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1 **Soil moisture profile estimation under bare and vegetated soils using combined L-band**
2 **and P-band radiometer observations: An incoherent modeling approach**

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31 **ABSTRACT**

32 Understanding the distribution of moisture throughout the soil profile is crucial for effective
33 water management in the field of agriculture. This knowledge enables farmers and water
34 managers to make informed decisions regarding the timing and amount of irrigation needed
35 to optimize crop growth. To estimate the soil moisture profile, this study utilized L-band and
36 P-band radiometry with three multilayer incoherent models, based on a zero-order (IZ), first
37 order (IF), and incoherent solution (IS) approximation, as well as the conventional tau-omega
38 (TO) model. The result of these models was also compared with the coherent model results
39 published by Brakhasi et al. (2023). Two mathematical shape functions - linear (Li) and
40 second-order polynomial (Pn2) - were used to represent the soil moisture profile.
41 Observations from a tower-based experiment were used under different land cover
42 conditions, namely bare, bare-weed, grass, wheat, and corn. The Root Mean Square Error
43 (RMSE) was calculated between the observed and estimated soil moisture profiles, with the
44 results indicating that RMSE values were similar for all four radiative transfer models, with
45 the Pn2 function outperforming the Li function in deeper layers. The multilayer incoherent
46 models generated slightly better results than the conventional TO model, particularly for the
47 shallow layers, but their complexity was not justified for the small gain in performance.
48 Additionally, the comparison between conventional and multi-layer incoherent models with
49 stratified coherent Njoku model was reveal that the latter slightly outperformed the formers
50 under dry bare soil condition. The conventional TO model provided an average profile
51 estimation depth ranging from 1cm (under corn) to 39cm (under bare), depending on the soil
52 moisture profile gradient and value in the shallow layers. These findings pave the way for
53 estimating soil moisture profile on a global scale using combined L-band and P-band
54 radiometry from future satellite missions operating at these two bands.

55 **Keywords:** Soil moisture profile, P-band, L-band, Incoherent, tau-omega, Estimation depth

56 **1. Introduction**

57 Soil moisture information is a must for all important ecological aspects and plays a critical
58 role in all physiological processes (Swaroop Meena and Datta, 2021). From a hydrological
59 perspective it is a small fraction (0.05%) of the freshwater globally (2.5%). However, its
60 importance to water, energy, and carbon cycles and the distribution of precipitation far
61 surpasses its physical amount (Oki and Kanae, 2006; Robinson et al., 2008). It is highly
62 variable both in space, especially in the top 20cm of the soil (Shi et al., 2014), and time, due
63 to variability in precipitation (Schoener and Stone, 2020; Manoj et al., 2022), vegetation, and
64 soil texture (Baroni et al., 2013). The roots of major agricultural crops with the highest
65 density are found at depths of 20cm or less, according to Haberle and Svoboda (2015). Lack
66 of adequate soil moisture in this region can therefore restrict plant growth and crop yield
67 (Svoboda, P. et al., 2020), thereby impacting food security (Sadri et al., 2020). In a study
68 conducted by Ma et al (2023), the effects of surface drip irrigation and direct root-zone
69 irrigation on the productivity of grapevine and berry were compared. The results revealed that
70 the implementation of direct root-zone irrigation substantially improved the crop productivity
71 and quality of Chardonnay grapes by 23 – 34%, while also reducing the necessary irrigation
72 amount by 16 – 23%.

73 Passive microwave remote sensing is a well-accepted technique for estimation of soil
74 moisture, with the two current missions of SMOS (Soil Moisture and Ocean Salinity) and
75 SMAP (Soil Moisture Active Passive) operating at L-band (~ 21cm wavelength). However,
76 they are limited to estimating soil moisture in the top ~ 5cm of the soil column. Currently
77 there are eight global root zone soil moisture products, including GLDAS NOAH, ERA-5,
78 MERRA-2, NCEP R1, NCEP R2, JRA-55, SMAP level 4 and SMOS level 4, which are
79 derived by model-based simulations sometimes combined with the shallow soil moisture
80 observations from satellite. But the accuracy of these products is highly dependent on several

81 factors, such as the forcing data, model structure and parameterization, data assimilation
82 method and assimilated variables (Xu et al., 2021).

83 The advent of P-band radiometry presents a novel opportunity for the remote sensing
84 community, enabling the investigation of soil moisture at deeper layers. Having a wavelength
85 of approximately 40cm, means that emissions can be observed from deeper in the soil than
86 other frequencies (Shen et al., 2020), such as L-band, and are also comparatively less
87 susceptible to interference from vegetation and surface roughness (Shen et al., 2022a, 2022b).
88 By integrating L-band and P-band signals, emanating from different depths of the soil, it is
89 expected that soil moisture can be estimated beyond the extent of each frequency
90 individually. Accordingly, Brakhasi et al. (2023a) successfully estimated the soil moisture
91 profile using a multilayer coherent approach through the utilization of combined L-band and
92 P-band radiometry on bare soil. Upon implementation of a second-order polynomial (linear)
93 profile shape function, the outcome yielded 28cm(20cm) and 5cm(5cm) as the respective soil
94 moisture profile estimation depths during dry and wet periods respectively.

95 The estimation of soil moisture variation within the profile from microwave observations
96 becomes increasingly complex when there is a layer of vegetation present on the surface, as
97 opposed to barren soil conditions. Furthermore, in comparison to incoherent models, coherent
98 models are more computationally intensive, yet their accuracy in estimated brightness
99 temperature is comparable to that of incoherent models (Brakhasi et al. 2023b). Additionally,
100 the linearity of soil moisture at depths of less than 30cm potentially allows for the utilization
101 of the conventional Tau Omega model as a replacement for multilayer incoherent models.
102 Therefore, this study assessed the multi-frequency soil moisture profile estimation capability
103 using combined L- and P-band with incoherent models under conditions of bare, bare-weed,
104 grass, wheat and corn.

105

106 2. Experimental Data

107 This study is based on radiometric measurements acquired from a tower-based experiment
108 established from December 2017 to June 2022 at Coral Lynn, Victoria, Australia (Brakhasi et
109 al, 2023b). The tower carrying two radiometers, namely PLMR (Polarimetric L-band Multi-
110 beam Radiometer) and PPMR (Polarimetric P-band Multi-beam Radiometer), was at the
111 center of a paddock (150m×150m). The paddock was divided into four quadrants and
112 managed with different conditions in terms of surface roughness and vegetation. For this
113 study, a variety of land surface conditions are explored, including dry and wet profiles under
114 two different bare soil periods (2nd to 30th April 2019, 3rd to 16th March 2020), one bare soil
115 with weeds (18th November 2020 to 8th December 2020), one grass (1st to 27th March 2018),
116 one wheat (1st to 23rd December 2018), and one corn (20th December 2020 to 4th March 2021)
117 with very low to high vegetation water contents (VWC from 0.5 to 22 kg/m³).

118 The dataset includes brightness temperature at L- and P-band frequencies at an incidence
119 angle of ~ 40°, soil moisture and soil temperature profile measurements at ground stations
120 installed at the border of the quadrants from the surface to a depth of 60cm in 5cm
121 increments, and weekly measurements of VWC and surface roughness. The radiometer was
122 calibrated weekly using cold/warm targets, and the representativeness of the ground stations
123 were investigate using weekly near-surface soil moisture measurements (~5cm) by the
124 Hydra-probe Data Acquisition System (HDAS; Merlin et al., 2007). The composition of the
125 soil texture, at an average depth of 0 to 60cm, is made up of 18.3% clay, 13.7% sand, and
126 68% silt. This composition indicates a silty loam type, with a surface layer having a bulk
127 density of 0.87 kg/m³.

128 The shapes of the soil moisture profile observed at the ground stations are presented in Fig. 2
129 for the periods investigated in this study. It is evident that the surface soil moisture has a
130 higher degree of variation compared to the bottom soil moisture in most cases, except during

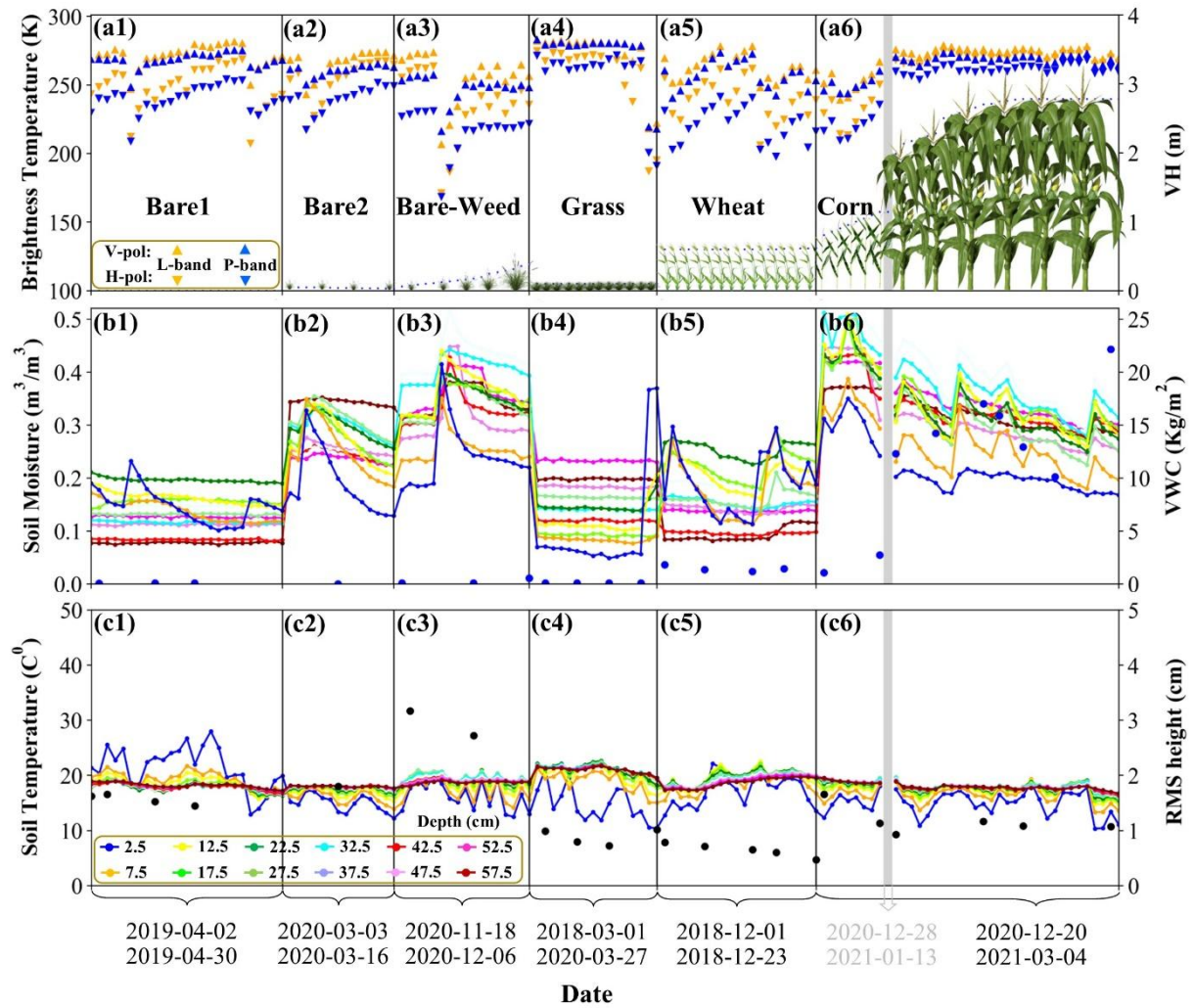


Fig. 1. Collected data over six periods including bare, grass, wheat, and corn conditions: a) TB observations from PLMR and PPMR instruments at 6 AM and PM; b) station time-series soil moisture; and c) station time-series soil temperature. The vegetation height (VH), vegetation water content (VWC) and RMS height are plotted as a secondary axis on the brightness temperature, soil moisture and soil temperature profile plots respectively. The gray area in the corn period is a 17-day gap where the tower was lowered due to unscheduled maintenance.

131 the corn period. Interestingly, the soil moisture at a depth of 15 to 40cm exhibits a higher
 132 degree of variability than the surface and bottom soil moisture during the corn period. During
 133 the bare period with weeds (bare-weed), the surface soil moisture shows a greater degree of
 134 variability than the deeper layer, although some variability is still observed. Notably, during
 135 the second bare period (bare2), as the depth increased, the variability of soil moisture

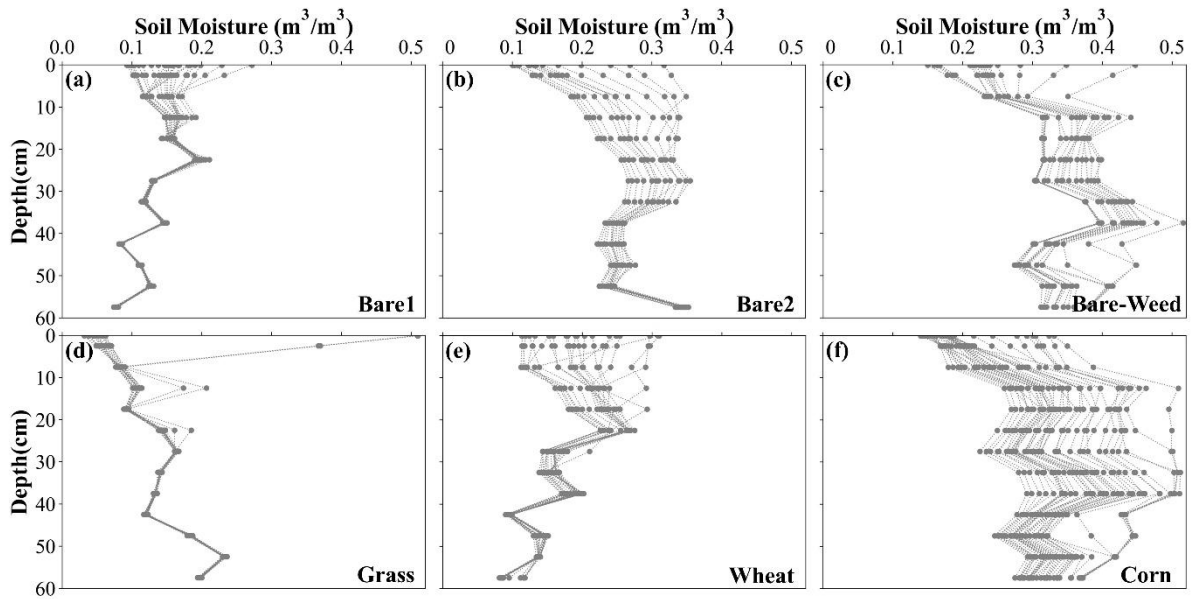


Fig. 2. Shape of the soil moisture profile (one profile per day) under different land cover conditions including a) bare1, b) bare2, c) bare-weed, d) grass, e) wheat, and f) corn.

136 decreased. During the first bare period (bare1), grass and wheat periods, the variability of soil
 137 moisture was observed to be mainly below 25cm. Low soil moisture values were noted
 138 throughout the grass period with the exception being a heavy rainfall event towards the end,
 139 resulting in a wet soil moisture profile with a high gradient in the shallow layer. Overall,
 140 these observations provide important insights into the distribution and variability of soil
 141 moisture across the different periods and depths.

142 3. Methodology

143 The goal of this study is to investigate the performance of the incoherent models for
 144 estimating soil moisture profile variation using combined L-band and P-band radiometer
 145 observations. Furthermore, these models will be evaluated in comparison to the performance
 146 of the stratified coherent Njoku model utilized by Brakhasi et al. (2023). Estimating soil
 147 moisture throughout the profile allows for a more detailed understanding of the distribution
 148 and availability of water in the soil, which can inform irrigation and water management
 149 decisions, as well as predictions of crop yield and water use efficiency. Additionally,
 150 monitoring soil moisture at different depths can provide insight into the movement of water

151 through the soil and the dynamics of the water cycle in a given area. In this study, the
152 performance of four different incoherent models is compared, including the conventional tau-
153 omega model and three multilayer incoherent models based on zero-order, first order and
154 incoherent solution approximation of volume scattering inside the soil, to determine which is
155 most effective at estimating the soil moisture profile.

156 *3.1 Radiative transfer models*

157 The soil moisture content of a near-surface layer of soil can be estimated by utilizing a
158 microwave emission model that converts brightness temperature observations from a
159 microwave radiometer to soil moisture. Almost all of the efforts from the early 1970s to
160 1990s were concentrated on developing, verifying and improving the basic microwave
161 emission models for smooth and rough soils (i.e. Mo et al., 1982; Njoku, 1976; Stogryn,
162 1970; Wilheit, 1978) using the data acquired from some controlled field campaigns including
163 ground-based (by a flatbed truck or a mobile tower; Lee, 1974; Wang et al., 1982) and
164 airborne (by an airplane or a helicopter; Ferrazzoli et al., 1992; Paloscia et al., 1993).

165 From these investigations, baseline approaches to account for three major variables; physical
166 temperature, surface roughness and vegetation water content, were developed. These
167 advances resulted in the current form of the radiative transfer equation that has been applied
168 to vegetative conditions (the tau-omega model; Mo et al., 1982), which serves as the basis for
169 almost all operational retrieval algorithms, including those used by the SMOS and SMAP
170 missions (Entekhabi et al., 2014; Kerr et al., 2012; Mladenova et al., 2014; Wigneron et al.,
171 2007). The conventional tau-omega model is a zero-order solution of the radiative
172 transfer equations which assumes that the scattering phase matrix term can be neglected.
173 Mathematically, brightness temperature at the top of vegetation (TB_{TOV}) can be estimated
174 from the tau-omega model by

$$TB_{TOV,P} = T_{eff}(1 - r_p)\Gamma_p + T_c(1 - \omega_p)(1 - \Gamma_p)(1 + r_p\Gamma_p) + TB^{Sky_down}r_p\Gamma_p^2, \quad (1)$$

175 where TB^{Sky_down} is the downward atmospheric contribution calculated to be to 5.3K and
 176 13.9K at L-band and P-band respectively (ITU, 2015), and T_{eff} is the effective physical
 177 temperature of the soil layer (K). When the soil temperature is non-uniform over the radiative
 178 emission depths the temperature is considered as an “effective” temperature (weighted
 179 average over the emission path). This is particularly important at lower frequencies which can
 180 penetrate into a deeper layer of the soil and has a greater sensing depth. Wigneron et al.
 181 (2008) developed a simple parametrization for this variable using just the surface temperature
 182 (T_{surf} in Kelvin) and the deep-soil temperature (T_{deep} in Kelvin) such that

$$T_{eff} = T_{deep} + (T_{surf} - T_{deep}) \times (sm / T_{surf}\omega_0)^{b_0}, \quad (2)$$

183 where ω_0 and b_0 depend on specific characteristics of the soil such as texture, structure and
 184 density, and were set to be 0.35 and 0.58 (Lv et al., 2014), respectively. The variable sm is
 185 the average soil moisture from the soil surface to a depth of 5cm for L-band and 7cm for P-
 186 band according to Shen et al. (2021). The variable T_c (K) is the physical temperature of the
 187 vegetation. The thermal differences between land cover types and the differences between
 188 canopy and soil temperatures is typically a minimum at 6 am (Fagerlund et al., 1970; Jackson
 189 and Kimball, 2009), and so it has been assumed that soil surface and vegetation continuum
 190 have equal temperatures (i.e. $T_{surf} \cong T_c$) at that time.

191 The vegetation attenuation factor (Γ_p) and single scattering albedo (ω_p) account for the
 192 vegetation attenuation (where P is polarization H or V), and are dependent on vegetation
 193 water content, vegetation structure, incidence angle, frequency and polarization.
 194 Consequently, Γ_p is calculated from the optical depth of the standing vegetation ($\tau_{veg,p}$) by

$$\Gamma_p = \exp\left(-\frac{\tau_{veg,p}}{\cos\theta}\right), \quad (3)$$

195 where θ is the incidence angle. Moreover, Jackson and Schmugge (1991) found that $\tau_{veg,p}$
 196 can be linearly related to VWC (kg/m^2) through

$$\tau_{veg,p} = b \cdot \text{VWC}, \quad (4)$$

197 where b is a factor which is mainly dependent on the frequency, the canopy type, and the
 198 vegetation dielectric constant. In this study, the b parameter was calibrated for L-band and P-
 199 band under grass (0.11, 0.11; by the authors from another period of the data), wheat (0.11,
 200 0.099; Shen et al., 2022), and corn (0.094, 0.053; Shen et al., 2023) conditions, respectively.
 201 The variable ω_p is defined as the ratio of the vegetation scattering to extinction coefficient
 202 ratio, calibrated for grass (0.05, 0.05; by the authors from another period of the data), wheat
 203 (0.05, 0.134; Shen et al., 2022), and corn (0.070, 0.086; Shen et al., 2023) conditions for L-
 204 band and P-band, respectively. It worth mentioning here that all of the models used in this
 205 study ignore multiple scattering within the vegetation layer, which is considered a reasonable
 206 assumption at the (low) frequency range used for soil moisture sensing.

207 The variable r_p is rough surface reflectivity and is calculated from the semi-empirical
 208 approach (referred here to as the hqn model) proposed by Wang and Choudhury (1981) and
 209 further developed by Wigneron et al. (2001) such that

$$r_p = \left[(1 - q_p)r_p^* + q_p r_q^* \right] \exp(-h_p \cos^{n_p}(\theta)), \quad (5)$$

210 where r_p^* is the smooth surface reflectivity (with $P = H$ and $Q = V$ or $P = V$ and $Q = H$) and
 211 calculated for H (Eq.6) and V (Eq.7) polarizations by the Fresnel equations

$$r_{H}^* = \left| \frac{\cos(\theta) - \sqrt{\epsilon_r - \sin^2(\theta)}}{\cos(\theta) + \sqrt{\epsilon_r - \sin^2(\theta)}} \right|^2 \quad (6)$$

$$r_{V}^* = \left| \frac{\epsilon_r \cdot \cos(\theta) - \sqrt{\epsilon_r - \sin^2(\theta)}}{\epsilon_r \cdot \cos(\theta) + \sqrt{\epsilon_r - \sin^2(\theta)}} \right|^2, \quad (7)$$

212 where $\varepsilon_r = \varepsilon_r' - i \cdot \varepsilon_r''$ is the relative soil dielectric constant which includes real (') and
 213 imaginary (") parts. Using this model h_p accounts for the intensity of the roughness effects
 214 and is calculated using the formulation of Wigneron et al. (2001)

$$h_p = 1.3972 * \left(\frac{rms}{lc} \right)^{0.5879}, \quad (8)$$

215 where rms and lc are the RMS surface roughness height and correlation length as measured
 216 in the field, q_p is a polarization decoupling factor set to zero for both L- and P- bands, while
 217 n_p accounts for multi-angular and dual-polarization measurements and was calibrated to
 218 another period of the data and set to -0.50 (1.80) and -0.333 (0.415) at H (V) polarizations for
 219 L-band and P-band respectively.

220 A stratified incoherent radiative transfer model was introduced by Stogryn (1970) to obtain
 221 approximate values of brightness temperature for media in which the dielectric constant
 222 profile is slowly-varying and in which the absorption is small. The model is fairly
 223 straightforward to implement and an assumption is made that the imaginary part of ε_r'' is
 224 small such that $\varepsilon_r'' \ll \varepsilon_r'$. Their model is based on a zero-order radiative transfer
 225 approximation in which reflections at interfaces are ignored (Ulaby et al., 1986) such that

$$TB_p = e_p \left\{ \int_{-\infty}^0 T(z) \left(\frac{2\pi}{\lambda_0} \cdot \frac{\varepsilon_r''(z)}{2\sqrt{\varepsilon_r'(z)}} \right) \exp \left[- \int_z^0 \alpha(z') dz' \right] dz \right\}, \quad (9)$$

226 where the expression in round parentheses represents the attenuation coefficient $\alpha(z)$, the
 227 integral expression in curly brackets represents the effective temperature, and λ_0 is the free-
 228 space wavelength (m). This model is referred to as IZ throughout this paper. In the existing
 229 literature, it is also commonly known as a radiative transfer model.

230 Burke and Paris (1975) and Liu et al. (2013), further developed the zero-order model
 231 presented (Eq.9) to a first-order model (referred to as IF) and an incoherent solution (IS)
 232 radiative transfer model, respectively. In the IF model, a single reflection at the layer

233 interfaces is considered, while in the IS model, the propagation of radiance through each
234 layer is taken into account. Detailed descriptions of these models are provided in Burke and
235 Paris (1975) and Liu et al. (2013) and so are not repeated here. The models IZ, IF, and IS are
236 multilayer and the number of layers and the profile depth were set to 100 and 1m
237 respectively. It is worth mentioning here that the differences between these models is in the
238 way that how they calculate the effective temperature. Thus, the output of these models is
239 primarily the effective temperature so and by inserting T_{eff} into Eq.1 the brightness
240 temperature at the top of vegetation ($TB_{TOV,P}$) accounting for surface roughness and
241 vegetation is calculated.

242 These radiative transfer models require an appropriate soil dielectric model to convert soil
243 moisture content to soil dielectric constant. Accordingly, the multi-relaxation generalized
244 refractive mixing dielectric model of Mironov et al. (2013) was utilized, as it accounts for the
245 interfacial (Maxwell-Wagner) relaxation of water in the soil, which is significant at P band
246 (Zhang et al., 2020).

247 3.2 Soil moisture profile shape functions and inversion

248 In this study, the soil moisture profile was considered as unknown, while the soil temperature
249 profile, VWC, and surface roughness were considered as known variables. Brakhasi et al.
250 (2023) found that when approximating the soil temperature profile with a simple method that
251 uses a trend of the profile together with a surface soil temperature measurement, there is little
252 degradation on the result as compared with condition when soil temperature considered
253 known. As a result, to minimize errors in soil moisture profile estimation, this variable is
254 considered as a known parameter. From their study it was also revealed that a linear
255 (hereafter referred to as Li; Eq.10) and a second-order polynomial function (hereafter referred
256 to as Pn2; Eq.11) were the most representative for soil moisture profile estimation when
257 compared with exponential, third-order polynomial, piecewise linear, simplified solution of

258 Richard Equation and a parametrized second-order polynomial shape functions (Brakhasi et
 259 al., 2023). According, the
 260 soil moisture profile shape functions used herein are given as

$$SM(z) = az + c \quad (10)$$

$$SM(z) = az^2 + bz + c, \quad (11)$$

261 where z is depth (positive downward) and a , b and c are coefficients of the related function.
 262 Parameter c is the surface soil moisture while parameter a in Eq.10 represents the profile
 263 slope of the near-surface soil moisture content, whereas Eq.11 has an additional parameter b
 264 that controls the curvilinear shape of the profile. These parameters are generated in such a
 265 way that strange profile shapes cannot be formed and that change (maximum – minimum) of
 266 soil moisture value throughout the profile does not exceed $0.35\text{m}^3/\text{m}^3$. The parameter
 267 boundaries of these function are shown in Table 1.

268 The estimation of soil moisture profile using L-band and P-band radiometry was done by
 269 employing two profile shape functions and a time series retrieval approach. The time series
 270 approach involved dividing the time series data of TB into dry down periods. During each
 271 period, the cost function's global minimum values exhibit a distinctive pattern resulting from

Table 1. The boundaries of parameters used in the mathematical functions. Parameter c is the surface soil moisture (m^3/m^3), a in equation 10 is the slope of the soil moisture profile and along with b in equation 11 represent the shape of the profile. The numbers in the brackets show the boundary [lower, upper] of each parameter.

Equation	a (-)	b (-)	c (m^3/m^3)
11	[-0.83, 0.83]	-	[0, 0.5]
12	[-1, 1]	[-1, 1]	[0, 0.5]

272 the temporal correlation of the soil moisture profile and are located in specific areas of the
 273 search space. As a result, it is easier to find multiple global minimum values at once rather
 274 than searching for them individually. Furthermore, the Particle Swarm Optimization (PSO;
 275 Eberhart and Kennedy, 1995) algorithm, which involves sharing information among the
 276 populations, was utilized as an optimization algorithm to invert the employed forward
 277 models. The PSO algorithm, when used in conjunction with the time series approach, proved
 278 to be more effective as it was able to utilize prior knowledge from the previous time step to
 279 determine the value for the next time step. The PSO algorithm with the parameter settings
 280 noted in Brakhasi et al. (2023) was employed to minimize the cost function

$$L(\bar{x}) = \frac{1}{N} \left[\sum_{P=H,V} |TB_{F,P}(\bar{x}) - TB_{F,P}|^2 \right] + \left(\frac{|\text{diff}_1^N(\text{sm}_{60\text{cm}})|}{N-1} * 10 \right) \quad (12)$$

281 to invert the above models for the soil moisture profile, where (\bar{x}) represents the parameters
 282 of interest (soil moisture profile shape function parameters in this study), $TB_{F,P}$ and $TB_{F,P}(\bar{x})$
 283 are the calculated and observed TB, N is the number of observations, $\text{sm}_{60\text{cm}}$ is the soil
 284 moisture at the bottom of the profile (depth of 60cm in this study), and P and F represent the
 285 polarization (H or V) and frequency (L or P), respectively. The invented term in round
 286 parentheses was employed to control the fluctuation of soil moisture at the bottom for the
 287 profile (here 60 cm).

288 **4. Results and discussion**

289 This study aimed to estimate the soil moisture profile under different land cover conditions
 290 including bare, grass, wheat, and corn using alternative incoherent models and it were also
 291 compared with the stratified coherent model results of Njoku model (NM; Njoku and Kong,
 292 1977) employed in Brakhasi et al. (2023). To ensure a fair comparison, the results was
 293 compared to a modified version of the Brakhasi et al. (2023) approach, which incorporated a
 294 new cost function as shown in Eq.12. To achieve this, an approach based on a combination of

295 L-band and P-band radiometry was employed, utilizing the incoherent TO, IZ, IF, and IS

296 models. The cumulative Root Mean Square Error (RMSE) was then calculated between the

297 observed and estimated soil moisture profiles at various depths, ranging from 0-5cm to 0-
 298 60cm. The results of this study contribute to the development of a more accurate
 299 understanding of soil moisture profile estimation under varying land cover conditions, with
 300 potential implications for a range of applications in the field of agriculture and hydrology.

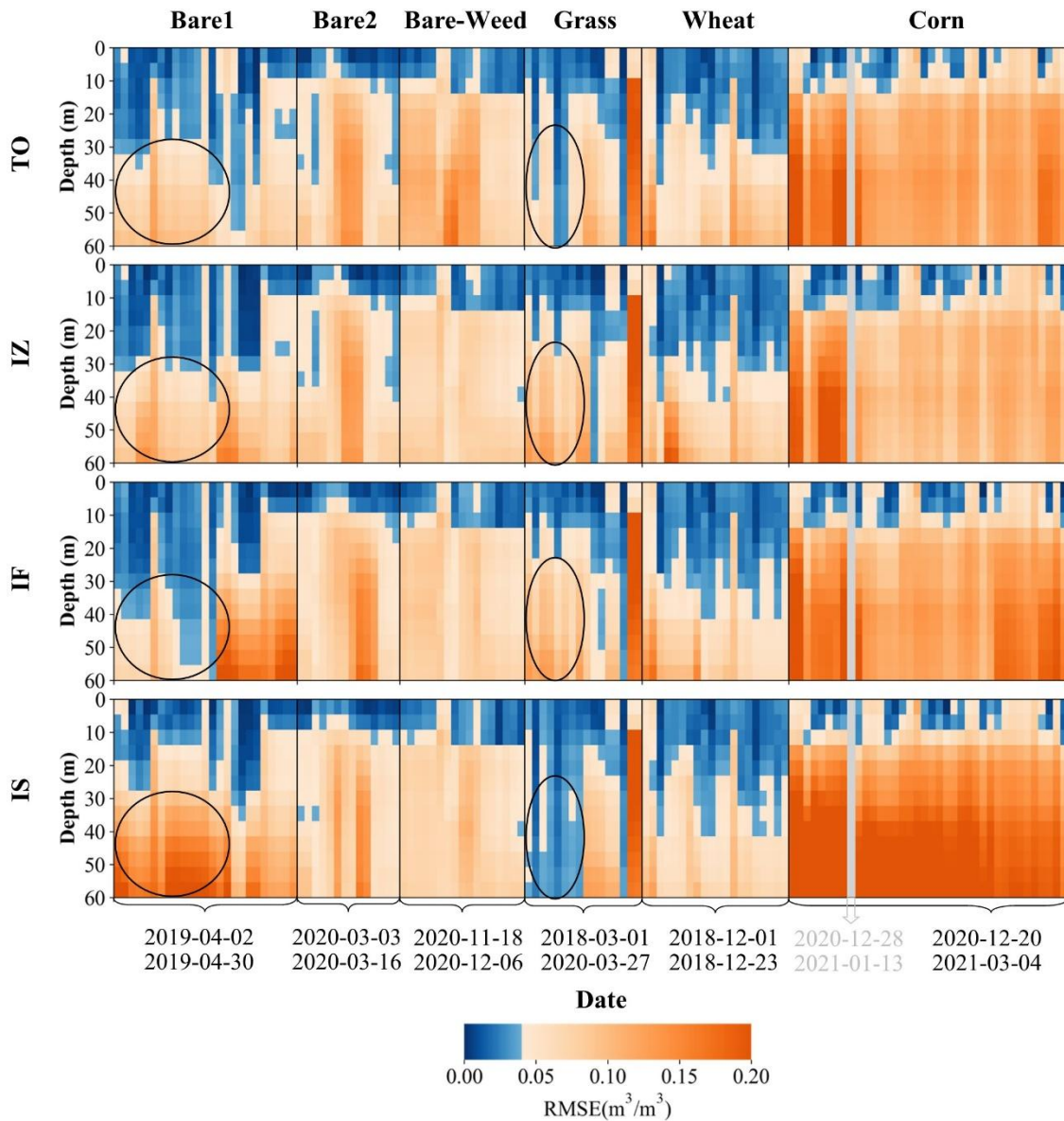


Fig. 3. Soil moisture profile estimation using combined L-band and P-band observations by utilizing the tau-omega model (TO) or a multilayer incoherent model based on zero-order (IZ), first-order (IF), or incoherent solution (IS) scattering and employing a linear profile shape function. The gray area in the corn period is a 17-day gap where the tower was lowered due to unscheduled maintenance.

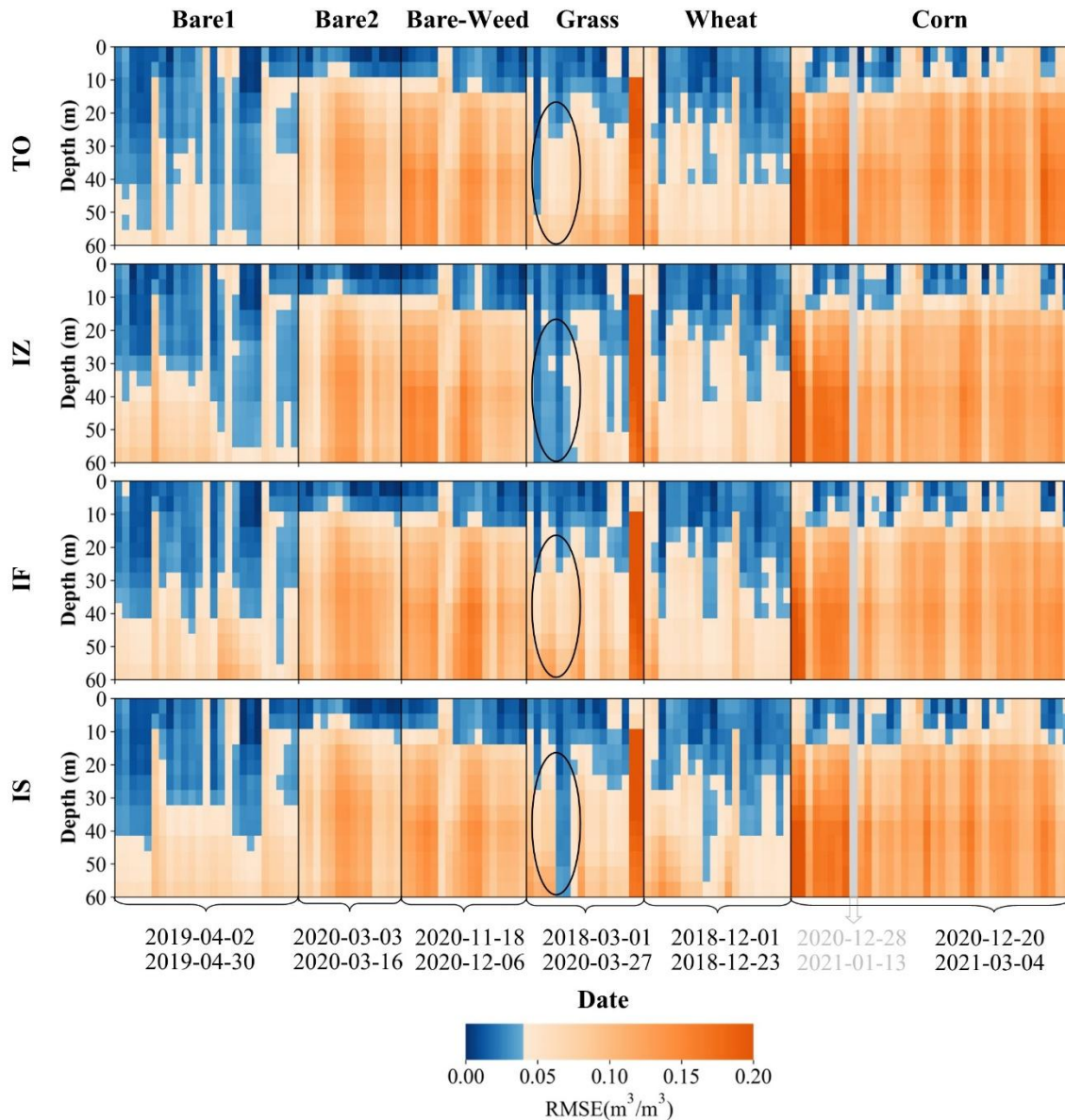


Fig. 4. Same as Fig.2 but using a second-order polynomial profile shape function.

301 The RMSE of the soil moisture estimate at different depths was calculated from comparing
 302 the observed and estimated soil moisture profiles obtained from the four different incoherent
 303 models. Fig. 3 and Fig. 4 present the RMSE results obtained when using the Li and Pn2
 304 profile shape functions, respectively. The results confirmed that irrespective of the selected
 305 model, profile shape function, and the landcover conditions, the RMSE values were
 306 consistently lower for the shallow layers when compared to the deeper layers. This can be
 307 attributed to two key reasons. First, the emission contribution at L-band and P-band decreases

308 with increasing depth, implying that the accuracy of the estimation should also reduce with
309 increasing soil depth due to signal loss through absorption, scattering and reflection by the
310 soil particles. Second, the correlation between soil moisture in the surface layer and the
311 bottom layer tends to weaken as the distance between the layers increases. Despite some
312 differences (black ovals in Fig. 3 and Fig. 4), the outcomes of all four models were quite
313 similar, particularly for the Pn2 profile shape function. The similarities between the results
314 obtained from the models is relatively higher during wet periods and lower during dry
315 periods. In particular, during dry periods, such as grass or bare periods, the L-band and P-
316 band wavelengths carry soil moisture information of deep layers of the soil. As a result, the
317 strength and limitations of multilayer models and mathematical functions representing the
318 soil moisture profile become more evident. Furthermore, the average RMSE across all land
319 cover conditions indicated that the Pn2 profile shape function outperformed the Li shape
320 function, particularly in deeper layers (Fig. 5). This suggests that Pn2 is more robust than Li,
321 and is able to more accurately capture the profile shape in the deeper layers. As Fig. 5 (a)
322 illustrates, there were only minor differences in the results of the mathematical functions and
323 models up to a depth of 12 cm. Therefore, any of these models and functions can be used if
324 the aim is to estimate soil moisture to this depth. Moreover, it also shows that there was only
325 slightly superior outcomes of the multilayer incoherent models IZ, IF, and IS when compared
326 to the conventional TO model, implying that utilizing a second-order mathematical function
327 and the conventional model yields almost identical outcomes to the more complex multilayer
328 incoherent models. This is an important finding, as the multilayer models also require
329 information on soil temperature throughout the entire profile, which can sometimes be
330 difficult to obtain, while the conventional model relies on soil temperature information from
331 just the surface and bottom layer of the profile. Irrespective of the mathematical shape
332 functions employed, the estimation performance was inferior at deeper layers during specific

333 periods, namely bare2, bare-weed, the last two days of grass (following the heavy rainfall
334 after the prolonged dry period), and corn periods. The probable cause for this could be the
335 high levels of near-surface soil moisture reducing the depth of emissions, and the steep
336 gradient of soil moisture in the upper layers of the soil weakening the correlation between
337 surface and deeper soil moisture (see Fig. 1 and Fig. 2). In contrast, during bare1, grass
338 periods (excluding the last two days), and wheat period, the soil moisture value and its
339 gradient at the upper layer were relatively lower as compared to the other periods, leading to
340 a greater estimation depth.

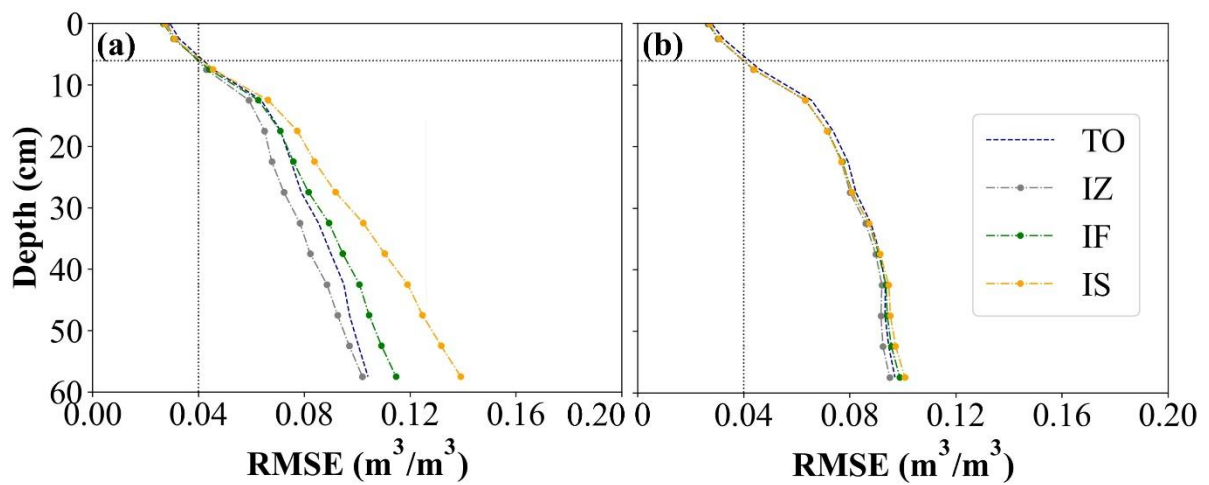


Fig. 5. Average RMSE between observed and estimated soil moisture profile as a function of depth over all the land cover conditions by utilizing the tau-omega model (TO) or multilayer incoherent model based on zero-order (IZ), first-order (IF) or incoherent solution (IS) scattering when employing the a) linear and b) second-order polynomial profile shape function. The vertical and horizontal dotted lines show the target RMSE ($0.04 \text{ m}^3/\text{m}^3$) and the associated maximum estimation depth respectively.

342 could be estimated within a target RMSE) was calculated for different levels of RMSE

343 ranging from $0.01 \text{ m}^3/\text{m}^3$ to $0.15\text{m}^3/\text{m}^3$, different incoherent models, and stratified coherent

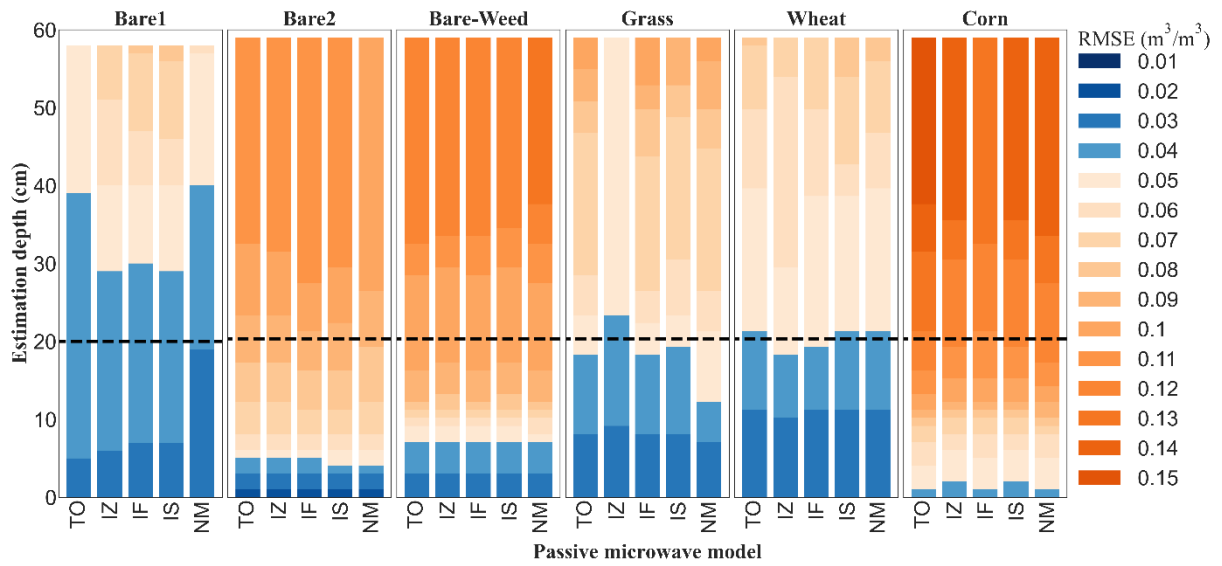


Fig. 6. Maximum estimation depth of soil moisture profile using combined L-band and P-band observations under different land cover conditions by utilizing a second-order polynomial profile shape function and employing a tau-omega model (TO), three multilayer incoherent models based on zero-order (IZ), first-order (IF), or incoherent solution (IS) scattering and the stratified coherent Njoku model (NM). The dashed line represents the 20cm estimation depth required by many applications.

344 model as shown in Fig. 6. The target RMSE $0.04\text{m}^3/\text{m}^3$ as defined by SMOS and SMAP
 345 missions, excluding regions of frozen ground, snow and ice, open water, complex
 346 topography, urban areas, and areas with vegetation with water content greater than $5\text{ kg}/\text{m}^2$,
 347 was also used as a reference here. It was found that under this target RMSE, the conventional
 348 TO model achieved an average profile estimation depth of 39cm (bare1), 5cm (bare2), 7cm
 349 (bare-weed), 18cm (grass), 21cm (wheat), and 1cm (corn). Although there are minor
 350 differences between the results of the models during dry periods, they exhibit near-identical
 351 results during wet periods such as bare 2 and bare-weed periods, with the lowest RMSE being
 352 $0.01\text{m}^3/\text{m}^3$ during bare 2. As mentioned earlier, this is attributed to the shallow sensing depth
 353 of L-band and P-band frequencies during wet periods. Consequently, multi-layered and
 354 conventional models, as well as coherent and incoherent models, yield comparable results.

355 The stratified coherent Njoku model exhibited superiority only during bare 1 period. This can
356 be attributed to the fact that, in the absence of vegetation and with low soil moisture content,
357 the sensing depth of both the bands increases. As a result, stratified coherent models can
358 surpass the performance of both conventional and multilayer incoherent models under such
359 conditions. The slight superiority of coherent models over incoherent models for estimating
360 brightness temperature under bare soil condition was also proved by Brakhasi et al. (2023a).

361 The estimation of soil moisture variation to a depth of 20cm is critical for two primary
362 reasons. First, this zone is characterized by high variability in both the temporal and spatial
363 domains, as noted by Shi et al. (2014). Second, the roots of major agricultural crops are
364 primarily situated in this region, as highlighted by Haberle and Svoboda, (2015). All the
365 employed models estimated the soil moisture profile to this depth with an RMSE of
366 approximately $0.04\text{m}^3/\text{m}^3$ in the periods bare1, grass and wheat. However, during bare2,
367 bare-weed and corn periods, the RMSEs were somewhat higher, at 0.09, 0.10, and
368 $0.12\text{m}^3/\text{m}^3$, respectively. The lower soil moisture profile estimation depth during the corn
369 period could be attributed to the high soil moisture (average 0.21 , 0.40 , and $0.31\text{m}^3/\text{m}^3$ at
370 depth 0-5cm, 35-40cm, and 55-60cm respectively) and its steepness near the surface, and also
371 the high vegetation water content (average $12.5\text{ kg}/\text{m}^2$ over the entire period). The evolution
372 time series of estimated and observed soil moisture using the models is shown in Fig. 7 and
373 Fig. 8 for depths of 0-30cm and 30-60cm respectively, in 5cm intervals. The results of the
374 models for the surface layers show a narrow range of variation, but as the depth of the soil
375 increases, differences between the models become more apparent. Moreover, the differences
376 between the models during the dry periods, such as bare1, grass and wheat, are more obvious
377 than during wet periods, such as bare2, bare-weed and corn, as depicted in Fig. 8. Except for
378 the grass period, the models overestimated the soil moisture at the deeper layers during the
379 dry periods and underestimated during the wet periods.

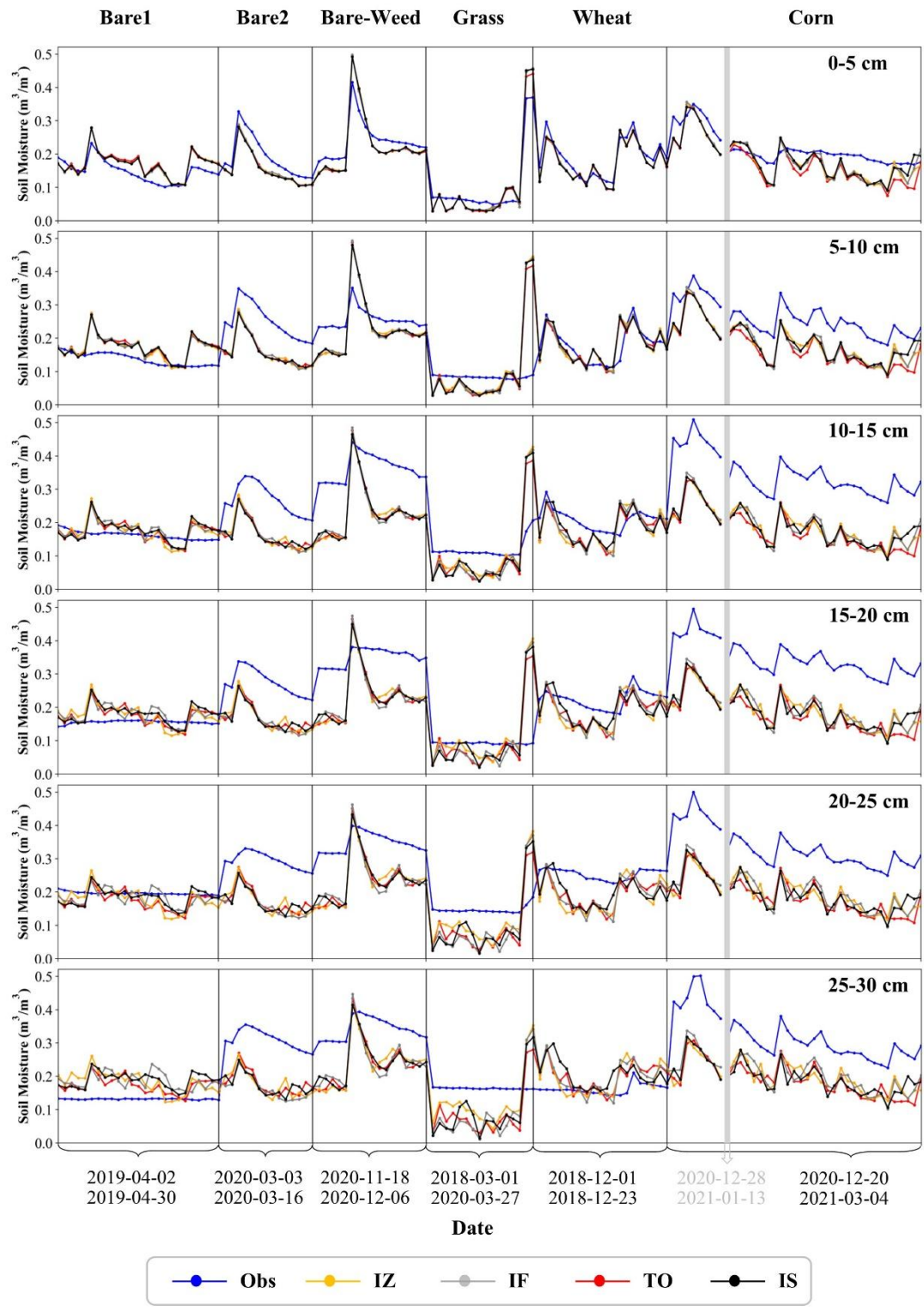


Fig. 7. Time series observations, estimated soil moisture at different depths from the surface to 30cm using four incoherent models being the tau-omega model (TO) or a multilayer incoherent model based on zero-order (IZ), first-order (IF) or incoherent solution (IS) scattering and employing a second-order polynomial profile shape function. Each row represents one depth.

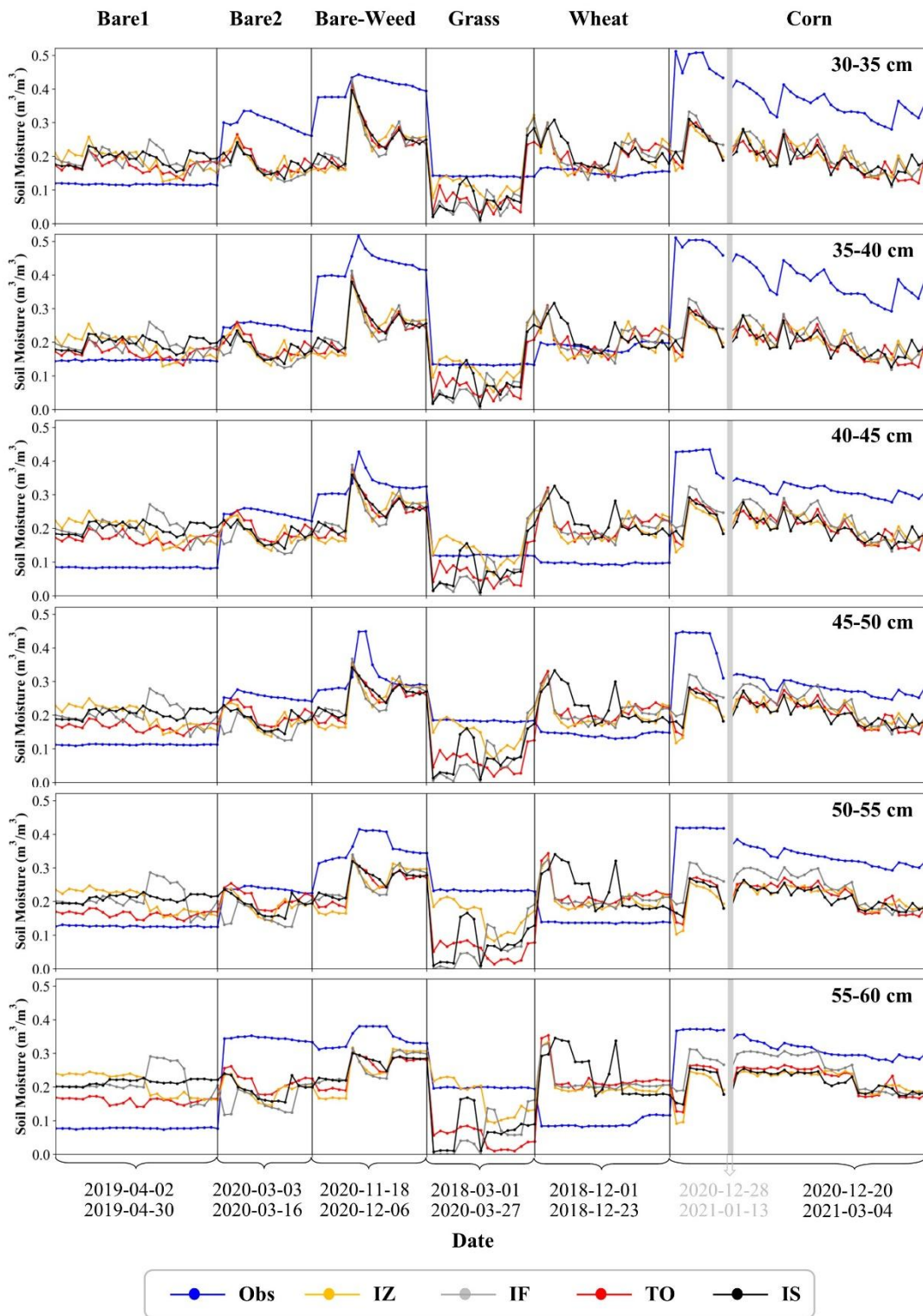


Fig. 8. As for Fig. 7 but for depths from 30cm to 60cm.

382 5. Conclusions

383 Four incoherent passive microwave models including the conventional tau-omega model
384 (TO), and three multilayers models based on zero-order (IZ), first-order (IF) and incoherent
385 solution (IS) scattering approximations were compared to estimate soil moisture profile. The
386 result of these models was also compared with the stratified coherent model results of Njoku
387 model (NM; Njoku and Kong, 1977) employed in Brakhasi et al. (2023). Observations from a
388 tower-based experiment at Cora Lynn, Victoria, Australia under different land cover
389 conditions (bare, bare-weed, grass, wheat, and corn) including L-band and P-band brightness
390 temperature, soil moisture and temperature at different depths in the profile to 60cm, along
391 with weekly measurements of vegetation water content and surface roughness were used. A
392 time series approach was employed by combining L-band and P-band brightness temperature
393 observations with either a linear (Li) or second-order polynomial (Pn2) profile shape function
394 to represent the soil moisture profile variation with depth. The RMSE between observed and
395 estimated soil moisture profiles was calculated at various depths, with the multilayer
396 incoherent models IZ, IF, and IS having slightly better results than the conventional TO
397 model, especially at shallow layers. However, the complexity of these multi-layer models and
398 the additional information on soil temperature throughout the profile, was found to be
399 unwarranted. Moreover, it was found that the Pn2 profile shape function outperformed the Li
400 shape function in terms of accuracy and robustness, particularly at deeper layers. However,
401 the estimation depth under the target RMSE of $0.04\text{m}^3/\text{m}^3$ varied widely depending on the
402 soil moisture conditions, ranging from 1cm to 39cm. Overall, the results of this study
403 showcase the potential of integrating L-band and P-band radiometry to estimate soil moisture
404 profile information at the global scale, utilizing incoherent models that perform just as
405 effectively as the coherent model. This has important implications for a wide range of
406 applications, including agriculture, climate science, and disaster management, and

407 demonstrates the value proposition for a combined L- and P-band passive microwave satellite
408 mission for global soil moisture profile mapping.

409

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416

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