  
458 against each other as they experienced different weather conditions during the recovery  
459 period (see Figure 5). Recovery patterns within each of the three areas are likely to be more  
460 useful for considering local variations in resilience, particularly where there are large  
461 differences within a small spatial area. The effects of wildfire in this method are complex. As  
462 stated in Section 4.1.1., it appears that fire increases SAR backscatter. This means that the  
463 Saddleworth site (Figure 8A) had higher than normal residuals after the fire in June 2018 at  
464 the peak of the drought, meaning that the drought effect is not recorded in the model. The  
465 areas affected by fire in spring 2019 (Figure 6A in the Flow country and 7B on Dartmoor)  
466 show slow but relatively comparable recovery times compared to the surrounding area. The  
467 higher post-fire results in 2019 affect the calculated seasonal cycle, thereby potentially  
468 exaggerating the effects of the 2018 drought, as can be seen in the Melvich wildfire area of  
469 Figure 6A.

470 Measuring recovery of water levels using SAR backscatter does not give a complete picture  
471 of peatland resilience to drought, as there may be chemical and structural changes which  
472 occur within the peat during the disturbance event but persist beyond the recovery of water  
473 levels (Worrall et al., 2006).

#### 474 4.4. Future directions

475 There are several areas of future research which could improve this method and expand its  
476 applicability. Considering limitations of the SAR method for estimating WTD identified the  
477 variable relationship between WTD and soil surface moisture as a challenge to gaining  
478 reliable WTD from SAR backscatter. Future work into the interactions between soil surface  
479 moisture and WTD with relation to specific yield would improve our understanding of how  
480 these factors are interrelated. Such work should explicitly consider how these relationships  
481 change under extreme conditions such as drought. The variations in WTD and SAR  
482 backscatter following fire could also be a target for future research. It seems likely that fire  
483 causes the SAR backscatter signal to lose correlation with soil moisture and WTD as other  
484 factors such as vegetation loss and surface roughness gain more influence (Zhou et al.,  
485 2019).

486 With regards to using SAR backscatter to monitor resilience, future work should consider the  
487 perturbation effect size (severity of drought) as well as the recovery time. This would make it  
488 possible to compare resilience between peatland areas in different parts of the country and  
489 internationally (De Keersmaecker et al., 2015). In the future, SAR backscatter could be  
490 considered as part of a range of measures to estimate peatland resilience, some of which  
491 would give more information over longer timescales. This would give a greater  
492 understanding of the stability of peatland ecosystems under climate change.

#### 493 4.5. Wider applicability

494 Using SAR backscatter as a measure of below-ground (hydrological) resilience has the  
495 potential to be applied to peatlands, and indeed other ecosystems, around the world. Using  
496 SAR to estimate WTD in highly organic soils has already been shown to give good results on  
497 sites across Germany (Asmuß et al., 2019; Bechtold et al., 2018), and it is therefore likely  
498 that using this method to monitor resilience following drought would also be successful in  
499 those ecosystems. In some landscapes, however, other factors affecting SAR backscatter

500 would need to be accounted for. In particular, areas subject to inundation would require the  
501 backscatter effects of flooding to be taken into account (Kasischke et al., 2009; Schlaffer et  
502 al., 2016). In ecosystems with different vegetation compositions, particularly treed areas, the  
503 SAR signal might be obstructed by the canopy, meaning that below-ground measures of  
504 resilience may not be achievable using this method (Millard & Richardson, 2018). The use of  
505 SAR backscatter is also complicated by the presence of permafrost, which may be a  
506 consideration when applying methods such as this to peatlands in the far north (Du et al.,  
507 2019). In all cases where this method for estimating resilience could be applied we  
508 recommend first validating the relationship of SAR and WTD, or soil moisture if available,  
509 with ground data.

510 In ecosystems where SAR backscatter has been shown to give reliable estimates of  
511 WTD/soil surface moisture, there are other applications of this technique besides monitoring  
512 resilience following drought recovery. One potential use could be to use a similar method to  
513 monitor peatland restoration success, by analysing whether measures such as drain-  
514 blocking have been successful in raising water tables across large areas without the need to  
515 invest in a significant number of replicate water table monitoring devices.

516 Although using methods such as this can give useful insights into peatland resilience, the  
517 decisions which are made using this understanding are not necessarily straightforward.  
518 Chambers et al. (2019) discussed the concept of 'coerced resilience', where an ecosystem is  
519 maintained by anthropogenic intervention. In such cases, which are likely to become more  
520 common due to climate change making certain ecosystems increasingly unstable, resilience  
521 is lost and the only way to maintain the preferred state is through human input. In some  
522 situations a degraded ecosystem is more resilient than the pristine ecosystem state (Côté &  
523 Darling, 2010). This may be the case in some peatland environments where management  
524 stressors have already forced the system into an alternative state, which is more resilient to  
525 both anthropogenic and climatic disturbances. In such a scenario, decisions must be made

526 as to whether it is worth investing in maintaining or restoring an ecosystem state which may  
527 be less resilient to future climate change.

## 528 5. Conclusions

529 In this study we developed a method using Sentinel-1 SAR data to estimate a peatland soil  
530 surface moisture proxy, which had an average Pearson's correlation of 0.77 when compared  
531 to WTD data. This method was used to derive the residual variation in the soil moisture  
532 proxy after the seasonal trend had been removed at three peatland areas in the UK. These  
533 residuals were used to assess the severity of the 2018 drought and the time period of  
534 recovery across the three sites.

535 We suggest that the areas which experienced longer recovery periods from the 2018  
536 drought are likely to be more vulnerable to future climate change effects. The results  
537 confirmed that there are clear interactions between peatland resilience and human activity,  
538 and in particular strong links between peatland drainage and recovery from drought. This  
539 supports the theory that compound disturbances weaken peatland resilience.

540 Our results should be useful for land managers in identifying areas which would benefit most  
541 from targeted restoration measures. The method could also in future be adapted to monitor  
542 ongoing restoration work. Future work should consider the relationship between peatland  
543 fires, soil surface moisture, and SAR data, in order to facilitate remote sensing studies of  
544 peatland resilience over areas which are regularly burnt for heather management, or which  
545 have experienced wildfire. A stronger understanding of the link between WTD and soil  
546 moisture in peatlands would also help to improve the validation of SAR data as a proxy for  
547 soil surface moisture, particularly under extreme conditions.

548 The method developed in this study can be used to provide large scale estimates of  
549 peatland resilience from freely available satellite data. This method has the potential to be  
550 used to estimate resilience in peatlands across the northern hemisphere, although further

551 validation would be needed on peatland areas with differing vegetation or underlain by  
552 permafrost.

553

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567

#### 568 References

- 569 Alderson, D. M., Evans, M. G., Shuttleworth, E. L., Pilkington, M., Spencer, T., Walker, J., &  
570 Allott, T. E. H. (2019). Trajectories of ecosystem change in restored blanket peatlands.  
571 *Science of the Total Environment*, 665, 785–796.  
572 <https://doi.org/10.1016/j.scitotenv.2019.02.095>
- 573 Asmuß, T., Bechtold, M., Tiemeyer, B., Asmuß, T., Bechtold, M., & Tiemeyer, B. (2019). On  
574 the Potential of Sentinel-1 for High Resolution Monitoring of Water Table Dynamics in  
575 Grasslands on Organic Soils. *Remote Sensing*, 11(14), 1659.  
576 <https://doi.org/10.3390/rs11141659>
- 577 Babaeian, E., Sadeghi, M., Jones, S. B., Montzka, C., Vereecken, H., & Tuller, M. (2019).  
578 Ground, Proximal and Satellite Remote Sensing of Soil Moisture. *Reviews of*  
579 *Geophysics*, 57(2), 2018RG000618. <https://doi.org/10.1029/2018RG000618>
- 580 Baghdadi, N., Boyer, N., Todoroff, P., El Hajj, M., & Bégué, A. (2009). Potential of SAR  
581 sensors TerraSAR-X, ASAR/ENVISAT and PALSAR/ALOS for monitoring sugarcane  
582 crops on Reunion Island. *Remote Sensing of Environment*, 113(8), 1724–1738.  
583 <https://doi.org/10.1016/J.RSE.2009.04.005>
- 584 Bartsch, A., Trofaier, A. M., Hayman, G., Sabel, D., Schlaffer, S., Clark, D. B., & Blyth, E.  
585 (2012). Detection of open water dynamics with ENVISAT ASAR in support of land  
586 surface modelling at high latitudes. *Biogeosciences*, 9(2), 703–714.  
587 <https://doi.org/10.5194/bg-9-703-2012>
- 588 Bastos, A., Ciais, P., Friedlingstein, P., Friedlingstein, P., Sitch, S., Pongratz, J., Pongratz,  
589 J., Fan, L., Wigneron, J. P., Weber, U., Reichstein, M., Fu, Z., Anthoni, P., Arneeth, A.,  
590 Haverd, V., Jain, A. K., Joetzjer, E., Knauer, J., Lienert, S., ... Zaehle, S. (2020). Direct  
591 and seasonal legacy effects of the 2018 heat wave and drought on European  
592 ecosystem productivity. *Science Advances*, 6(24), eaba2724.

- 593 <https://doi.org/10.1126/sciadv.aba2724>
- 594 Bechtold, M., Schläffer, S., Tiemeyer, B., De Lannoy, G., Bechtold, M., Schläffer, S.,  
595 Tiemeyer, B., & De Lannoy, G. (2018). Inferring Water Table Depth Dynamics from  
596 ENVISAT-ASAR C-Band Backscatter over a Range of Peatlands from Deeply-Drained  
597 to Natural Conditions. *Remote Sensing*, *10*(4), 536. <https://doi.org/10.3390/rs10040536>
- 598 Brown, L. E., Holden, J., Palmer, S. M., Johnston, K., Ramchunder, S. J., & Grayson, R.  
599 (2015). *Effects of fire on the hydrology, biogeochemistry, and ecology of peatland river*  
600 *systems*. <https://doi.org/10.1086/683426>
- 601 Carless, D., Luscombe, D. J., Gatis, N., Anderson, K., & Brazier, R. E. (2019). Mapping  
602 landscape-scale peatland degradation using airborne lidar and multispectral data.  
603 *Landscape Ecology*, *34*(6), 1329–1345. <https://doi.org/10.1007/s10980-019-00844-5>
- 604 Chambers, J. C., Allen, C. R., & Cushman, S. A. (2019). Operationalizing Ecological  
605 Resilience Concepts for Managing Species and Ecosystems at Risk. *Frontiers in*  
606 *Ecology and Evolution*, *7*, 241. <https://doi.org/10.3389/fevo.2019.00241>
- 607 Clark, J., Gallego-Sala, A., Allott, T., Chapman, S., Farewell, T., Freeman, C., House, J.,  
608 Orr, H., Prentice, I., & Smith, P. (2010). Assessing the vulnerability of blanket peat to  
609 climate change using an ensemble of statistical bioclimatic envelope models. *Climate*  
610 *Research*, *45*, 131–150. <https://doi.org/10.3354/cr00929>
- 611 Clay, G. D., Worrall, F., Clark, E., & Fraser, E. D. G. (2009). Hydrological responses to  
612 managed burning and grazing in an upland blanket bog. *Journal of Hydrology*, *376*(3–  
613 4), 486–495. <https://doi.org/10.1016/J.JHYDROL.2009.07.055>
- 614 Côté, I. M., & Darling, E. S. (2010). Rethinking Ecosystem Resilience in the Face of Climate  
615 Change. *PLoS Biology*, *8*(7), e1000438. <https://doi.org/10.1371/journal.pbio.1000438>
- 616 De Keersmaecker, W., Lhermitte, S., Tits, L., Honnay, O., Somers, B., & Coppin, P. (2015).  
617 A model quantifying global vegetation resistance and resilience to short-term climate  
618 anomalies and their relationship with vegetation cover. *Global Ecology and*  
619 *Biogeography*, *24*(5), 539–548. <https://doi.org/10.1111/geb.12279>
- 620 Díaz-Delgado, R., Lloret, F., Pons, X., & Terradas, J. (2002). SATELLITE EVIDENCE OF  
621 DECREASING RESILIENCE IN MEDITERRANEAN PLANT COMMUNITIES AFTER  
622 RECURRENT WILDFIRES. *Ecology*, *83*(8), 2293–2303. [https://doi.org/10.1890/0012-9658\(2002\)083\[2293:SEODRI\]2.0.CO;2](https://doi.org/10.1890/0012-9658(2002)083[2293:SEODRI]2.0.CO;2)
- 624 Du, J., Watts, J. D., Jiang, L., Lu, H., Cheng, X., Duguay, C., Farina, M., Qiu, Y., Kim, Y.,  
625 Kimball, J. S., & Tarolli, P. (2019). Remote Sensing of Environmental Changes in Cold  
626 Regions: Methods, Achievements and Challenges. *Remote Sensing*, *11*(16), 1952.  
627 <https://doi.org/10.3390/rs11161952>
- 628 Evans, M., & Warburton, J. (2007). Geomorphology of Upland Peat. In M. Evans & J.  
629 Warburton (Eds.), *Geomorphology of Upland Peat: Erosion, Form and Landscape*  
630 *Change*. Blackwell Publishing Ltd. <https://doi.org/10.1002/9780470798003>
- 631 Gallego-Sala, A. V., Clark, J. M., House, J. I., Orr, H. G., Prentice, I. C., Smith, P., Farewell,  
632 T., & Chapman, S. J. (2010). Bioclimatic envelope model of climate change impacts on  
633 blanket peatland distribution in Great Britain. *Climate Research*, *45*(1), 151–162.  
634 <https://doi.org/10.3354/cr00911>
- 635 Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017).  
636 Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote*  
637 *Sensing of Environment*, *202*, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- 638 Gorham, E. (1991). Northern Peatlands: Role in the Carbon Cycle and Probable Responses

- 639 to Climatic Warming. *Ecological Applications*, 1(2), 182–195.  
640 <https://doi.org/10.2307/1941811>
- 641 Hillebrand, H., & Kunze, C. (2020). Meta-analysis on pulse disturbances reveals differences  
642 in functional and compositional recovery across ecosystems. *Ecology Letters*, 23(3),  
643 575–585. <https://doi.org/10.1111/ele.13457>
- 644 Holden, J., Palmer, S. M., Johnston, K., Wearing, C., Irvine, B., & Brown, L. E. (2015).  
645 Impact of prescribed burning on blanket peat hydrology. *Water Resources Research*,  
646 51(8), 6472–6484. <https://doi.org/10.1002/2014WR016782>
- 647 Holden, J., Wallage, Z. E., Lane, S. N., & McDonald, A. T. (2011). Water table dynamics in  
648 undisturbed, drained and restored blanket peat. *Journal of Hydrology*, 402(1–2), 103–  
649 114. <https://doi.org/10.1016/J.JHYDROL.2011.03.010>
- 650 Huang, W., DeVries, B., Huang, C., Lang, M., Jones, J., Creed, I., & Carroll, M. (2018).  
651 Automated Extraction of Surface Water Extent from Sentinel-1 Data. *Remote Sensing*,  
652 10(5), 797. <https://doi.org/10.3390/rs10050797>
- 653 JNCC. (2011). *Towards an assessment of the state of UK peatlands*.  
654 [http://jncc.defra.gov.uk/pdf/jncc445\\_web.pdf](http://jncc.defra.gov.uk/pdf/jncc445_web.pdf)
- 655 Kasischke, E. S., Bourgeau-Chavez, L. L., Rober, A. R., Wyatt, K. H., Waddington, J. M., &  
656 Turetsky, M. R. (2009). Effects of soil moisture and water depth on ERS SAR  
657 backscatter measurements from an Alaskan wetland complex. *Remote Sensing of*  
658 *Environment*. 113: 1868-1873, 113, 1868–1873.  
659 <https://www.fs.usda.gov/treesearch/pubs/38928>
- 660 Kettridge, N., Humphrey, R. E., Smith, J. E., Lukenbach, M. C., Devito, K. J., Petrone, R. M.,  
661 & Waddington, J. M. (2014). Burned and unburned peat water repellency: Implications  
662 for peatland evaporation following wildfire. *Journal of Hydrology*, 513, 335–341.  
663 <https://doi.org/10.1016/J.JHYDROL.2014.03.019>
- 664 Kettridge, N., & Waddington, J. M. (2014). Towards quantifying the negative feedback  
665 regulation of peatland evaporation to drought. *Hydrological Processes*, 28(11), 3728–  
666 3740. <https://doi.org/10.1002/hyp.9898>
- 667 Lamentowicz, M., Gałka, M., Marcisz, K., Słowiński, M. S., Kajukał-Drygalska, K., Dayras,  
668 M. D., & Jassey, V. E. J. (2019). *Community ecology Unveiling tipping points in long-*  
669 *term ecological records from Sphagnum-dominated peatlands*.  
670 <https://doi.org/10.1098/rsbl.2019.0043>
- 671 Li, Z., Xu, D., & Guo, X. (2014). Remote sensing of ecosystem health: Opportunities,  
672 Challenges, and future perspectives. In *Sensors (Switzerland)* (Vol. 14, Issue 11, pp.  
673 21117–21139). MDPI AG. <https://doi.org/10.3390/s141121117>
- 674 Lowe, J. A., Bernie, D., Bett, P., Bricheno, L., Brown, S., Calvert, D., Clark, R., Eagle, K.,  
675 Edwards, T., Fosser, G., Fung, F., Gohar, L., Good, P., Gregory, J., Harris, G., Howard,  
676 T., Kaye, N., Kendon, E., Krijnen, J., ... Belcher, S. (2018). *UKCP18 Science Overview*  
677 *Report*. [www.metoffice.gov.uk](http://www.metoffice.gov.uk)
- 678 Łuców, D., Lamentowicz, M., Obremaska, M., Arkhipova, M., Kittel, P., Łokas, E.,  
679 Mazurkevich, A., Mróz, T., Tjallingii, R., & Słowiński, M. (2020). Disturbance and  
680 resilience of a *Sphagnum* peatland in western Russia (Western Dvina Lakeland) during  
681 the last 300 years: a multiproxy, high-resolution study. *The Holocene*,  
682 095968362094106. <https://doi.org/10.1177/0959683620941064>
- 683 Met Office. (2012). *Met Office Integrated Data Archive System (MIDAS) Land and Marine*  
684 *Surface Stations Data (1853-current)*. NCAS British Atmospheric Data Centre. NCAS



- 685 British Atmospheric Data Centre
- 686 Millard, K., & Richardson, M. (2018). Quantifying the relative contributions of vegetation and  
687 soil moisture conditions to polarimetric C-Band SAR response in a temperate peatland.  
688 *Remote Sensing of Environment*, 206, 123–138.  
689 <https://doi.org/10.1016/j.rse.2017.12.011>
- 690 Minayeva, T. Y., Bragg, O. M., & Sirin, A. A. (2017). *Towards ecosystem-based restoration*  
691 *of peatland biodiversity*. 19. <https://doi.org/10.19189/MaP.2013.OMB.150>
- 692 Müller, F., Bergmann, M., Dannowski, R., Dippner, J. W., Gnauck, A., Haase, P., Jochimsen,  
693 M. C., Kasprzak, P., Kröncke, I., Kümmerlin, R., Küster, M., Lischeid, G., Meesenburg,  
694 H., Merz, C., Millat, G., Müller, J., Padisák, J., Schimming, C. G., Schubert, H., ...  
695 Theuerkauf, M. (2016). Assessing resilience in long-term ecological data sets.  
696 *Ecological Indicators*, 65, 10–43. <https://doi.org/10.1016/j.ecolind.2015.10.066>
- 697 Page, S. E., & Baird, A. J. (2016). Peatlands and Global Change: Response and Resilience.  
698 *Annual Review of Environment and Resources*, 41(1), 35–57.  
699 <https://doi.org/10.1146/annurev-environ-110615-085520>
- 700 Pimm, S. L. (1984). The complexity and stability of ecosystems. *Nature*, 307(5949), 321–  
701 326. <https://doi.org/10.1038/307321a0>
- 702 Pimm, S. L., Donohue, I., Montoya, J. M., & Loreau, M. (2019). Measuring resilience is  
703 essential to understand it. In *Nature Sustainability* (Vol. 2, Issue 10, pp. 895–897).  
704 Nature Publishing Group. <https://doi.org/10.1038/s41893-019-0399-7>
- 705 Price, J. S. (1996). Hydrology and microclimate of a partly restored cutover bog, Quebec.  
706 *Hydrological Processes*, 10(10), 1263–1272. [https://doi.org/10.1002/\(SICI\)1099-1085\(199610\)10:10<1263::AID-HYP458>3.0.CO;2-1](https://doi.org/10.1002/(SICI)1099-1085(199610)10:10<1263::AID-HYP458>3.0.CO;2-1)
- 708 R Core Team. (2017). *R: A language and environment for statistical computing*.
- 709 Rowland, C. S. ., Morton, R. D. ., Carrasco, L. ., McShane, G. ., O'Neil, A. W. ., & Wood, C.  
710 M. (2017). *Land Cover Map 2015 (vector, GB)*. NERC Environmental Information Data  
711 Centre. <https://doi.org/10.5285/6c6c9203-7333-4d96-88ab-78925e7a4e73>
- 712 Schlaffer, S., Chini, M., Dettmering, D., Wagner, W., Schlaffer, S., Chini, M., Dettmering, D.,  
713 & Wagner, W. (2016). Mapping Wetlands in Zambia Using Seasonal Backscatter  
714 Signatures Derived from ENVISAT ASAR Time Series. *Remote Sensing*, 8(5), 402.  
715 <https://doi.org/10.3390/rs8050402>
- 716 Sherwood, J. H., Kettridge, N., Thompson, D. K., Morris, P. J., Silins, U., & Waddington, J.  
717 M. (2013). Effect of drainage and wildfire on peat hydrophysical properties. *Hydrological*  
718 *Processes*, 27(13), 1866–1874. <https://doi.org/10.1002/hyp.9820>
- 719 Swindles, G. T., Morris, P. J., Mullan, D. J., Payne, R. J., Roland, T. P., Amesbury, M. J.,  
720 Lamentowicz, M., Turner, T. E., Gallego-Sala, A., Sim, T., Barr, I. D., Blaauw, M.,  
721 Blundell, A., Chambers, F. M., Charman, D. J., Feurdean, A., Galloway, J. M., Gałka,  
722 M., Green, S. M., ... Warner, B. (2019). Widespread drying of European peatlands in  
723 recent centuries. *Nature Geoscience*. <https://doi.org/10.1038/s41561-019-0462-z>
- 724 Swindles, G. T., Morris, P. J., Wheeler, J., Smith, M. W., Bacon, K. L., Turner, T. E.,  
725 Headley, A., & Galloway, J. M. (2016). *Resilience of peatland ecosystem services over*  
726 *millennial timescales: evidence from a degraded British bog*.  
727 <https://doi.org/10.1111/1365-2745.12565>
- 728 Verbesselt, J., Umlauf, N., Hirota, M., Holmgren, M., Van Nes, E. H., Herold, M., Zeileis, A.,  
729 & Scheffer, M. (2016). Remotely sensed resilience of tropical forests. *Nature Climate*  
730 *Change*, 6(11), 1028–1031. <https://doi.org/10.1038/nclimate3108>

- 731 Waddington, J. M., Morris, P. J., Kettridge, N., Granath, G., Thompson, D. K., & Moore, P. A.  
732 (2015). Hydrological feedbacks in northern peatlands. *Ecohydrology*, 8(1), 113–127.  
733 <https://doi.org/10.1002/eco.1493>
- 734 Wallage, Z. E., Holden, J., & McDonald, A. T. (2006). Drain blocking: An effective treatment  
735 for reducing dissolved organic carbon loss and water discolouration in a drained  
736 peatland. *Science of the Total Environment*, 367(2–3), 811–821.  
737 <https://doi.org/10.1016/j.scitotenv.2006.02.010>
- 738 Washington-Allen, R. A., Ramsey, R. D., West, N. E., & Norton, B. E. (2008). *Quantification*  
739 *of the Ecological Resilience of Drylands Using Digital Remote Sensing*. Resilience  
740 Alliance. <https://agris.fao.org/agris-search/search.do?recordID=AV2012093728>
- 741 Worrall, F., Burt, T. P., & Adamson, J. K. (2006). Trends in drought frequency - The fate of  
742 DOC export from British peatlands. *Climatic Change*, 76(3–4), 339–359.  
743 <https://doi.org/10.1007/s10584-006-9069-7>
- 744 Zelnik, Y. R., Arnoldi, J.-F., & Loreau, M. (2018). The Impact of Spatial and Temporal  
745 Dimensions of Disturbances on Ecosystem Stability. *Frontiers in Ecology and Evolution*,  
746 6, 224. <https://doi.org/10.3389/fevo.2018.00224>
- 747 Zhou, Z., Liu, L., Jiang, L., Feng, W., & Samsonov, S. V. (2019). Using Long-Term SAR  
748 Backscatter Data to Monitor Post-Fire Vegetation Recovery in Tundra Environment.  
749 *Remote Sensing*, 11(19), 2230. <https://doi.org/10.3390/rs11192230>
- 750