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A new soil roughness parameter for the modelling of radar backscattering over bare soil

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Abstract

The characterisation of soil surface roughness is a key requirement for the correct analysis of radar backscattering behaviour. It is noteworthy that an increase in the number of surface roughness parameters in a model also increases the difficulty with which data can be inverted for the purposes of estimating soil parameters. In this paper, a new description of soil surface roughness is proposed for microwave applications. This is based on an original roughness parameter, Z_g , which combines the three most commonly used soil parameters: root mean surface height, correlation length, and correlation function shape, into just one parameter. Numerical modelling, based on the moment method and integral equations, is used to evaluate the relevance of this approach. It is applied over a broad dataset of numerically generated surfaces characterised by a large range of surface roughness parameters. A strong correlation is observed between this new parameter and the radar backscattering simulations, for the HH and VV polarizations in the C and X bands. It is proposed to validate this approach using data acquired in the C and X bands, at several agricultural sites in France. It was found that the parameter Z_g has a high potential for the analysis of surface roughness using radar

26 measurements. An empirical model is proposed for the simulation of backscattered radar
27 signals over bare soil.

28 **Keywords: Soil, Roughness, Moisture, Zg, Radar, Backscattering coefficient, Model**

29

30 **1. Introduction**

31 Soil moisture and roughness parameters play a key role in hydrological and climate studies. In
32 recent years, various efforts have been devoted to the analysis of the backscattering
33 characteristics of bare soils. Initially, different backscattering models (theoretical, semi-
34 empirical and empirical) were developed (Ulaby et al., 1986, Fung et al., 1992, Oh et al.,
35 1992, Dubois et al., 1995, Chen et al., 2003, Zribi et al., 2008). More recently, several studies
36 have proposed various approaches for the improvement of roughness descriptions (Oh et al.,
37 1998, Mattia et al., 1999, Zribi et al., 2000, Davison et al., 2000, Li et al., 2002, Callens et al.,
38 2006, Verhoest et al., 2008, Bretard et al., 2013), which are essential to the accurate analysis
39 and interpretation of backscattering behaviour and soil moisture estimation (Lievens et al.,
40 2009). An analysis based on a fractal representation has been proposed (Rouvier et al., 1997;
41 Zribi et al., 2000) allowing a multi-scale description, which is not limited to the use of a
42 single scale based on the correlation length parameter. Zribi et al. (2000) introduced fractal
43 and Brownian approaches to describe the correlation function, whereas Li et al. (2002)
44 proposed a general power law description of roughness spectra. Fung et al. (1994), Shi et al.
45 (1997) and Zribi et al. (2005) have proposed different types of analytical correlation function,
46 used to fit the experimental data. Although all of these studies have led to improvements in
47 the direct backscattering simulations, the availability of a limited number of radar
48 configurations makes it generally impossible to retrieve the volumetric soil moisture with all
49 of the roughness parameters. In this context, Zribi and Dechambre (2003) introduced a
50 description based on the parameter $Zs = s^2/l$, where s is the rms surface height and l is the

51 correlation length (Bretard et al., 2013, Lawrence et al., 2013). Baghdadi et al. (2004, 2006,
52 2011) proposed an empirical correlation length, computed as a function of the rms height,
53 radar frequency, incidence angle and polarization, in order to obtain a better fit between
54 Integral Equation Model (Fung et al., 1992) simulations and radar observations. Lievens et al.
55 (2011) show that roughness parameters differ between SAR acquisitions, as they are related to
56 the observed backscatter coefficients and variations in local incidence angle. A statistical
57 model was thus developed, to allow the effective roughness parameters to be estimated from
58 microwave backscattering observations. Despite these contributions, the influence of
59 roughness is still poorly modelled in currently known inversion techniques.

60 In the present study, a new surface description is proposed, in which the analysis uses the
61 moment method to numerically simulate the backscattering integral equations. Our paper is
62 organised into five sections, of which Section 2 presents the principles of the numerical
63 backscattering simulations, Section 3 discusses the influence of roughness on the
64 backscattering simulations and introduces the new roughness parameter, Z_g . Section 4
65 describes the potential of this parameter, through the use of experimental analyses based on
66 different types of ground and radar measurements. Finally, our conclusions are presented in
67 Section 5.

68 **2. Numerical backscattering simulations - methodology**

69 A numerical backscattering model based on the moment method is used to simulate radar
70 signals over bare soils (Harrington, 1968, Chen et al., 1990, Johnson et al., 1996, Mattia et al.,
71 2000, Soriano et al., 2002, Zribi et al., 2010). With this approach, the computations are made
72 using simulated surfaces, with various roughness and soil moisture characteristics. The first
73 step in this process thus involves the generation of soil roughness profiles.

74 *2.1 Roughness profile generation for different types of correlation function*

75 In this section, it is proposed to generate soil surfaces with different correlation functions

76 $\rho(x) = \exp\left[-\left(\frac{x}{l}\right)^\alpha\right]$, in which the parameter α can range between 1 and 2 (Li et al., 2002),

77 with these extremes corresponding to exponential and Gaussian functions, respectively (Fung

78 et al., 1985). The approach described by (Fung et al, 1985) is used as follows:

79 The surface heights are written as:

80
$$h(k) = \sum_{i=-M}^{i=M} W(i)X(i+k) \quad (1)$$

81 where $X(i)$ is a Gaussian random variable $N(0,1)$, and $W(i)$ is the weighting function given by

82 $W(i) = F^{-1}\left[\sqrt{F[C(i)]}\right]$, in which $C(i)$ is the correlation function and $F[]$ denotes the Fourier

83 transform operator. In the numerical simulations, a Fast Fourier Transformation (FFT) is used

84 to compute the corresponding values of $W(i)$.

85 Fig. 1 shows three soil profiles generated using different values of α ($\alpha=1$, $\alpha=1.5$ and $\alpha=2$).

86 In this case, the rms surface height is equal to 0.6 cm and the correlation length is equal to

87 6 cm. It can be clearly seen that a decrease in the value of α leads to an increase in the

88 presence of high frequency structures.

892.2 Moment Method simulations

90 In this section, a limited description of the moment method, used to compute radar

91 backscattering over generated surfaces, is proposed. The analyses presented here make use of

92 two-dimensional simulations, which are adequate for the purposes of the present study, and

93 are based on the use of isotropic surfaces only (Chen et al., 1994, Fung, 1994). The

94 backscattering computation is based on the numerical resolution of integral equations, in

95 which the medium is considered to be air (Chen et al., 1990):

$$96 \quad \vec{n} \times \vec{E}^i(\vec{r}) = -\frac{1}{2} \vec{K} + \vec{n} \times \int_c \left[j\omega\mu_0 G_1 \vec{J} - \vec{K} \times \nabla G_1 - \frac{\nabla' \cdot \vec{J}}{j\omega\epsilon_1} \nabla G_1 \right] dl'$$

$$97 \quad \vec{n} \times \vec{H}^i(\vec{r}) = -\frac{1}{2} \vec{J} + \vec{n} \times \int_c \left[j\omega\epsilon_1 G_1 \vec{K} + \vec{J} \times \nabla G_1 - \frac{\nabla' \cdot \vec{K}}{j\omega\mu_0} \nabla G_1 \right] dl' \quad (2)$$

98 When the medium is soil rather than air, the corresponding integral equations are:

$$99 \quad 0 = -\frac{1}{2} \vec{K} - \vec{n} \times \int_c \left[j\omega\mu_0 G_2 \vec{J} - \vec{K} \times \nabla G_2 - \frac{\nabla' \cdot \vec{K}}{j\omega\epsilon_2} \nabla G_2 \right] dl'$$

$$100 \quad 0 = -\frac{1}{2} \vec{J} - \vec{n} \times \int_c \left[j\omega\epsilon_0 G_2 \vec{K} + \vec{J} \times \nabla G_2 - \frac{\nabla' \cdot \vec{K}}{j\omega\epsilon_2} \nabla G_2 \right] dl' \quad (3)$$

101 where μ_0 is the permeability of air, ϵ_1 and ϵ_2 are the dielectric constants of air and soil,
 102 respectively, and \vec{n} is the unit outward normal to the surface. $\vec{J} = \vec{n} \times \vec{H}$ is the equivalent
 103 surface electric current density, and $\vec{K} = -\vec{n} \times \vec{E}$ is the equivalent surface magnetic current
 104 density.

105 The Green functions are defined in cylindrical coordinates, by the zeroth order Hankel
 106 function of the second kind, as:

$$107 \quad G_i = -\frac{j}{4} H_0^{(2)}(k_i |\vec{\rho} - \vec{\rho}'|), i = 1, 2 \quad (4)$$

108 In this paper, we present integral equations and method of resolution only for horizontal
 109 polarisation. For vertical polarisation, the approach is similar with just minor modifications
 110 (Chen et al., 1990).

111 For the horizontal polarisation, the incident electric and magnetic fields are written as:

$$112 \quad \vec{E}^i = -\vec{y} e^{jk_1(x \sin \theta + z \cos \theta)}$$

113
$$\vec{H}^i = \frac{1}{\eta} (-\vec{x} \cos \theta + \vec{z} \sin \theta) e^{jk_1(x \sin \theta + z \cos \theta)} \quad (5)$$

114 With $\vec{J} = \vec{y} J(l')$ and then $\nabla' \cdot \vec{J} = 0$

115 The integral equations could be written as:

116
$$\vec{n} \times \vec{E}^i(\vec{r}) = -\frac{1}{2} \vec{K} + \vec{n} \times \int_c [j\omega\mu_0 G_1 \vec{J} - \vec{K} \times \nabla G_1] dl'$$

117
$$0 = -\frac{1}{2} \vec{K} - \vec{n} \times \int_c [j\omega\mu_0 G_2 \vec{J} - \vec{K} \times \nabla G_2] dl' \quad (6)$$

118 where:

119
$$\vec{K} \times \nabla G_i = (-\vec{n}' \times \vec{E}) \times \nabla G_i = -\vec{E} (\vec{n}' \cdot \nabla G_i), \quad i = 1, 2$$

120 The integral equations can then be simplified to:

121
$$E_y^i(\vec{\rho}) = \frac{1}{2} E_y(\vec{\rho}) + \int_c [j\omega\mu_0 G_1 J_y + E_y(\vec{n}' \cdot \nabla G_1)] dl'$$

122
$$0 = \frac{1}{2} E_y(\vec{\rho}) - \int_c [j\omega\mu_0 G_2 J_y + E_y(\vec{n}' \cdot \nabla G_2)] dl' \quad (7)$$

123 These equations can then be rewritten in the form of a matrix system:

124
$$\begin{bmatrix} Q^{11} & Q^{12} \\ Q^{21} & Q^{22} \end{bmatrix} \begin{bmatrix} E_y \\ J_y \end{bmatrix} = \begin{bmatrix} E_y^i \\ 0 \end{bmatrix} \quad (8)$$

125 The details of the different terms in these matrices are described in (Chen et al., 1989).

126 The solution for this system allows the electric field and electric field density to be estimated

127 over the studied surface. The backscattered field can then computed as:

128
$$E_y^s = - \int_c \left[j\omega \mu_0 G_1 J_y + E_y (\vec{n}' \cdot \nabla G_1) \right] dl' \quad (9)$$

129 This leads to the following expression for the backscattered signal:

130
$$\sigma^0 = \frac{2\pi\rho}{PL_{eff}} \left[\sum_{j=1}^P |E_j^s|^2 - \frac{1}{P} \left| \sum_{j=1}^P E_j^s \right|^2 \right] \quad (10)$$

131 Where L_{eff} is the effective illumination length of Gaussian antenna pattern.

132 On the basis of the outcome of several convergence tests, the profile length was set to 1 m and
 133 the number of profiles as taken to be 100. For each profile, the size of the cells was taken to
 134 be $\lambda/10$, where λ is the wavelength of the radar signal.

135 **3. Analysis of simulated radar backscattering as a function of roughness**

136 *3.1 Influence of roughness on the backscattering simulations*

137 In order to study the influence of the soil roughness parameters on radar signal backscattering,
 138 Moment Method (MM) simulations were run in the *HH* and *VV* polarizations, at 20 and 40°
 139 incidence angles, and at three different values of soil moisture: 10%, 20% and 30%. The
 140 results shown in Figs. 2, 3, 4 and 5 were computed at a 40° incidence angle, since the radar
 141 signals are known to be more sensitive to roughness at higher incidence angles (Fung, 1994,
 142 Zribi et al., 1997). Various surface parameters were used: rms heights $s=0.4$ cm, $s=0.6$ cm, s
 143 $=0.8$ cm, $s=1$ cm, $s=1.2$ cm, $s=1.4$ cm, $s=1.6$ cm; correlation lengths $l=4$ cm, $l=6$ cm, $l=8$
 144 cm and $l=10$ cm; α parameter $\alpha=1$, $\alpha=1.25$, $\alpha=1.5$ and $\alpha=1.75$. The latter range (for the
 145 parameter α) was based on the values retrieved during various experimental campaigns (Zribi
 146 et al., 2005).

147 Fig. 2 shows the simulated backscattered signal, for the *HH* polarization, assuming volumetric
148 moisture conditions of 10% and 30% in the C and X bands at 40° incidence, for all of the
149 above roughness configurations, plotted as a function of the rms surface height. These
150 simulations show that the backscattered signal is moderately well correlated with the rms
151 surface height (in the C band, R^2 is equal to 0.65 and 0.66, and in the X band it is equal to
152 0.58 and 0.51, for volumetric moistures of 10% and 30%, respectively). This outcome is
153 influenced, in particular, by the correlation length, which is not taken into account in the
154 above relationships. Fig. 3 plots the simulated backscattered radar signals for the HH
155 polarization, for volumetric moistures of 10% and 30%, in the C and X bands at 40°
156 incidence, for all of the above roughness configurations, plotted as a function of the parameter
157 Z_s . Since the latter parameter is defined as $Z_s = s^2/l$ (Zribi and Dechambre, 2003), it combines
158 the influence of both the soil's *rms* height and its correlation length: it is in effect given by the
159 product of the *rms* height s , which is related to the power of the surface height variations, and
160 the ratio s/l , which represents the local slope of the soil. The underlying motivation for the
161 introduction of Z_s was to introduce the influence of *slope*, which is an important soil feature
162 in the estimation of σ° . It can clearly be seen that the simulated backscattering is more
163 strongly correlated with Z_s ($R^2 = 0.82, 0.81$ in the C band, and $R^2 = 0.71, 0.62$ in the X band,
164 for volumetric moistures of 10% and 30%, respectively), than with the rms height. When the
165 exponential correlation function is considered alone, the correlation between Z_s and the
166 simulated backscattered signal is very high ($R^2 > 0.9$). When different function shapes are
167 considered, corresponding to different values of α (1, 1.25, 1.5 and 1.75), the correlation
168 coefficient decreases, as shown in Fig. 3. This outcome could be explained by the influence of
169 the slope component (s/l) on backscattering, which depends on the shape of the correlation
170 function.

171 3.2 Generating the Z_g parameter

172

173 The parameter Z_s was initially proposed for use with an exponential correlation (Zribi and
174 Dechambre, 2003), and weaker correlations are observed between Z_s and the simulated
175 backscattering when other correlation function shapes are considered. However, with
176 agricultural and natural soils, differing correlation function shapes are retrieved during the
177 same period. In practice, new tillage is often associated with an exponential function, whereas
178 rain-eroded and ploughed soils are often found to have correlation functions with a shape
179 lying between that of an exponential and a Gaussian function (Zribi et al., 1997, Zribi et al.,
180 2005). For these reasons, the use of a single roughness parameter, with an rms height,
181 correlation length and correlation function shape, could be very useful for inversion studies
182 based on the analysis of radar measurements, which generally make use of a small number of
183 radar configurations.

184 Since the contribution of the ratio s/l must be different from one correlation shape to another,
185 as a result of differences in the high frequency spectrum of the soil profile, we propose to
186 introduce a new parameter, which is a global representation of the Z_s parameter, written as:

$$187 \quad Zg = s \cdot \left(\frac{s}{l} \right)^{g(\alpha)} \quad (11)$$

188

189 where $g(\alpha)$ is a power function accounting for the influence of the ratio (s/l) on Zg , and α is
190 the power of the correlation function.

191 In the following, it is assumed that $g(\alpha)$ can be written as:

$$192 \quad g(\alpha) = a \alpha + b$$

193 where a and b are constants.

194 All of the backscattering simulations made in the C- and X- bands, using three values of
195 volumetric moisture (10%, 20% and 30%), a large range of values of rms height (from 0.4 to
196 1.6 cm), correlation length (from 4 cm to 10 cm), and α (from 1 to 1.75), were reviewed. The

197 best correlation between the global roughness parameter Z_g and the simulations was
198 determined by least squares regression. This is obtained when the function g is written as:

199
$$g(\alpha) \approx \alpha \quad (12)$$

200 such that (from Eq. 11):

201
$$Z_g = s \left(\frac{s}{l} \right)^\alpha \quad (13)$$

202 In Zribi and Dechambre (2003), it was proposed to use a roughness parameter $Z_s = (s.s/l)$, in
203 the case of simulations corresponding to the special case of an exponential correlation
204 function ($\alpha=1$).

205 For a fixed value of α , small values of Z_g correspond to small values of s and/or large values
206 of l , whereas large values of Z_g correspond to large values of s or small values of l . In the case
207 of a fixed correlation length, small values of Z_g correspond to small values of s and/or large
208 values of α , whereas large values of Z_g correspond to large values of s or small values of α . A
209 smooth soil surface (without clods) is generally characterised by a small value of s and a
210 medium to large value of l , thus to a small value of Z_g . Ploughed soil, corresponding to new
211 tillage, is generally associated with a large value of s , a medium to large value of l , and a
212 value of α close to 1, and thus to a large value of Z_g . Ploughed surfaces, corresponding to
213 eroded soils, are often characterised by a large value of s , a medium to large value of l and a
214 value of α close to 2, thus to a medium value of Z_g . Even when its *rms* height (s) is small, a
215 cloddy soil is characterised by a very small value of l and a value of α close to 1, thus leading
216 to large values of Z_g (Zribi et al., 1997, zribi et al., 2005).

217 Fig. 4 shows a plot of simulated backscattered signals as a function of Z_g , for various ranges
218 of roughness and four correlation function shapes ($\alpha=1$, $\alpha=1.25$, $\alpha=1.5$, $\alpha=1.75$), in the C
219 and X bands and for the *HH* polarization, with volumetric moisture values of 10% and 30%.

220 Firstly, it can be seen that the simulated backscattering increases with Z_g , and that there is a
221 strong correlation between the backscattering and Z_g , equal to 0.97 and 0.97 for 10% and
222 30% volumetric moistures in the C-band and equal to 0.97 and 0.93 for 10% and 30%
223 volumetric moistures in the X-band. A high dynamic range can be observed at small values of
224 Z_g , and near saturation can be seen when Z_g reaches approximately 0.3-0.35. The highest
225 values of α produce the weakest backscattering. From this initial result, Z_g appears to be a
226 useful parameter for the characterization of surface roughness, in the case of a given (fixed)
227 radar configuration. This result can be explained by the fact that Z_g takes the influence on
228 radar backscattering behaviour of s , l and the correlation function shape into account.

229 Table 1 provides a summary of the correlations determined from backscattering simulations,
230 using different roughness parameters (s , Z_s and Z_g), for all combined conditions of incidence
231 angle, moisture, polarisation, and frequency. It can be seen that under almost all conditions of
232 radar transmission, the strongest correlations are obtained with the parameter Z_g , rather than
233 with s or Z_s . This conclusion is not completely verified in the C-band, in the case of a 20°
234 incidence angle, for which the empirical logarithmic relationship can be seen to less well
235 correlated.

236 To simplify the combination of backscattering simulations made at different radar
237 frequencies, the former were considered as a function of electromagnetic roughness, written
238 in the form: $k.Z_g$ (k : radar wave number). Fig. 5 plots the simulated backscattered signals as a
239 function of $k.Z_g$, in the HH and VV polarizations, at a 40° incidence angle, and with the
240 volumetric moisture equal to 10% and 30%, thus allowing all roughness conditions and C-
241 and X-band simulations to be combined.

242 A least squares approach was then used to establish an empirical relationship between $k.Z_g$
243 and the backscattered signals, taking the form:

244
$$\sigma^0 = \alpha + \beta \left(1 - e^{-\mu k Zg} \right) \quad (14)$$

245 where σ^0 is expressed in dB, k in cm^{-1} , and Zg in cm.

246 The backscattered signals can be seen to be strongly correlated with $k.Zg$. Table 2 lists the
247 coefficients α , β and μ , together with R^2 and the RMS error, for different moisture conditions
248 ($Mv=10\%$, 20% and 30%), two incidence angles, 20° and 40° , and for the *HH* and *VV*
249 polarisations. All of these configurations are characterised by a strong correlation between
250 $k.Zg$ and the radar simulations (greater than 0.77).

251 **4. Experimental analysis**

252 In this study, we use data acquired over agricultural watersheds, during the course of three
253 experimental campaigns (Orgeval'94, Pays de Caux'94, Villamblain'2003) (Fig. 6). For each
254 of these campaigns, radar data (SIRC, ERASME, ASAR/ENVISAT) was acquired with
255 different configurations (Table 3). Simultaneously to the radar acquisitions, ground
256 measurements were carried out in a large number of test fields: the soil moisture was
257 measured within the top 5 cm soil using a gravimetric method and/or a TDR probe, and
258 roughness measurements were made using a pin-profiler (total length equal to 2 m, resolution
259 equal to 10 mm).

260 *4.1 Description of the database*

261 • *Orgeval'94*

262 The Orgeval watershed is located to the East of Paris (France). An experimental campaign
263 was conducted during the SIRC/XSAR mission in April 1994 (Zribi et al., 1997). The soil
264 texture is relatively constant over the whole basin: clay 17%, silt 78%, sand 5%. Ground
265 measurements (roughness and moisture) were made in 5 fields.

266 • *Pays de Caux'94*

267 This test site corresponds to the Blosseville watershed, located in the Pays de Caux in
268 Northern France (49°47' N; 0°50' W). The loamy soils of the northern European loess belt are
269 sensitive mainly to soil structure degradation, and are commonly exposed to erosion caused
270 by concentrated runoff. The site's soil is characterized by a very homogenous loamy texture
271 (13% clay, 65% loam, and 22.5% sand). ERASME FM-CW scatterometer airborne
272 measurements were recorded in 1994, over 10 large test fields.

273 • *Villamblain'2003*

274 This site is located approximately 80 km west of Paris (48°10'N; 01°48'E), and is
275 characterized by large agricultural fields, which are mainly bare soil fields with a
276 homogenous soil composed of approximately 60% loam, 30% clay and 10% sand.
277 Simultaneously to the radar measurements acquired by the ASAR-ENVISAT radar in 2003,
278 ground measurements were made over a large number of bare soil test fields.

279 • *Soil moisture measurements*

280 The mean volumetric moisture (M_v) was estimated for each test field, within the top 5 cm,
281 and using a gravimetric method. As a result of relatively rainy winters, this parameter
282 remained high and nearly constant (approximately $0.3 \text{ cm}^3/\text{cm}^3$), at all three sites.

283 • *Soil roughness measurements*

284 Roughness measurements were made using a pin profiler (with a total length of 2 m and a
285 resolution of 1 cm). Ten surface profiles were taken for each test field, in order to ensure that
286 roughness parameters were determined with sufficient statistical accuracy. For each profile,
287 we computed the correlation function (Ogilvy, 1991), as well as the two statistical parameters,
288 the rms height (s) and the correlation length (l). The parameter α , corresponding to the shape
289 of the correlation function, is computed for the first scales up to the correlation length from
290 experimental functions, using a least squares optimisation approach.

291 Fig. 7-a plots the parameter α , corresponding to the correlation function shapes retrieved for
292 all test fields, as a function of the *rms* soil height, showing a moderate degree of correlation.
293 In general, the value of α is found to be close to 1 for smooth soils, and higher for ploughed
294 soils. This type of relationship was also observed by (Zribi et al., 2005). The measured values
295 of Z_g (Fig.7-b) ranged between 0.01 and 0.03 for smooth soils. In the case of cloddy soils, Z_g
296 ranged between approximately 0.04 and 0.2, and for ploughed soils it ranged between 0.2 and
297 0.62 (Zribi et al., 2005).

298 *4.2 Comparing backscattering simulations with radar signal data*

299 In Figs. 8-a and 8-b, the results derived from the moment method simulations made in two
300 dimensions are compared with real radar data, for the *HH* and *VV* polarizations, respectively.
301 Two-dimensional (rather than three-dimensional) simulations were used, since the analysed
302 experimental fields had very little directional structure. For each individual test field, ground
303 measurements (*rms* height, correlation length, α parameter, soil moisture) were used as input
304 for the radar backscattering simulations. Fig. 8-a shows the *HH* polarization data obtained
305 from several different configurations: C and X bands, and five different incidence angles: 20°,
306 25°, 30°, 35° and 44°, whereas Fig. 8-b shows *VV* polarization results for the same set of
307 configurations. In the *HH* polarization, the simulations can be seen to deviate from the radar
308 measurements, with an RMSE equal to 3.34 dB. In the *VV* polarization, a good agreement can
309 be observed, with an RMSE equal to 1.62 dB. These results illustrate some of the limitations
310 encountered, particularly in the *HH* polarization, when the MM model is used to simulate all
311 surface conditions. This is probably due to the greater sensitivity of *HH* polarization to soil
312 roughness (Fung, 1994, Zribi et al., 1997). In the following section, it is proposed to use
313 empirical relationships to express the backscattered radar signals as a function of the surface
314 parameters.

315 *4.3 Analysis of the relationship between roughness and radar data*

316 All of the ground data analysed in the present study was acquired under very similar soil
 317 moisture conditions (close to 30%). Fig. 9 shows the radar signals measured over the test
 318 fields, as a function of kZg , for various configurations (both polarizations and several
 319 incidence angles). As in the case of the simulations described in section 3, the radar signals
 320 are characterized by a high dynamic range at small values of kZg , and near saturation can be
 321 observed when kZg reaches approximately 0.3-0.35.

322 Figs. 9a, 9b, 9c, 9d, 9e, and 9f correspond to observations made at the Pays de Caux site,
 323 using the ERASME airborne FM-CW scatterometer. This data was acquired in the HH and
 324 VV polarizations, in the C-and X-bands at 20° , 25° , 30° and 35° incidence. In both
 325 polarizations, the roughness parameter kZg and the radar measurements are strongly
 326 correlated.

327 Fig. 9g corresponds to data acquired by SIR-C and ASAR-ENVISAT over the Orgeval and
 328 Villamblain sites, at HH polarization in the C band and an incidence of approximately 44° .
 329 These radar measurements are also found to be strongly correlated with kZg . Empirical
 330 relationships can be used to express the backscattered radar signals as a function of $k.Zg$, for
 331 various multi-incidence and polarization configurations. These are written:

$$332 \quad \sigma_{p\theta}^0 = \alpha_{p\theta} + \beta_{p\theta} \left(1 - e^{-\mu_{p\theta} k Zg} \right) \quad (15)$$

333 where the coefficients $\alpha_{p\theta}$, $\beta_{p\theta}$ and $\mu_{p\theta}$ are adjusted using a least squares optimisation, p
 334 is the polarization and θ is the incidence angle. Table 2 lists the values of $\alpha_{p\theta}$, $\beta_{p\theta}$ and
 335 $\mu_{p\theta}$, together with the statistical parameters R^2 and RMSE, for the nine configurations
 336 analysed in this study.

337 Table 5 indicates the general improvement found in the statistical parameters (R^2 and RMSE)
 338 when $k.Zg$ is used, rather than $k.Zs$, in the same empirical model. Only the last configuration
 339 (HH polarization at 44°) leads to better results with the parameter $k.Zs$.

340 From the empirical relationships established for the nine radar configurations, a general
 341 empirical model is proposed, in which the radar signal is expressed as a function of kZg , θ and
 342 the radar polarisation:

$$343 \quad \sigma_p^0 = (a_p \theta + b_p) + (c_p \theta + d_p) \times \left(1 - e^{(e_p \theta^2 + f_p \theta + g_p) k Z g} \right) \quad (16)$$

344 This model is found to be valid when θ lies between 20° and 44° .

345 The values of the parameters used in Eq. 16 are listed, for the *HH* and *VV* polarizations, in
 346 Table 6.

347 In Fig. 10, the radar signal levels predicted by the model are compared with the measured
 348 data, over the full range of experimental incidence angles. The modelled and measured signals
 349 are found to be strongly correlated, with R^2 equal to 0.79 and 0.88 and the *RMSE* equal to
 350 1.42 dB and 1.19 dB, in the *HH* and *VV* polarizations, respectively.

351 **5. Conclusion**

352 It is very difficult to separately estimate the influences of rms height (s), correlation length (l)
 353 and correlation function shape, on the backscattering behaviour of a rough soil surface. In
 354 practice, the availability of only a limited number of radar configurations can make it
 355 impossible to retrieve all of these parameters with soil moisture.

356 In the present study, a new approach is proposed for the description of surface roughness and
 357 its influence on the backscattering behaviour of radar signals. The resulting expressions make
 358 use of a numerical backscattering algorithm based on the moment method, applied to
 359 synthetically generated surfaces and assuming a correlation function described by

$$360 \quad \rho(x) = \exp \left[- \left(\frac{x}{l} \right)^\alpha \right].$$

The correlation between the simulated and measured rms soil heights is

361 weak, as a consequence of influences related to the correlation length of the surface roughness
 362 and the shape of the correlation function. These influences must be accounted for, in order to

363 retrieve accurate surface roughness or moisture estimations. The parameter Z_s , which allows
364 the influence of soil surface height and slope to be taken into account, can be used to improve
365 the correlation strength. Nevertheless, the simulated radar signals are still affected by strong
366 fluctuations, resulting from variations in the shape of the correlation function. By introducing
367 a new roughness parameter (Z_g), written in the form $Z_g = s \left(\frac{s}{l} \right)^\alpha$, the influence of the *rms*
368 surface height, the slope of the soil surface, and a third parameter α related to the shape of the
369 correlation function, can be taken into account. A very good correlation is then observed
370 between $k \cdot Z_g$ and the simulated radar signals in the C and X bands, with R^2 equal to 0.93 and
371 0.9 at 40° incidence for the *HH* and *VV* polarizations, respectively. Empirical functions are
372 proposed to describe these relationships. The usefulness of this new parameter is
373 demonstrated through the analysis of radar signal data acquired at three experimental sites in
374 France (Orgeval, Pays de Caux and Villamblain). In the case of smooth soils, Z_g is found to
375 range between 0.01 and 0.03. In the case of cloddy soils, Z_g lies between approximately 0.04
376 and 0.45, and in the case of ploughed soils, it ranges between 0.2 and 0.62. A high correlation
377 ($R^2 > 0.7$ and $RMSE < 1.54$ dB) is observed between kZ_g and the experimental radar signals
378 acquired in the C and X bands, at incidence angles ranging between 20° and 44° . An
379 empirical model is proposed for the relationship observed between the measured radar signals
380 and kZ_g , θ , and the polarization parameters. This is found to be in excellent agreement with
381 the radar measurements, with the $RMSE$ equal to 1.42 dB and 1.19 dB in the *HH* and *VV*
382 polarizations, respectively. These results are particularly useful for the improvement of
383 empirical or semi-empirical inversion models used in soil moisture estimations. In the past,
384 these models were often based on the rms height roughness parameter only, leading to a high
385 level of noise and a lower accuracy in the soil moisture estimation, resulting from the
386 influence of the correlation length and shape of the correlation function.

387 **Acknowledgements**

388
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392

393 **References**

- 394 Baghdadadi, N., Gherboudj, I., Zribi, M., Sahebi, M., Bonn, F., and King, C. (2004). Semi-
395 empirical calibration of the IEM backscattering model using radar images and moisture
396 and roughness field measurements. *International Journal of Remote Sensing*, 25, 3593-
397 3623.
- 398 Baghdadadi, N., Holah, N., and Zribi, M. (2006). Calibration of the Integral Equation Model for
399 SAR data in C-band and HH and VV polarizations. *International Journal of Remote*
400 *Sensing*, 27 (4), 805-816.
- 401 Baghdadadi, N., Abou Chaaya, J., and Zribi, M. (2011). Semi-empirical calibration of the
402 Integral equation Model for SAR data in C-band and cross polarization using radar images
403 and field measurements. *IEEE Geoscience and Remote Sensing Letters*, 8 (1), 14-18.
- 404 Bretar, F., Arab-Sedze, M., Champion, J., Pierrot-Deseilligny, M., Heggy, E., Jacquemoud, S.
405 (2013). An advanced photogrammetric method to measure surface roughness:
406 Application to volcanic terrains in the Piton de la Fournaise, Reunion Island. *Remote*
407 *Sensing of Environment*, 135, 1-11.
- 408 Callens, M., Verhoest, N.E.C., Davidson, M.W.J. (2006). Parameterization of tillage-induced
409 single-scale soil roughness from 4-m profiles. *IEEE Transaction on. Geoscience and*
410 *Remote Sensing*. 44, 878-888.
- 411 Chen, M. F., and Bai, S. Y. (1990). Computer simulation of wave scattering from a dielectric
412 random surface in two dimensions cylindrical case. *J. Electromagn. Waves Appl.* 4, 10,
413 963-982.
- 414 Chen, K. S., Wu, T. D., Tsang, L., Li, Q., Shi, J., and Fung, A. K. (2003). Emission of rough
415 surfaces calculated by the integral equation method with comparison to three-dimensional
416 moment method simulations. *IEEE Transaction on. Geoscience and Remote Sensing*, 41
417 (1), 90–101.
- 418 Davidson, M. W. J., Le Toan, T., Mattia, F., Satalino, G., Manninen, T., and Borgeaud, M.
419 (2000). On the characterisation of agricultural soil roughness for radar remote sensing
420 studies. *IEEE Transaction on. Geoscience and Remote Sensing*, 38, 630-640.
- 421 Dubois, P. C., Van Zyl, J., and Engman, T. (1995). Measuring soil moisture with imaging
422 radars. *IEEE Transaction on Geoscience and Remote Sensing*, 33, 915-926.

- 423 Fung, A., and Chen, M. F. (1985). Numerical Simulation of Scattering from Simple and
424 Composite Random Surfaces, *J. Opt. Am. A*, 2 (12).
- 425 Fung, A. K. (1994). *Microwave Scattering and Emission Models and their Applications*,
426 Norwood: Artech House.
- 427 Fung, A. K., Li, Z., and Chen, K. S. (1992). Backscattering from a randomly rough dielectric
428 surface. *IEEE Transaction on Geoscience and Remote Sensing*, 30, 356-369.
- 429 Harrington, R. F. (1968). *Field Computation by Moment Method*. IEEE PRESS, Series on
430 Electromagnetic Waves.
- 431 Johnson, J. T., Tsang, L., Shin, R. T., Pak, K., Chan, C. H., Ishimaru, A., Kuga, Y. (1996).
432 Backscattering enhancement of electromagnetic waves from two-dimensional perfectly
433 conducting random rough surfaces: a comparison of Monte Carlo simulations with
434 experimental data. *IEEE Transactions on Antennas and Propagation* , 44, 5.
- 435 Lawrence, H., Wigneron, J.-P., Demontoux, F., Mialon, A., Kerr, Y.H. (2013). Evaluating the
436 Semiempirical H - Q Model Used to Calculate the L-Band Emissivity of a Rough Bare
437 Soil . *IEEE Transactions on Geoscience and Remote Sensing*, 51 (7, Part: 2), 4075 –
438 4084, Digital Object Identifier: 10.1109/TGRS.2012.2226995.
- 439 Li, Q., Shi, J. C., and Chen, K. S. (2002). A generalised Power Law Spectrum and its
440 Applications to the Backscattering of soil surfaces Based on the Integral Equation
441 Model. *IEEE Transaction on Geoscience and Remote Sensing*, 40, 271-281.
- 442 Lievens H., Vernieuwe H., Alvarez-Mozos J., De Baets B., Verhoest N.E.C. (2009). Error in
443 SAR-derived soil moisture due to roughness parameterization: An analysis based on
444 synthetical surface profiles. *Sensors*, 9(2), 1067-1093; doi:10.3390/s90201067.
- 445 Lievens H., Verhoest N.E.C., De Keyser E., Vernieuwe H., Matgen P., Álvarez-Mozos J., De
446 Baets B. (2011). Effective roughness modelling as a tool for soil moisture retrieval from
447 C- and L-band SAR. *Hydrology and Earth System Sciences*, 15(1), 151-162.
- 448 Mattia, F. and Le Toan, T. (1999). Backscattering properties of multi-scale rough surfaces. *J.*
449 *Electro. Waves Appl.*, 13, 491-526.
- 450 Mattia, F., Le Toan, T., Davidson, M. (2001). An analytical, numerical, and experimental
451 study of backscattering from multiscale soil surfaces. *Radio Science*, 36, 1, 119–135,
452 DOI: 10.1029/2000RS002327

453 Oh, Y., Sarabandi, K., and Ulaby, F. T. (1992). An empirical model and an inversion
454 technique for radar scattering from bare soil surfaces. *IEEE Transactions on Geoscience
455 and Remote Sensing*, 30, 370–381.

456 Oh, Y., and Kay, Y. C. (1998). Condition for precise measurement of soil surface roughness.
457 *IEEE Transactions on Geoscience and Remote Sensing*, 36(2), 691–695.

458 Shi, J., Wang, J., Hsu, A. Y., O’Neill, P. E., and Engmann, T. (1997). Estimation of Bare
459 Surface Soil Moisture and Surface Roughness Parameter Using L-Band SAR Image
460 Data. *IEEE Transaction on Geoscience and Remote Sensing*, 35, 1254-1265.

461 Soriano, G., Guérin, C. A., Saillard, M. (2002). Scattering by two-dimensional rough
462 surfaces: comparison between the method of moments, Kirchhoff and small-slope
463 approximations. *Waves Random Media*, 12, 1, 63-83, **DOI:10.1088/0959-
464 7174/12/1/305**.

465 Ulaby, F. T., Moore, R. K., and Fung, A. K. (1986). *Microwave Remote Sensing Active and
466 Passive*. Norwood: Artech House, inc.

467 Verhoest, N. E. C., Lievens, H., Wagner, W., Alvarez-Mozos, J., Moran, M. S., and Mattia, F.
468 (2008). On the soil roughness parameterization problem in soil moisture retrieval of
469 bare surfaces from Synthetic Aperture Radar. *Sensors*, 8 (7), 4213–4248.

470 Wu, T. D., Chen, K. S., Shi, J., and Fung, A. K. (2001). A transition model for the reflection
471 coefficient in surface scattering. *IEEE Transaction on Geoscience and Remote Sensing*,
472 39, 2040-2050.

473 Zribi, M., Taconet, O., Le Hégarat-Masclé, S., Vidal-Madjar, D., Emblanch, C., Loumagne,
474 C., and Normand, M. (1997). Backscattering behavior and simulation comparison over
475 bare soils using SIRC/XSAR and ERASME 1994 data over Orgeval. *Remote Sensing of
476 Environment*, 59, 256-266.

477 Zribi, M., Ciarletti, V., and Taconet, O. (2000). Validation of a rough surface model based on
478 fractional brownian geometry with SIRC and ERASME radar data over Orgeval site.
479 *Remote Sensing of Environment*, 73, 65-72.

480 Zribi, M. and Dechambre, M. (2003). A new empirical model to retrieve soil moisture and
481 roughness from Radar Data. *Remote Sensing of Environment*, 84 (1), 42-52.

- 482 Zribi, M., Baghdadi, N., Holah, N., Fafin, O., and Guérin, C. (2005). Evaluation of a rough
483 soil surface description with ASAR-ENVISAT Radar Data. *Remote sensing of*
484 *environment*, 95, 67-76.
- 485 Zribi, M., André, C., Decharme, B. (2008). A method for soil moisture estimation in
486 Western Africa based on ERS Scatter meter. *IEEE Transactions on Geoscience and*
487 *Remote Sensing*, 46, 2, 438-448.
- 488 Zribi, M., Le Morvan, A., Dechambre, M., Baghdadi, N. (2010). Numerical backscattering
489 analysis for rough surfaces including a cloddy structure. *IEEE Transactions on*
490 *Geoscience and Remote Sensing*, 48 (5), 2367 – 2374, 10.1109/TGRS.2009.2038710.
491

492 **Figures captions**

493 Fig. 1: Three synthetically generated surface profiles, with *rms* height=0.6 cm, correlation
494 length=6 cm, and a) $\alpha=1$, b) $\alpha=1.5$ and c) $\alpha=2$.

495 Fig. 2: Backscattering simulations in the *HH* polarisation at 40° incidence, as a function of the
496 rms height: a) C band, *mv*=10%, b) C band, *mv*=30%, c) X band, *mv*=10%, d) X band,
497 *mv*=30%

498 Fig. 3: Backscattering simulations in the *HH* polarisation at 40° incidence, as a function of the
499 parameter *Zs*. a) C band, *mv*=10%, b) C band, *mv*=30%, c) X band, *mv*=10%, d) X band,
500 *mv*=30%

501 Fig. 4: Backscattering simulations in the *HH* polarisation at 40° incidence as a function of the
502 parameter *Zg*, in the parameter space defined by *s* ranging from 0.4 to 1.6cm, *l* ranging from 4
503 to 10 cm, and α ranging from 1 to 1.75: a) C band, *mv*=10%, b) C band, *mv*=30%, c) X band,
504 *mv*=10%, d) X band, *mv*=30%

505 Fig. 5: Backscattering simulations as a function of the parameter *kZg*, at 40° incidence: a) *HH*
506 polarization, *mv*=10%, b) *HH* polarization, *mv*=30%, c) *VV* polarization, *mv*=10%, d) *VV*
507 polarization, *mv*=30%

508 Fig. 6: Map showing the location of the studied sites

509 Fig. 7: Roughness parameters for all test fields at the three studied sites (Orgeval, Pays de
510 Caux, Villamblain) (a) rms heights and alpha, the power of the correlation function, (b) rms
511 heights and *Zg* parameters.

512 Fig. 8: Numerically simulated radar signals as a function of measured radar signals, a) *HH* pol
513 (C and X bands, at five incidence angles: 20°, 25°, 30°, 35° and 44°), (b) *VV* pol (C and X
514 bands, at four incidence angles: 20°, 25°, 30° and 35°).

515 Fig. 9: Relationship between *kZg* and measured radar signals, for: a) *HH* polarization at 20°
516 incidence, b) *VV* polarization at 20° incidence, a) *HH* polarization at 25° incidence, b) *VV*

517 polarization at 25° incidence, c) *HH* polarization at 30° incidence, d) *VV* polarization at 30°
518 incidence, e) *HH* polarisation, at 35° incidence, f) *VV* polarisation at 35° incidence, g) *HH*
519 polarisation at 44° incidence.

520 Fig. 10: Inter-comparison between radar data acquired at different incidence angles, and the
521 signals given by the proposed empirical model: (a) *HH* polarization, (b) *VV* polarisation

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534 **Tables:**

535 Table 1: The statistical parameter R^2 , computed for different backscattering simulations, as a
 536 function of the rms height (s), the parameters Z_s and Z_g , and various different values of soil
 537 moisture, incidence angle and polarisation.

configuration		$\sigma_0=f(s)$		$\sigma_0=f(Z_s)$		$\sigma_0=f(Z_g)$	
		C-band	X-band	C band	X band	C band	X band
$M_v=10\%$	HH-20°	0.77	0.53	0.89	0.66	0.9	0.95
	VV-20°	0.73	0.63	0.8	0.78	0.8	0.82
	HH-40°	0.65	0.58	0.82	0.71	0.97	0.97
	VV-40°	0.58	0.68	0.77	0.76	0.97	0.96
$M_v=20\%$	HH-20°	0.79	0.63	0.89	0.78	0.9	0.92
	VV-20°	0.58	0.66	0.89	0.8	0.81	0.86
	HH-40°	0.66	0.48	0.82	0.64	0.97	0.95
	VV-40°	0.58	0.55	0.76	0.73	0.97	0.94
$M_v=30\%$	HH-20°	0.79	0.6	0.91	0.74	0.90	0.91
	VV-20°	0.76	0.61	0.88	0.76	0.8	0.86
	HH-40°	0.66	0.51	0.81	0.62	0.97	0.93
	VV-40°	0.58	0.46	0.75	0.6	0.95	0.96

538

539 Table 2: Values of α , β and μ (parameters from Eq. 14), together with the statistical
 540 parameters R^2 and $RMSE$, for various different simulated values of soil moisture, incidence
 541 angle and polarisation.

Configuration		α	β	μ	R^2	$RMSE$ (dB)
$M_v=10\%$	HH-20°	-16.14	12.34	23.71	0.86	1.44
	VV-20°	-15.11	10.21	38.31	0.77	1.53
	HH-40°	-24.19	18.13	11.27	0.93	1.57
	VV-40°	-20.71	15.10	14.02	0.90	1.63
$M_v=20\%$	HH-20°	-14.15	12.11	22.81	0.88	1.37
	VV-20°	-12.54	10.68	33.41	0.84	1.31
	HH-40°	-22.57	17.87	11.28	0.92	1.66
	VV-40°	-21.04	15.46	15.48	0.89	1.72
$M_v=30\%$	HH-20°	-13.05	12.01	22.95	0.87	1.35
	VV-20°	-11.09	10.86	32.26	0.86	1.24
	HH-40°	-22	-17.21	13.43	0.92	1.64
	VV-40°	-17.01	-14.92	17.65	0.92	1.34

542

543 Table 3: Radar satellite configurations corresponding to the radar data acquisitions, for the
 544 three studied sites.

Campaign	Sensor	date	Configuration
Orgeval'94	SIRC	12/04/94 - 18/04/94	C band, HH, 44°
Pays de Caux'94	ERASME	February 1994	C and X bands, HH, VV 20°, 25°, 30°, 35°
Villamblain'03	ASAR/ENVISAT	October 2003	C band, HH, ~43°

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548 Table 4: Values of $\alpha_{p\theta}$, $\beta_{p\theta}$ and $\mu_{p\theta}$ (parameters of Eq. 15) together with the statistical
 549 parameters R^2 and $RMSE$, for the nine configurations analysed in this study.

	$\alpha_{p\theta}$	$\beta_{p\theta}$	$\mu_{p\theta}$	R^2	$RMSE$ (dB)
HH-20°	-14.11	12.63	35.95	0.77	1.29
VV-20°	-12.41	12.22	32.16	0.83	1.16
HH-25°	-12.85	10.91	22.45	0.76	1.4
VV-25°	-12.61	11.55	21.03	0.85	1.1
HH-30°	-12.68	10.08	15.68	0.76	1.38
VV-30°	-11.98	10.11	11.32	0.75	1.45
HH-35°	-12.56	9.41	12.05	0.7	1.54
VV-35°	-12.88	10.14	11.72	0.86	1.02
HH-44°	-10.28	5.63	4.62	0.7	0.89

550

551 Table 5: The statistical parameters R^2 and $RMSE$, corresponding to the use of different
 552 relationships between the radar data and the parameters kZs and kZg .

	kZs		kZg	
	R^2	$RMSE$ (dB)	R^2	$RMSE$ (dB)
HH-20°	0.67	1.5	0.77	1.29
VV-20°	0.79	1.21	0.83	1.16
HH-25°	0.65	1.69	0.76	1.4
VV-25°	0.77	1.39	0.85	1.1
HH-30°	0.67	1.6	0.76	1.38
VV-30°	0.67	1.69	0.75	1.45
HH-35°	0.65	1.66	0.7	1.54
VV-35°	0.8	1.2	0.86	1.02
HH-44°	0.86	0.6	0.71	0.86

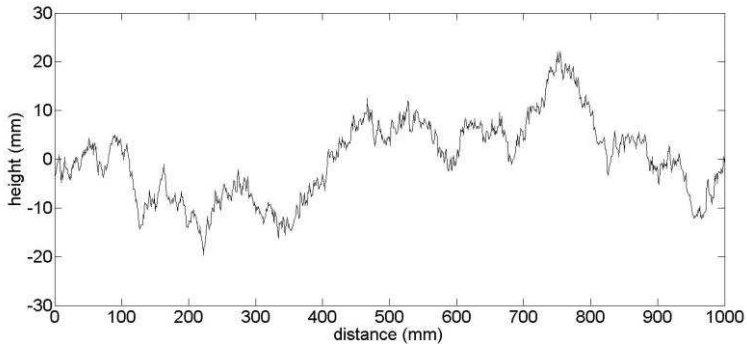
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554 Table 6: values of the parameters used in Eq. 16 for the HH and VV polarizations

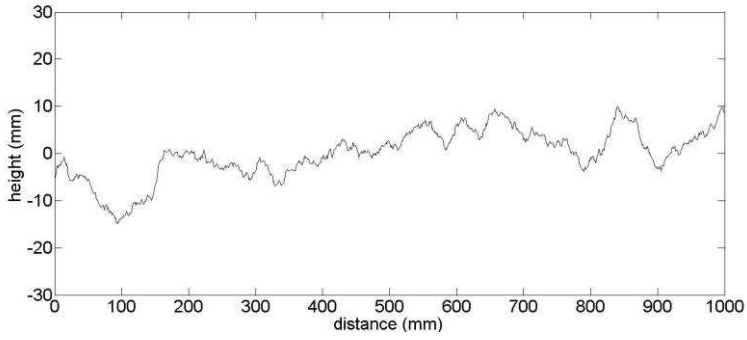
	a_p	b_p	c_p	d_p	e_p	f_p	g_p
HH pol	0.046	-12.81	-0.026	10.55	0.05	-4.38	97.99
VV pol	-0.089	-9.88	-0.062	12.63	0.109	-7.346	134.61

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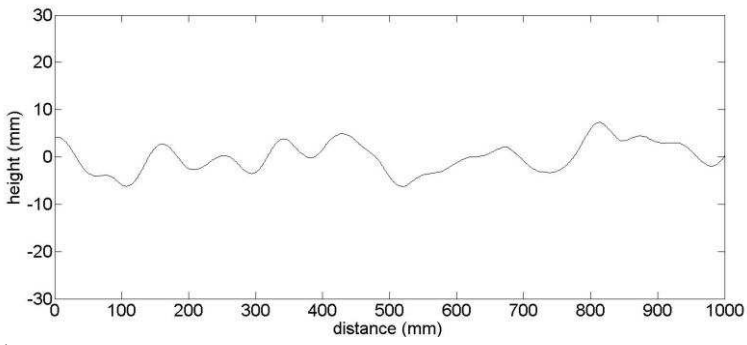
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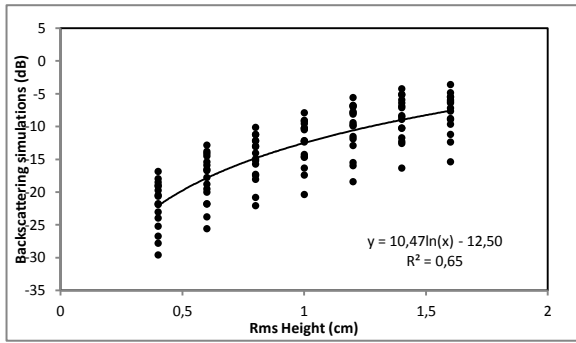
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560 Fig. 1

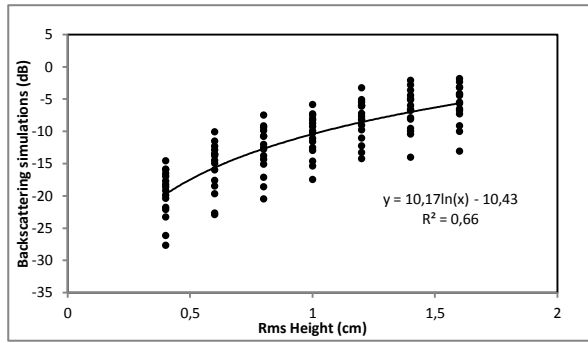
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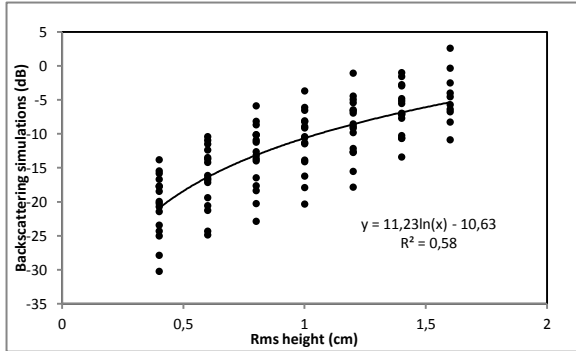


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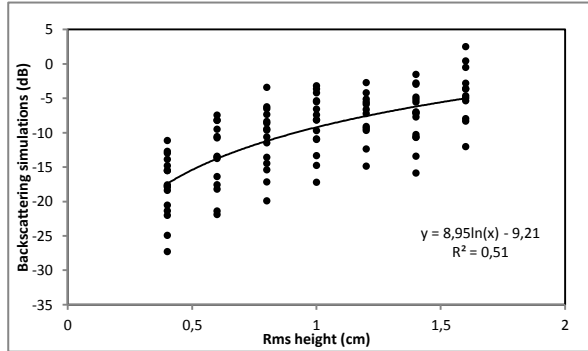


b)

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c)



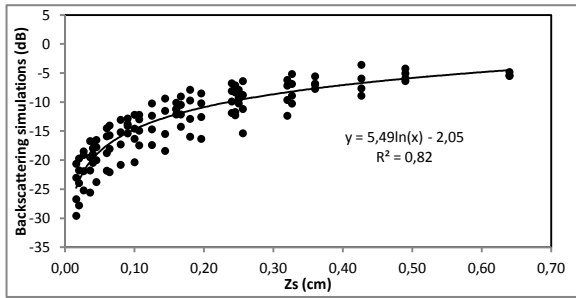
d)

567 Fig. 2

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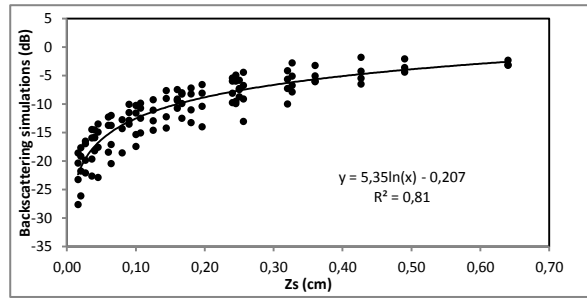
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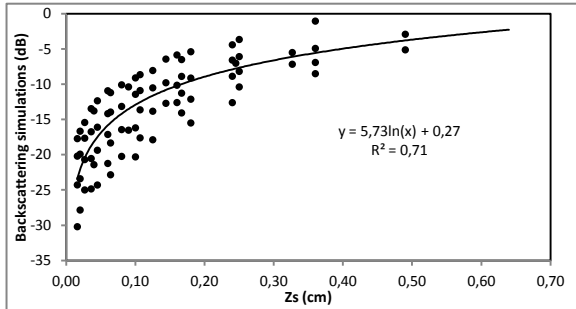
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a)



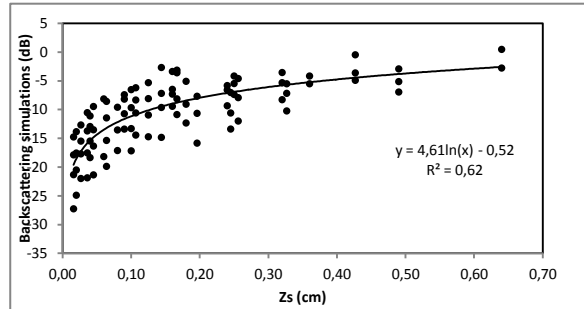
b)

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c)

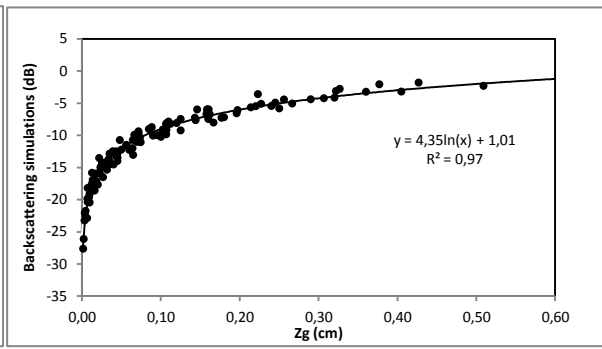
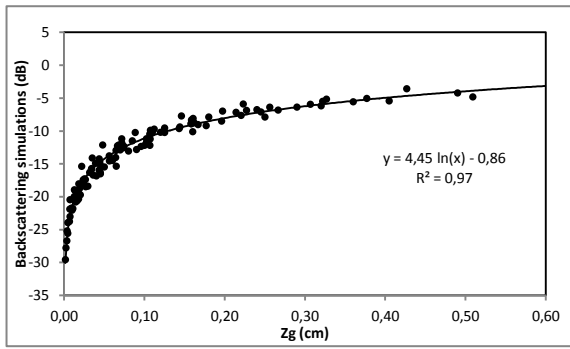


d)

574 Fig. 3

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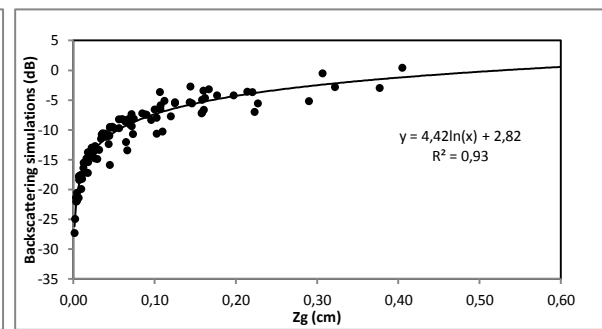
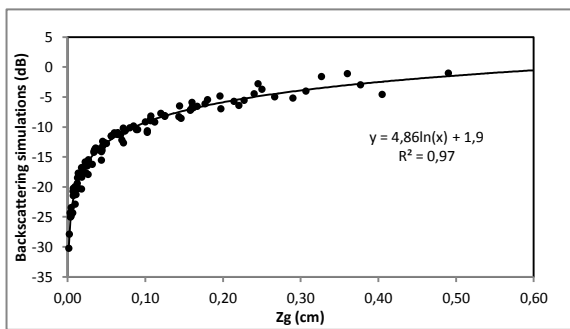


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a)

b)



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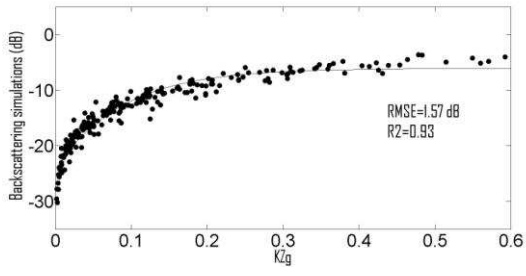
580

c)

d)

581 Fig. 4

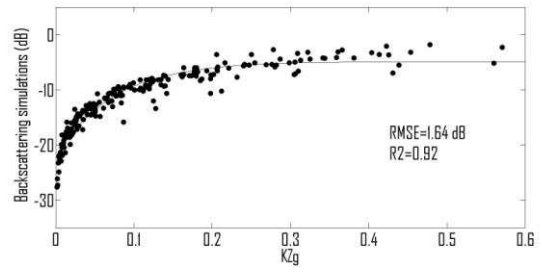
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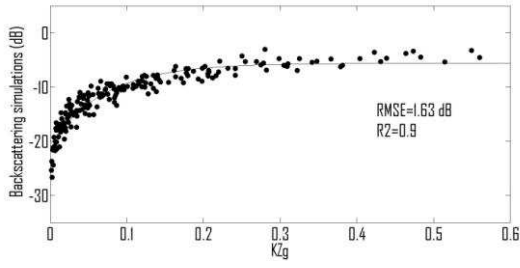
583

584

a)



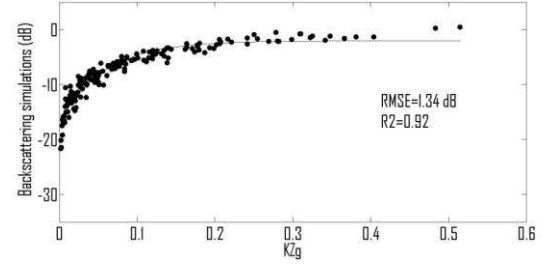
b)



585

586

c)



d)

587 Fig. 5

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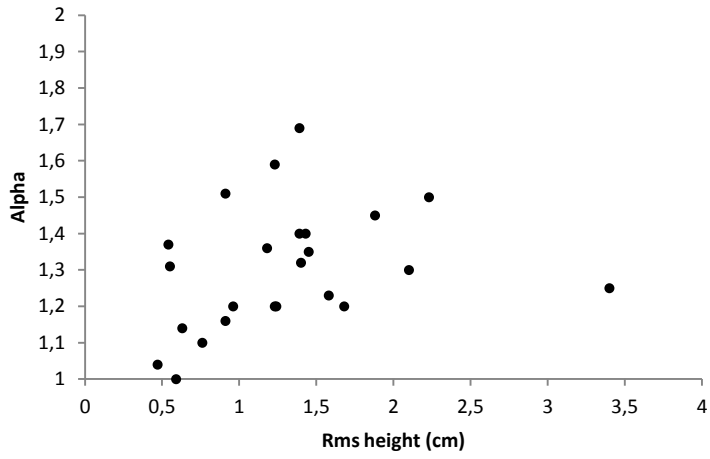
591 Fig. 6

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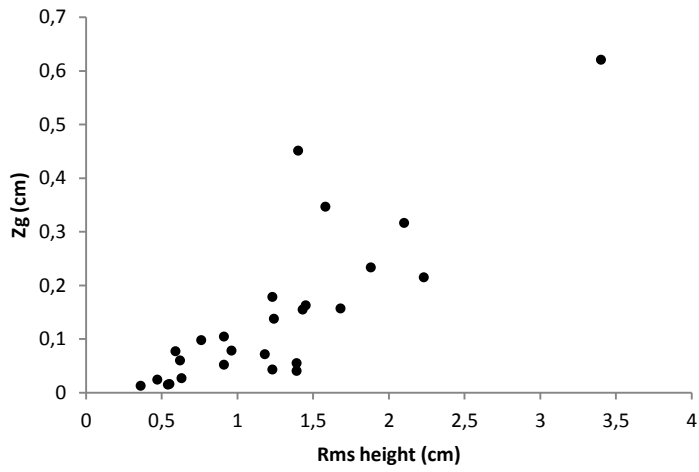
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597 (a)



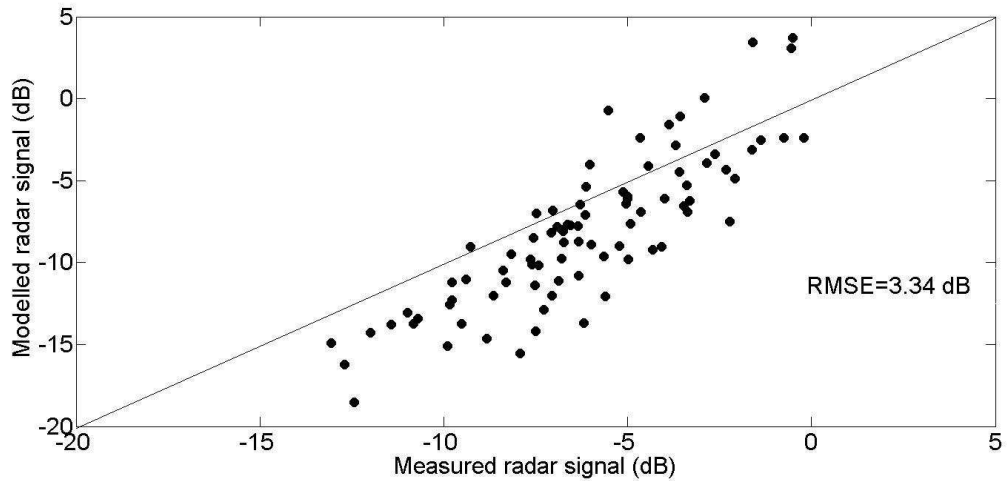
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599 (b)

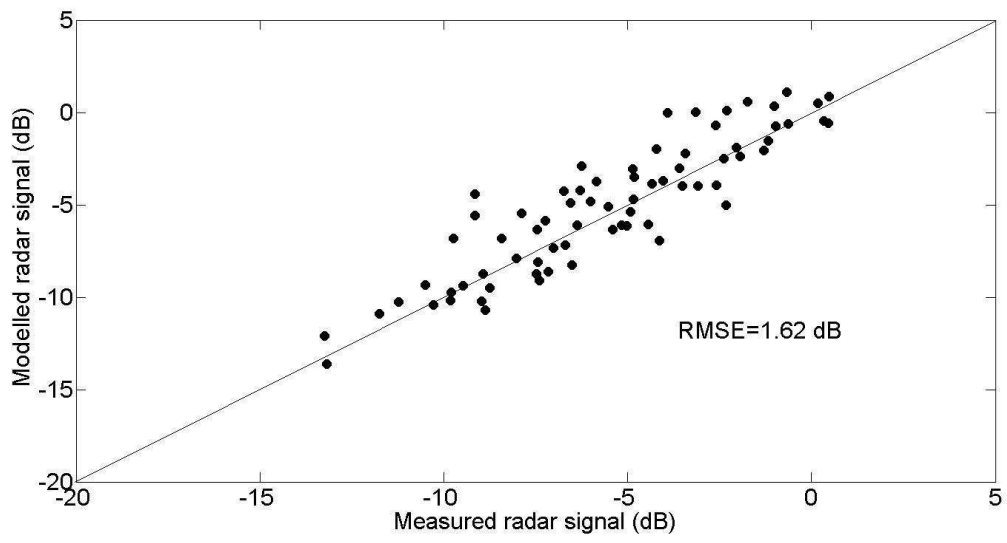
600 Fig. 7

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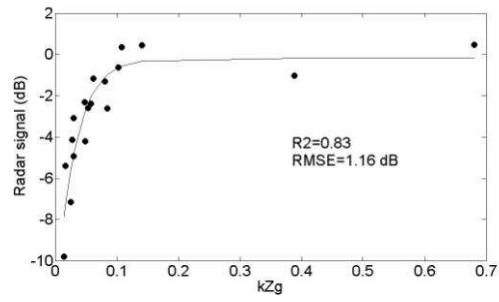
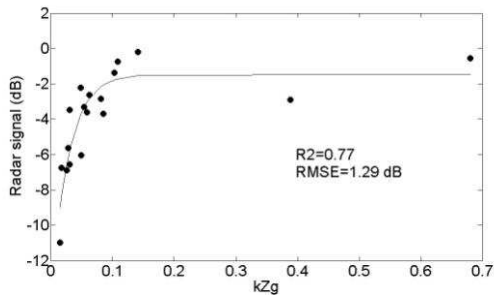
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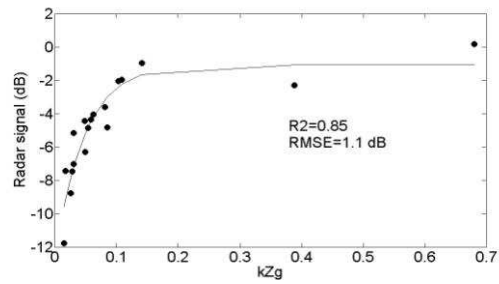
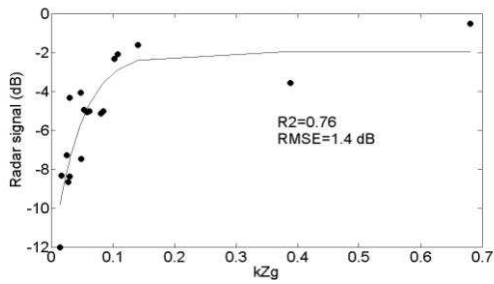
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Fig. 8

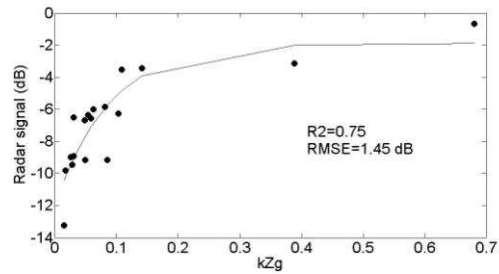
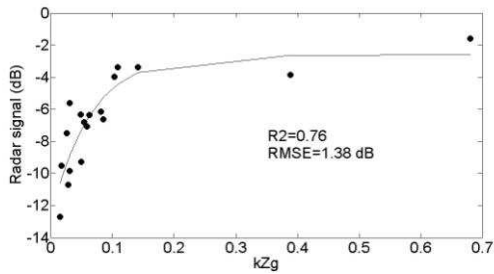
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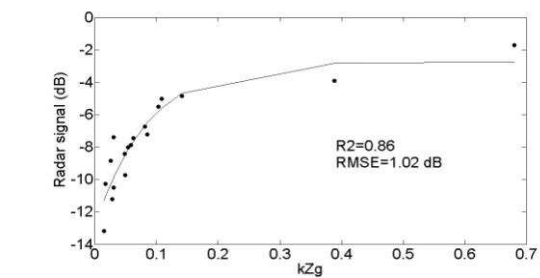
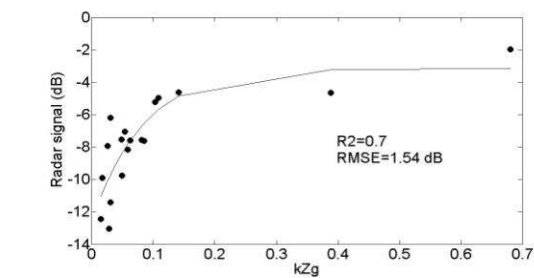
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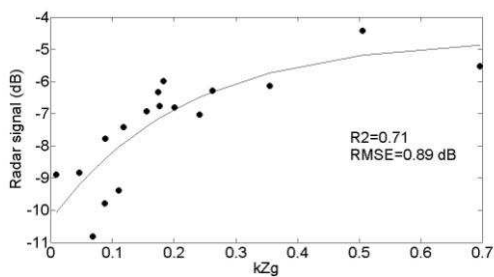
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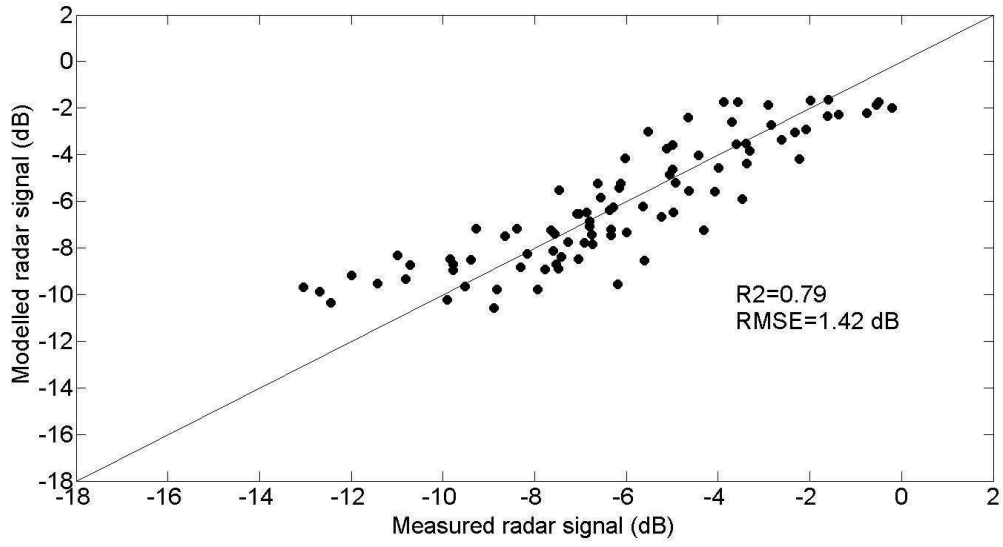
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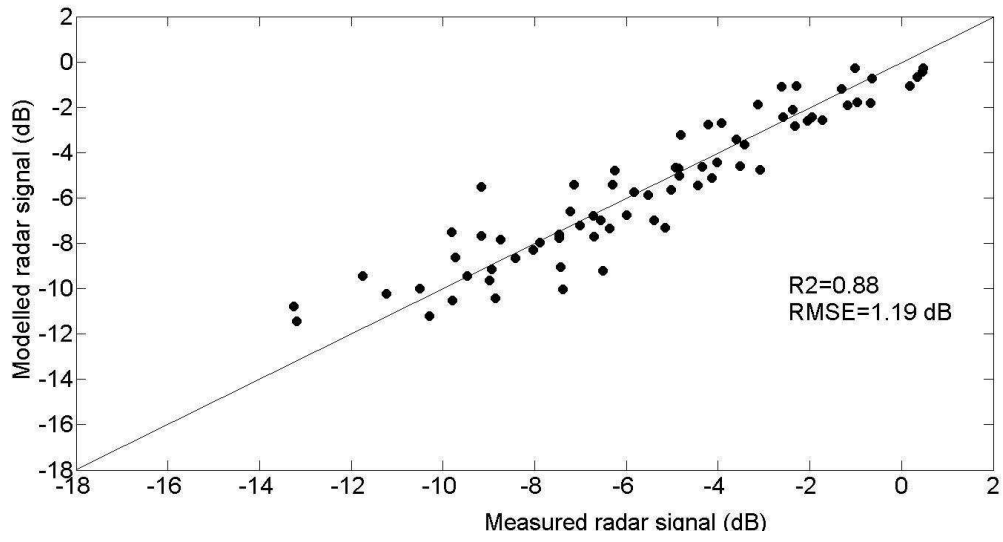
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614 Fig. 9



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617 Fig. 10

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