Assessment of Paddy Rice Height: Sequential Inversion of Coherent and Incoherent Models

Onur Yuzugullu, Esra Erten, Member, IEEE, and Irena Hajnsek, Fellow, IEEE

Abstract—This paper investigates the evolution of canopy height of rice fields for a complete growth cycle. For this purpose, copolar interferometric Synthetic Aperture Radar (Pol-InSAR) time series data were acquired during the large across-track baseline (>1 km) science phase of the TanDEM-X mission. The height of rice canopies is estimated by three different model-based approaches. The first approach evaluates the inversion of the Random Volume over Ground (RVoG) model. The second approach evaluates the inversion of a metamodel-driven electromagnetic backscattering model by including a priori morphological information. The third approach combines the previous two processes. The validation analysis was carried out using the Pol-InSAR and ground measurement data acquired between May and September in 2015 over rice fields located in Ipsala district of Edirne, Turkey. The results of presented height estimation algorithms demonstrated the advantage of Pol-InSAR data. The combined RVoG model and EM metamodel height estimation approach provided rice canopy heights with errors less than 20 cm for the complete growth cycle.

Index Terms—Agriculture, copolar, height estimation, metamodel, polarimetry, polarimetric interferometry, synthetic aperture radar (SAR), stochastic approach.

I. INTRODUCTION

RICE is the main source of food for several highly populated countries and has an increasing demand due to rapid population growth. Researchers aim to improve the production yield for the development of new management systems by monitoring the phenological evolution of rice [1]. From various phenological properties, canopy height is an important parameter for the biomass estimation and detection of growth anomalies. The traditional way of monitoring by visual inspection requires great workforce for kilometer-square scaled areas; remote sensing systems can systematically provide regional to global scaled information.

Among different remote sensing data sources, Synthetic Aperture Radar (SAR) has been used to observe rice fields since the end of 1980s [2]. Since then, SAR based methodologies have become popular in rice monitoring with their sensitivity to changes in physical and dielectric properties of plants. During the past years, different SAR image analysis techniques have been exploited for rice monitoring: multi-polarimetric SAR (PolSAR) [3]–[5], interferometric SAR (InSAR) [6], [7], and multi-polarimetric interferometric SAR (Pol-InSAR) [8], [9].

The methods that exploit PolSAR data investigate the polarization dependent interaction between plants and electromagnetic waves using two main groups of approaches, namely: temporal trend analysis and electromagnetic scattering (EM) models. The first group focuses on explaining the temporal changes in polarimetric observables [10]–[12]. However, the differences in cultivation practices and plant genotypes make the applicability of temporal trend analysis in different test sites challenging. The second group investigates the phenological evolution of plants using EM models. Although, in this group, the multi-dimensional algorithms [13]–[17] suffer from high computation costs. Hence, metamodel approaches [18] have been recently proposed to obtain a better performance for models.

The InSAR image analysis techniques focus on the phase difference between two SAR acquisitions that are either separated by a spatial or temporal baseline. The acquisition geometry provides a vertical sensitivity for a particular polarization and allows for the calculation of digital elevation models [19].

Pol-InSAR permits the characterization of the scattering contributions in height by coherently combining polarimetric and interferometric observables [20]. However, phenological monitoring applications are challenging particularly with spaceborne Pol-InSAR data due to rapid changes in plant morphologies, leading to temporal decorrelation, and the right sensitivity to canopy height. Recently, the TanDEM-X mission, which has twin X-band SAR satellites, has collected single pass InSAR data. The single pass configuration has eliminated the temporal decorrelation between the interferometric image pair and allowed crop height estimation with interferometric techniques [8], [9], [21]. Additionally, TanDEM-X, with its short wavelength, leaves the canopy as the main scattering contributor and therefore is favored for agricultural studies. The science phase of
the TanDEM-X mission, proceeded between May and September 2015, recorded as the first spaceborne mission that provided sensitivity to short vegetation with the height of ambiguities less than 5 m in mid-latitudes.

This research investigates the evolution of rice canopy height from space for a complete growth cycle with three different approaches using copolar Pol-InSAR data. The first approach exploits the Pol-InSAR data employing the three-stage inversion of the coherent Random Volume over Ground (RVoG) model [22]. The second approach employs copolar PolSAR data together with the multidimensional incoherent EM model [13] inversion with a priori phenological information. In the second approach, polynomial chaos expansion (PCE) metamodels [23] were involved to reduce the computation cost of the EM model simulations. The third approach uses the RVoG model inversion based height estimations as a constraint to the EM model inversion instead of a priori phenological stage. In all algorithms, stochastic principles are employed to consider the morphological and structural variances within rice fields.

The paper is organized as follows. Section II provides the proposed methodologies for the rice plant height estimation. Then, Section III presents the information on the ground campaigns and the TanDEM-X time series data. Section IV shows how to express the Pol-InSAR data with scattering vectors and provides some conclusions.

II. METHODOLOGY

In this paper, we present three different model inversion based approaches (Fig. 1) to estimate the rice canopy height from space using X-band copolar Pol-InSAR data. The approaches are RVoG model inversion, EM model inversion, and the sequential inversion of RVoG and EM model.

The TanDEM-X mission provides a pair of copolar SAR data through bistatic acquisition. In this study, the Pol-InSAR data were acquired in HH and VV polarization channels. It is possible to express the Pol-InSAR data with scattering vectors $\vec{k}_1$ and $\vec{k}_2$ in the Pauli basis as formulated in (1)

$$\vec{k}_i = \frac{1}{\sqrt{2}} \left[ S_{i1}^H + S_{i2}^H, S_{i1}^V, S_{i2}^V \right] i = 1, 2. \tag{1}$$

In (1), $S_{i1}^H$ and $S_{i2}^H$ stand for the complex scattering matrices of the $i$th SAR acquisition. For the distributed targets, $\vec{k}_1$ and $\vec{k}_2$ are given with the coherency matrix $[T_4]$

$$[T_4] = \begin{bmatrix} \vec{k}_1^\dagger \\
\vec{k}_2^\dagger \\
\vec{k}_1 \\
\vec{k}_2 
\end{bmatrix} = \begin{bmatrix} T_{11} & T_{12} \\
T_{21} & T_{22} \end{bmatrix}. \tag{2}$$

Using the $[T_4]$, the measured complex Pol-InSAR coherence $\vec{\gamma}$ value, as the input of RVoG model inversion, is defined as

$$\vec{\gamma} = \frac{\langle \vec{\omega} | \Omega_{12} | \vec{\omega} \rangle}{\sqrt{\langle \vec{\omega} | T_{11} | \vec{\omega} \rangle \langle \vec{\omega} | T_{22} | \vec{\omega} \rangle}} \tag{3}$$

where $\vec{\omega}$ vectors are the unitary vectors for polarization combinations and $\langle \cdot \rangle$ represents the spatial multilooking. The value of $\vec{\gamma}$ depends on several sensor and object related factors such as temporal difference, acquisition geometry, signal-to-noise ratio (SNR), data quantization and vertical distribution of scatterers within the volume ($\tilde{\sigma}_{\text{vol}}$). Further information about the Pol-InSAR image analysis technique can be found in [20] and [22].

Besides the $\vec{\gamma}$ value, the Pol-InSAR data also allows for the measurement of backscattering intensities ($\tilde{\sigma}$), employed in the EM model inversion, described in Section II-B. The $\tilde{\sigma}_{\text{HH}}$ and $\tilde{\sigma}_{\text{VV}}$ are calculated from the expressions in (4),

$$\tilde{\sigma}_{\text{HH}} = 10 \log_{10} (|S_{\text{HH}} S_{\text{HH}}^\dagger|) \tag{4}$$

$$\tilde{\sigma}_{\text{VV}} = 10 \log_{10} (|S_{\text{VV}} S_{\text{VV}}^\dagger|).$$

A. Approach 1: RVoG Model Inversion

The RVoG model inversion, shown by red lines in Fig. 1, is used to estimate canopy height from the $\tilde{\sigma}_{\text{vol}}$ value by implementing the procedure detailed in [22]. Before proceeding with the model inversion, the effect of decorrelation sources are needed to be reduced on the $\vec{\gamma}$ value. For this purpose, the data was preprocessed with range common band filtering [24], flat earth phase removal and signal-to-noise ratio correction [25].

The RVoG model [26], describes a canopy with two layers (a vegetation volume and ground surface) to simulate the Pol-InSAR coherence ($\vec{\gamma}$) using the formula given in (5). The volume layer is described with a thickness $h_V$ and contains randomly oriented particles.

$$\vec{\gamma} = e^{j \phi_0} \cdot \left( \gamma_{\text{vol}} + \frac{\mu(\omega)}{1 + \mu(\omega)} \right) \tag{5}$$

In (5), $\phi_0$ and $\mu$ are defined as the interferometric phase at the ground layer and the ground-to-volume amplitude ratio, respectively. The model describes the volume and ground scattering phases located on a vertical line between the ground surface and the top of the canopy. Regarding this assumption the $\gamma_{\text{vol}}$ is approximated with exponential decay of the electromagnetic waves by

$$\gamma_{\text{vol}} = \frac{2 \beta}{\cos(\theta)} \left( e^{\frac{2 \beta}{\cos(\theta)}} - 1 \right) \frac{e^{\frac{2 \beta}{\cos(\theta)} + j \kappa \pi}}{2 \beta \cos(\theta) + j \kappa \pi} - 1. \tag{6}$$

In (6), $\theta$, $\beta$, and $\kappa$ symbolize the incidence angle, wave extinction coefficient of the medium and the interferometric vertical wave number (i.e., sensitivity to the vertical location of the phase center), respectively. The $\kappa$ is calculated as in (7) with baseline $B$, wavelength $\lambda$, and range $R$ parameters.

$$\kappa = \frac{4 \pi \Delta B}{\lambda R \sin(\theta)}. \tag{7}$$

In rice fields, plants are expected to have similar growth rates under normal conditions. However, factors like different soil properties, the presence of weed and the applied plant growth regulators may result in structural heterogeneity, leading to spatially varying extinctions. As shown in Fig. 2(a), the $\vec{\gamma}$ distribution involves the effect of such variations. The proposed inversion exploits the $\vec{\gamma}$ distribution by modifying the last step.
of the three-step inversion procedure to provide the height of the canopy [22].

The modification is implemented to consider the structural variation within a field. As it would not be realistic to define a single $\beta$ for the whole area, the modification proposes to use a range of $\beta$ values for each multilooked resolution cell instead of a single $\beta$ value for the average $\gamma$ of the field.

The modification in the last step of the inversion procedure is repeated for each $\beta$ value between 1 and 10 dB/m with 0.1 dB/m increments. This range is selected to consider both low and high density canopies. The estimated canopy height is considered to be valid when the estimated $\gamma_{vol}$ is higher than the $\gamma$ of minimum ground contribution, as shown in Fig. 2(b) with the green color.

The inversion of $\gamma_{vol}$ from a single pixel provides a range of $h_V$ values for given range of $\beta$ values. The estimated $h_V$ ranges are aggregated for all pixels. The result is reported with the most likely value of the $h_V$ distribution and its standard deviation as shown in Fig. 2(c) with the green shading.

B. Approach 2: EM Model Inversion

The EM model inversion, shown by green lines in Fig. 1, is implemented to estimate the average morphological properties of plants in a canopy from the measured $\tilde{\sigma}_{\text{HH}}^0$ and $\tilde{\sigma}_{\text{VV}}^0$ values, by considering a priori plant phenology descriptors. The EM model [13], $\mathcal{M}(\xi)$, is employed to simulate the $\tilde{\sigma}_{\text{HH}}^0$ and $\tilde{\sigma}_{\text{VV}}^0$ values from 18 different plant morphology parameters, $\xi$, through Monte Carlo simulations.

The inversion of the $\mathcal{M}(\xi)$ is an ill-posed problem as the number of inputs are higher than the number of equations. Therefore, the inversion of the $\mathcal{M}(\xi)$ has multiple $\xi$ vectors as solutions. Here, we propose a stochastic optimization approach for the inversion of the $\mathcal{M}(\xi)$ algorithm, which aims to find a set of $\xi$ vectors through several initiations of the procedure. Considering the stochastic optimization, the inversion of the multidimensional $\mathcal{M}(\xi)$ is computationally expensive with sophisticated algorithms and the Monte Carlo simulations. In this study, we overcome the computation cost issue using metamodels.

**EM model:** The chosen EM model [13], $\mathcal{M}(\xi)$, is used to simulate $\tilde{\sigma}_{\text{HH}}^0$ and $\tilde{\sigma}_{\text{VV}}^0$ values by describing the rice canopies with uniformly distributed plants over flooded ground. In the $\mathcal{M}(\xi)$, each plant is considered to have vertical tillers with leaves and panicles. The model follows finite cylinder approximation [27], [28] for stalks and panicles, and physical optics approximation [29] for leaves. Besides, the locations of the plants are randomized within the Monte Carlo simulations to obtain the average scattering behavior from the canopy.
The $M(\xi)$ provides a relation between incident, $\bar{E}$, and scattered wave, $\bar{E}^s$, using the coherent combination of four scattering mechanisms, $S_n$, namely the following:

1. direct scattering from canopy;
2. scattering from the canopy followed by reflection from the water;
3. reflection from the water followed by scattering from the canopy;
4. reflection from the water followed by scattering from the canopy, followed by reflection from the water.

For the data acquired from the TanDEM-X mission, the relation is defined as in (8)

$$\sigma_{qq}^o = M(\xi) = \frac{4\pi r^2}{A} \frac{\langle |E_q^s|^2 \rangle}{\langle |E_q|^2 \rangle} = \left\langle \frac{e^{i kr}}{r} \left( \sum_{n=1}^{4} S_n \right) \right\rangle^2, \quad (8)$$

In equation (8), $k$, $r$, and $q$ are defined as free-space wavenumber, the distance between the receiving antenna and the target, and linear polarization channels, respectively. The $\sigma^o$ values for copolar channels are estimated from the ratio between amplitudes of the scattered and incident waves over the illuminated area, $A$.

**Metamodeling**: The high computation cost of the $M(\xi)$ simulations is reduced by substituting the $M(\xi)$ with its PCE metamodel [23]. The PCE metamodels can mimic any mathematical form a polynomial basis on its expected values. In this study, for the $M(\xi)$ with multidimensional input set $\xi \in \mathbb{R}^M$ and $\sigma^o$ as output, the PCE metamodel, $PCE_{EM}$, is defined as

$$M(\xi) \approx PCE_{EM}(\xi) = \sum_{j=0}^{\infty} a_j \Psi_j(\xi). \quad (9)$$

In (9), $a_j \in \mathbb{R}$ is a set of scalar coefficients and the $\Psi_j(\xi) \in \mathbb{R}$ form a polynomial basis on its expected values. In this study, the $PCE_{EM}$ is implemented using the Uncertainty Quantification Laboratory (UQLab) toolbox [30] in MATLAB. The toolbox is used to calculate the $a_j$ and $\Psi_j(\xi)$ terms using least-square minimization techniques [31] from a training set of full model evaluations of $M(\xi)$ for once. Compared to the $M(\xi)$, the $PCE_{EM}(\xi)$ requires significantly lower computational effort. For 10 000 simulations the computation time was measured up to $10^4$ times lower [32].

**Parameter Space Search Algorithm**: The $PCE_{EM}$ is inverted by comparing the measured and estimated backscattering intensities. The presented approach employs a multidimensional parameter space $\mathbb{P}$, a priori growth phase and a set of simplifying constraints. The $\mathbb{P}$, is defined as a multidimensional grid with height $h$, diameter $d$, length $l$, width $w$, structural density $n$ and dielectric constants $\epsilon_{r,i}$ of tillers, leaves, flag leaves, and panicles. Every node in the $\mathbb{P}$ is a $\xi$ vector during the inversion procedure and initially considered as a candidate

$$\mathbb{P} = [\text{tiller}(\bar{h}, \bar{d}, \bar{n}, \bar{\epsilon}_{r,i}), \text{leaf}(\bar{I}, \bar{w}, \bar{n}, \bar{\epsilon}_{r,i}), \text{flag}(\bar{I}, \bar{w}, \bar{\epsilon}_{r,i}), \text{panicle}(\bar{d}, \bar{n}, \bar{\epsilon}_{r,i}), \text{ground}(\bar{\epsilon}_{r,i})]. \quad (10)$$

The inversion starts by limiting the $\mathbb{P}$ with ranges of the morphological parameters, which are experimentally determined. Later, natural limitations for morphological parameters are considered in the form of a convex hull process calculated on ground measurements including stalk height, stalk diameter, leaf length, and leaf width. Natural limitations prevent the inclusion of biologically impossible structures as a plant with 1 m height with 2 mm diameter stalks and 5 cm long and 2 cm wide leaves.

The candidate $\xi$ vectors for the $\tilde{\sigma}_{HH}^o$ and $\sigma_{VV}^o$ values are searched for in the $\mathbb{P}$ by employing two different constraints. The implemented limitations ensure positivity in morphological solutions, the consistency of measured and estimated backscattering intensities, and of $\xi$ vectors for HH and VV channels.

The first constraint eliminates the $\xi$ vectors based on the $\tilde{\sigma}_{HH}^o$ and $\sigma_{VV}^o$ values. To this aim, the $PCE_{EM}$ is employed to simulate the $\sigma_{HH}^o$ and $\sigma_{VV}^o$ from each point in $\mathbb{P}$ grid. The simulated $\sigma^o$ values, which stay in the range defined by mean with standard deviation of the measured $\sigma^o$ values for a field, are assigned to parameter space subsets $\mathbb{B}_{HH}$ and $\mathbb{B}_{VV}$.

The second constraint provides the physical uniqueness of plant morphology, which is represented by $\xi$, for different polarimetric channels. This limitation takes the intersection of $\mathbb{B}_{HH}$ and $\mathbb{B}_{VV}$ subsets and determines the unique set of candidate rice plant morphologies for all parameters included in $\mathbb{P}$. From the intersection set, the information regarding the possible range of rice plant height is determined.

**C. Approach 3: The Integrated RVoG and PCE_{EM} Inversion**

The third approach employs both $\tilde{\gamma}$, $\tilde{\sigma}_{HH}^o$ and $\sigma_{VV}^o$ values to obtain the rice plant height. As shown in Fig. 1 with the blue line, the a priori growth stage limitation in the parameter space of $PCE_{EM}$ inversion is substituted with the canopy height range provided by the RVoG model inversion. The combined RVoG and $PCE_{EM}$ inversion starts by obtaining a range of height values using the RVoG model inversion. The output of the RVoG model inversion is then used to constrain the $\mathbb{P}$ for stalk height of the whole field including the natural limitations. Finally, $PCE_{EM}$ inversion provides the canopy height estimations.

**III. Datasets**

**A. Ipsala Test Site and Ground Data**

This research was conducted on the broadcast seeded rice fields located in the Ipsala region of Turkey. The central coordinates of the area are given as N 40°47’59” and E 26°1’14”. Fig. 3 presents the location of the rice cultivation region using HH and VV channel interferograms, calculated from the TanDEM-X mission data acquired on the 11.08.2015. The given flat earth removed interferograms shows that the study area has a rather flat topography as commonly observed in lowland rice fields. For the phenological descriptors, the ground campaigns were conducted by the Directorate of Trakya Agricultural Research Institute during the cultivation periods (May–September) of 2013–2015. With these campaigns, more than 400 measurements were collected for plant morphology (stalk diameter and height, leaf length and width, and the number of stalks, tillers, leaves) parameters. Fig. 4 presents the temporal trend of the measured rice canopy height for five spatially independent test fields.
Fig. 3. Location of the study area with HH and VV interferograms calculated using the data acquired on 11.08.2015. The test fields of the ground campaigns are also marked in over the interferogram.

Fig. 4. Acquisition dates in 2015 for different Pol-InSAR data with $\kappa_z$ values and measured plant height above water surface with respect to time and growth phases presented by International Rice Research Institute [1]. [P1] early vegetative. [P2] late vegetative. [P3] early reproductive. [P4] late reproductive. [P5] maturative.

Besides, during the last years the test site has been widely exploited with SAR to monitor rice growth [8], [9], [18], [33], [34].

Fig. 5 shows the growth phase based rice canopy height distributions, which are useful in understanding the plant height boundaries. Correspondingly, Fig. 6 visualizes the limits of the morphological parameters as a box-whisker plot for various growth phases. It should be emphasized that while all significant morphological and density descriptors rise and stabilize during the phenological cycle, the stalk diameter starts to decrease with the early reproductive phase due to reducing plant water content.

B. SAR Data

In this study, we collected the SAR data from the science phase of the TanDEM-X mission, which allowed to acquire in single-pass bistatic imaging mode with large across-track baselines. The TanDEM-X mission employs twin satellites, TanDEM-X (TDX) and TerraSAR-X (TSX), and provides copolar PolSAR data. The satellites operate at a central frequency of 9.65 GHz ($\lambda = 31$ mm) and a temporal resolution of 11 days. For the analysis, the acquired copolar Pol-InSAR time series data were processed by the German Aerospace Center to provide level 1b (Single Look Complex, SLC) data. Later, the SLC data were coregistered using bi-linear interpolation algorithm by achieving an average root mean squared (RMS) accuracy of 0.1 pixels. Before the analysis, speckle noise was eliminated from Pol-InSAR data using a $15 \times 15$ box-car filter, covering an approximate area of thousand square-meter.

The copolar Pol-InSAR time series data were acquired with 30.7° incidence angle, between May and September of 2015. During this period, a total number of seven Pol-InSAR acquisitions were acquired, covering the complete phenological cycle of rice plants. The dates of the acquisitions and corresponding baselines are given in Fig. 4.

IV. RESULTS AND DISCUSSIONS

In this paper, we compared the accuracy of three stochastic canopy height estimation approaches, which are based on the inversion of the RVoG model, PCE$_{EM}$ metamodel, and their integration, over a stack of copolar spaceborne X-band Pol-InSAR data. This section presents and discusses the results for the complete growth cycle of rice plants by focusing on all five growth phases, namely: early vegetative, late vegetative, early reproductive, late reproductive, and maturative.

A. Applicability of the RVoG Model Inversion

In the RVoG model inversion, the estimation accuracy is known to be dependent on the $\kappa_z$ value, and the available interferometric coherence [35], [36]. In Cloude et al., [22], it was
stated that the optimum configuration is achieved with a $\kappa_z h_c / 2$ between 1 and 1.25 for a vegetative canopy. In the available data, $\kappa_z h_c / 2$ ratio changes between 0.08 and 1.05 for the rice canopies considering the available $\kappa_z$ of 1.68 rad/m and the height range between 0.1 and 1.25 m for the full growth cycle. The applicability of the RVoG model inversion was investigated by conducting two different analysis that are given in Fig. 7 calculated as the mean of 200 in-field pixels.

In the first analysis, Fig. 7(a), the required $\kappa_z$ values was calculated for two different $\beta$ values (1 and 10 dB/m) in RVoG model concerning the $\bar{\gamma}$ values. The plot shows that for plants taller than 0.46 m, the available $\kappa_z$ of 1.68 rad/m allows for canopy height estimation. The optimal $\kappa_z$ is also observed to be approximately 2 rad/m for the $\bar{\gamma}$ values, which would allow estimating the height of the canopies taller than 36 cm.

The second analysis, Fig. 7(b) presents the evolution of $\bar{\gamma}$ values for each rice canopy against their heights. The $\bar{\gamma}$ values are provided as box plot expressing the mean and the range of the $\bar{\gamma}$ measurements. The same figure also includes the RVoG model simulation results with gray curves for $\kappa_z$ of 1.68 rad/m, $\beta$ of 1 and 10 dB/m and the measured canopy heights for the complete growth cycle. The range of $\bar{\gamma}$ values exist between the two gray curves show the applicability of the RVoG model inversion. The analysis show that canopy should be at least 0.5 m tall for an accurate estimation. The gray curves can also be interpreted as, if the $\bar{\gamma}$ values fall between these two curves, there exists a $\beta$ value for an accurate inversion. The whisker plots, given in Fig. 7(b), show that most of the $\bar{\gamma}$ distributions are either left or right tailed concerning the mean value of the distribution. Even though the data were already filtered to reduce the effect of the speckle noise, the spatial variance can still be observed in the data. This situation can be observed due to the morphological heterogeneity of the plants in the field. For a detailed explanation of the data variance and the accurate inversion possibility, we investigated the behavior of the $\bar{\gamma}$ for five major growth phases concerning the RVoG model simulations in the 1 to 10 dB/m range of extinction coefficients.

**Early Vegetative:** The $\bar{\gamma}$ values in early vegetative stage lies below the $\beta = 1$ dB/m curve. One of the main reasons behind this condition is the inappropriate selection of the $\kappa_z$ value. The second main reason is the absence of the volumetric behavior with plants having short leaves. Besides, the exclusion of double bounce effect between the canopy and the underlying surface lowers the estimation accuracy. However, limiting $\kappa_z$ is observed to be the main reason of strong overestimated of canopy heights.

**Late Vegetative:** During the beginning of this growth phase, the effect of insufficient $\kappa_z$ is reduced as the canopy height increases. Through the end, $\bar{\gamma}$ values lie between the high and low extinction case curves. During this growth phase, rice canopy starts to act as a volume with increasing canopy height above the surface and structural density. The effect of double bounce between the canopy and the underlying water, as well as the presence of speckle noise, continue to exist. It is noted that
the low variance in the $\bar{\gamma}$ during the early times of the late vegetative phase increases significantly with taller canopies at the end of the growth phase.

**Early Reproductive**: According to the values of the $\bar{\gamma}$, it is reasonable to assume that the rice canopy starts to behave as a random volume during this growth phase. Considering the available $\kappa_x$, the $\bar{\gamma}$ values mostly (>50%) lie between the RVoG model simulations with 1 dB/m and 10 dB/m extinction coefficients. Along with this, the variance of the $\bar{\gamma}$ values within a field increases in this period with a shift towards lower Pol-InSAR coherence values. The increase can be explained by the formation of vertical flag leaves, causing raising structural heterogeneity on top of the canopy.

**Late Reproductive**: For the first time during the phenological cycle of the rice plant, a negligible portion (<25%) of the $\bar{\gamma}$ lie outside of the low and high $\beta$ curves. Regarding this condition, it is possible to achieve an efficient inversion by relating the morphological properties of a rice canopy to an optimum $\beta$ through the late reproductive phase. However, this may also lead to an underestimation condition in case of a misleading $\beta$ selection. Besides, it is observed that the $\bar{\gamma}$ has a skewed distribution towards the lower values, as in the earlier stages of the growth cycle. From the phenological development point of view, the formation of flag leaves is followed by the panicles formation, which can be considered as an additional source of spatial structural heterogeneity.

**Maturative**: In the last growth phase of the rice growth cycle underlying surface becomes highly moist soil. Concerning the $\bar{\gamma}$ values, the minority (<15%) of the values lie outside of the RVoG model simulated ranges. It is plausible to comment that there exists an $\beta$ value valid for a given rice plant morphology and structural density to provide an accurate plant height estimation. Moreover, as plants become mature, they lose their plant water and decrease their structural randomness within the field. The effects of the changes can be seen in the decreasing variance of $\bar{\gamma}$ values.

Considering the chosen $\kappa_x$ value, the evolution of $\bar{\gamma}$ values through the growth cycle of rice plants shows that the practical applicability of the RVoG model inversion increases with phenological development. Besides, the variance of the $\bar{\gamma}$ values indicates the effect of flag leaves and panicles on the height estimation accuracy.

### B. Applicability of the EM Model Inversion

The accuracy of the EM model is evaluated by assessing the difference between measured and estimated backscattering intensities. In this study, the parameters given in the Table I are assumed to be constant for the EM model simulations. The accuracy analysis showed the coefficient of determination ($R^2$) values higher than 0.85 and root-mean-square error (RMSE) values less than 1.7 dB for both polarimetric channels. The computation cost of the EM model was decreased using PCE channel specific PCEEM algorithms have a $R^2$ of 0.86 and 0.92 for the HH and VV channel, respectively. Also, RMSE values are calculated to be 5.3 and 4.4 dB for HH and VV channels.

### C. Inversion Results of the Models

Until this point, the applicability of the proposed RVoG model and PCEEM metamodel inversion algorithms are investigated. From this point on, this paper presents the rice canopy height estimation results over five spatially independent fields in a total of seven acquisitions for the complete growth cycle. The plant height estimation accuracy is quantified for each proposed algorithm with the normalized relative mean error (RME [%]) and normalized variance (NV [%]) parameters as formulated in (11). Both of the given accuracy quantification parameters are calculated concerning canopy height above the water surface

$$\text{RME} = \frac{(h_{\text{estimated}} - h_{\text{measured}})}{h_{\text{measured}}}$$

$$\text{NV} = \frac{h_{\text{estimated variance}}}{h_{\text{measured}}}.$$  

(11)

The first parameter, RME explains the relative difference between measured and estimated canopy height. With RME, the positive results indicate overestimations and the negative values indicate underestimations. The second parameter, NV compares the variance of the estimated height to the measured height. NV values can be interpreted as sensitivity information about the estimations.

In this study, the accuracy analysis is conducted over 35 measurements ($n = 35$) from 5 fields in 7 acquisitions through the complete growth cycle using the copolar Pol-InSAR data. Based on the available growth phase information, there are six early vegetative, ten late vegetative, nine early reproductive, six late reproductive, and four maturative growth phase data. Below,
the growth phase-specific estimation results are discussed with the support of the representative plant morphology drawings (Fig. 9), evolution of coherence region over the complex plane for a representative field. In terms of the shape of the copolar coherence, the separation of the two ends of the coherence region has an important effect on the performance of the RVoG inversion [37]. Here, it is important to mention that the other test fields behave similarly. Besides, similar trends have been observed previously [8] in rice fields located in Sevilla, Spain. (Fig. 10), scatter plots of accuracy analysis (Fig. 11) and the RME and NV values (Table II) for the available data.

*Early Vegetative Phase* \(\{n = 6\}\): As shown in Fig. 9(a), a rice canopy can be described by short sprouts having small leaves in a flooded field. In this stage of the phenological evolution, the points within the coherence region converge to a single point while neglecting the effect of polarization. The main reason for this behavior is interpreted with the surface scattering.

*Late Vegetative Phase* \(\{n = 6\}\): Evolution of coherence loci calculated at the central pixel of a chosen representative field for the five growth phases and measured canopy heights.

*Early Reproductive Phase* \(\{n = 6\}\): Photos and drawings of rice plants during major growth phases of the phenological cycle showing the overall view of the plant structure and density. (a) Early Vegetative. (b) Late Vegetative. (c) Early Reproductive. (d) Late Reproductive. (e) Maturative.

*Late Reproductive Phase* \(\{n = 6\}\): Evolution of coherence loci calculated at the central pixel of a chosen representative field for the five growth phases and measured canopy heights.

*Maturative Phase* \(\{n = 6\}\): Results of the accuracy analysis for each growth phase with RME and NV using: RVoG model inversion, PCEEM inversion and RVoG model inversion constrained PCEEM inversion.

<table>
<thead>
<tr>
<th>Growth Phase</th>
<th>RME</th>
<th>PCEEM</th>
<th>RVoG+PCEEM</th>
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<tbody>
<tr>
<td>Early Veg.</td>
<td>5.38</td>
<td>0.06</td>
<td>N/A</td>
</tr>
<tr>
<td>Late Veg.</td>
<td>0.41</td>
<td>0.07</td>
<td>0.28</td>
</tr>
<tr>
<td>Early Rep.</td>
<td>0.17</td>
<td>-0.03</td>
<td>0.12</td>
</tr>
<tr>
<td>Late Rep.</td>
<td>-0.21</td>
<td>-0.06</td>
<td>-0.19</td>
</tr>
<tr>
<td>Mat.</td>
<td>-0.33</td>
<td>-0.06</td>
<td>N/A</td>
</tr>
</tbody>
</table>

(a) RVoG \(RME = 5.38, NV = 2.03\): The inversion results in a strong overestimation of the rice canopy height leading to low
accuracies. This condition can be related to four main reasons. The first two reasons would be the effect of the underlying water surface, resulting in low SNR value and the double bounce effect between the canopy and the underlying water surface. The others are related to the RVoG model assumptions, which requires sufficient $\kappa_z$ value to detect randomly oriented volume in short canopies.

(b) PCEEM [RME = 0.06, NV = 1.01]: The application of the PCEEM metamodel inversion has provided successful results with low RME values. In the canopy height estimations, there is no clear over or underestimation condition in the mean values. However, due to growth phase bounded morphological limitations, the resulting distributions have high variances.

(c) RVoG & PCEEM [RME = NA, NV = NA]: The combination of two methods are not possible due to nonoverlapping height ranges by the results of the RVoG and the PCEEM algorithms.

(d) Overview: The PCEEM metamodel inversion has a higher accuracy in mean values compared to that of the RVoG model inversion. This condition is an effect of a priori phenological limitations. However, since it is not possible to employ the RVoG model inversion due to available $\kappa_z$, the PCEEM inversion is advantageous for the early phase.

Late Vegetative Phase [n = 10]: As visualized in Fig. 9(b), rice canopies become structurally dense and taller with longer leaves. Concerning the shape of the coherence region, an elongation is observed. This behavior shows the response of the rice canopy in different polarizations. The shape of the coherence region can be interpreted as the presence of a volume and surface scattering at the same time.

(a) RVoG [RME = 0.43, NV = 0.59]: The RVoG model assumptions continue to overestimate at the beginning of this growth phase. Even though the canopy has higher structural density with taller plants compared to its early vegetative phase, due to insufficient $\kappa_z$, and the deficiency of volumetric behavior, the inversion algorithm continues to overestimate the plant height. Compared to RVoG model inversion results for the early vegetative phase, reduced NV can be acknowledged as an indicator for lower structural heterogeneity within the field.

(b) PCEEM [RME = 0.07, NV = 1.45]: As shown in Fig. 5, during the late vegetative phase canopy height varies between 10–120 cm. The inversion algorithm provides a comparable RME to the early vegetative phase with a higher NV value.

(c) RVoG & PCEEM [RME = 0.28, NV = 0.40]: Considering the RVoG model inversion results, the RVoG model inversion constrained PCEEM metamodel inversion achieved a lower NV than the PCEEM metamodel inversion. The results have improved to 0.11 in RME and 0.19 in NV compared to the RVoG model inversion itself.

(d) Overview: In the late vegetative phase, due to the insufficient $\kappa_z$, the RVoG model inversion continues to overestimate the rice canopy height until the canopies are taller than 50 cm. Backscattering intensity based PCEEM metamodel inversion was also able to provide a high accuracy but with a comparably higher NV value. Thus, the proposed combined approach provides a compromise between the RME and the NV that leads to an accurate estimation of canopy height.

Early Reproductive Phase [n = 9]: Rice plants, visualized in Fig. 9(c), complete the significant part of their morphological development during this phase by becoming structurally denser. This phase is essential for the formation of the flag leaves, which are found in the top layer of the canopy, having the purpose of protecting the flowers and the grains. Besides, in the early reproductive phase, the shape of the coherence region stays elongated with a higher phase difference between a minimum and maximum ground contribution points compared to the late vegetative phase.

(a) RVoG [RME = 0.17, NV = 0.35]: The structurally dense rice canopies start to satisfy the RVoG model assumptions with the available $\kappa_z$ value. Based on the calculated RME and NV values, the RVoG inversion algorithm has higher accuracy compared to both early and late vegetative phases. Although, a small degree of overestimation is still an issue. The overestimation conditions can be explained by the double-bounce effect between the canopy and the underlying surface [38].

(b) PCEEM [RME = −0.03, NV = 0.43]: The rice plants in this growth phase have higher morphological similarity within the field (Fig. 6) due to reduced growth rate. By including the effect of the flag leaves in the PCEEM, the accuracy of the inversion approach increases by resulting a lower RME compared to each vegetative phases. However, as the PCEEM inversion considers all possible solutions in a given range, the results continue to present high NV values.

(c) RVoG & PCEEM [RME = 0.12, NV = 0.16]: The results of the combined approach had lower NV values compared to RVoG model and PCEEM metamodel inversion algorithms in the same growth phase. Lower NV values can be explained by the size of the intersection set of possible canopy heights obtained from the RVoG model inversion and the natural morphological limitations of the rice canopy.

(d) Overview: In the early reproductive phase, the RVoG model inversion is observed to be overestimating the rice canopy height with a lower NV compared to earlier vegetative phases. Likewise, PCEEM was also able to provide a high accuracy while the resulting distributions with lower NV values. The suggested RVoG and PCEEM combined approach increased the estimation accuracy with lower NV and higher RME values than both standalone inversions.

Late Reproductive Phase [n = 6]: Rice plants [see Fig. 9(d)] develop their panicles in the top layer of the canopy that acts as an additional scatterer. The flooded condition of the fields is reduced from the midlate reproductive stage by either leaving the fields with a lower water depth or highly moist soil surface. The shape of the coherence region changes with the changing plant phenology. In this growth phase, the difference between minimum and maximum ground contribution points slightly decreases compared to their difference in the previous phase. Concerning the change in the shape, it is possible to comment that, the volume behavior of the canopy becomes more substantial compared to previous growth phases.

(a) RVoG [RME = −0.21, NV = 0.22]: The overestimation behavior of the inversion changes to underestimation with the increasing extinction of the wave inside the canopy. This leads
to the movement of Pol-InSAR phase center closer to the phase center of the ground component. This can be related to declining vegetative water content of the plants.

(b) $PCE_{EM}$ \(RME = -0.06, NV = 0.46\): The $PCE_{EM}$ metamodel is capable of including the effect of the flag leaves and panicles in the simulations as oriented scatterers. Hence, by relying on the values given in Table II, it is possible to comment that the $PCE_{EM}$ metamodel inversion continues to provide accurate results, while suffering from the high output variance, which is as large as the morphologically constrained height range given in Fig. 5.

(c) RVoG & $PCE_{EM}$ \(RME = -0.19, NV = 0.12\): Integration of the RVoG model and the $PCE_{EM}$ metamodel inversions can compensate the misleading estimations with a highly accurate plant height estimation and low variance. Previously discussed narrow overlapping height ranges are also observed in this growth phase. While this overlap helps to reduce the NV value, it limits the improvement of RME within the ranges of RVoG model inversion.

(d) Overview: The RVoG model and the $PCE_{EM}$ metamodel combined inversion approach provided higher accuracy and lower variance results compared to their standalone implementations. However, $PCE_{EM}$ metamodel inversion could not be able to avoid the underestimated height range results due to limiting RVoG model inversion ranges.

Maturative Phase \(n = 4\): Within the last phase of the growth cycle [see Fig. 9(e)] farmers stop flooding the rice fields. In a short time, this leads to a reduction in the moisture content of the plants, resulting to a lower dielectric constant, and osmotic pressure in the plant structure. With lower osmotic pressure, plant structures cannot support the biomass that they suppose to carry and lodge. This condition is also noticed in the shape of the coherence region. During this period, the phase difference between minimum and maximum ground contribution points decreases to lower values than the late reproductive step.

(a) RVoG \(RME = -0.38, NV = 0.17\): The canopy height above ground suffers from a strong underestimation during this growth phase. Since drier plants allow deeper penetration of the electromagnetic waves inside the vegetative canopy, the location of the volume phase center goes lower inside the canopy. The underestimation might be related to the changing structural density as well. Also, with the developed morphology and structural density of the fields, the growth rate differences between plants decreases, which can be observed on the decreasing NV values.

(b) $PCE_{EM}$ \(RME = -0.06, NV = 0.43\): The plants in this growth phase are successfully estimated using the $PCE_{EM}$ metamodel inversion by assuming constant moisture content for the flooded underlying surface. According to the inversion results, it is possible to state that the $PCE_{EM}$ inversion has errors less than 10 cm from the mean of the height range as observed in RVoG model inversion case.

(c) RVoG & $PCE_{EM}$ \(RME = NA, NV = NA\): Due to the overlapping height ranges from RVoG model and $PCE_{EM}$ metamodel inversions are calculated to be a null set, the combined approach became inapplicable for the maturative phase using the available Pol-InSAR dataset.

(d) Overview: In the maturative phase, $PCE_{EM}$ metamodel inversion has a higher estimation accuracy than the RVoG model inversion due to the location of the Pol-InSAR phase center and the tilted plants. Such factors lead to underestimation of the rice canopy height range, which prevented the application of the combined approach. However, similarly to the early vegetative phase, if the \textit{a priori} growth phase information exists, the $PCE_{EM}$ metamodel inversion should be considered for the plant height estimation in the growth phase.

As a result of the detailed investigation, it is observed that the accuracies of the canopy height estimation algorithms vary during the phenological cycle. Considering a system with a fixed baseline, Fig. 12 presents the results of the optimum approaches for each growth phase. For this purpose, $PCE_{EM}$ metamodel inversion is employed for the first and the last growth phases, while the combined RVoG model and $PCE_{EM}$ metamodel inversion approach is employed for the intermediate phases. On the other hand, if a single approach is used for the complete growth cycle the RME values are calculated as 4.67, 0.03, and 0.13 for the RVoG, $PCE_{EM}$, and RVoG & $PCE_{EM}$ algorithms, respectively. However, today varying baselines are available, which can be adapted to an optimal setup depending on the vegetation height.

V. OVERVIEW AND FUTURE WORK

This paper has demonstrated that the rice canopy height estimations can be improved with the combined implementation of RVoG model and $PCE_{EM}$ stochastic inversion algorithms using X-band large across-track baseline Pol-InSAR data. The achieved improvements are closely related to the available $\nu_2$ of the interferometric system and the sensitivity of the backscattering signatures to small scaled morphological changes for the complete growth cycle.
In this study, the validation analysis was carried out at the field level by providing mean and variance errors on measured canopy height. The errors of the implemented RVoG model and the PCE\textsubscript{EM} metamodel inversions for the complete growth cycle were calculated to be in the range of 0.23–5.60 and 0.03–0.06 for RME with 0.17–2.03 and 0.43–1.45 for NV values. On the other hand for the combined approach of RV oG model and PCE\textsubscript{EM} metamodel inversion, RME values changed between 0.13 and 0.32, while the NV values varied between 0.12 and 0.40 throughout the phenological cycle.

The proposed combined stochastic inversion approach improved the standalone RVoG model inversion in estimating the rice canopy height. Considering the achieved accuracies, this study is expected to encourage agricultural industries and local authorities to use PolSAR and Pol-InSAR data more frequently for their growth monitoring applications. The strengths, opportunities, and weaknesses of the proposed algorithm are described hereafter.

**Strengths**

1) The proposed stochastic inversion for the RVoG model considers multiple solutions as a probability distribution of height values. While the methods in the literature use distinct \( \beta \) values by neglecting the subfield morphological heterogeneity, the proposed approach handles the structural variance by examining a range of \( \beta \) values between 0.1–10.0 dB/m. The modified approach decreases the dependency to the unknown structural density of the scatterers.

2) The implemented PCE\textsubscript{EM} metamodel inversion can be updated to consider a wider range of rice plant morphologies using new sets of measurements or agronomical growth rules. The inclusion of a universal dataset for different types of rice plants strengthens the inversion algorithm by allowing it to consider various plant morphologies. Each new experimental data improves the constraint of natural limitations and helps to preserve the physical structure of plants.

3) The PCE\textsubscript{EM} inversion is implemented at the field level, and it provides general information about the field itself. However, by implementing a clustering algorithm, such as the one provided in [39], it would be possible to monitor subfield morphological growth irregularities, particularly for large-sized fields.

**Limitations**

1) The effectiveness of the RVoG model inversion strongly depends on the value of the \( \kappa_z \), which is a function of the across-track interferometric baseline and the incidence angle. The science phase of the TanDEM-X mission boosted the vertical sensitivity of the interferometric system. However, it was not enough to monitor vegetative and early reproductive phases of the rice growth cycle. As presented in the results section, a \( \kappa_z \) of 1.68 m/rad would not be sufficient for short (<46 cm) rice canopies.

2) In this research, some aspects of the EM model were neglected. In the simulations, the curvature of the leaves and panicles and the properties of the underlying ground as its roughness in the absence of water were assumed constant. Besides, when implemented alone, the PCE\textsubscript{EM} metamodel inversion needs the corresponding growth phase as \textit{a priori} information since same scattering behavior can be observed in different periods of the growth cycle [40].

3) The performance of the PCE\textsubscript{EM} metamodel inversion strongly depends on the performance of the chosen EM model. As the selected EM model can only simulate the backscattering intensity, it misses the phase information. Besides, the algorithm was developed and implemented for rice fields with either flooded or strongly moist and smooth underlying surfaces. Therefore, misleading results can be obtained with dry soil conditions.

4) As stated with its name, the RVoG model inversion was developed for the simulation of randomly oriented scatterers within a volume over a ground surface. However, in some stages of the phenological cycle, the scatterers can present a particular orientation and therefore may lead to over or underestimation of the Pol-InSAR coherence values as a random volume. Unfortunately, it would not be possible to implement the Oriented Volume over Ground (OVoG) model using the available data due to higher number of model parameters. In the current implementation of the RVoG model inversion, the effect of the double bounce between the ground and the plant was neglected. This may have caused a shift in the scattering phase center and influence the estimated canopy height at different stages of the phenological cycle [8], [38].

**Opportunities**

1) Rice yield estimations are closely related to height and density of canopies. The large baseline science phase of the TanDEM-X mission is a good option for SAR based rice yield estimations.

2) By providing a suitable across-track baseline, the combined stochastic approach allows for the estimation of the simplified plant morphology. An ideal Pol-InSAR data may eliminate the requirement of \textit{a priori} growth phase information for the PCE\textsubscript{EM} metamodel inversion.

3) The suggested PCE\textsubscript{EM} metamodel stochastic inversion is flexible from the scattering model point of view. Therefore, any other morphology-based backscattering model can be used instead of the recently implemented one [13]. A coherent model can make it possible to tackle the estimations with high variance by an observable space, which considers the full polarimetric covariance matrix.

4) As the RVoG model focuses on the canopy volume over the structural density, the inversion algorithm is less sensitive to the plant type. Therefore, the proposed combined approach can be used for different plants as long as the EM backscattering model can simulate the scattering behavior of plants with different morphologies. Additionally, by including the metamodels, the computation cost of the inversion algorithm decreases drastically. The reduction in computation cost may lead to the development of new and more accurate morphology-based backscattering models for new agriculture management systems.

In the future, the algorithm can be enhanced by providing the growth phase based on the shape of the coherence region. The trend of the coherence region shape seems to be common for rice crops and might be used as an additional information. Also, different vertical structure functions shall to be evaluated
for their applicability on the rice morphology monitoring. All in all, the proposed methodology shall be tested for the other major crop types such as wheat, barley, and corn with the suggested improvements.

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Onur Yuzugullu received the Doctoral degree in environmental engineering from the Earth Observation and Remote Sens. Group at Swiss Federal Institute of Technology (ETH) Zurich, Switzerland, in 2017. During his doctoral studies he focused on the growth stage determination of rice crops considering the relation between crop morphology and the polarimetric signatures from a stochastic point of view. He is currently working as a Data Analyst and Remote Sensing Expert in AgriCircle, Rapperswil-Jona, Switzerland, where he develops methods to find innovative solutions to the problems in agriculture by using multispectral, SAR and hyperspectral data from spaceborne and UAV platforms. His research interests include stochastic optimization, multispectral and SAR image processing and multivariate statistics.

Irena Hajnsek (AM’01–M’06–SM’09–FM’14) received the Diploma degree (Hon.) from the Free University of Berlin, Berlin, Germany, in 1996, and the Dr. degree (Hon.) from the Friedrich Schiller University of Jena, Jena, Germany, in 2001.

Since November 2009, she has been a Professor of the Earth Observation with the Swiss Federal Institute of Technology (ETH) Zürich Institute of Environmental Engineering and at the same time Head of the Polarimetric SAR Interferometry research group at the German Aerospace Center Microwave and Radar Institute. Her main research interests include electromagnetic propagation and scattering theory, radar polarimetry, SAR and interferometric SAR data processing techniques, environmental parameter modeling and estimation. Since 2010, she is the science coordinator of the German satellite mission TanDEM-X and proposed satellite mission Tandem-L. She was Technical Program Co-Chair of the IEEE IGARSS 2012 Symposium in Munich.

Dr. Hajnsek is a member of the IEEE GRSS AdCom and since 2016 she is the vice president of the IEEE GRSS Technical Committees.

Esra Erten (S’06–M’10) received the Ph.D. degree in computer vision and remote sensing from the Department of Computer Engineering and Microelectronics, Berlin University of Technology, Berlin, Germany, in 2010.

She was with the High-Frequency Institute, German Aerospace Center, Oberpfaffenhofen, Germany, from 2008 to 2010, where she worked on information theory for multichannel SAR images. From 2010 to 2012, she was with the Chair of Earth Observation and Remote Sensing, Institute of Environmental Engineering, ETH Zurich, Zurich, Switzerland, where she researched on applied radar remote sensing for environmental parameter estimation. In 2018 she was a visiting professor at Satellite Applications Catapult, U.K. She is currently an Associate Professor at the Department of Geomatics Engineering, Faculty of Civil Engineering, Istanbul Technical University, Istanbul, Turkey and a Space Research Fellow at The Open University, Milton Keynes, U.K. Her research interests include information extraction and image understanding from SAR and optical images; in particular information theory, multivariate statistics, polarimetry, and interferometry.

Mrs. Erten was a Vice President for the IEEE GRSS Turkey Chapter from 2012 to 2015. She is the President of the IEEE GRSS Turkey Chapter since 2015.