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Investigating vegetation water dynamics and drought using Metop ASCAT over the North American Grasslands

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Abstract

In this study, we examined the ASCAT backscatter data from Metop-A from 2007-2016 to characterize spatial and temporal variability in the vegetation parameters of the TU Wien Soil Moisture Retrieval approach (TUW SMR) across the North American Grasslands. The vegetation parameters are the slope and curvature of a second order Taylor polynomial used to describe the incidence angle dependence of backscatter σ° . A recent development allows the vegetation parameters to be determined dynamically using the local slope values within a prescribed temporal window. Seasonal, interannual and diurnal variations in the vegetation parameters were found to vary across grassland cover types, reflecting variations in soil moisture availability and growing season length. While the slope has always been considered a measure of vegetation density, our results show that curvature also contains information about vegetation. Drought events in 2011 and 2012 resulted in extensive negative σ_{40}° and soil moisture anomalies during the maximum biomass period. Contiguous anomalies in slope and curvature were observed where the severity and persistence of the drought were enough to impact vegetation. Observed diurnal differences in slope and curvature suggest that daily moisture transport within the vegetation influences

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the relative dominance of scattering from the vegetation and soil surface.

Keywords: Advanced Scatterometer (ASCAT); Radar Remote Sensing;
Vegetation; Soil Moisture; Drought; Grasslands.

1. Introduction

2 Following the launch of ERS-1 in 1991, several early studies identified the
3 potential value of C-band scatterometry for global and regional vegetation mon-
4 itoring [1, 2, 3]. The Advanced Scatterometer (ASCAT) instrument carried by
5 a series of Metop satellites builds on the success of the European scatterometer
6 (ESCAT), which flew onboard the ERS-1/2 satellites from 1990 to 2011 [4, 5].
7 ASCAT is a real aperture radar operating at 5.255 GHz (C-band) with VV
8 polarization. At present, there are two ASCAT instruments in orbit, on board
9 Metop-A (launched in October 2006) and Metop-B (launched in September
10 2012), operated by the European Organization for the Exploitation of Meteorolo-
11 gical Satellites (EUMETSAT). Furthermore, plans to launch SCA on Metop-
12 SG in 2022 mean that the combined data record from ERS-1/2, Metop-A/B/C
13 ASCAT and Metop-SG SCA will extend for at least 40 years [6]. C-band scat-
14 terometer data from this series of satellites can therefore be considered as a
15 potentially valuable climate record for land surface monitoring.

16 Many studies have shown that backscatter data from C-band scatterometry
17 correlates with the seasonal dynamics of vegetation growth and senescence. Fri-
18 son et al. [2] analyzed three years of ERS-1 ESCAT data in a Sahel Region and
19 used a semi-empirical backscatter model combined with an ecosystem grassland
20 model to interpret the σ_{45}° observations. They concluded that, although soil
21 contributions were large, biomass variations were apparent in σ_{45}° . They also
22 noted that the maximum backscatter did not coincide with either the peak in
23 vegetation water content or green biomass, highlighting the confounding effects
24 of soil moisture, vegetation water content and other surface characteristics on
25 the total backscatter. Jarlan et al. [7] demonstrated that seasonal variations in
26 total backscatter in the Sahel were dominated by the contributions of the soil

27 and herbaceous vegetation component. However, it proved difficult to separate
28 their effects using model inversion. In a subsequent study, they used a global
29 stochastic nonlinear inversion method to map herbaceous mass production in
30 the Sahel [8]. Results were consistent with NDVI observations. One limitation
31 of this approach was that the the soil moisture content needed to be calculated
32 *a priori* and the herbaceous mass estimates were sensitive to errors in the as-
33 sumed soil moisture. Zine et al. [9] found that the limited herbaceous mass in
34 agro-pastoral sites (a mixture of cultivated fields, fallow fields and natural vege-
35 tation) made soil moisture retrieval in these areas easier than in pastoral areas.
36 Woodhouse and Hoekman [10] used a mixed target model to demonstrate the
37 applicability of using the ERS-1 WS data to monitor vegetation dynamics and
38 soil moisture in the Sahel. The seasonality in fractional cover was consistent
39 with NDVI observations, and the expected lag between reflectivity (soil mois-
40 ture) and vegetation peaks was detected. A subsequent application in Spain
41 found that while soil moisture retrieval might be possible, the ability to retrieve
42 vegetation cover parameters was highly site-specific [11]. A recent comparison
43 of backscatter signatures from altimetry and scatterometry over West Africa
44 re-affirms the suitability of side-looking scatterometers for sensing vegetation
45 dynamics [12]. However, the challenge of disentangling soil and vegetation ef-
46 fects remains.

47 Recent studies have indicated that C-band scatterometry could be useful
48 for detecting the onset of water stress or drought. Friesen et al. [13] identified
49 differences between the morning and evening σ_{40}° overpasses of ERS-1/2 ES-
50 CAT. Friesen subsequently used hydrological modeling to argue that the largest
51 differences found between morning and evening σ_{40}° in West Africa coincided
52 with the start of the dry season and the onset of stress [14]. Schroeder et al.
53 [15] showed that negative anomalies in σ_{54}° from ASCAT on Metop-A were spa-
54 tially and temporally consistent with patterns of drought severity from the U.S.
55 Drought Monitor during the 2011 and 2012 droughts. Both studies identified
56 differences between observations collected during the descending and ascending
57 passes. Similar differences in backscatter have also recently been detected at

58 higher frequencies and attributed to vegetation water dynamics [16, 17].

59 The current study is motivated by recent developments in the TU Wien Soil
60 Moisture Retrieval (TUW SMR) approach which offer a new perspective on veg-
61 etation dynamics using the ASCAT backscatter data record. A recent algorithmic
62 development allows for the estimation of so-called "vegetation parameters"
63 on a daily basis. The vegetation parameters are the slope and curvature of a
64 second order Taylor polynomial used to describe the incidence angle dependence
65 of σ° . Until recently, the entire data record was used to generate climatological
66 values of the parameters used to account for vegetation [18]. A new approach
67 proposed by Melzer et al. [19] determines the slope and curvature dynam-
68 ically using the local slope values within a prescribed temporal window. This
69 is significant because it allows the TUW SMR to take interannual variations
70 in vegetation into account in the soil moisture retrieval. It has recently been
71 shown that dynamic vegetation parameters also benefit estimates of vegetation
72 optical depth (VOD), which have been validated against Leaf Area Index and
73 used to assess interannual variability in vegetation dynamics [20]

74 While the studies above used backscatter itself, this study explores the po-
75 tential value of the time series of slope and curvature as a source of information
76 about vegetation phenology and canopy water dynamics including sub-daily
77 variations. The first 10 years of the ASCAT backscatter data record (from
78 Metop-A) are used to generate a time series of slope and curvature for a domain
79 that spans the North American Grasslands. This land cover type is associated
80 with the largest annual variations in slope, i.e. backscatter values over grass-
81 lands exhibit a huge change in sensitivity to soil moisture and vegetation during
82 the year. The seasonal cycles of the parameters calculated from the descend-
83 ing overpasses, ascending overpasses and the combination of both overpasses
84 are analyzed to determine the extent to which they reflect vegetation and soil
85 dynamics. Interannual variability is assessed by comparing anomalies in the
86 parameter values to drought severity indices from the same period.

87 2. TU Wien Soil Moisture Retrieval Approach

88 The TUW SMR approach is used to generate several satellite-derived soil
89 moisture products from ASCAT backscatter observations. This change detec-
90 tion approach was first developed for ERS-1/2 data [21, 22] and was used to
91 generate the first global multi-year soil moisture dataset from remote sensing
92 [23]. Bartalis et al. [24] used the ERS long-term parameter database with
93 the first ASCAT backscatter observations to demonstrate that the TUW SMR
94 could be applied to ASCAT observations as well. Naeimi et al. [18] introduced
95 several algorithmic improvements, addressing the vegetation and azimuthal ef-
96 fects in particular. The resultant WARP5 software implementation of TUW
97 SMR forms the basis of the operationally used algorithm to produce the soil
98 moisture products generated, distributed by and archived by the EUMETSAT
99 Satellite Application Facility on Support to Operational Hydrology and Water
100 Management (H SAF). The combined ERS and ASCAT soil moisture prod-
101 ucts constitute one of the longest global soil moisture datasets. These data are
102 essential for numerical weather prediction, natural hazard monitoring and mit-
103 igation, water management and agricultural applications [5, 25, 26]. They are
104 also a key component of the European Space Agency Climate Change Initiative
105 (ESA CCI) soil moisture product [27].

106 A year long time series of backscatter coefficient is shown in Figure 1(a)
107 to illustrate the TUW SMR approach. The backscattering coefficient (σ°) se-
108 ries consists of all ASCAT observations at a single grid point, normalized to
109 a reference angle of 40° . The backscattering coefficient from the land surface
110 is influenced by a combination of static and dynamic factors. Static compo-
111 nents include soil composition, surface roughness and land cover type which are
112 assumed to be temporally stable at the scatterometer measurement scale (25-
113 50 km). Dynamic variations are due to the combined influence of vegetation
114 and soil moisture on backscatter.

115 The backscattering coefficient σ° in decibels [dB] is assumed to be linearly
116 related to surface soil moisture so that the soil moisture in the surface layer at

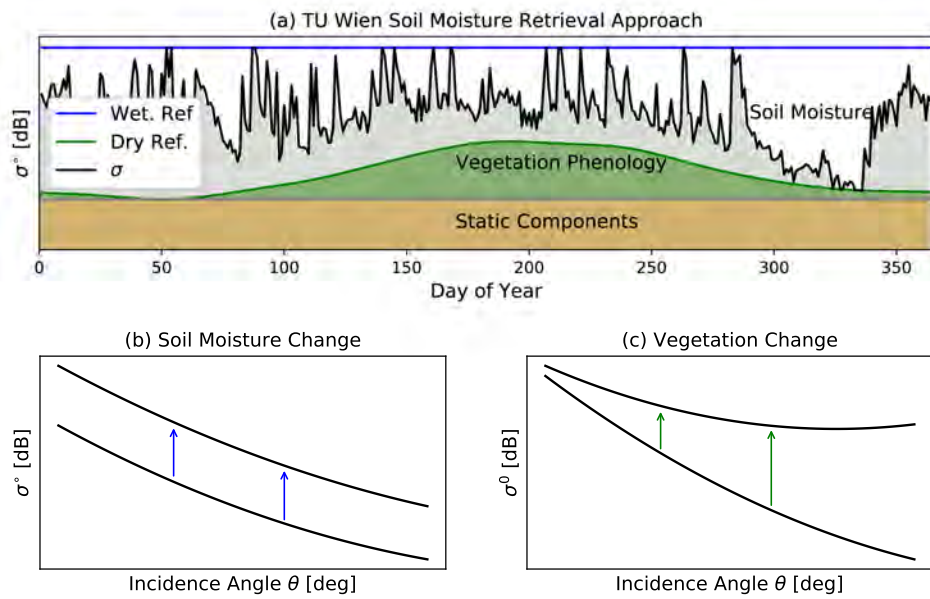


Figure 1: The top panel shows a time series of ASCAT data for a grid point in Nebraska to illustrate the concepts of dry reference, wet reference and observed normalized backscatter in the TU Wien Soil Moisture Retrieval (TUW SMR). The lower panel illustrates the impact of increasing soil moisture (b) and vegetation (c) on the incidence angle dependence of backscatter.

117 some time t is given by:

$$\Theta_s(t) = \frac{\sigma^\circ(\theta_r, t) - \sigma_d^\circ(\theta_r, t)}{\sigma_w^\circ(\theta_r, t) - \sigma_d^\circ(\theta_r, t)} \quad (1)$$

118 where σ_w° , σ_d° , and σ° are the wet and dry references, and backscattering coeffi-
 119 cients (in dB) at the reference incidence angle θ_r and time t . Seasonal variations
 120 in vegetation density determine the so-called "Dry Reference" backscattering co-
 121 efficient. For a given date, this represents the lower limit of the range within
 122 which the backscattering coefficient varies due to soil moisture. The upper
 123 limit ("Wet Reference") is time-independent and reflects the highest value of
 124 backscattering coefficient observed at that grid point.

125 The relationship between backscattering coefficient and incidence angle is
 126 at the core of this TUW SMR approach. It is used to normalize the ASCAT
 127 backscatter measurements to the reference angle θ_r . Wagner et al. [21] used
 128 ERS data to demonstrate that the slope (σ') depends linearly on incidence angle
 129 (θ):

$$\sigma'(\theta) = \sigma'(\theta_r) + \sigma''(\theta_r) \cdot (\theta - \theta_r) \quad [dB/deg] \quad (2)$$

130 where θ_r is a reference incidence angle, set to 40° in the TUW SMR approach.
 131 Hence, the dependence of backscattering coefficient on incidence angle can be
 132 described as a second order polynomial:

$$\sigma^\circ(\theta) = \sigma^\circ(\theta_r) + \sigma'(\theta_r) \cdot (\theta - \theta_r) + \frac{1}{2}\sigma''(\theta_r) \cdot (\theta - \theta_r)^2 \quad [dB] \quad (3)$$

133 Once the slope ($\sigma'(\theta_r)$) and curvature ($\sigma''(\theta_r)$) are known, the scatterometer
 134 measurements at any incidence angle can be extrapolated to the reference angle
 135 of θ_r as follows:

$$\sigma^\circ(\theta_r) = \sigma^\circ(\theta) - \sigma'(\theta_r) \cdot (\theta - \theta_r) - \frac{1}{2}\sigma''(\theta_r) \cdot (\theta - \theta_r)^2 \quad (4)$$

136 This expression can also be re-arranged to extrapolate the backscatter at any
 137 incidence angle if the slope, curvature and $\sigma^\circ(\theta_r)$ are known.

138 The incidence angle behaviour of σ° depends on whether total backscatter is
 139 dominated by volume scattering from the vegetation or surface scattering from

140 the soil. Over bare soils, σ° is expected to decrease sharply with increasing
 141 incidence angle due to the dominance of surface scattering. Figure 1(b) shows
 142 the $\sigma^\circ - \theta$ relationship on Days 334 (dry) and 353 (wet) to illustrate that an in-
 143 crease in soil moisture results in an increase in σ° for all incidence angles, i.e. a
 144 vertical offset in the $\sigma^\circ - \theta$ curve. Zribi et al [28] showed that soil roughness also
 145 influences slope and curvature. However soil roughness is assumed to be tem-
 146 porally stable at the scatterometer measurement scale (25-50 km). Over dense
 147 vegetation σ° becomes less sensitive to θ at steeper incidence angles. Figure
 148 1(c) shows the difference between the $\sigma^\circ - \theta$ relationship on Day 334 (minimum
 149 vegetation) to that on 200 (maximum vegetation). An increase in vegetation
 150 cover is associated with a rotation, i.e. a change in slope and curvature, of this
 151 curve. In this way, variations in the slope and curvature are used in the TUV
 152 SMR to account for the influence of vegetation.

153 The slope and curvature coefficients of the Taylor polynomial are estimated
 154 from the backscatter triplets (fore, mid and aft beam) provided by Metop AS-
 155 CAT. ASCAT is a fixed fan-beam scatterometer, with two sets of three sideways-
 156 looking antennas each illuminating a 550 km wide swath on either side of the
 157 satellite track. The three antennas on each side are oriented at 45° (fore), 90°
 158 (mid) and 135° (aft) to the satellite track. The incidence angle range of the fore
 159 and aft antennas is $34 - 65^\circ$, while the mid antenna covers $25 - 55^\circ$. This viewing
 160 geometry means that each location on the surface is observed with three slightly
 161 asynchronous, independent backscatter measurements ("backscatter triplets")
 162 with three independent viewing directions. The simultaneous backscatter ob-
 163 servations of the three beams allow us to compute an instantaneous backscatter
 164 slope, also called the "local slope":

$$\sigma' \left(\frac{\theta_{mid} - \theta_{a/f}}{2} \right) = \frac{\sigma_{mid}^\circ(\theta_{mid}) - \sigma_{a/f}^\circ(\theta_{a/f})}{\theta_{mid} - \theta_{a/f}} \quad [dB/deg] \quad (5)$$

165 where 'mid' indicates the midbeam antenna and the subscript 'a/f' indicates
 166 the aft beam or fore beam antenna.

167 A large number of local slope values must be combined to account for the
 168 substantial noise in individual values [29] and to ensure that the slope is sam-

169 pled across a wide range of incidence angles. Hahn et al. [30] provide a detailed
170 review of the different approaches that have been used to estimate the slope
171 and curvature for various generations of soil moisture products from the ERS
172 and ASCAT observations. The current suite of operational ASCAT-derived soil
173 moisture products use several years of local slope data to produce a seasonal
174 climatology of slope and curvature coefficients [22, 31]. This approach was es-
175 sential for ERS-1/2 scatterometer data to ensure robust parameter estimates.
176 However, the second set of three fan-beam antennas on ASCAT increased the
177 number of backscatter observations available for the determination of the local
178 slope values. This increased data density makes it possible to determine the
179 slope and curvature dynamically, and hence to account for interannual varia-
180 tions.

181 Recently, Melzer [19] proposed a Kernel Smoother (KS) approach to deter-
182 mine the slope and curvature dynamically. An Epanechnikov kernel with width
183 $\lambda=21$ is used to weight the local slope estimates by their temporal distance
184 from a given day. Hence, the estimate of slope and curvature for a given day
185 is based on all local slope values within a 42-day window, with those closer
186 in time assigned higher weights. This kernel width was found to provide an
187 acceptable balance between bias and variance in the estimate. Hahn et al.
188 [30] performed a cross-comparison of the dynamic slope and curvature values
189 estimated separately from Metop-A and Metop-B. The consistency of the esti-
190 mated parameters from the two satellites is an indicator of the robustness of
191 the estimate. Hövmoller diagrams, and time series plots at a limited number of
192 locations demonstrated that the slope and curvature series exhibit both seasonal
193 and interannual variations. The current study examines the temporal and spa-
194 tial features of the slope and curvature variations more closely to evaluate their
195 value as a source of information on vegetation phenology and water dynamics.

196 **3. Data and Methods**

197 *3.1. Study Area*

198 The study domain is mapped in Figure 2 and extends from 28.6 N to 55 N,
199 and 90 W to 115 W. The ASCAT data are organized on a fixed Earth grid
200 described by Naeimi et al. [18]. Grid points considered as Grasslands (class 130)
201 were identified using the ESA CCI Land Cover product. The original sampling
202 resolution of this product is 300 m, therefore the land cover class assigned to
203 each grid point represents the mode within a 25 km x 25 km window [32]. The
204 study domain includes 14,585 grid points and encompasses the contiguous North
205 American Temperate Grasslands extending from Alberta and Saskatchewan to
206 Texas [33]. The Köppen Geiger Climate Classes (KGCC) of the grid points
207 are mapped in Figure 2. These are based on temperature and precipitation
208 observations for the period 1951-2000 [34]. An overview of the KGCCs, including
209 the climate type, precipitation class, temperature sub-class and prevalence in
210 the study domain is provided in Table 1. The four dominant Köppen Geiger
211 Classes are BSk, Cfa, Dfb and Dfa, which together cover 96.6% of the domain.

212 The ecoregions in the study domain are mapped in Figure 3 based on the
213 WWF Terrestrial Ecosystems of the World [33]. The arid, cold steppe (BSk)
214 class is dominated by short grasslands. The temperate class (Cfa) is more
215 diverse and includes short grassland in the Texas panhandle, the Texas Black-
216 land Prairies and stretches through mixed grasslands, and the forest-grasslands
217 transition to the forests of Eastern Texas and Oklahoma. The Dfa class extends
218 from the mixed grasslands of Nebraska and Kansas to tall grasslands and the
219 grasslands/forest transition to the east. Further north, the Dfb class transitions
220 from tall grasslands at the 100 W meridian to mixed and short grasslands fur-
221 ther west. The diversity of KGCC and ecoregions within the domain highlights
222 the heterogeneity within the "grasslands" land cover class. Furthermore, while
223 "grasslands" may be the mode (most commonly occurring class) within a 25 km
224 x 25 km window, examination of the 300 m product shows that the grassland
225 ecosystems are increasingly being encroached by agricultural land use. This is

KGCC	Climate Type	Class (Precipitation)	Sub-class (Temperature)	% of grid points in study area
Bsk	Arid	Steppe	Cold	34.2
Cfa	Temperate	Without dry season	Hot Summer	24.4
Dfb	Cold	Without dry season	Warm Summer	20.0
Dfa	Cold	Without dry season	Hot Summer	18.0
Dfc	Cold	Without dry season	Cold Summer	1.1
BWk	Arid	Desert	Cold	<1
Dwb	Cold	Dry Winter	Warm Summer	<1
Dsb	Cold	Dry Summer	Warm Summer	<1
BSh	Arid	Steppe	Hot	<1
Dwa	Cold	Dry Winter	Hot Summer	<1
Dsa	Cold	Dry Summer	Hot Summer	<1
Cfb	Temperate	Without dry season	Warm Summer	<1

Table 1: Dominant Köppen Geiger Climate Classes (KGCC) [34], and their prevalence in the study area.

226 particularly true of the tall and mixed grassland areas [35].

227 3.2. ASCAT data

228 Ten years of Metop-A ASCAT SZR Level 1b Fundamental Climate Data
229 Record backscatter data, using the 12.5 km swath grid sampling, were obtained
230 from the EUMETSAT Data Centre. Three standard pre-processing steps were
231 performed: (1) the backscatter observations were resampled to a fixed Earth
232 grid using a Hamming window function and the procedure described by Naeimi
233 et al. [18]; (2) An intra- and interbeam calibration was performed using natural
234 extended calibration targets over land [36]; and (3) the empirical approach of
235 Bartalis et al. [37] was used to account for azimuthal effects.

236 Metop-A and Metop-B fly in a sun-synchronous orbit with a 29-day repeat
237 cycle orbit and equatorial crossing times of 09:30 AM and PM (Local Solar
238 Time) in descending and ascending nodes [38]. Further steps were performed

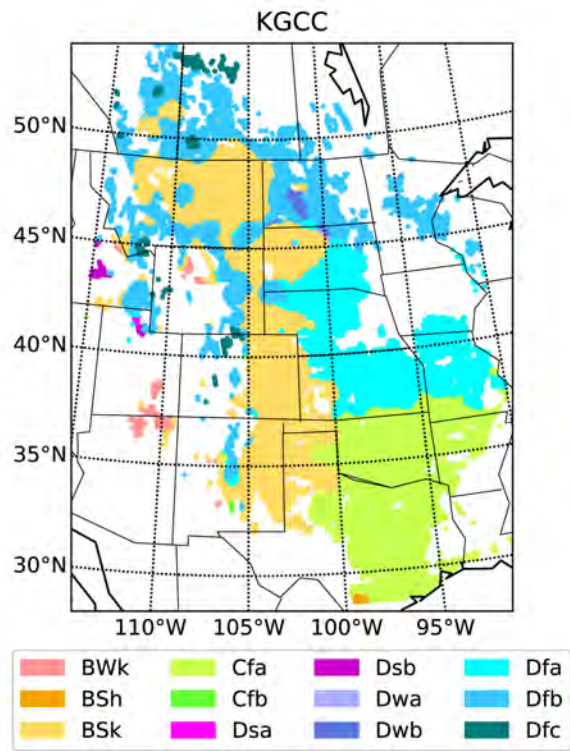


Figure 2: Grid points in the study domain, colored by their Köppen Geiger Climate Class (KGCC)[34]

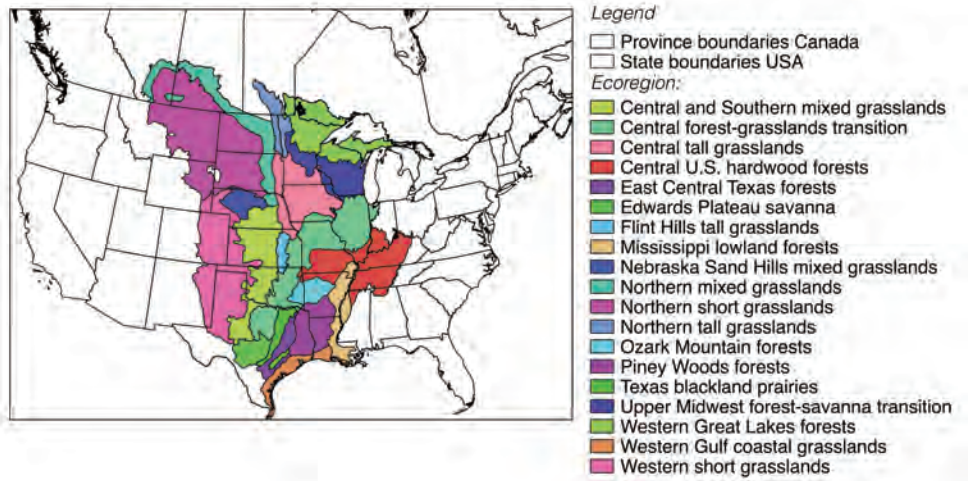


Figure 3: Ecoregions in the study domain [33]

239 on (1) descending overpasses only, (2) ascending overpasses only or (3) the entire
 240 dataset consisting of both the descending and ascending overpasses. For each of
 241 these overpass combinations, the backscatter triplets were used to calculate the
 242 local slope using equation (5). The methodology proposed by Melzer [19] was
 243 used to estimate the slope and curvature from these local slopes, assuming a
 244 kernel width of 21 days. These slope and curvature values were combined with
 245 the corresponding (i.e. descending, ascending or all) normalized backscattering
 246 coefficient (σ_{40}°) to derive soil moisture using the TUW SMR.

247 For each grid point in the study domain, the 10-year time series of slope,
 248 curvature, normalized (40°) backscattering coefficient and derived soil moisture
 249 were extracted. For the slope and curvature, the seasonal climatology was de-
 250 termined by averaging the daily values across the 10 years. The revisit time
 251 dictates that observations from the descending and ascending overpasses are
 252 unlikely to occur on the same day, and that a limited number of values are
 253 available for a given day of the year. Therefore, the seasonal climatology of σ_{40}°
 254 and soil moisture were determined after first aggregating their data into 10 day

Abbreviation	Northwest Corner	Southeast Corner	KGCC	Ecoregion	No. grid points
N. Shortgrass	(48.87°N, 107.63°W)	(46.03°N, 104.15°W)	Bsk	Northern Shortgrass Prairie	544
W. Shortgrass	(40.97°N, 104.06°W)	(37.03°N, 102.07°W)	Bsk	Western Shortgrass Prairie	460
Mixed Grass	(36.96°N, 99.59°W)	(33.98°N, 98.21°W)	Cfa	Central-Southern U.S. Mixed Grasslands	243
Transition	(40.54°N, 95.73°W)	(38.57°N, 93.42°W)	Dfa	Central Forest-Grasslands Transition	207

Table 2: Description of the four Regions of Interest used to examine the seasonal climatology of the ASCAT data.

255 intervals (dekads).

256 Four Regions of Interest (ROIs) are used to investigate the seasonal clima-
257 tology and interannual variability of the nominal parameters and their diurnal
258 differences as a function of landscape. The KGCC, ecoregion and bounding co-
259 ordinates of each of the ROIs is given in Table 2. Spatial averaging is performed
260 after the seasonal climatologies and anomalies have been determined for the
261 individual grid points.

262 4. Results and Discussion

263 4.1. Seasonal Climatology

264 Figure 4 shows that the time series of slope and curvature are smoother
265 than that of σ_{40}° (c) itself. This is partly due to each daily estimate of slope
266 and curvature being based on local slope estimates within a 42-day window.
267 Also, the physical and biological processes driving the slope and curvature act
268 on time scales longer than changes in soil surface wetness. Slope values (Figure
269 4 (a-d)) increase from west to east due to the increased vegetation density from
270 the short grasslands, through the mixed grasslands and into the forest/grassland
271 transition ROIs. The seasonal dynamics of slope in the four ROIs are markedly
272 different. The shortest peak is observed in the northern shortgrass while double
273 peaks are observed in both the western shortgrass and mixed grasslands ROIs.
274 The higher slope values of the mixed grasslands suggest some vegetation cover
275 persists year-round. Spring brings an increase which is sustained until early
276 September. The highest vegetation density is observed in the transition ROI,
277 also the wettest part of the domain. Mixed forest and agricultural production in
278 this ROI explain the comparatively high slope values, the increase in vegetation
279 density from April to mid-July and the relatively rapid decrease in the autumn.

280 The seasonal dynamics observed in Figure 4(e-h) suggest that curvature is
281 related to vegetation, though the curvature is clearly not directly related to
282 slope. Across most land covers, the curvature is close to zero and relatively
283 constant. Hahn et al. [30] showed that grasslands typically have a positive
284 curvature, i.e. the $\sigma_{40}^{\circ} - \theta$ relationship flattens out or curves upwards at high
285 incidence angles. Positive curvature has been simulated and observed in grasses,
286 wheat and barley and has been linked to their vertical structure [39, 40, 41].
287 Stiles et al. [42] discussed this phenomenon using modeled and measured data
288 for a wheat canopy prior to the emergence of the grain head. At lower incidence
289 angles ($< 30^{\circ}$), scattering is dominated by mechanisms involving a "ground-
290 bounce". As θ increases, the electric field of the vertically polarized incidence
291 wave becomes increasingly coupled with the vertical structure of the plant. The

292 impact is two-fold. First, the increasing θ results in increased attenuation of
293 the ground-bounce terms. Second, direct scattering from the upper portion of
294 the vertical stalk and the grain (inside) increases with θ . In the wheat canopy,
295 Stiles et al. observed that the combination of these two effects is a backscatter
296 minimum at around 40-50 degrees. The positive curvature values and their
297 seasonal variations observed in Figure 4(e-g), indicate that a similar mechanism
298 may be evident in the North American grasslands.

299 In all of the grasslands ROIs, the curvature increases during the spring. This
300 could be explained by the development of the predominantly vertical structure.
301 In the Northern short grasslands, the large positive curvature values are sus-
302 tained until the vegetation density (slope) decreases in the autumn. In the
303 Western Shortgrass and Mixed grasslands (ROI), both the slope and curva-
304 ture exhibit a dip during the maximum biomass period. This suggests that the
305 strength of the influence of the vertical structure varies during the summer. This
306 could be related to either a change in the water content of the vertical stalks,
307 or to the emergence of flowers, fruit or other plant types with more randomly-
308 oriented scatterers. In the mixed grasslands ROI, the curvature decreases to the
309 winter value in the late summer, i.e. the influence of the vertical structure is
310 greatly diminished. The seasonal cycle in the transition ROI differs considerably
311 from the grasslands. It decreases to almost zero during the maximum biomass
312 period and is occasionally negative due to the presence of forest and agriculture
313 in this ecosystem.

314 Seasonal variations in backscatter and soil moisture are limited in all four
315 ROIs. The increasing (soil and vegetation) moisture from west to east is ap-
316 parent in σ_{40}° Fig 4(i to l). Seasonal variations are about 2 dB in all ROIs.
317 The largest seasonal variation in soil moisture is observed in the Transition
318 ROI while the variation is limited to 25% in the grasslands. The interannual
319 variations in backscatter and soil moisture are comparable in magnitude to the
320 seasonal variations in all but the Transition ROI. The standard deviation is
321 typically about 17% of the seasonal range of the vegetation parameters. Given
322 the strength of the seasonal cycle, this suggests that interannual variability in

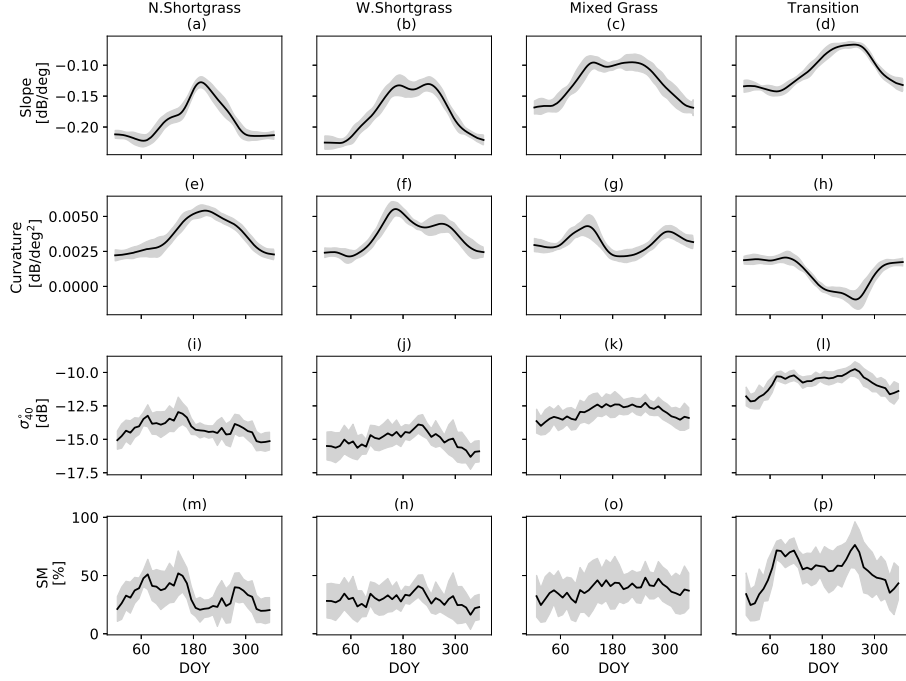


Figure 4: Mean annual cycle of slope (a)-(d), curvature (e)-(h), σ_{40}° (i)-(l) and soil moisture (m)-(p), averaged across each of the four Regions of Interest. Results are presented from the combined dataset that uses data from both the descending and ascending overpasses. The black line corresponds to the mean seasonal cycle, and the grey area indicates \pm one standard deviation as a measure of the interannual variability.

323 soil moisture has a significant effect on the vegetation parameters.

324 A convenient way to synthesize the influence of the changes observed in the
 325 slope, curvature and σ_{40}° is to consider their combined impact on the $\sigma^{\circ} - \theta$
 326 relationship which is shown in Figure 5 to vary considerably during the year.
 327 The steepest curves and the largest variations during the year are observed in
 328 the shortgrass areas (Fig. 5(a)) and Fig. (5(b)). This indicates that the influence
 329 of vegetation on soil moisture sensitivity is highly dynamic in these areas. The
 330 presence of some vegetation throughout the year results in less negative slope
 331 values in the mixed grass (Fig. 5(c)) and transition area (Fig. 5(d)).

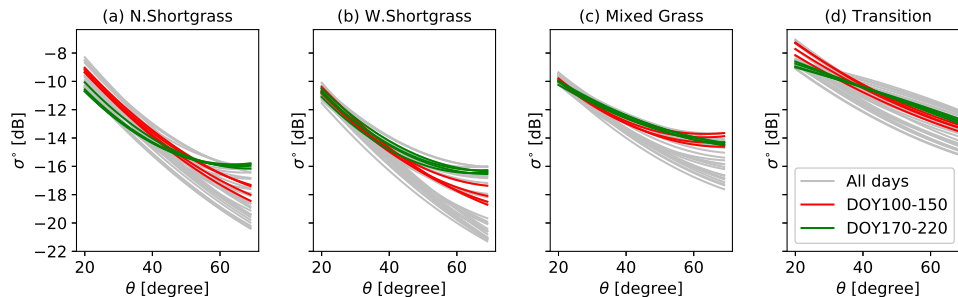


Figure 5: Backscattering coefficient as a function of incidence angle for each of the four ROIs, calculated using all data (i.e. combined descending and ascending overpasses). Each grey line corresponds to the climatology of a single 10-day period (dekad) during the year, averaged across the KG climate class. The red and green lines indicate dekads in the early growing season (DOY 100-150) and maximum biomass period (DOY 170-220).

332 In each of the cover types, the winter months are characterized by the low-
 333 est backscatter and steepest slopes of the year. The start of the growing season
 334 (around DOY 100-150) corresponds to a period of increased soil moisture in the
 335 Northern Shortgrass (a) and the Transition area (d). The red curves, corre-
 336 sponding to this period, are vertically offset but parallel to the winter values.
 337 In the Western Shortgrass (b) and Mixed Grass (d), the soil moisture is more
 338 constant throughout the year, so this vertical offset is not evident. In the short-
 339 grass ROIs, the combined changes in slope and curvature during the biomass
 340 accumulation period result in a clear rotation in the $\sigma^\circ - \theta$ curve. During the
 341 biomass peak, the sensitivity to incidence angle at higher incidence angles is
 342 reduced. In the mixed grass, the curvature is at a minimum during the peak, so
 343 the $\sigma^\circ - \theta$ curve is almost linear. In the transition area, the $\sigma^\circ - \theta$ curve even
 344 becomes convex during the biomass peak.

345 As an indicator of interannual variability, Fig 6 (a)-(c) shows drought severity
 346 during the maximum biomass period in 2007, 2011 and 2012. The maps are
 347 weekly assessments of drought intensity in the previous week based on data
 348 through to the preceding Tuesday morning. The study domain was almost
 349 drought-free during the maximum biomass period in 2007, with D2 conditions

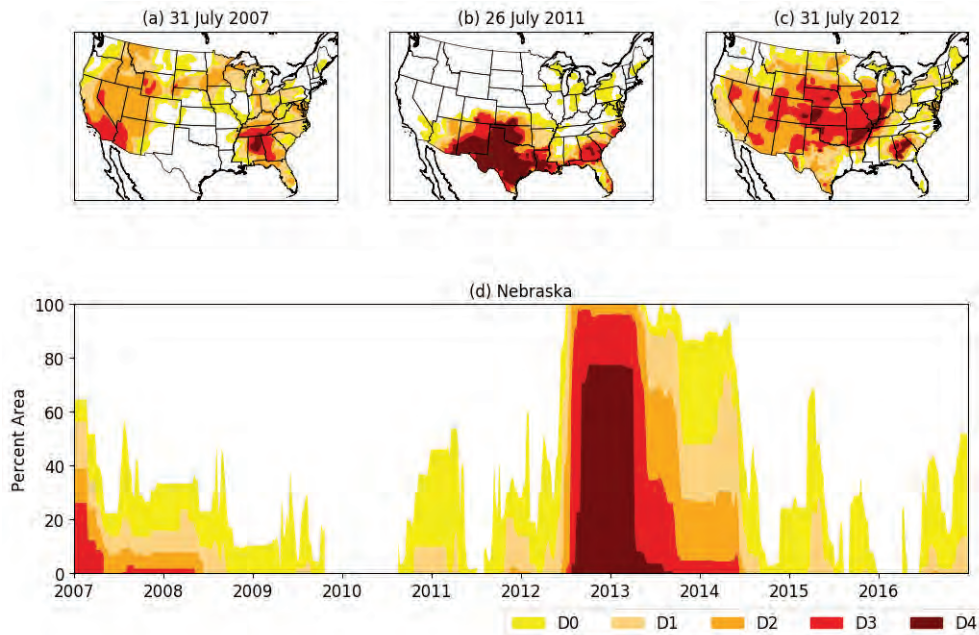


Figure 6: The top panel shows maps (a)-(c) from the United States Drought Monitor showing the drought severity at the end of July for 2007, 2011 and 2012. The lower panel (d) shows the time series of drought severity for the state of Nebraska, which includes the Nebraska Sand Hills. Map and time series courtesy of NDMC-UNL.

350 limited to western Nebraska, and South Dakota. A severe drought occurred
 351 in 2011 but its extent was limited to the southern part of the domain, namely
 352 Texas and much of Oklahoma. In 2012 a less severe, though more widespread,
 353 drought was observed with Oklahoma and Nebraska being particularly severely
 354 affected.

355 Figure 7 shows the influence of inter-annual variability on the $\sigma^\circ - \theta$ rela-
 356 tionship in each of the ROIs. Each curve was calculated using the average slope,
 357 curvature and σ_{40}° value for the the maximum biomass period (DOY 170-220) in
 358 a given year. The extensive drought in 2012 yielded the lowest $\sigma^\circ - \theta$ curve in
 359 all but the Mixed Grass class. In N. Shortgrass, the interannual variability and
 360 the 2012 drought are primarily apparent as an offset of up to 1.5 dB, suggesting
 361 that the soil moisture anomaly did not have a serious effect on the vegetation.

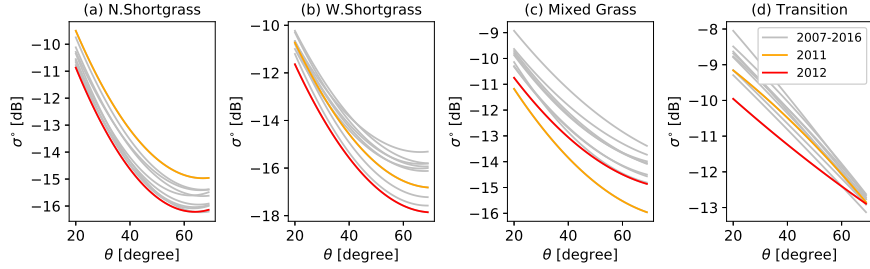


Figure 7: Backscattering coefficient as a function of incidence angle, during the maximum biomass period (DOY 170-220) for each of the four ROIs. Each grey line corresponds to the average value per year from 2007 to 2016. The "drought years" of 2011 and 2012 are highlighted in orange and red respectively.

362 In the W. Shortgrass, a difference in slope is apparent, suggesting that the soil
 363 moisture anomaly impacted vegetation. In general, interannual variability in
 364 the Mixed Grass ROI appears to be a vertical offset due to soil moisture avail-
 365 ability. However, the extreme drought in 2011 in this ROI also produced a
 366 change in slope and curvature. The effect of drought is most apparent at lower
 367 incidence angles in the Transition ROI. This suggests that drought conditions
 368 primarily affect the soil moisture. Interannual variability at $\theta = 60^\circ$ is less than
 369 1 dB suggesting limited interannual variability in scattering from vegetation.

370 Figure 8 shows the seasonal cycle of the diurnal difference of the slope, cur-
 371 vature, σ_{40}^0 and soil moisture for each of the four ROIs. During the summer, the
 372 slope is steeper during the descending pass (9:30 AM) than during the ascending
 373 pass (9:30 PM). The largest difference (0.0105 dB/deg) is observed in the North-
 374 ern Shortgrass ROI, at around day 200 (~ 20 July). Note that this corresponds
 375 to more than 10% of the annual dynamic range, so the diurnal variations are
 376 substantial. Given the assumption that the slope represents "vegetation den-
 377 sity", one might expect vegetation water content to be higher in the morning
 378 and to be reduced due to transpiration during the day. However, this apparent
 379 contradiction may be due to the overpass time. Plant water content has a pre-
 380 dawn maximum. Transpiration rates, particularly in anisohydric species, are
 381 very high in the early morning. Until stomatal control limits ET, water losses

382 due to transpiration may lead to a transient reduction in plant water content,
383 and particularly leaf water content, before midday.

384 Diurnal differences in curvature are positive during the summer months, and
385 they do not co-vary with those observed in the slope. Curvature differences of
386 around 0.0005 dB/deg² (12% of the annual dynamic range) are observed in all
387 but the Mixed Grassland ROI. Lower curvature values in the ascending (evening)
388 pass suggest that the ground-bounce contribution to total backscatter is more
389 important in the evening. In addition to plant water variations, slope and
390 curvature may be affected by geometry effects, e.g. heliotropism or leaf rolling
391 to control stomatal conductance. The timing and sign of diurnal differences
392 in backscatter and soil moisture are similar. Both are higher in the morning
393 throughout the growing season in the Northern shortgrass ROI. In the other
394 cover types, both are lower during the descending pass during the biomass peak.

395 Figure 9 shows how the $\sigma_{40}^{\circ} - \theta$ relationship differs between the descend-
396 ing and ascending passes during the biomass peak. There is no vertical offset
397 between the curves, but there is some rotation in all ROIs. This rotation sug-
398 gests that the diurnal differences are dominated by differences in the vegetation
399 parameters. The largest difference is observed in the N. Shortgrass ROI. The
400 difference at 40°, the reference angle for soil moisture retrieval in TUW SMR, is
401 barely discernible. Figure 9 suggests that variations in vegetation water content
402 and structure during the day result in changes to the relative importance of
403 the ground-bounce and direct scattering from the vertical constituents of the
404 canopy.

405 *4.2. Spatial Patterns*

406 Figure 10 shows the 10-year average of the vegetation parameters, σ_{40}^0 and
407 soil moisture across the study domain during the start of the growing season.
408 From Figure 10 (a), the shallowest slopes are observed in the southeast where
409 the lack of dry season means that there is vegetation present even during the
410 winter months. Conversely, the steepest slopes are observed in the north of
411 the study domain, where bare and possibly frozen soil delays the start of the

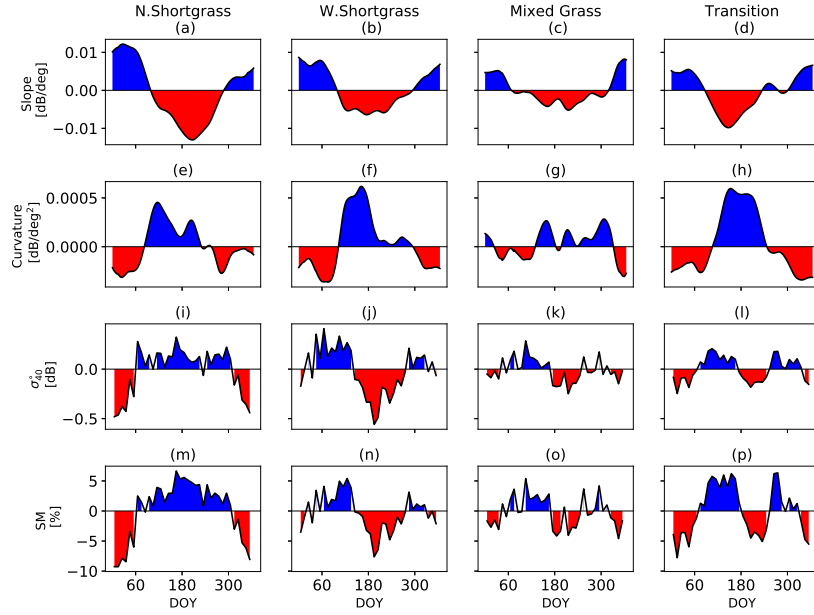


Figure 8: Annual cycle of the diurnal (descending - ascending) difference in slope (a)-(d), curvature (e)-(h), σ_{40}° (i)-(l), and soil moisture (m)-(p). Each column corresponds to values averaged across all grid points in each of the four Regions of Interest.

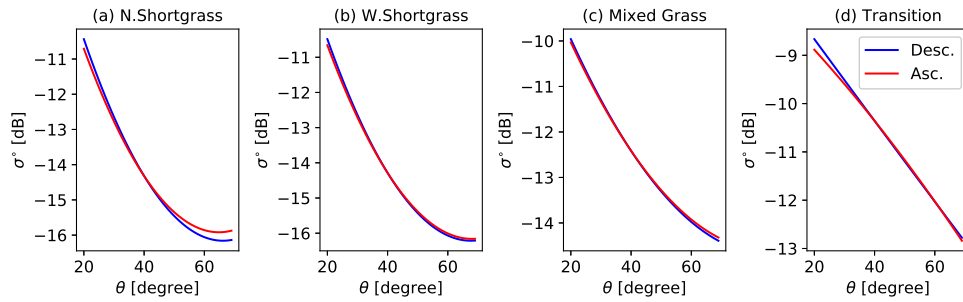


Figure 9: Backscattering coefficient as a function of incidence angle during the maximum biomass period (DOY 170-220) for each of the four dominant Köppen Geiger climate classes. The blue and red lines correspond to the curve estimated using data from the descending and ascending overpasses respectively.

412 growing season. The curvature (Fig 10 (b)) is positive everywhere except in the
413 southeast, probably due to the presence of forest. A clear east-west gradient is
414 apparent in the σ_{40}° and soil moisture values. The wettest areas are found in
415 eastern Oklahoma, eastern Kansas, Missouri and Arkansas where mixed and tall
416 grasslands transition to forest. The σ_{40}° values are also highest in the southeast,
417 due to the higher soil moisture and higher slope (vegetation). The driest areas
418 are to the west of the 100 W meridian in the short grassland areas.

419 Figure 11 shows the diurnal difference in the same quantities. Both σ_{40}°
420 (Fig. 11(c)) and soil moisture (Fig. 11(d)) are generally higher during the de-
421 scending (morning) overpass than during the ascending pass (evening). This is
422 consistent with backscatter being dominated by soil moisture contribution at
423 this time of year, and soil moisture decreases due to evaporation during the day.
424 The slope (Fig. 11(a)) is steeper and the curvature (Fig. 11(b)) is more positive
425 during the descending pass. This suggests that the vegetation is less opaque
426 during the descending pass. One possible explanation for this counter-intuitive
427 result is the ASCAT acquisition time (10 a.m/10 p.m. local time). Observa-
428 tions from the descending overpass are acquired after the vegetation has been
429 transpiring for several hours and before the stomata may adjust to limit tran-
430 spiration. Observations from the ascending pass are acquired several hours after
431 peak transpiration when the vegetation has had time to draw moisture from the
432 root zone.

433 Figure 12 shows the mean vegetation parameters, σ_{40}° and soil moisture
434 values during the biomass peak (DOY 170-220). Generally, vegetation is denser
435 than in Figure 10. The slope is less negative, so the backscatter is more sensitive
436 to vegetation and less sensitive to soil moisture than in the earlier part of the
437 growing season. The curvature remains positive everywhere except in the south
438 east of the domain. The backscatter values still exhibit an east-west gradient,
439 with a minimum to the west of the 100 W meridian. Soil moisture is lower
440 everywhere compared to Figure 10(d), particularly in the short grasslands.

441 The spatial pattern of the diurnal differences in σ_{40}° and soil moisture are
442 very different to those observed at the start of the growing season, particularly

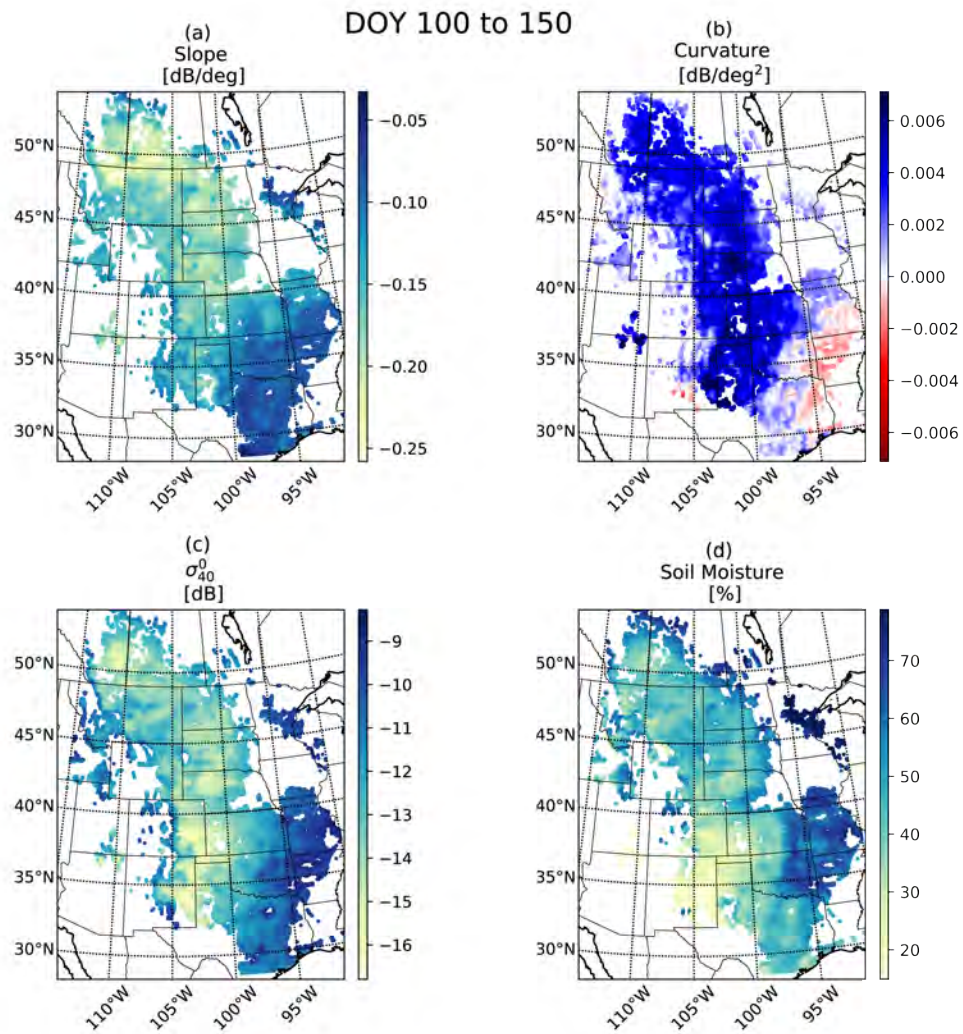


Figure 10: Climatological mean slope (a), curvature (b), σ_{40}^2 (c) and soil moisture (d) for each grid point during the period from DOY 100-150, calculated using all (descending and ascending) data.

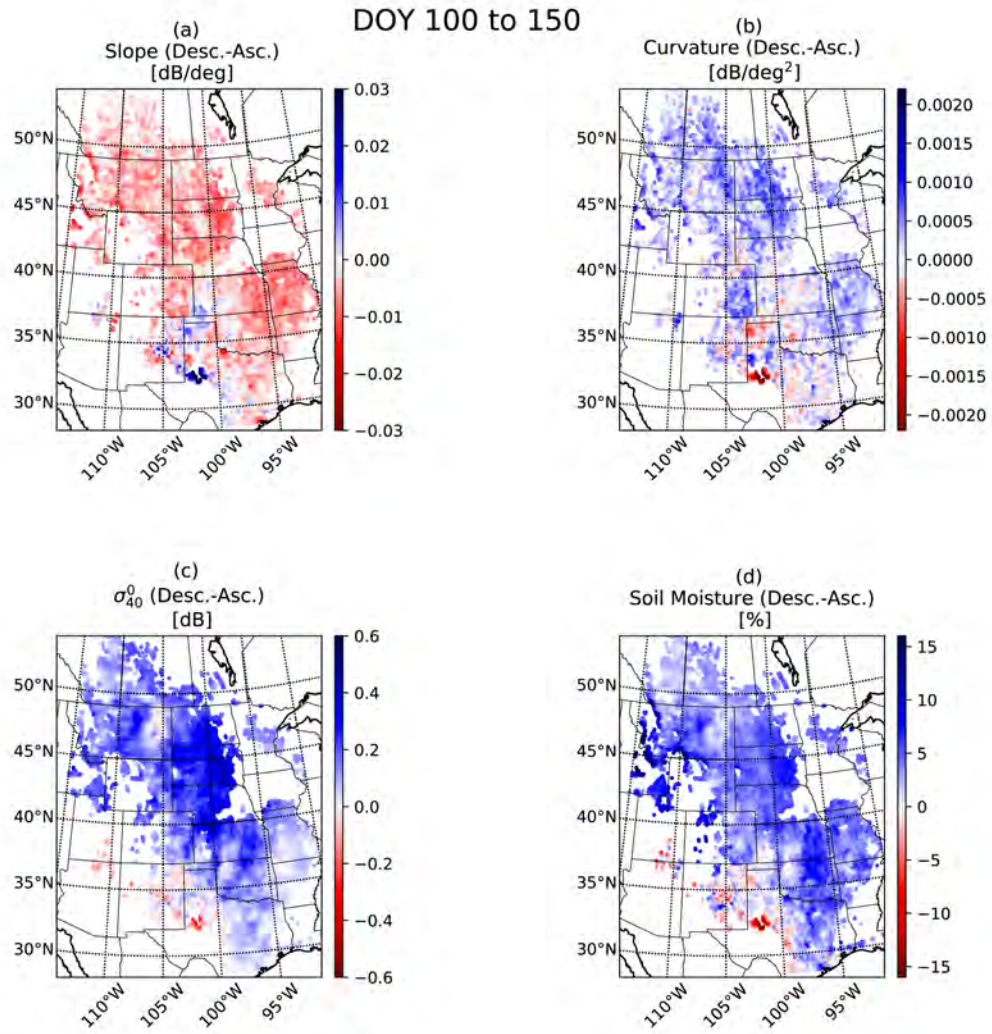


Figure 11: The difference between the values of slope (a), curvature(b), σ_{40}^0 (c) and soil moisture (d) calculated using the descending and ascending overpass data alone for the period DOY 100-150.

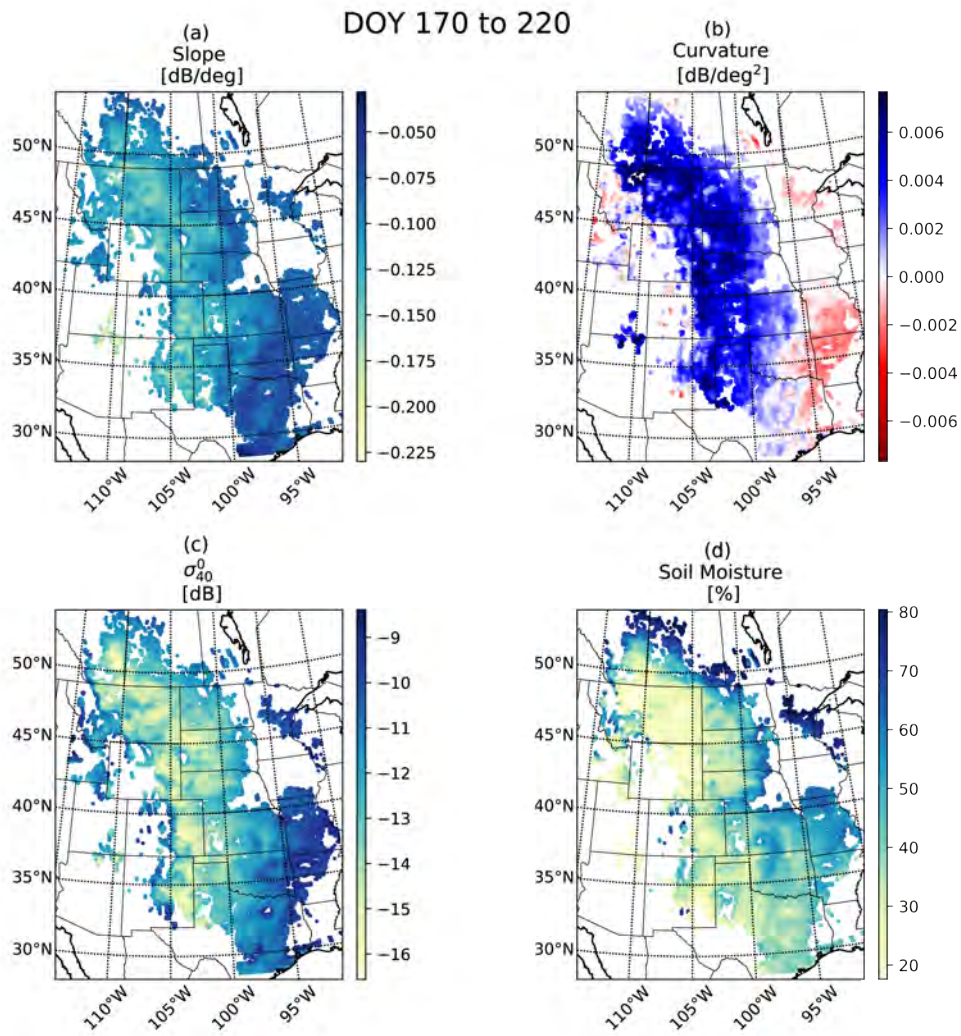


Figure 12: Climatological mean slope (a), curvature (b), σ_{40}^2 (c) and soil moisture (d) for each grid point during the period from DOY 170-220, calculated using all (descending and ascending) data.

443 west of the 100 W meridian (Fig 13). In the Northern Short grasslands, σ_{40}° and
444 soil moisture from the descending overpass (10 am) are still higher those from
445 the ascending pass (10 pm). However, in the Western Shortgrass Prairie, the
446 opposite is true. It is particularly striking that the daily dynamics of the soil
447 moisture are distinct from those of the vegetation, and that there is such strong
448 difference between the Northern and Western Shortgrass areas. The magnitude
449 of the diurnal difference in slope (Fig. 13 (e)) is considerably higher than earlier
450 in the season, and the effect is particularly strong in the shortgrass prairies west
451 of the 100 W meridian. The strongest negative backscatter and soil moisture
452 differences are observed in areas with the highest abundance of C₄ shortgrass
453 (New Mexico and Colorado) and C₃ shortgrass (east Wyoming) [43].

454 Figure 14 shows that contiguous anomalies in slope and curvature are ob-
455 served in areas affected by drought. Negative slope anomalies are observed in
456 western Nebraska and South Dakota in 2007. They are also observed in the
457 short grassland areas centered around the Texas Panhandle in 2011. In 2012,
458 the negative slope anomalies are generally found further north in Nebraska,
459 South Dakota and Colorado where the D3 conditions are indicated by the US
460 Drought Monitor. Positive curvature anomalies are observed in the drought-
461 affected areas in the south in 2011, and further north in 2012. Particularly
462 strong positive anomalies in curvature are observed in the Nebraska Sand Hills
463 (41 N to 42.5 N, 101 W to 102 W) in 2007 and 2012. These coincide with
464 negative slope anomalies in the same area. The Dfa area in the north shows
465 a positive anomaly during the dry conditions in 2007 and 2012 and a negative
466 anomaly during 2011.

467 Similar spatial patterns are observed in the σ_{40}° and soil moisture anomalies
468 (Fig. 15). The large positive anomalies in the south of the domain in 2007 are
469 due to extreme rainfall events in mid-June when a frontal system resulted in
470 heavy rains and extensive flooding in Texas and Oklahoma. The severe drought
471 event of 2011 resulted in a 2 dB negative anomaly in σ_{40}° and anomalies of
472 around 40% in soil moisture. In 2012, a negative soil moisture anomaly is
473 observed across the study domain, with the most severe values in the eastern

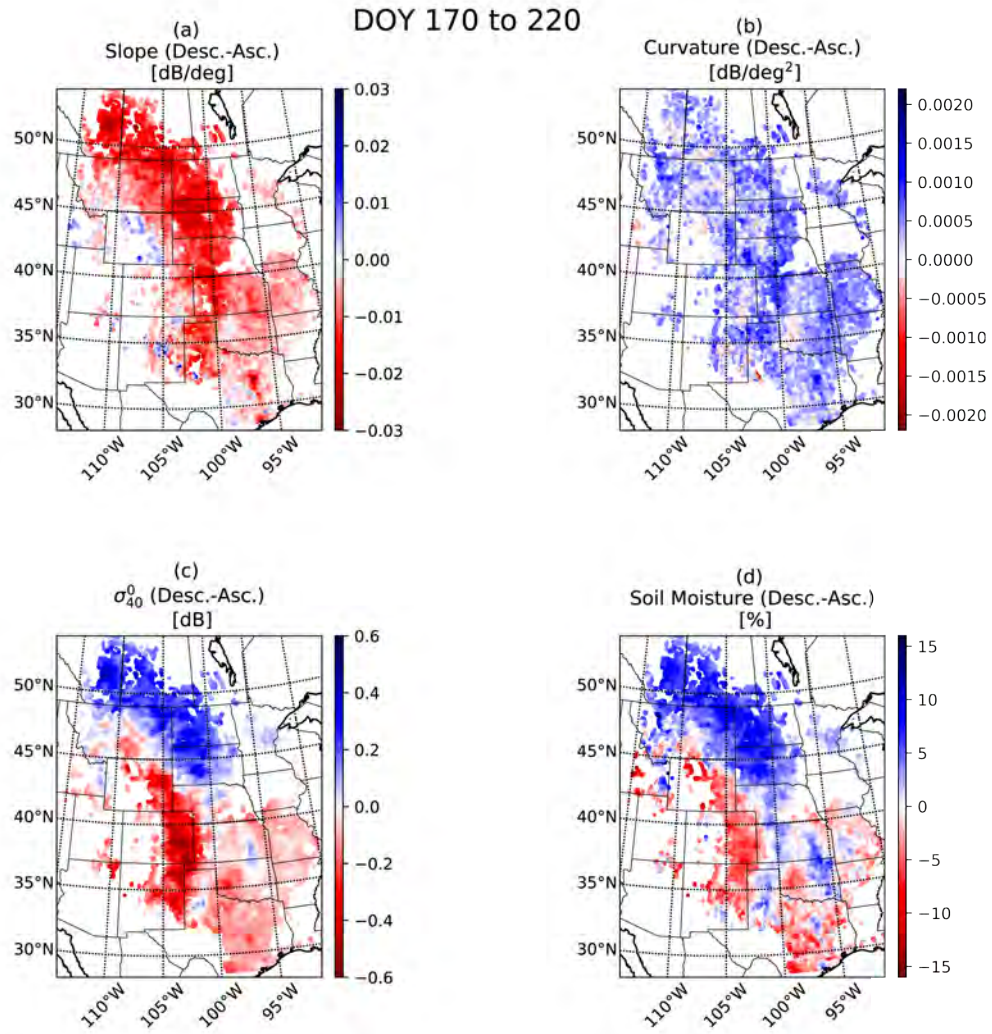


Figure 13: The difference between the values of slope (a), curvature(b), σ_{40}^0 (c) and soil moisture (d) calculated using the descending and ascending overpass data alone for the period DOY 100-150.

474 part of the study area. The largest backscatter anomalies are observed between
475 the 100 W and 105 W meridians, in the mixed grassland areas. Together with
476 the observed anomalies in slope, this suggests that backscatter contributions
477 from the vegetation were also lower than normal.

478 The occurrence of contiguous anomalies in areas affected by drought during
479 the maximum biomass period suggests that the slope and curvature contain
480 information on the impact of drought on vegetation. The difference in spatial
481 patterns between the vegetation parameter anomalies and the soil moisture
482 anomalies suggests that the impact of the soil moisture anomaly had a bigger
483 impact on some vegetation types. The observed anomalies in slope are consistent
484 with the interpretation of slope as an indicator of vegetation density. The
485 increased soil moisture deficit reduces both the fresh biomass and the vegetation
486 water content. The dynamics of the curvature provide insight into the dominant
487 scattering mechanism, which in turn is determined by species abundance and
488 the grass response to limited moisture availability.

489 *4.3. Nebraska Sand Hills*

490 The Nebraska Sand Hills ecoregion is the largest grass-covered sand dune
491 area in the western hemisphere and is regarded as one of the most important
492 groundwater-recharge areas for the Ogallala aquifer [44, 45]. The region is al-
493 most 85% intact natural grasslands [46]. The upland prairies are dominated by
494 C₄ grasses, namely sand bluestem (*Andropogon hallii* Vitman), little bluestem
495 [*Schizachyrium scoparium* (Michx.) Nash], prairie sandreed [*Calamovilfa longi-*
496 *folia* (Hook) Scribn.] and switchgrass (*Panicum virga-* tum L.) [47]. These C₄
497 grasses are better-adapted to periodic drought than other plant types. The
498 following results are spatially averaged across all grid points between (41.5 N,
499 101 W) and (42.5 N, 102 W).

500 Figure 6(d) shows a time series of the cumulative percent area of the state of
501 Nebraska experiencing each of the five levels of drought intensity. Less than 20%
502 of the state was affected by the D2 conditions in 2007. Figure 6 (a) suggests the
503 drought was primarily in western Nebraska including the Nebraska Sand Hills.

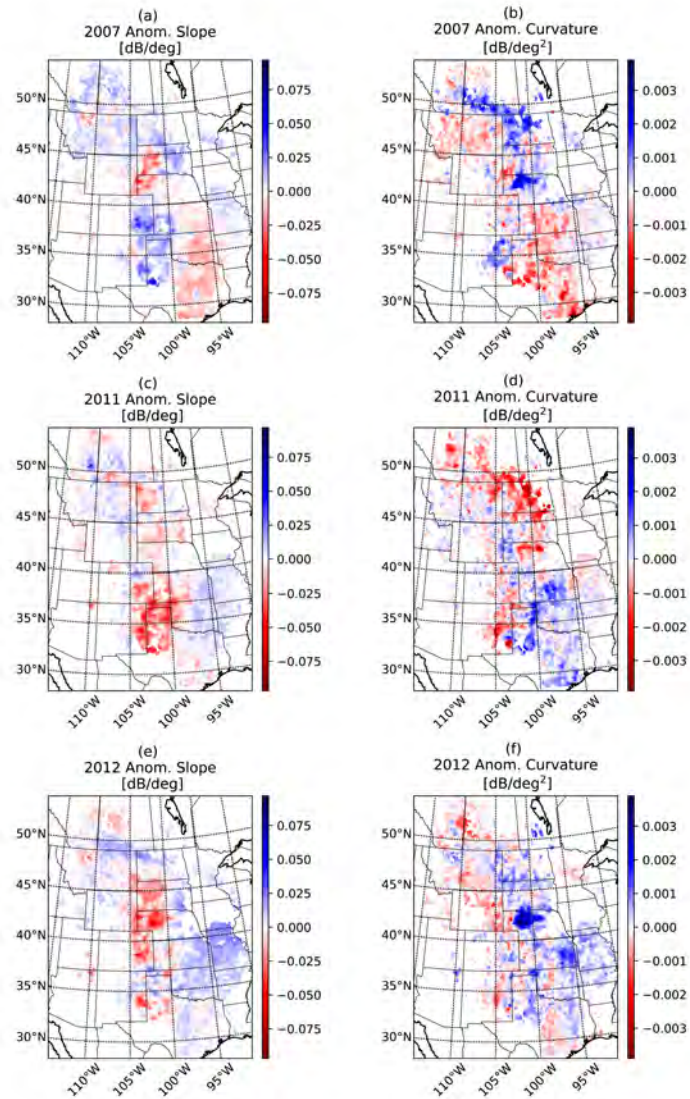


Figure 14: Anomalies in slope (left) and curvature (right) values during the biomass peak (DOY 170-220). Values are determined using all data (i.e. including descending and ascending overpass data).

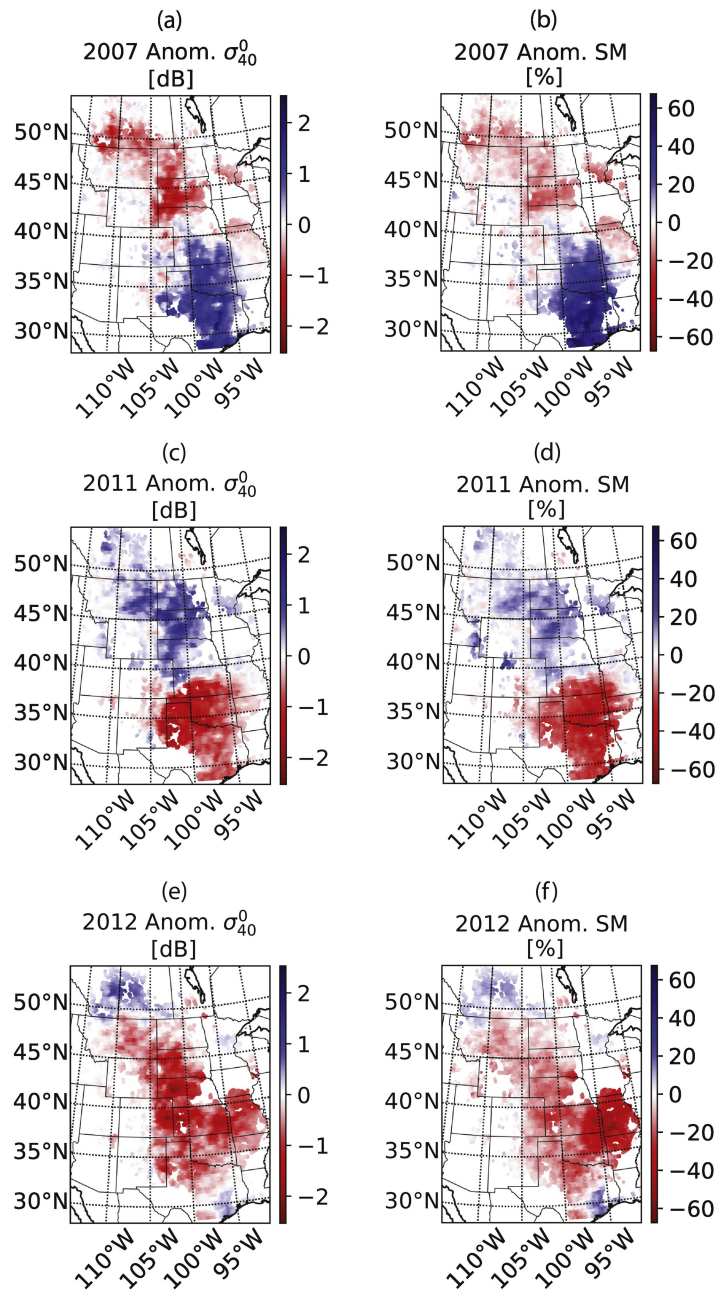


Figure 15: Anomalies in σ_{40}° (left) and soil moisture (right) values during the biomass peak (DOY 170-220) in 2007, 2011, and 2012. Values are determined using all data (i.e. including descending and ascending overpass data).

504 The rapid escalation in severity, and duration of the 2012-2013 drought is very
505 striking. The spring rains of 2013 succeeded in lowering the intensity, but even
506 by the summer of 2013, more than 60% of the state was still experiencing D2
507 conditions.

508 Figure 16 shows the seasonal climatology (a)-(d) and the time series of
509 anomalies (e)-(h) for the vegetation parameters, σ_{40}° and soil moisture in the
510 Nebraska Sand Hills. Winter and summer slope values are beyond the range
511 observed in the aggregated grassland ROIs, and curvature is higher than that
512 observed in any of the ROIs. The seasonal cycles of curvature, σ_{40}° and soil
513 moisture are markedly different than those observed in Figure 4. Soil is very
514 dry during November/December, and the maximum soil moisture occurs in the
515 Spring. σ_{40}° therefore has a winter minimum, and a summer maximum which
516 coincides with the maximum slope values. This suggests that vegetation makes
517 a significant contribution to total backscatter during the summer months.

518 The severity of the 2012-2013 soil moisture anomaly and its duration are
519 apparent in Figure 16(h). An initial negative soil moisture anomaly in soil
520 moisture occurs in late 2011-January 2012, though it is dissipated by precip-
521 itation in February-April. A significant anomaly, up to 20%, initiated in the
522 summer of 2012 persists through to January 2013. This anomaly is also very
523 clear in the σ_{40}° data, where backscatter is up to 2 dB lower than usual. At the
524 start of 2012, slope is higher than normal, though it starts to decrease abruptly
525 in early June and this negative anomaly persists until June 2013. A large posi-
526 tive curvature anomaly persists from April to October 2012, with the maximum
527 deviation from climatology (0.0035 dB/deg^2) occurring at the start of August.
528 The asynchronous anomalies in slope and curvature produce the unexpected
529 combination of a negative slope anomaly with a positive curvature anomaly
530 during the maximum biomass period. This suggests that vegetation density is
531 less than normal, but a stronger dominance of the direct scattering from the
532 canopy over the ground-bounce term. Given the low water-holding capacity of
533 the sandy soils, and the magnitude of the soil moisture and σ_{40}° anomalies, it
534 seems plausible that the soils were completely dry and therefore contributed less

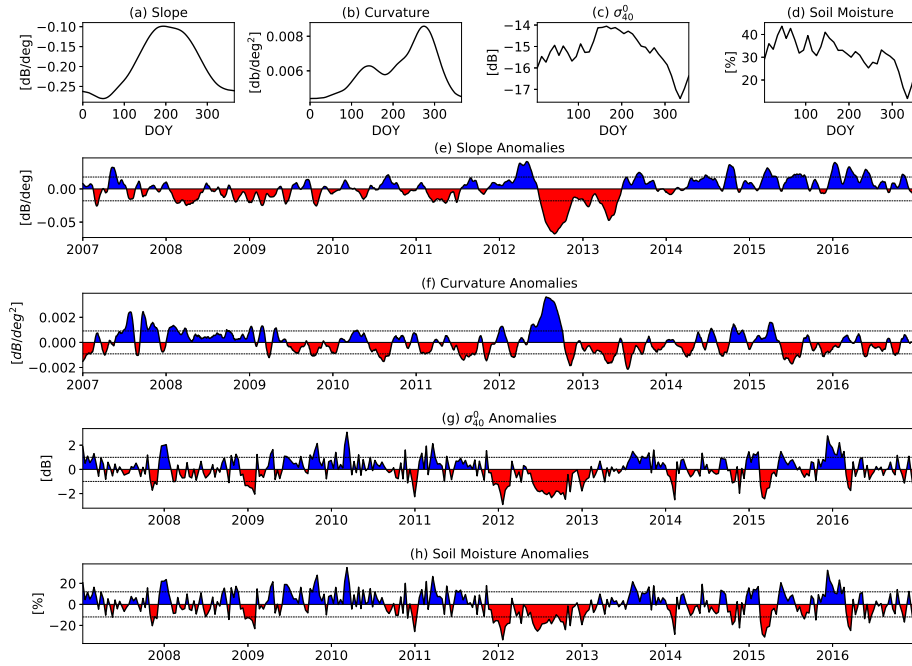


Figure 16: Climatology of slope(a), curvature (b), normalized backscatter (c) and soil moisture (d) values averaged across the Nebraska Sand Hills, followed by the time series of anomalies observed in the same quantities (e)-(h) during the study period.

535 to total backscatter than the vegetation. The C_4 grasses of the upland prairie in
 536 the Nebraska sandhills are better adapted to withstand periodic drought than
 537 other plant types. Stomatal closure and leaf rolling in these grasses reduces
 538 transpiration and prolongs survival to drought [47]. This supports the idea that
 539 moisture was present in the vegetation long after the soil surface dried, allowing
 540 direct scattering to dominate over ground-bounce term.

541 5. Conclusions

542 The first ten years of ASCAT backscatter data from Metop-A were analyzed
543 to characterize the spatial and temporal variability in the vegetation parameters
544 of the TUV SMR approach. Seasonal climatology, spatial patterns and inter-
545 annual variability in the slope vary between grassland cover types, reflecting
546 variations in the soil moisture availability and growing season length. While the
547 seasonal cycle of the slope support its interpretation in the TUV SMR approach
548 as a measure of "vegetation density", it would be useful to be able to relate this
549 directly to biomass or vegetation water content.

550 Until now, the TUV SMR curvature parameter has not been explored as
551 a source of information about vegetation. Results presented here demonstrate
552 that curvature is clearly influenced by vegetation phenology, with significant
553 variations occurring at the start and end of the growing season. Its seasonal
554 cycle varies considerably across the different land cover types, but does not
555 appear to have a simple relationship with slope. Results are consistent with
556 the idea that the curvature is a measure of the relative dominance of direct
557 scattering from vertical vegetation constituents over a ground-bounce contribu-
558 tion. This has been observed in wheat and barley that, similar to many grasses,
559 have a predominantly vertical structure. The relative dominance of these two
560 scattering mechanisms is influenced by the total vegetation water content, its
561 vertical distribution within the vegetation, and the geometry of the vegetation
562 constituents. The seasonal dynamics, and anomalies observed in the curvature
563 values during drought conditions suggest that the curvature may yield valuable
564 insight into the drought response of vegetation in grasslands. The potential
565 value of the curvature values as a source of information about the vegetation in
566 other land cover types needs to be further investigated.

567 The drought events in 2011 and 2012 resulted in extensive negative σ_{40}° and
568 soil moisture anomalies during the maximum biomass period. The impact on
569 slope and curvature was more spatially heterogeneous. However, contiguous
570 anomalies were observed in locations where the severity and persistence of the

571 drought were enough to impact vegetation. A time series of observations from
572 the Nebraska Sand Hills confirmed that prolonged drought conditions, indicated
573 by soil moisture anomalies, resulted in lagged anomalies in both the slope and
574 curvature. This suggests that anomalies in these vegetation parameters might
575 be useful to detect when a soil moisture anomaly is severe enough that it impacts
576 the vegetation.

577 The results presented here suggest that considering the slope and curvature
578 dynamics in combination with the backscatter itself could yield valuable insights
579 into canopy water dynamics. The incidence angle dependence of backscatter
580 depends on the relative dominance of surface, volume and multiple scattering
581 which, in turn, depend on vegetation structure, total water content and the
582 vertical distribution of moisture within the vegetation. The dynamics of slope
583 and curvature contain information on how these quantities are changing in time.
584 The vegetation parameters could therefore be useful for attributing backscatter
585 variations to moisture or structural changes associated with vegetation phenol-
586 ogy or environmental stress.

587 It is particularly noteworthy that diurnal differences have been identified in
588 the vegetation parameters. This shines a new light on previous studies in which
589 diurnal differences in ASCAT observations were detected. Friesen et al. [13] and
590 [48] analyzed data processed using WARP5.0, in which long-term climatologi-
591 cal values of vegetation parameters were used to normalize backscatter to the
592 reference angle of 40° . Using the new approach of Melzer [19], not only can the
593 interannual variability be taken into account, but vegetation parameters can be
594 calculated separately for the ascending and descending overpasses. Using these
595 distinct parameter values, it is possible to take into account changes in the rel-
596 ative importance of different scattering mechanisms between the ascending and
597 descending overpasses. The value of the split (descending/ascending) vegetation
598 parameters is expected to be greatest in cover types in which total backscatter
599 is influenced by a combination of soil surface and vegetation contributions, e.g.
600 grasslands, savannas. Grasslands proved particularly interesting in this regard
601 because their structure plays a role in the relative dominance of the soil and

602 vegetation contributions.

603 In order to relate ASCAT observations to canopy water dynamics, the over-
604 pass time needs to be considered from a plant-physiological point of view.
605 Metop’s 9:30 AM (local) overpass time is advantageous in the sense that dew
606 should be less than pre-dawn values. However, it also means that vegetated
607 surfaces are observed after several hours of evapotranspiration. The impact on
608 the moisture content of individual constituents (leaves, branches, trunk/stalk)
609 and total vegetation water content varies considerably by vegetation and cli-
610 mate type. This underscores the need for an improved understanding of the
611 vertical distribution of moisture within vegetation, its daily cycle, how it varies
612 in response to environmental stress and how it influences total backscatter.

613 Dynamic estimation of the vegetation parameters will guide improvements in
614 the TUW SMR approach for retrieving soil moisture from ASCAT observations.
615 Furthermore, results presented here suggest that the ability to dynamically es-
616 timate the slope and curvature of the $\sigma^\circ - \theta$ relationship may yield new insights
617 into vegetation dynamics using C-band scatterometry. This offers many oppor-
618 tunities to use the current archive of ASCAT data for vegetation monitoring.
619 This study also highlights the need for improved understanding of the influence
620 of soil-vegetation water dynamics on scattering mechanisms. This would benefit
621 exploitation of data from both ASCAT on-board the series of Metop satellites
622 and the next generation instrument SCA on-board Metop-SG.

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629 spheric Administration. Maps and time series data are courtesy of NDMC-UNL
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