

The Backscattering Contribution of Soybean Pods at L-band

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Abstract

L-band (1.25 GHz) radar measurements of a soybean canopy indicate that the emergence of seed pods is a significant contributor to the backscatter during the late stages of the growing season. In order to validate the measured data, a realistic scattering model of the soybean canopy is developed. The parameters of the soybean canopy and underlying soil used in the model vary over the growing season based on *in situ* measurements. Scattering amplitudes for soybean leaves are modeled analytically by using a thin disk approximation; stem and pods are jointly modeled using a numerical electromagnetic field solver. These scattering amplitudes are together incorporated into a coherent scattering model to obtain the backscattering coefficient for VV- and HH-polarizations. The modeling results show good agreement with the radar field measurements, having RMSEs of 0.51 dB for VV-pol and 1.1 dB for HH-pol. Both measured data and modeled results show that the change of soil moisture can be accurately monitored by L-band backscatter. It is also found that the difference between HH- and VV-polarized backscatter increases as the size of the soybean pods becomes larger. A method is developed here to estimate the number of pods in a soybean canopy based on polarimetric radar backscatter at L-band.

28 Keywords

29 Radar backscatter, Soybean growth and development, Soybean pods, ComRAD, Soil Moisture

30 1. Introduction

31

32 A model describing the microwave backscatter from a layer of vegetation is important for
33 the study of active remote sensing of soil moisture and vegetation dynamics. The scattering
34 amplitudes of the canopy scatterers are dependent on each plant and their density throughout the
35 canopy (Steele-Dunne et al., 2017). To model an individual plant, the density, dielectric
36 properties, size, and orientation of the major components of vegetation (e.g. stem, leaves, and
37 fruit) need to be considered. The backscattering contributions of plant fruits, in particular, have
38 important bearing on remote sensing of agricultural harvests. In the past, C-band or higher
39 frequency radars have often been used to monitor agricultural crops due to their high sensitivity
40 to vegetation constituents (Joerg et al., 2018). The penetration into the vegetation canopy of
41 these high-frequency radars, however, is too weak to monitor the underlying soil moisture. The
42 motivation of this paper is to explore the use of radar backscatter data at low microwave
43 frequency (L-band) to monitor the growth of soybean pods, as well as the underlying soil
44 conditions.

45 The reason for choosing L-band in this study is because radars operating at this frequency
46 have been widely used by a number of Earth-observing satellites to sense the Earth's surface due
47 to their strong penetration through clouds and vegetation canopies. The Advanced Land
48 Observing Satellite (ALOS) was an Earth Observation satellite mission launched by the Japan
49 Aerospace Exploration Agency in 2006 (Rosenqvist et al., 2007). It employed a Phased Array L-
50 band Synthetic Aperture Radar (Palsar) to monitor the Earth's surface. Its operation stopped in

51 2011 and ALOS-2 (Kankaku et al., 2013) was launched in 2014 to continue Earth monitoring at
52 L-band (1.2 GHz). Soil Moisture Active Passive (SMAP) is a NASA satellite launched in 2015
53 (Entekhabi et al., 2010). SMAP carries a combined radar and radiometer system for its primary
54 mission of measuring soil moisture; its radar operates at 1.25 GHz and its radiometer operates at
55 1.4 GHz. The SMAP radar, however, stopped operating about 5 months after launch due to a
56 power supply failure, although its radiometer continues to provide quality passive observations to
57 the present time. The NASA-ISRO SAR (NISAR) is a new joint satellite mission developed by
58 the USA and India whose main goal is to exploit synthetic aperture radar to map Earth's surface
59 every 12 days (Rosen et al., 2015). It operates at the dual frequencies of L-band at 1.25 GHz and
60 S-band at 3 GHz. The launch of NISAR is planned for 2022.

61 In order to assist the research of land remote sensing at L-band, the ComRAD (Combined
62 Radar-Radiometer) truck-mounted microwave instrument system has been developed jointly by
63 George Washington University and NASA Goddard Space Flight Center (O'Neill et al., 2006).
64 ComRAD includes a quad-pol 1.25 GHz radar and a dual-pol 1.4 GHz radiometer sharing the
65 same 1.22-m parabolic dish antenna. The resolution of ComRAD is about 4-5 m (depending on
66 boom height and incidence angle), which is much higher than most of the satellite missions. Its
67 main use is to obtain active/passive L-band data as a simulator of satellite sensors to refine the
68 soil moisture retrieval algorithms for Earth-observing satellite missions.

69 In the past, there were very few research papers that describe the modeling of scattering
70 from the fruits of agricultural crops at L-band. Monsivais-Huertero and Judge (2011) analyzed
71 the backscatter from growing corn at L-band using the Michigan Microwave Canopy Scattering
72 Model (MIMICS) (Ulaby et al., 1988) and the coherent model developed by Thirion et al. (2004).
73 Their analysis indicated a possibility of monitoring the growth of corn at L-band. De Roo et al.

74 (2001) developed a semi-empirical backscattering model for a soybean canopy at L- and C- band
75 with soil moisture inversion. Huang et al. (2015) developed a coherent scattering model for
76 soybeans at L-band. In both De Roo and Huang models, however, the soybean pods were not
77 taken into consideration.

78 Coherent scattering effects have been considered in this paper to model the scattering of a
79 soybean canopy. Different from the energy-based radiative transfer method (Tsang, 1985), the
80 coherent scattering model is based on electromagnetic waves in random media (Chauhan et al.,
81 1991). The model consists of a layer of discrete random media over a dielectric half-space, with
82 the mean field computed using the Foldy method (Foldy, 1945). The scatterers are then
83 embedded in the mean medium and the Distorted Born Approximation (DBA) is employed to
84 obtain the scattering coefficients for the canopy (Lang and Sidhu, 1983). Since the coherent
85 method has shown significant improvements on matching radar data for a corn field (Lang et al.,
86 2017; Sharma et al., 2020), it has been chosen to model the soybean canopy.

87 In this paper, the backscattering contribution of soybean pods at L-band is discussed based
88 on modeled results and measured data taken by ComRAD over the reproductive stages of a
89 soybean canopy prior to senescence. Ground truth data are used as parameters of the soybean
90 scattering model to understand the relationship between the polarimetric L-Band radar
91 backscatter and the dynamics in the soybean canopy and underlying soil moisture. Comparison
92 between the modeled results and measured data provides a sound validation of the robustness of
93 the model due to the large variation in soybean canopy parameters over the reproductive stages.

94 The paper is structured as follows: Section 2 introduces the *in situ* measurements taken
95 from the soybean field. Measurements collected include the dimensions, biomass, and density of
96 the plant constituents as well as the soil moisture and the surface roughness underlying the

97 soybean canopy. In addition, backscatter observations from the soybean canopy by the ComRAD
98 radar are presented in this section. In Section 3, a coherent model of the scattering of a soybean
99 field is presented. For a single soybean plant, the leaves are represented by thin dielectric
100 elliptical discs and their scattering amplitudes are computed via a thin disc approximation from
101 Le Vine et al. (1985). The combined scattering amplitudes of soybean pods and a stem are found
102 using a numerical EM solver. The scattering amplitudes of leaves, stems, and pods are then
103 employed in the coherent discrete scatter model developed by Chauhan et al. (1991) to obtain
104 backscatter from the soybean field over the reproductive stages. In Section 4, the backscattering
105 coefficients from the soybean canopy - with and without the pods - are compared in order to
106 demonstrate the contributions of soybean pods. The modeled results are also compared with the
107 actual measurement results obtained by the ComRAD radar. The comparison is used to establish
108 a relationship between the polarimetric radar backscatter and the counts of soybean seeds per
109 square meter. Finally, the conclusion is presented in Section 5.

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111 2. Soybean canopy measurements

112

113 2.1 Plant dimension and biomass measurements

114 The soybean fields used in this study were located at the Optimizing Production Inputs for
115 Economic and Environmental Enhancement (OPE³) site, which has been maintained and
116 instrumented by the U.S. Department of Agriculture - Agricultural Research Service (USDA-
117 ARS) located in Beltsville, MD. The soybeans were planted on June 14, 2012 and the *in situ*
118 measurements were started on June 26, 2012, i.e. day of year (DOY) 178, and taken
119 approximately once every week over the growing season. Plants were randomly selected from
120 the measurement site for destructive sampling. The measured dimensions of leaf, stem, and pod

121 are plotted in Fig. 1 for DOY 178-269 (Jun. 26 - Sep. 25). For each DOY in the figure, the points
 122 for plant height represent the average results of three different plants; the points for leaf represent
 123 the average results of fifteen leaves and the points for pod represent the average results of nine
 124 pods. In Fig.1, the point with error bar represents the mean \pm standard error (SE). The standard
 125 error of the mean can be computed by:

$$126 \quad SE_{i,j} = \frac{SD_{i,j}}{\sqrt{N_j}}, \quad (1)$$

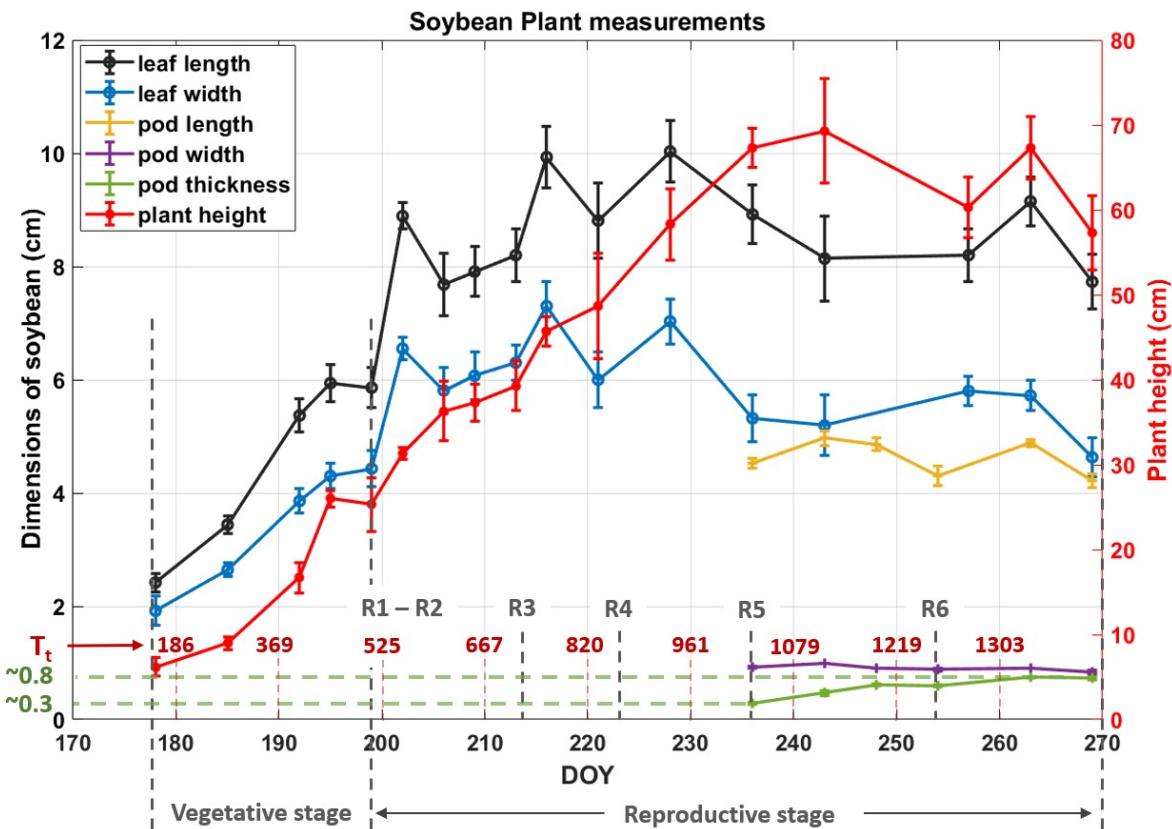
127 where $SD_{i,j}$ is the standard deviation of the measurements of jth type of soybean constituents at
 128 ith day of experiment; N_j is the number of measurements made for jth type of constituents.

129 There are two main stages in the growth of a soybean plant: vegetative stage and
 130 reproductive stage, which correspond to the periods before and after the flowering of soybean
 131 plants, respectively. In Fig.1, DOY 178-198 is the period for the vegetative stage during which
 132 the leaves and stems develop. It is seen from the figure that the dimensions of leaf and stem
 133 increase rapidly until around DOY 200, when the reproductive stage starts.

134 The period from DOY 200 to DOY 269 is the reproductive stage of the soybean plants.
 135 The reproductive stage of soybeans can be further categorized into sub-stages of R1-R8 based on
 136 the growth of pods (Pederson, 2004). The period of each stage of a soybean's growth is
 137 dependent on the thermal time (T_t) with a unit of $^{\circ}\text{C}\cdot\text{day}$. The expression of thermal time is given
 138 as (Togliatti et al., 2019):

$$139 \quad T_t(n) = \sum_1^n \left(\frac{T_{\max}(n) + T_{\min}(n)}{2} - T_{\text{base}} \right) \quad (2)$$

140 where n represents the number of days passed since planting; $T_{\max}(n)$ and $T_{\min}(n)$ are the
 141 maximum and minimum temperature for the n^{th} day after planting, respectively; T_{base} is the base
 142 temperature, below which the development of crop will no longer occur. Here, T_{base} is set to be
 143 10°C (Togliatti et al., 2019; Abendroth, 2011). For the period of 2012 soybean measurements,
 144 the temperature data are obtained from an online source (<https://www.timeanddate.com/weather/>)
 145 and the thermal time is computed correspondingly. In Fig. 1, the thermal time, T_t , is given above
 146 the x-axis in red color. The information of thermal time can be used by future studies for
 147 comparing the growth of soybean plants in other locations and years that experience different
 148 weather conditions.



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Fig. 1. Soybean plant dimensions as a function of DOY/Thermal time.

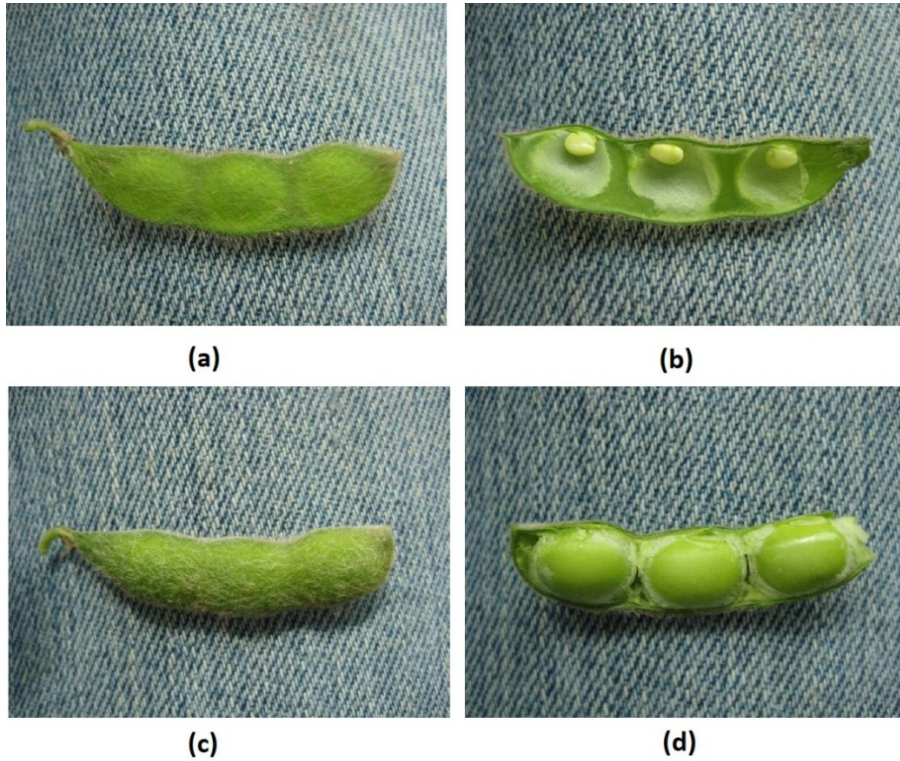
151 Based on thermal time, the approximate start dates of different R-stages are estimated and
152 marked in Fig. 1. In the figure, DOY 213-269 covers from R3–R4 (beginning pod – full pod) to
153 R5–R6 (beginning seed – full seed) and stops right before R7 (beginning of maturity). The
154 recording of the pod dimensions started on DOY 236 where approximately the R5 (beginning
155 seed) stage starts. It is seen that the dimensions of leaves and stems stay relatively consistent
156 during the reproductive stage. Different from the other constituents, the pods become thicker
157 during the reproductive stage as the seeds within the pods grow. The thickness of the pods
158 changes approximately from 0.3 cm to 0.8 cm while the length and width of the pods remain
159 almost constant as DOY goes from 236-269. The field measurement data for DOY 213-269 are
160 documented in Table A.1 to provide a more detailed track of the growth of soybean plant
161 constituents.

162 During the period of measurements, i.e. stages R3-R6, soybean pods are green. For stages
163 R3-R4, a soybean pod is formed by a green shell with a thin layer of dry matter enclosed. The
164 dry matter provides the nutrients for the development of beans (seeds). The forming of beans
165 starts at stage R5. A soybean pod usually contains 2-4 beans covered with a green shell during
166 stages R5-R6. Fig. 2 (Casteel, 2011) shows a closer look at soybean pods for stages R5 and R6.
167 It is seen from Fig. 2 that the length and the width of pods stop growing while the thickness of
168 the pods increases due to the forming of beans during stages R5-R6. The effects of the bean
169 growth will be considered in the development of the soybean backscattering model in this paper.

170 The orientation of leaves is also recorded in the measurements and the leaf angle statistics
171 for DOY 213-269 are plotted in Fig. 3. It is seen that the statistics of the leaf angle can be
172 approximated by a $\cos\theta$ distribution function, with $0^\circ \leq \theta \leq 90^\circ$. Here, θ is the angle between

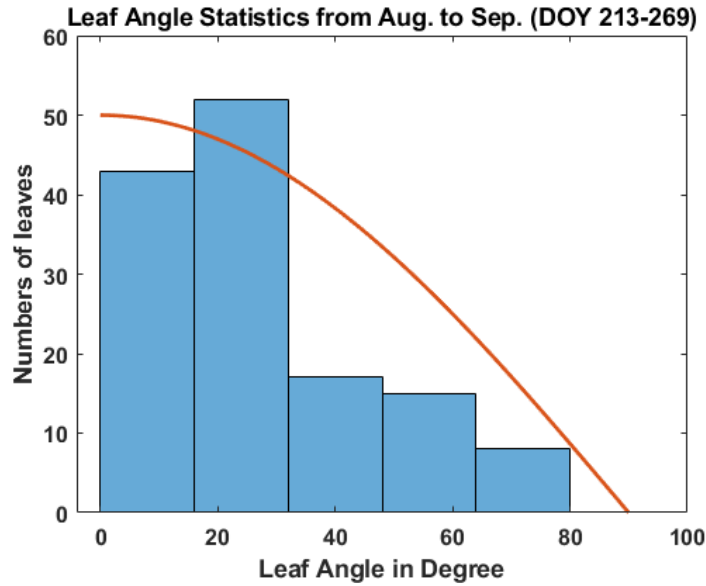
173 the normal direction of the leaf surface and the normal direction of the ground. This information
174 will be employed to model the backscatter of the soybean canopy in Section 3.

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177 Fig. 2. Soybean pods - (a): soybean pod at the beginning of stage R5; (b): soybean pod of (a) with half the
178 shell removed; (c): soybean pod at stage R6; (d): soybean pod of (c) with half the shell removed.



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Fig. 3. Histogram of leaf orientation.

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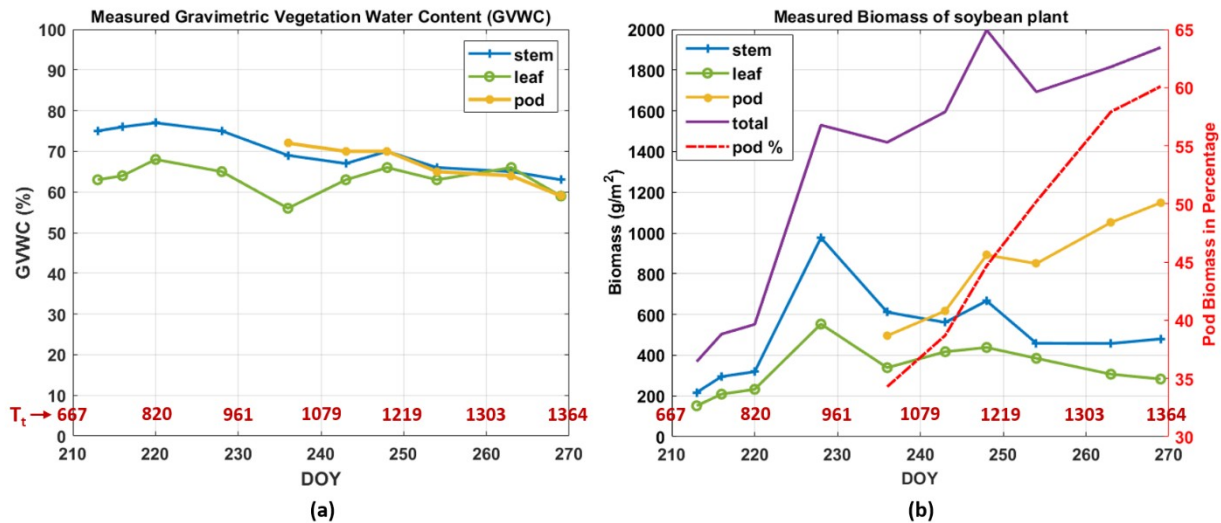
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The gravimetric vegetation water content (GVWC) of the soybean plant constituents was also measured over the growing season. In this paper, GVWC is defined as the ratio of the difference between the fresh and dry mass of vegetation to the vegetation fresh mass (Wang et al., 2015). Three soybean plants were randomly picked on each sampling day and cut into stem, leaf and pod components. The petioles, which are the thin branches for supporting the leaves, are not considered since their effect on scattering is assumed to be small at L-band. The chosen components were sorted and placed into individual bags. The mass of the bags was recorded and then oven-dried for about 3 days at 70° C until the mass did not change. Finally, the mass of the bags was found again and the GVWC from the individual components was computed in percentage. The GVWC are plotted for stem, leaf, and pod through DOY 213-269 (stages R3-R6) in Fig. 4(a). It is seen that the GVWC of the soybean stem and pods decays slightly, while the GVWC of soybean leaves stay quite consistent during stages R3-R6. These results indicate that the dielectric constant of the soybean components remains approximately the same during this period.

195 The GVWC can then be converted to the wet biomass using the plant mass and density
 196 measurements. The wet biomass measurement results are plotted in Fig. 4(b) for stem, leaf, pod
 197 and whole plant. The red dashed line, which corresponds to the right y-axis, represents the
 198 percentage of the biomass of pods to the total biomass. Compared with other soybean
 199 constituents, pods have much greater contribution to the total biomass in the later stages. The
 200 rise of the pod biomass is mainly due to the increase of the pod size/thickness. Fig. 4(b)
 201 demonstrates that the soybean pods are the dominant contributor to the total biomass during
 202 reproductive stages and their scattering contributions need to be included in any accurate
 203 scattering model. The thermal time, T_t , is also given in Fig. 4(a) and (b) to provide a reference
 204 for future studies.

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206
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Fig. 4. (a): GVWC of soybean plant constituents; (b): Wet Biomass of soybean plant constituents.

208 2.2 Dielectric measurements

209

210 The dielectric constant of soybean pods was determined by a reflection technique. Since
 211 no dielectric measurements of soybean pods were performed in the summer of 2012, the
 212 measurements were made in 2019 for soybean plants in adjacent fields similar to those grown in

213 2012. The dielectric measurements were performed by an open coaxial probe which connected to
 214 a portable vector network analyzer (Keysight Fieldfox N9923A) to measure the reflection
 215 coefficient, Γ , from the surface of the soybean pods. The dielectric constant can then be
 216 determined by the formula from Stuchly, M and Stuchly, S (1980). Methanol was used as the
 217 calibration solution in the experiment since its dielectric constant is close to that of the soybean
 218 constituents; the dielectric constant of methanol is obtained from Gregory and Clarke (2012).

219 The dielectric measurements were made for soybean shells and beans separately by
 220 inserting the probe perpendicular to their cross-sections at various locations. Three different pods
 221 were used in each measurement and the average dielectric constants were recorded. The
 222 measurements were performed for two different fields during a three-week period (DOY 261–
 223 274/ Sep.18–Oct. 1). Three sets of the data were obtained from field #1 and one set of data was
 224 obtained from field #2. The soybean plants from field #1 were planted on Jun. 28 and the plants
 225 from field #2 were planted on May. 18. The results are shown in Table 1.

226 Based on the thermal time of planting, the pods from field #1 should have approximately
 227 reached stage R5-R6, which are comparable to the soybean measurements performed on DOY
 228 242-256 in 2012. It is seen from the table that the dielectric constants of green pods stay
 229 relatively consistent during this period. The pods from field #2, which have already reached
 230 stage R7, have a much lower dielectric constant due to the loss of moisture. Since the stage R7 is
 231 later than the stages of soybeans in the 2012 measurements, the dielectric constants of soybean
 232 pods from field #2 are not considered in this study.

Days passed since planting	Thermal Time (°C-day)	Soybean Field	Sample stage	Parts	Dielectric Constants	
					Real	Imag.
82	1120	#1	R5	Beans	47	16
				Shells	46	8

89	1185	#1	R5	Beans	41	18
				Shells	37	15
95	1252	#1	R6	Beans	51	16
				Shells	49	9
130	1631	#2	R7	Beans	25	12
				Shells	22	8

Table 1 Soybean dielectric measurement data

233
 234 In section 3, a pod will be modeled in one piece to avoid the complexity of modeling the
 235 shells and beans separately. Thus, the effective dielectric constant of the pods, ϵ_{eff} , is computed
 236 based on the percentage volume and the averaged dielectric constant of beans and shells. The
 237 dimensional measurements for a pod reaching R6 stage show that the beans and shells make up
 238 about 70% and 30% of the volume of an individual pod, respectively. Based on Table 1, the ϵ_{eff}
 239 of pods is estimated as 46-15j. These dielectric measurements and the previous GVWC results
 240 together indicate that the dielectric constant of soybean pods can be considered as a constant over
 241 the reproductive stages prior to R7.

242 Based on the measured data documented in Lang et al. (2004), the dielectric constants of
 243 soybean leaves and stems are set to be 23-9j and 15-5j, respectively. These dielectric constants
 244 are used in this paper for obtaining the analytic and the numerical solutions of soybean scattering.
 245 Note that the dielectric constants only have a small effect on the backscattering coefficients. For
 246 example, decreasing the dielectric constant of the pods by 20% only changes the backscattering
 247 coefficients by 0.4 dB.

248 2.3 Soil Type

249

250 Besides the soybean constituents, the underlying soil has a significant influence on radar
 251 backscatter. The test site has a soil texture that is characterized as a sandy loam, with 23.5% silt,

252 60.3% sand and 16.1% clay. The soil has a bulk density of $1.25 \text{ g}\cdot\text{cm}^{-3}$. To determine the soil
253 moisture, several locations away from the radar footprint were sampled. A Delta-T theta probe
254 was inserted into the surface and provided a measurement of the near-surface soil moisture. The
255 probe is 6 cm in length, but the approximate depth contribution of L-band radiometry is generally
256 taken to be about 0-5 cm. Therefore, the theta probe is calibrated to gravimetrically collect soil
257 samples with a 0-5 cm depth. This method has been used throughout all of the soil moisture field
258 experiments used for SMAP calibration/validation. The measured daily averaged volumetric soil
259 moisture is documented in Table A.1 for DOY 213-269. Based on the soil type and moisture, the
260 complex dielectric constant of the soil was computed using the Dobson model (Dobson et al.,
261 1985, Peplinski et al., 1995a, 1995b).

262 The surface roughness of the soil was measured by a metal grid board. Numbers of points
263 were chosen from two fields in the surface roughness measurements and the experiments were
264 done along and across the soybean rows. The number of measurements and the measured results
265 are given in Table 2. Due to the randomness of the measurements, the surface roughness was
266 also calibrated by matching the radar backscatter data of the bare soil to the analytic rough
267 surface model using the small perturbation method given by Fung and Chen (2009). The
268 backscatter of the bare soil was measured for the soybean field after planting but before the
269 emergence of soybean plants. The calibrated surface roughness has an RMS height of 0.7 cm and
270 a correlation length of 12 cm, which has reasonable agreement with the measured data given in
271 Table 2. Note that the largest change of surface roughness generally occurs during the first rain
272 event since planting, which tends to smooth the surface. The surface roughness measurements in
273 this study were made after the first rain event. The soil roughness was visually observed through

274 the course of the experiment and it did not noticeably change. Therefore, surface roughness is
275 treated as a constant in this study.

	# of Meas.	RMS height (cm)	Correlation Len. (cm)
Field #1 along	85	0.57	3.0
Field #2 along	110	0.56	20.2
Field #1 across	139	1.98	11.8
Field #2 across	77	1.84	13.2

276 Table 2 Surface roughness measurement results

277

278 2.4 ComRAD Radar measurements

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280 The Combined Radar/ Radiometer (ComRAD) truck-mounted microwave instrument
281 (O'Neill et al., 2006) is a combined system operating as a radar at 1.25 GHz and as a radiometer
282 at 1.413 GHz. It is mounted on a 19-m hydraulic boom truck as seen in Fig. 5. The radar and
283 radiometer share a parabolic dish antenna with a Cassegrain-like feed. The feed is implemented
284 with a circular waveguide having two orthogonally placed wire probes, one to support horizontal
285 polarization (HH-pol) and the other to support vertical polarization (VV-pol). The cross-pol data
286 are not considered in this study due to the difficulties in the calibration of cross-pol channels
287 compared to co-pol channels. For this study, the radar has a fixed incident (elevation) angle of
288 40° to the soybean field. The radar acquires data by sweeping in a 120° azimuth range with a 2°
289 increment; the sweeps are repeated every few hours throughout the day. The daily averaged
290 backscattering coefficients are plotted in Fig. 6 with error bars. Similar to Fig. 1, the error bars
291 represent the standard error of the mean. The measured volumetric soil moisture (VSM) results
292 are also plotted in Fig. 6 to compare with the backscattering coefficients from the radar.

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Fig. 5. ComRAD system mounted on a 19-m boom truck.

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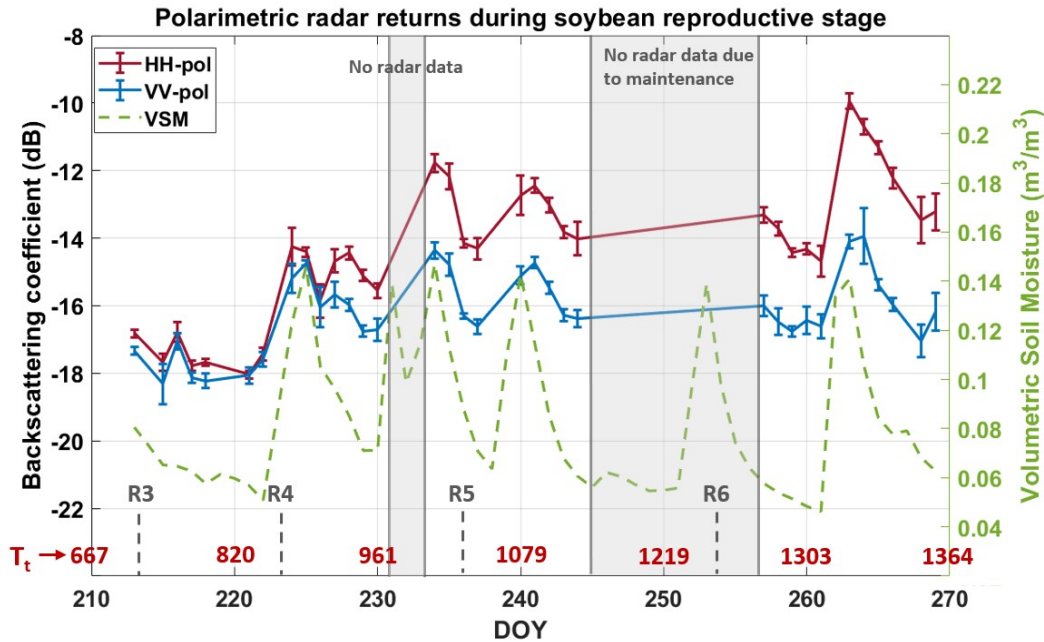
It is seen from Fig. 6 that most of the soil moisture peaks are well captured by the radar backscattering data. Note that there are no data between DOY 230-234 and DOY 244-257 due to radar maintenance. The correlation between radar backscatter and VSM is evaluated by the correlation coefficient (R); the results of R are provided in Table 3 for HH- and VV-pol. To further investigate the variation of the radar data corresponding to the change in VSM, temporal series of the difference in radar backscatter (dB) on two consecutive measurements, i.e.

$\sigma^0(n+1) - \sigma^0(n)$, and the ratio of VSM on the corresponding dates, i.e. $VSM(n+1)/VSM(n)$, are generated (Balenzano et al., 2011). Here, n is the sequential number of the measured data. The correlation coefficient between these two temporal series is computed and denoted as R_{Δ} , which has been given for HH- and VV-pol in Table 3. It is seen that the R coefficient for VV-pol is slightly greater than the R of HH-pol. This difference might be due to the effect of the soybean canopy, which will be discussed in the next paragraph. The coefficient R_{Δ} shows that the

308 changes in both HH- and VV-pol backscatter are strongly correlated to the changes in VSM over
 309 the reproductive stage.

Backscatter vs. VSM	R	R _Δ
HH-pol	0.52	0.89
VV-pol	0.78	0.81

310 Table 3 correlation coefficient between Radar Backscatter and VSM



311
 312 Fig. 6. Polarimetric radar backscattering data vs. volumetric soil moisture.

313 To better understand the relationship between backscatter and vegetation dynamics, the
 314 reproductive stages are also marked in this figure. From R3-R4 stages (beginning - full pod), the
 315 radar backscatter for HH-pol and VV-pol are about the same. As the pods reached the full stage
 316 (around DOY 223), the beans inside the pods started to form and the pods became thicker. It can
 317 be seen from Fig. 6 that the HH-pol and VV-pol begin to diverge after stage R4 and onwards,
 318 with HH-pol being higher while VV-pol remaining about the same level. The later the
 319 reproductive stage is, the bigger the difference between HH-pol and VV-pol that can be observed.
 320 The increase in HH-pol due to the growing of pods could be the reason why the correlation
 321 between HH-pol and VSM is slightly weaker than the correlation between VV-pol and VSM.

322 This phenomenon indicates that the growth of beans can be observed by the radar at L-Band
323 frequencies. It motivates the study of soybean pod modeling in this paper. In the next section, a
324 combined numerical and analytic model will be proposed to analyze the difference between the
325 backscatter for HH and VV polarization.

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327 3. Soybean canopy backscattering model

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329 3.1 Soybean Canopy Coherent Backscattering Model

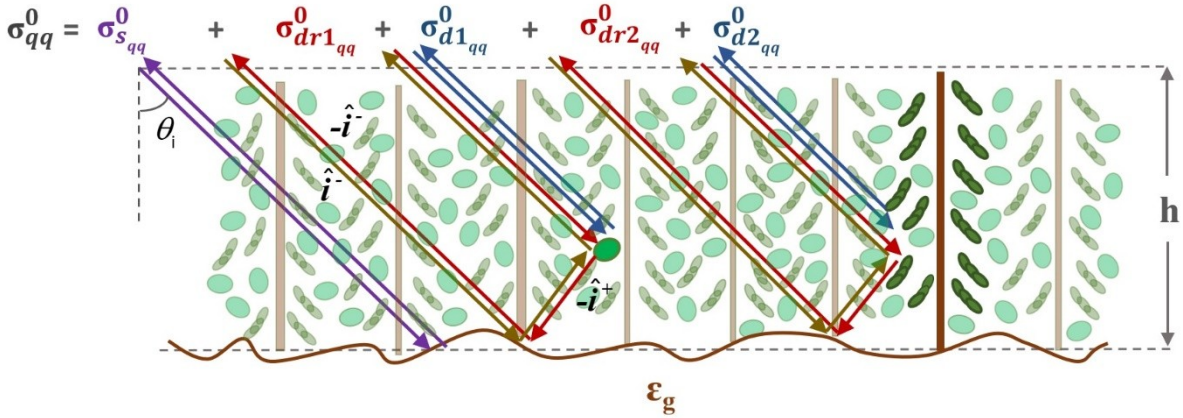
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331 The soybean canopy is modeled as a single layer of discrete random scatterers over a
332 dielectric half-space that has a rough underlying surface. The random layer consists of three
333 types of scatterers: leaf, stem and pod. The pod and stem will be modeled together in FEKO
334 (commercially available software package) as one type of scatterer. The other type of scatterer is
335 soybean leaves, which are modeled analytically. Fig. 7 shows the medium layer with two
336 individual components highlighted to represent the two types of scatterers. These two types of
337 scatterers are assumed to be statistically independent in zenith and azimuth direction. Note that
338 the soybean petioles have not been taken into account since they are too small to have a
339 significant contribution to the total backscatter at L-band. Numerical results show that their
340 backscatter is about 15-25 dB less than the total backscatter of soybean plants.

341 There are three dominant types of backscatter: direct (or volume) backscatter, direct-
342 reflected (or double-bounce) backscatter, and surface backscatter. The total backscatter is
343 approximately the sum of all of the three backscattering terms, which can be written as,

$$344 \sigma_{qq}^0 = \sigma_{d,q}^0 + \sigma_{d\tau,q}^0 + \sigma_{s,q}^0 \quad (3)$$

345 where subscript $q \in (h, v)$ is the polarization type, σ_{dq}^0 is the direct backscattering coefficient;
 346 σ_{drq}^0 is the coherent direct-reflected backscattering coefficient, and σ_{sq}^0 is the surface
 347 backscattering coefficient with attenuation from the soybean canopy. Note that only the like-pol
 348 is considered in this analysis.



349 Fig. 7. Ray trajectories for the soybean canopy scattering model.
 350

351 These three types of scattering are also depicted in Fig. 7. In the figure, σ_{d1q}^0 , σ_{dr1q}^0 and
 352 σ_{d2q}^0 , σ_{dr2q}^0 represent the direct and direct-reflected backscatter for the leaves and pods-stem,
 353 respectively. Here subscript 1 refers to leaves and subscript 2 refers to stems/pods. Since
 354 scatterers of type 1 and 2 are independent of each other, eq. (3) can be written as:

$$355 \quad \sigma_{qq}^0 = \sigma_{d1q}^0 + \sigma_{dr1q}^0 + \sigma_{d2q}^0 + \sigma_{dr2q}^0 + \sigma_{sq}^0 \quad (4)$$

356 It can be seen from the figure that σ_{dr1q}^0 and σ_{dr2q}^0 are the combined backscatters from the
 357 fields with two different paths (see red and brown arrow-lines in Fig. 7). Coherent terms have
 358 been taken into account for computing the direct-reflected backscatter; the equations to compute
 359 the total backscatter are documented in Chauhan et al. (1991). Note that a time variation of

360 $\exp(j\omega t)$ is assumed and suppressed in this paper. In this section, the equations for computing the
 361 soybean backscattering terms are reproduced below:

$$362 \quad \sigma_{\text{dlsq}}^0 = 4\pi\rho_j \left\langle \left| f_{\text{lsq}}(-\hat{i}^-, \hat{i}^-) \right|^2 \right\rangle \left[\frac{1 - e^{-4\text{Im}\kappa_q h}}{4\text{Im}\kappa_q} \right]; \quad \sigma_{\text{drlsq}}^0 = 16\pi\rho_j R_{\text{sq}} \left\langle \left| f_{\text{lsq}}(-\hat{i}^+, \hat{i}^-) \right|^2 \right\rangle \cdot h \quad \text{for } j=1,2 \quad (5)$$

363 where ρ_j is the volume density of j^{th} -scatterer type; h is the canopy height; $f_{\text{lsq}}(-\hat{i}^-, \hat{i}^-)$ and

364 $f_{\text{lsq}}(-\hat{i}^+, \hat{i}^-)$ are the backscattering and bistatic scattering amplitudes of the j^{th} -scatterer type,

365 respectively. Here, \hat{i}^- is the direction of the incident wave with an angle of θ_i ; \hat{i}^+ is the

366 direction of the reflected wave. In eq. (5), κ_q is the propagation constant through the canopy; it

367 can be written as $\kappa_q = k_0 \cos(\theta_i) + \delta\kappa_q$ where k_0 is the free space propagation constant, with $\delta\kappa_q$

368 given in Chauhan et al. (1991):

$$369 \quad \delta\kappa_q = \sum_{j=1}^2 \frac{2\pi\rho_j}{k_0 \cos(\theta_i)} \left\langle f_{\text{lsq}}(\hat{i}^-, \hat{i}^-) \right\rangle \quad (6)$$

370 Here, $\left\langle f_{\text{lsq}}(\hat{i}^-, \hat{i}^-) \right\rangle$ is the forward scattering amplitude.

371 The factor R_{sq} appearing in eq. (5) is the reflectivity at the surface of the canopy. R_{sq} can

372 be expressed as the reflectivity of the ground, R_{gq} , times the two-way attenuation factor within the

373 canopy as follows:

$$374 \quad R_{\text{sq}} = R_{\text{gq}} e^{-2\alpha_q h}, \quad (7a)$$

375 where $\alpha_q = 2 \text{Im}(\delta\kappa_q)$ is the attenuation constant in the canopy. The reflectivity of the ground
 376 can be decomposed into a product of the rough surface factor times the reflectivity of the flat
 377 ground surface:

$$378 \quad R_{gq} = \exp \left[- (2k_0 \sigma_h \cos \theta_i)^2 \right] R_{gq}^0, \quad (7b)$$

379 where σ_h is the RMS height of the rough surface and $R_{gq}^0 = |\Gamma_{gq}|^2$. Here, Γ_{gq} is the Fresnel
 380 reflection coefficient for $q \in (h, v)$ polarization.

381 In eq. (5) and (6), $\langle \rangle$ is the sign for average. It indicates that the scattering amplitudes
 382 are averaged over the orientation angles, θ (zenith angle) and ϕ (azimuth angle) with a
 383 probability density $p(\theta, \phi)$. Here, θ and ϕ are assumed to be independent random variables.

384 As a result, $p(\theta, \phi)$ can be written as $p(\theta, \phi) = p(\theta)p(\phi)$. For leaf, $\langle f_{1_{qt}}(-\hat{i}, \hat{i}) \rangle$ can be
 385 expressed as:

$$386 \quad \langle f_{1_{qt}}(-\hat{i}, \hat{i}) \rangle = \int_{\theta=0}^{\pi/2} \int_{\phi=0}^{2\pi} f_{1_{qt}}(-\hat{i}, \hat{i}, \theta, \phi) p(\theta) p(\phi) d\theta d\phi \quad (8)$$

387 In this study, $\langle f_{1_{qt}}(\square) \rangle$ is the average scattering amplitude of a single leaf, which can be
 388 solved analytically via a thin disc approximation from Le Vine et al. (1985). In the analytical
 389 model, the leaves are assumed to have a uniform distribution in azimuth direction, i.e.

390 $p(\phi) = \frac{1}{2\pi}, 0 < \phi < 2\pi$. For the zenith direction, the distribution follows the statistics given in

391 Fig. 3, which has an approximate cosine distribution, i.e. $p(\theta) = \cos \theta, 0 < \theta < \pi/2$. The other

392 scattering amplitude, $\langle f_{2_{\text{st}}}(\theta) \rangle$, is the average of the numerical solution of the pods-stem model.

393 The procedure for averaging $f_{2_{\text{st}}}$ will be discussed in section 3.2.

394 The surface backscattering coefficient is computed by using the Small Perturbation

395 Method introduced by Fung and Chen (2009). The σ_{st}^0 in eq. (4) can be obtained by multiplying

396 the surface backscattering coefficient with the attenuation factor from the soybean canopy.

397 Finally, by substituting σ_{st}^0 , $\sigma_{\text{d}1_{\text{st}}}^0$, $\sigma_{\text{dr}1_{\text{st}}}^0$ and $\sigma_{\text{d}2_{\text{st}}}^0$, $\sigma_{\text{dr}2_{\text{st}}}^0$ into eq. (4), the backscattering coefficient

398 for the soybean canopy can be computed.

399 3.2 Numerical modeling of the scattering of stems and pods for a soybean plant

400

401 In the past, a dielectric cylinder model (Seker and Schneider, 1988) was used to model the

402 fruits of agricultural crops in order to find their scattering amplitudes. The analytic method,

403 however, is not accurate enough for the case of soybean pods since their cross-section is not a

404 typical cylinder. In addition, since soybean pods are usually clustered, another advantage of using

405 the numerical model is that the total contributions from the pod clusters can be determined from

406 the model. The clusters act as bigger scatterers which can significantly enhance the contribution

407 of pods in scattering. In this paper, a numerical model built in FEKO is proposed for solving for

408 the scattering amplitude of soybean pods.

409 As previously mentioned, a soybean pod is formed by a green shell with 2-4 ellipsoid

410 beans aligned inside. In the numerical model, a single pod is assumed to have three beans, which

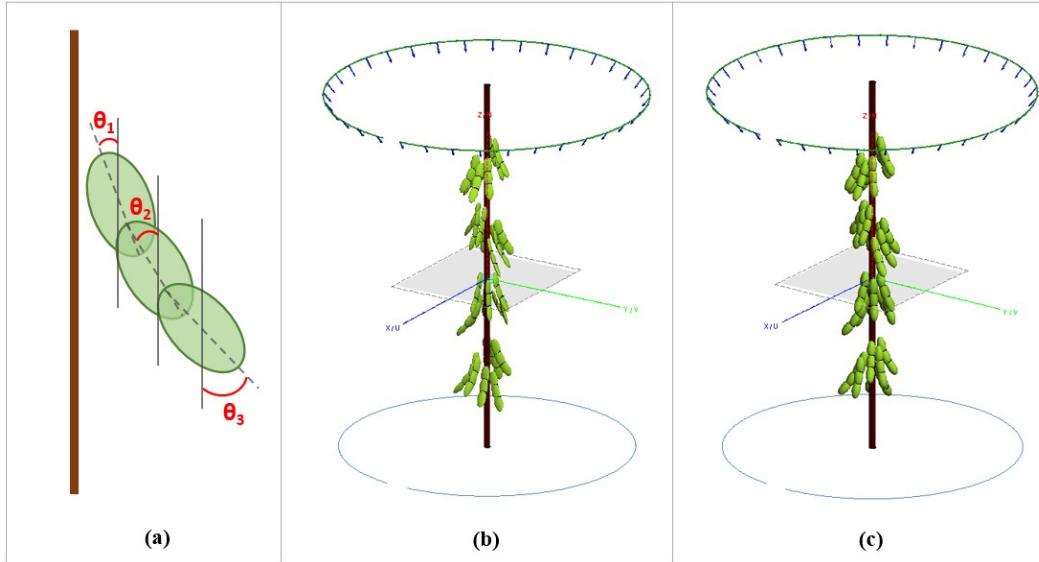
411 is the most common case in nature. The three beans are modeled by three adjacent ellipsoids.
412 Based on the measured thickness of the soybean shells, the short and long radii of these adjacent
413 ellipsoids are then expanded by 1.5 mm to account for the layer of shell in the model. Note that
414 since there is not a big difference between the dielectric constant of the shell and the beans (see
415 Table 1), it is not necessary to define different dielectric objects in FEKO to distinguish the shell
416 and beans. This assumption also simplifies the model and reduces the time required for the
417 simulation. In the model, each one of the ellipsoids has a slightly different orientation angle (see
418 Fig. 2). In the 2012 field measurements, the number of beans of an individual soybean plant was
419 only recorded for DOY 236, 248 and 263 (Aug. 23rd, Sep. 4th and Sep. 19th). The average number
420 of beans per plant from the measurements is 94. In this study, the number of pods per plant is set
421 to be 32, or equivalently, 96 beans. This assumption also agrees with the normal range of 26-38
422 pods recorded in Casteel (2011). The soybean pods are modeled together with a vertical stem.
423 The stem has an approximate dielectric constant of $15-5j$ (Lang et al., 2004) and the averaged
424 radius and height of the stems is 3.5 mm and 43 cm, respectively; these dimensions do not vary
425 much over the reproductive stages. The leaves are not considered in the numerical model since
426 they are so thin (0.2 mm to 0.3 mm) compared with wavelength that the interaction between
427 leaves and other scatterers is very small. The analytic method is quite accurate for finding the
428 scattering amplitude of leaves.

429 Most of the soybean pods emerge on or near the stems of plants, a condition which has
430 been assumed for constructing the numerical model in FEKO. The variations in the vertical
431 orientations of the pods are simulated by assigning different orientation angles to the ellipsoids
432 that are used to form the pod. These orientation angles are represented by θ_1 , θ_2 and θ_3 for the
433 three ellipsoids from top to bottom; see Fig. 8(a). There are three different combinations for the

434 orientation angles of pods defined in the numerical model --- type I: $\theta_1=5^\circ$, $\theta_2=10^\circ$, $\theta_3=15^\circ$; type
435 II: $\theta_1=10^\circ$, $\theta_2=20^\circ$, $\theta_3=30^\circ$ and type III: $\theta_1=20^\circ$, $\theta_2=30^\circ$, $\theta_3=40^\circ$. For a soybean plant, the number
436 of the three different types of pods are in a ratio of 1:2:1 since most of the pods have orientations
437 that are close to type II in nature.

438 The numerical model also considers the growth of the beans by varying their dimensions
439 within the pod over the bean growing season. The growth of beans is categorized in three
440 different stages: beginning seed or full-pod (R4), medium-seed (R5-R6), and full-seed (R6). As
441 mentioned previously, the growing of beans only increases the thickness of the pods while the
442 length and the width of pods do not change significantly. Based on this fact, the dimensions
443 (length \times width \times thickness) of the pods are set to be 4.6 cm \times 0.9 cm \times 0.3 cm, 4.6 cm \times 0.9 cm \times 0.6
444 cm and 4.6 cm \times 0.9 cm \times 0.9 cm for the stages of beginning-seed, medium-seed and full-seed,
445 respectively. The numerical models for a soybean plant at beginning-seed and full-seed stage are
446 shown in Fig. 8(b) and (c), respectively.

447 In the numerical model, electromagnetic waves are incident at a 40° angle; this is the
448 same incident angle used by the ComRAD system. H and V polarized waves are analyzed
449 separately to obtain the backscattering amplitudes of the pods and the stem.



450

451 Fig. 8. Scattering model of soybean pods and stems in FEKO - (a): structure of soybean pod model; (b):
 452 multiple pod and stem model at beginning-seed stage; (c): multiple pod and stem model at full-seed stage.

453

454 As mentioned previously, the model is a compound of a single vertical stem and clusters
 455 of pods. The clustered pods are placed near the stem at selected heights and selected azimuth
 456 orientations (based on visual evidence) to represent a typical structure found in a soybean plant.
 It is assumed that the pod-stem scatterer is uniformly distributed in the azimuth coordinates.

457 Thus, the averaging of the scattering amplitude, $\langle f_{\theta}(\phi) \rangle$, can be done by a uniform azimuthal
 458 rotation of the structure.

459

460 When using the numerical model, it is more convenient to rotate the incident waves rather
 461 than rotate the model; this technique simplifies the processing of the EM solver. In performing
 462 the azimuthal average, the incident waves are distributed uniformly in a step size of 10° . These
 incident waves are shown by the blue arrows above the plant models in Fig. 8 (b) and (c).

463

464 At each individual incident angle, the back, forward and bistatic scattering amplitudes are
 465 computed (see Fig. 7). Averaging is then performed based on the scattering amplitudes from all
 incident waves for each model (beginning-seed model, medium-seed model, and full-seed

466 model). This numerical solution of pod-stem compound and the analytic solution of leaves are
 467 integrated into the coherent canopy backscattering model to obtain the backscattering coefficient
 468 of the soybean canopy.

469 4. Comparison between the modeled results and measured data

470

471 4.1 Analysis of the modeled results

472

473 In this section, a comparison between the measured data and modeled results is presented.
 474 This analysis focuses on the reproductive stage of soybean plants from Aug.11th, 2012 to Sep.
 475 25th, 2012 (DOY 224-269) since the pod data are documented for this period. A program is used
 476 to calculate the scattering amplitude of a single soybean leaf analytically. The density and
 477 dimensional parameters of soybean leaves used in the program are based on a least-squares fit to
 478 the measurement data given in Table A.1 for DOY 224-269. The fitted results are plotted in Fig.
 479 9. As introduced in section 3.2, the scattering amplitudes of the pods-stem scatterer for three
 480 different reproductive stages are obtained by FEKO. Finally, the total coherent backscattering
 481 coefficient from the soybean canopy is computed using eq. (3). Table 4 summarizes the
 482 parameters that are used in the numerical and analytic model. Most of the parameters in the
 483 table have already been explained in the previous sections.

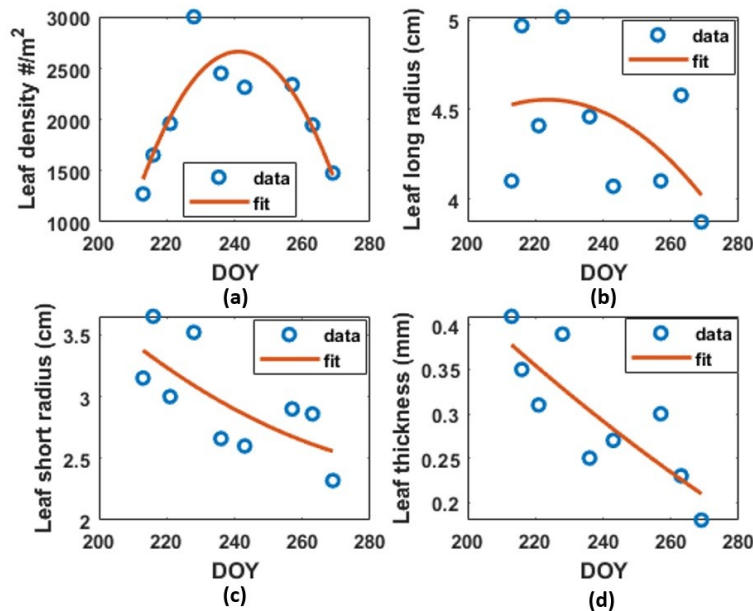
484 Based on the numerical results and parameters given in Table 4, the total backscattering
 485 coefficient is computed for HH-pol and VV-pol on each individual DOY. The pod size in the
 486 numerical model changes as DOY increases. The stages of beginning-, medium-, and full-seed
 487 correspond to DOY 224-230, DOY 234-244 and DOY 257-269, respectively.

Incident Angle		40°
Frequency		1.25 GHz
Stem and pods for a single plant (numerical model by FEKO)	Stem dimensions (cm): radius × length	Average of measured data given in Table A.1: 0.35×43

	Dielectric constant of stems	Obtained from literature: 15-5j
	Number of stems per plant	1
	Pod dimensions (cm): length × width × thickness	Average of the measured data given in Table A.1: -Beginning seed: 4.6×0.9×0.3 -Medium seed: 4.6×0.9×0.6 -Full seed: 4.6×0.9×0.8
	dielectric constant of pods	measured in the lab: 46-15j
	number of pods per plant	32
Single leaf (analytic model in Fortran)	Leaf major and minor radius, Leaf thickness	Fitted values based on measurement data in Table A.1
	Dielectric constant of leaf	Obtained from literature: 23-9j
Macro parameters (canopy scatter model in Fortran)	Canopy height	Fitted values based on measurement data given in Table A.1
	Density of leaves (#/m ²)	Fitted values based on measurement data given in Table A.1
	PDF of leaves	$\cos(\theta), \quad 0^\circ \leq \theta \leq 90^\circ$
	Density of soybean plants (#/m ²)	13
	Volume soil moisture	<i>In situ</i> measured data

488

Table 4 Summary of the input parameters to the canopy scatter model



489

490

491

Fig. 9. Leaf parameters fitting - (a): Leaf density (#/m²); (b): Leaf long radius (cm);
(c): Leaf short radius (cm); (d): Leaf thickness (mm).

492

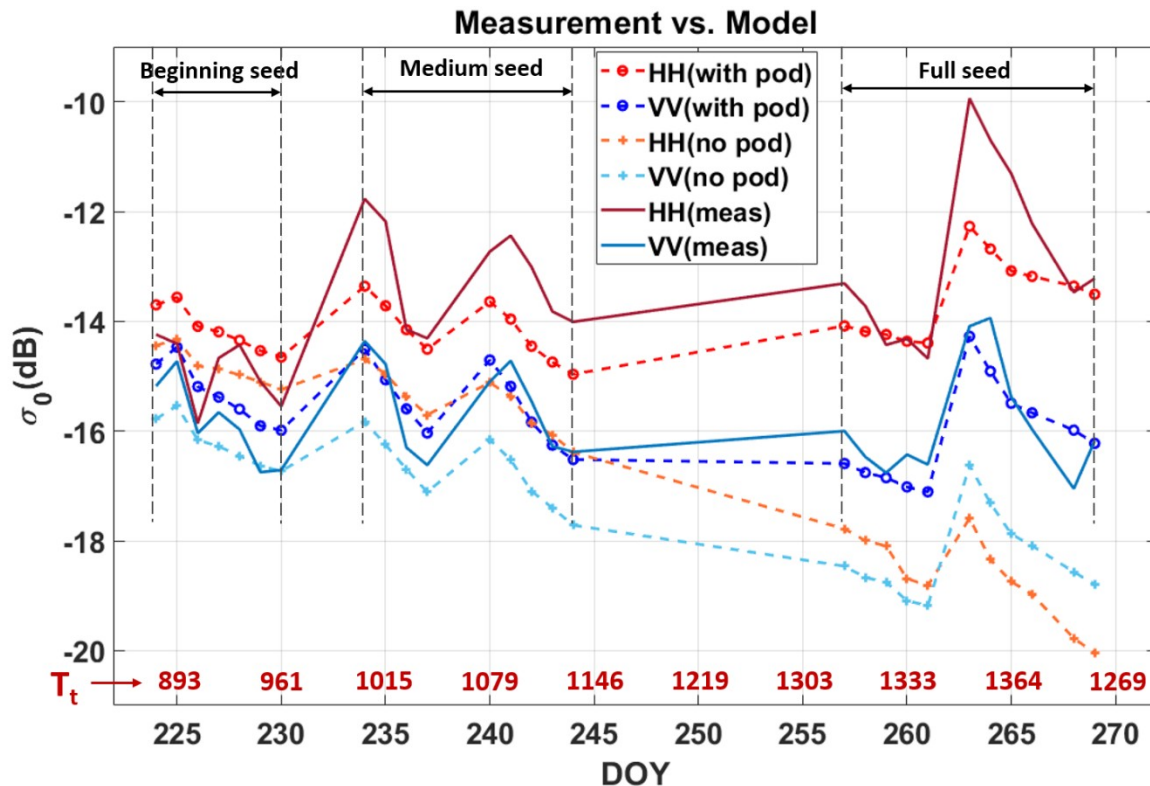
493

494

Besides the model for the soybean plant with pods, the backscattering coefficient of a soybean plant without pods is also computed. In the rest of this paper, the models with and without pods will be denoted as soybean-pod model and no-pod model for convenience. The no-

495 pod model is an analytic model that only takes the leaves and stems into account. The scattering
 496 of leaves is computed analytically using the same method as mentioned before. The stem is
 497 treated as a thin cylinder and its scattering amplitude is found by using the formula in Chauhan et
 498 al. (1994). All the other parameters remain the same in this model except for the non-existence
 499 of pods.

500 Comparisons between the modeling results and the radar backscattering data are plotted in
 501 Fig. 10 as a function of DOY as well as thermal time, T_t . In general, the soybean-pod model has
 502 higher backscattering for both HH and VV polarizations compared with the no-pod model. The
 503 soybean-pod model has much better agreement with both HH- and VV-pol measurements, while
 504 the no-pod model underestimates the backscatter, especially during full-seed stage.



505
 506

Fig. 10. Measured data vs. modeling results

507 At the beginning-seed stage, the soybean-pod model slightly overestimates the backscatter
 508 for HH and VV pol while the no-pod model has a good match to the data. During this period, the
 509 leaf is the dominant contributor to the backscatter; thus, both the soybean-pod and no-pod model
 510 strongly depend on the leaf size and density. During the medium-seed stage, the scattering from
 511 the pods becomes greater as the pods get thicker. The soybean-pod model hence predicts higher
 512 HH- and VV-pol backscattering compared with the no-pod model. The increase in total
 513 backscatter due to pod backscattering leads to better agreement between the soybean-pod model
 514 and the measurement data. At the full-seed stage, the soybean-pod model, which successfully
 515 predicts the slight increase of VV-pol and the large enhancement of HH-pol backscatter, has a
 516 much better match to the measurement data compared with no-pod model. The no-pod model
 517 predicts even lower HH-pol due to the loss of leaves and the shrinkage of leaf size. It can also be
 518 seen from both the measured and the modeled results that the difference between the HH-pol and
 519 VV-pol is strongly dependent on the size of the soybean pods. Hereinafter, the difference in
 520 backscatter between HH-pol and VV- pol is denoted as $\Delta\sigma_{HH,VV}^0$.

521 The peaks in the soybean-pod and no-pod model correspond to rain events as would be
 522 expected. However, most of the peak values for HH-pol predicted by the models are
 523 underestimated when compared to the data. This underestimation may be due to the presence of
 524 dew or rain drops on the surface of soybean plants that increases the effective dielectric constant
 525 of plant scatterers. This effect, however, is not considered in the modeling of soybean plants.

526 To quantitatively evaluate the performance of the soybean-pod and no-pod models, the
 527 root mean square error (RMSE) between the modeling results and measurements is computed by:

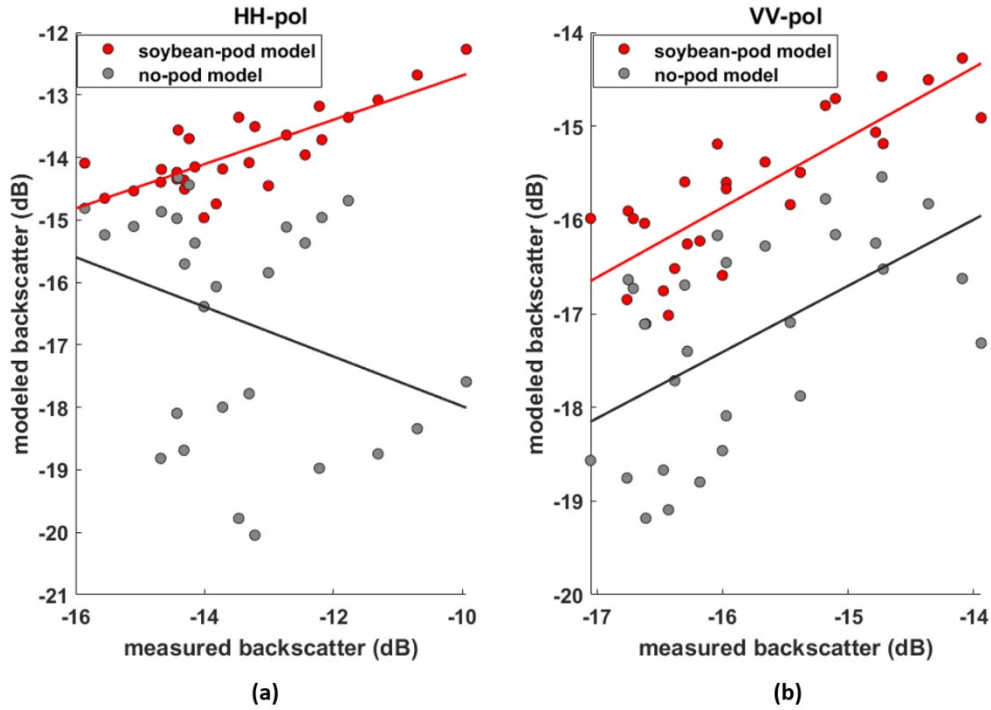
$$528 \quad RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N [\sigma_{meas}^0(i) - \sigma_{model}^0(i)]^2} \quad (9)$$

529 where N is the total number of samples shown in Fig. 10, $\sigma_{\text{meas}}^0(i)$ and $\sigma_{\text{model}}^0(i)$ are the measured
 530 and modeled backscattering coefficients for i^{th} day of experiment, respectively. The RMSE is
 531 computed based on results in dB and given in Table 5. It is clearly seen that the soybean-pod
 532 model has better agreement with the measured data for both VV and HH polarization than the no-
 533 pod model. For both the soybean-pod and no-pod models, VV-pol has better agreement with the
 534 measured data.

Polarization	RMSE (dB)		R Coefficient	
	With pods	No pods	With pods	No pods
VV	0.51	1.8	0.78	0.56
HH	1.1	4.1	0.52	-0.31

535 Table 5 RMSE and R coefficient between modeling results and measured data

536 To further understand the correlation between the measurements and the model, the
 537 correlation coefficient (R) between σ_{meas}^0 and σ_{model}^0 is reported in Table 5 and σ_{model}^0 is plotted
 538 against σ_{meas}^0 in Figure 11. As expected, Table 5 shows that the soybean-pod model has a
 539 stronger correlation with the measured data compared to the no-pod model. Therefore, the
 540 scattered points of the soybean-pod model, as shown in Fig. 11, are closer to the linear-least-
 541 squares line than the no-pod model. Note that the correlation coefficient for the no-pod model is
 542 a negative value, which indicates that the behavior of the no-pod model is opposite to that of the
 543 measured data. This behavior can also be observed from Fig. 11(a). In summary, both the
 544 RMSE and R coefficient clearly demonstrate that the accuracy of the soybean scattering model is
 545 significantly improved by including the contribution of pods.



546

547 Fig. 11. Scatter plot of measured data against modeled results, where the line represents the least square fit
 548 of the scattered points. (a): is for HH-pol and (b): is for VV-pol.

549 4.2 Analysis of the difference between HH-pol and VV-pol backscatter

550 As previously mentioned, the difference in backscatter between HH- and VV-pol,

551 $\Delta\sigma_{HH-VV}^0$, indicates the growing of the pods. To understand this phenomenon, the values of

552 $\Delta\sigma_{HH-VV}^0$ are computed by converting the scattering coefficients σ_{HH}^0 and σ_{VV}^0 into their linear

553 values and subtracting σ_{VV}^0 from σ_{HH}^0 . The difference $\Delta\sigma_{HH-VV}^0$ is then converted back to dB and

554 plotted in Fig. 12 (a) for the soybean-pod model, no-pod model, and the measured data as a

555 function of DOY. The growth stages of the pods are also given in the figure. As expected, the

556 $\Delta\sigma_{HH-VV}^0$ for the no-pod model has a poorer performance than the performance of the soybean-

557 pod model, in particular for the full-seed stage. Note that the curve for the no-pod model stops at

558 DOY 261 due to the fact that σ_{VV}^0 is greater than σ_{HH}^0 after DOY 261. For the soybean-pod
559 model, $\Delta\sigma_{HH.VV}^0$ is not linearly related to the pod size. The modeled $\Delta\sigma_{HH.VV}^0$ increases slightly
560 from beginning-seed to medium-seed stage, while it has a big enhancement from the medium-
561 seed to full-seed stage. Considering all of the reproductive stages, the modeled $\Delta\sigma_{HH.VV}^0$ is closest
562 to the measured $\Delta\sigma_{HH.VV}^0$ when the pods reach full-seed stage. This is the time when the beans
563 are large enough to be detected by the L-band radar. As a result, it is more accurate to use the
564 polarimetric L-band radar data to predict the soybean yield at the full-seed stage. Compared with
565 the measured data, the soybean-pod model underestimates $\Delta\sigma_{HH.VV}^0$ for rainy days. Again, this
566 might be due to the fact that the model hasn't taken the presence of water on the surface of plant
567 into account.

568 An investigation has also been made into the relationship between the number of pods and
569 $\Delta\sigma_{HH.VV}^0$. Based on the analytic model, $\Delta\sigma_{HH.VV}^0$ is computed for three cases: 24 pods per plant,
570 32 pods per plant and 40 pods per plant. The test is based on the data from Sep. 25th (DOY 269)
571 because the measurement and the model have the best agreement on that day. The results are
572 plotted in Fig. 12(b) both in dB and linear form. It is seen from the figure that the number of
573 pods per plant has an approximate linear relationship to the linear $\Delta\sigma_{HH.VV}^0$. Therefore, the
574 number of the pods per plant can be estimated by a least-squares fitting technique to a straight
575 line based on the linear values of $\Delta\sigma_{HH.VV}^0$. In this study, since each pod is assumed to have three

576 beans and there are 13 plants/m², the total number of beans/m² is 39 times the number of pods per

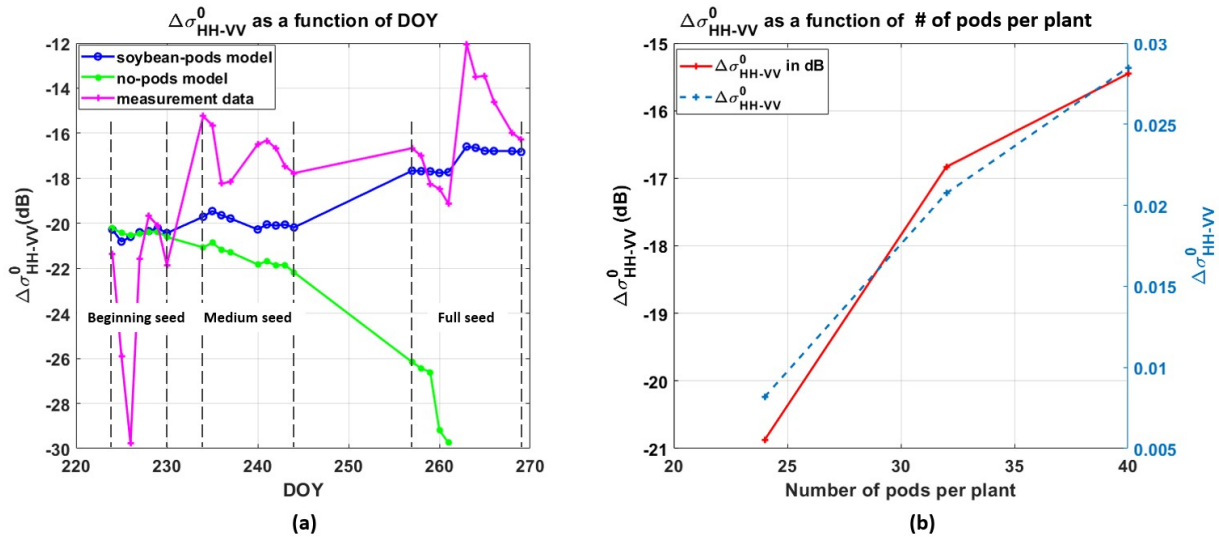
577 plant. Finally, the number of beans/m² is given as a function of $\Delta\sigma_{HH-VV}^0$:

578
$$N = a \cdot \Delta\sigma_{HH-VV}^0 + b \tag{10}$$

579 where $a = 30165$ and $b = 671$. Note that this approximation can only be applied to the cases in

580 the range 24-40 pods/plant which is a common range for soybean pod counts per plant. In

581 addition, the prediction should not be based on day on which it rains.



582
583 Fig. 12. Relationship between soybean pods and $\Delta\sigma_{HH-VV}^0$ - (a): $\Delta\sigma_{HH-VV}^0$ in dB as a function of DOY;
584 (b): $\Delta\sigma_{HH-VV}^0$ as a function of number of pods per plant.

585 **5. Conclusion**

586

587 This paper introduces a methodology for analyzing the polarimetric radar backscatter

588 from a soybean field at L-band. A soybean backscattering model is developed by a combined

589 numerical and analytical method to validate the radar experimental data and analyze the

590 contribution of soybean constituents to the backscatter. The numerical method simulates the

591 clustered structure of soybean pods along a vertical stem, while the analytical method treats

592 soybean leaves as thin elliptical discs. Temporal *in situ* data are used in the model to interpret the
593 vegetation dynamics of the soybean field over the growing season.

594 It is found that the accuracy of the soybean backscatter model is significantly improved
595 when the pods are taken into account. For the model with pods, the RMSEs between the radar
596 data and modeled results are 0.51 dB for VV-pol and 1.1 dB for HH-pol. If the pods are removed
597 from the model, the RMSEs are increased to 1.8 dB for VV-pol and 4.1 dB for HH-pol. Both
598 measured data and modeled results show that the growth of soybean pods results in an increase in
599 the difference between the HH-pol and the VV-pol backscattering ($\Delta\sigma_{HH-VV}^0$). An estimation
600 model is developed to predict the number of beans per square meter from $\Delta\sigma_{HH-VV}^0$ for the full-
601 seed (R6) stage.

602 The research reported in this paper shows that scientists can not only use L-band radar to
603 monitor the soil moisture, but also to detect the growth of soybean pods. In the future, more field
604 measurements for soybean pods, such as the orientations of pods, can be used to improve the
605 accuracy of the soybean backscattering model. Similar methodology can be applied to other
606 types of crops to further investigate the possibility of using low microwave frequency to detect
607 crop growth and development. Most importantly, extension of these results to larger scales are
608 highly desirable as this can lead to global or regional biophysical parameter retrieval and
609 monitoring.

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613

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709

710 Appendix A

DOY	plant height	stem size (l×r)	leaf size (l×w×t)	pod size (l×w×t)	stem #/m ²	leaf #/m ²	stem biomass	leaf biomass	pod biomass	VSM (m ³ /m ³)	Radar HH(dB)	Radar VV(dB)
213	39.3	19×0.25	8.2×6.3×0.041	-	13	1274.3	217	151	-	0.0805	-16.82	-17.34
215	-	-	-	-	-	-	-	-	-	0.0652	-17.68	-18.32
216	45.7	33×0.31	9.9×7.3×0.035	-	13	1654.7	294	209	-	0.0647	-16.78	-17.05
217	-	-	-	-	-	-	-	-	-	0.0627	-17.77	-18.13

218	-	-	-	-	-	-	-	-	-	0.0575	-17.68	-18.22
221	48.7	33×0.28	8.8×6.0 ×0.031	-	13	1963.3	319	232	-	0.0568	-18.04	-18.06
222	-	-	-	-	-	-	-	-	-	0.0509	-17.43	-17.59
224	-	-	-	-	-	-	-	-	-	0.1225	-14.24	-15.19
225	-	-	-	-	-	-	-	-	-	0.1460	-14.40	-14.73
226	-	-	-	-	-	-	-	-	-	0.1052	-15.86	-16.04
227	-	-	-	-	-	-	-	-	-	0.0963	-14.67	-15.66
228	58.3	41×0.37	10×7.0 ×0.039	-	13	3006	977	553	-	0.0853	-14.43	-15.97
229	-	-	-	-	-	-	-	-	-	0.0711	-15.10	-16.75
230	-	-	-	-	-	-	-	-	-	0.0711	-15.55	-16.71
234	-	-	-	-	-	-	-	-	-	0.1470	-11.77	-14.36
235	-	-	-	-	-	-	-	-	-	0.1131	-12.18	-14.78
236	67.3	49×0.29	8.9×5.3 ×0.025	4.5×0.92 ×0.29	13	2454	611	339	496	0.0882	-14.15	-16.31
237	-	-	-	-	-	-	-	-	-	0.0709	-14.31	-16.62
240	-	-	-	-	-	-	-	-	-	0.1427	-12.73	-15.10
241	-	-	-	-	-	-	-	-	-	0.1144	-12.44	-14.72
242	-	-	-	-	-	-	-	-	-	0.0853	-13.01	-15.46
243	69.3	43×0.34	8.1×5.2 ×0.027	5.0×1.0 ×0.47	13	2318	560	417	617	0.0680	-13.82	-16.28
244	-	-	-	-	-	-	-	-	-	0.0605	-14.01	-16.38
248	-	-	-	4.9×0.90 ×0.61	-	-	667	438	892	-	-	-
254	-	-	-	4.3×0.88 ×0.59	-	-	458	384	850	-	-	-
257	60.3	32×0.42	8.2×5.8 ×0.03	-	13	2343	-	-	-	0.0577	-13.31	-16.00
258	-	-	-	-	-	-	-	-	-	0.0539	-13.72	-16.47
259	-	-	-	-	-	-	-	-	-	0.0514	-14.43	-16.76
260	-	-	-	-	-	-	-	-	-	0.0483	-14.32	-16.43
261	-	-	-	-	-	-	-	-	-	0.0463	-14.68	-16.61
263	67.3	50×0.33	9.2×5.7 ×0.023	4.9×0.90 ×0.75	13	1948	458	306	1052	0.1410	-9.94	-14.09
264	-	-	-	-	-	-	-	-	-	0.1054	-10.70	-13.94
265	-	-	-	-	-	-	-	-	-	0.0845	-11.31	-15.38
266	-	-	-	-	-	-	-	-	-	0.0778	-12.22	-15.97
268	-	-	-	-	-	-	-	-	-	0.0682	-13.47	-17.05
269	57.3	54×0.33	7.7×4.6 ×0.018	4.9×0.83 ×0.73	13	1478	480	283	1148	0.0628	-13.22	-16.18

711 Table A.1 Soybean measurement data. (Dimensional unit: cm, Biomass unit: g/m²)

712 List of Figure Captions

713

714 Fig. 1. Soybean plant dimensions as a function of DOY/thermal time.

715 Fig. 2. Soybean pods - (a): soybean pod at the beginning of stage R5; (b): soybean pod of (a) with
716 half the shell removed; (c): soybean pod at stage R6; (d): soybean pod of (c) with half the
717 shell removed.

718 Fig. 3. Histogram of leaf orientation.

719 Fig. 4. (a): GVWC of soybean plant constituents; (b): Wet Biomass of soybean plant constituents.

720 Fig. 5. ComRAD system mounted on a 19-m boom truck.

721 Fig. 6. Polarimetric radar backscattering data vs. volumetric soil moisture.

722 Fig. 7. Ray trajectories for the soybean canopy scattering model.

723 Fig. 8. Scattering model of soybean pods and stems in FEKO - (a): structure of soybean pod
724 model; (b): multiple pod and stem model at beginning-seed stage; (c): multiple pod and
725 stem model at full-seed stage.

726 Fig. 9. Leaf parameters fitting: (a) Leaf density ($\#/m^2$); (b) Leaf long radius (cm); (c) Leaf short
727 radius (cm); (d) Leaf thickness (mm).

728 Fig. 10. Measured data vs. modeling results.

729 Fig. 11. Scatter plot of measured data against modeled results, where the line represents the least
730 square fit of the scattered points. (a) is for HH-pol and (b) is for VV-pol.

731 Fig. 12. Relationship between soybean pods and $\Delta\sigma_{HH,VV}^0$: (a) $\Delta\sigma_{HH,VV}^0$ in dB as a function of
732 DOY; (b) $\Delta\sigma_{HH,VV}^0$ as a function of number of pods per plant