MONITORING RICE FIELDS
USING SYNTHETIC APERTURE RADAR

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To my dear father who has always supported me in this journey since the first day...

O Gemi Bir Gün Gelecek
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Abstract

The increase in world population during the last century has led to a higher crop production. Due to limited arable lands and growing demand for crops, agricultural monitoring practices require modern techniques to improve management systems. For an effective monitoring, crop phenology (morphology and growth stage) is an important descriptor for the dynamic assessment of crop vitality and productivity. Precision agriculture is a new crop monitoring concept, which aims to improve agricultural management practices through remotely sensed data. It uses spatially and temporally high-resolution satellite data for inter- and intra-field variability of crop phenology. To this aim, Synthetic Aperture Radar (SAR) data is employed to monitor the phenological changes using the interaction between crops and electromagnetic waves. Even though in recent years a lot of research has been conducted, there is still room for improvement in large-scale precision agriculture applications to improve the management practices.

This thesis presents two physical model based rice crop monitoring approaches to estimate the phenological state of rice plants for large-scale implementations. The first approach employs Polarimetric SAR (PolSAR) to invert an electromagnetic scattering model using parameter search space algorithm. The second approach uses Polarimetric Interferometric SAR (Pol-InSAR) data for the inversion of the random volume over ground model. Both approaches are developed to consider phenological variability in fields for large scale implementations.

The proposed methodologies in this thesis rely on the stochastic inversion of electromagnetic scattering models. The stochastic inversion procedures consider the uncertainties in morphology based dimensional uncertainties. For the validation of the inversion procedures, we used PolSAR data from dual-pol TerraSAR-X in X-band and RADARSAT-2 in C-band. Furthermore, we used Pol-InSAR data from the large baseline bistatic science phase of the dual-pol TanDEM-X mission to improve the overall phenological state estimation accuracy.

The performances of the phenological state estimation algorithms are evaluated with ground measurements conducted in Seville (Spain - 2008) and Ipsala (Turkey - 2013 to 2015). The assessment makes a significant contribution to rice crop monitoring research. The stochastic inversion of the physical models indicates that the estimation of crop height using PolSAR is possible with an error less than 15 cm. The combination of PolSAR and Pol-InSAR based crop height estimation algorithms improved the accuracy and led to errors less than 10 cm. For the first time, the study provides quantitative estimations of stalk and leaf dimensions with a good accuracy ($R^2 \geq 0.6$). Moreover, the proposed phenological stage (BBCH) determination algorithm achieves less than 10% error on the validation data.

This dissertation presents a new precision agriculture approach, which broadens the applicability of physical models using PolSAR data. The proposed approach allows for the detection of sub-field phenological irregularities, which can be used to identify under- or overgrowth conditions.
Zusammenfassung


guter Genauigkeit ($R^2 \geq 0.6$). Zudem erreicht der vorgeschlagene Algorithmus zur Feststellung der Phänologie (BBCH) weniger als 10% Abweichung zu den Validierungsdaten.

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Chapter 1

Introduction

1.1 Motivation

Rice is consumed as a staple crop by more than half of the world’s population. It is also an important source of revenue for some of the highest populated countries such as China and India [1–3]. According to the International Rice Research Institute (IRRI), by 2025 the demand for rice is expected to escalate by nearly 70% [2]. However, arable areas for rice cultivation are limited. To increase the yields, better agricultural practices are needed, which in turn necessitate frequent monitoring. The end-users, such as farmers and decision makers, require detailed information on the crop phenology (i.e. temporal evolution of morphology, density, and vitality) to facilitate a failure-free production with the timely application of fertilizers and pesticides, as well as detection of plant diseases and growth irregularities. At present, visual inspection is the prevalent method for phenological monitoring. Although cost-effective for small scale monitoring (m²), it becomes expensive and inefficient for large scale (km²) plantations due to logistical (e.g. workforce, time, cost) limitations. In such situations, remote sensing systems play a vital role in the frequent monitoring of the evolution of rice fields at large scales for cost-effective implementations. Among other systems, Spaceborne Synthetic Aperture Radar (SAR) is well suited for rice crop monitoring with meter-scale resolution in all weather and light conditions.

There are multiple techniques to analyze SAR images, such as polarimetry (PolSAR), interferometry (InSAR) and polarimetric interferometry (Pol-InSAR). PolSAR exploits the phase and amplitude information of electromagnetic waves in multiple polarization states e.g. horizontal and vertical. It uses multiple polarimetric channels (i.e. HH, HV, VH, HH) to characterize the scattering behavior of objects according to their geometric and dielectric properties [4–6]. InSAR, on the other hand, measures the phase difference obtained from the superposition of electromagnetic waves [7–9]. It is used to locate the phase center, allowing the derivation of the digital elevation models for a particular polarization. Lastly, Pol-InSAR is the coherent combination of PolSAR and InSAR. It permits the characterization of the scattering contributions in height using SAR data with multiple polarizations [10–12]. The frequency and the look angle of the antenna can modify SAR image analysis techniques, providing flexibility towards feature of interest. Considering their differences, different image analysis techniques are essential for monitoring phenological properties of plants with their enhanced sensitivity to the changes in geometric (i.e. morphology) and dielectric (e.g. volumetric water content) properties.

Temporal analysis and electromagnetic scattering (EM) model based approaches have been used to monitor phenological cycle of rice fields with various frequencies and SAR image analysis techniques. Temporal analysis exploit the changes in different polarimetric [13–73] and interferometric [67, 74–79] observables to provide information on phenological properties of plants, such as plant height, biomass, leaf area index and growth stage. However, presence of varying conditions such as different cultivation practices and growth rates, limits the developed algorithms to their specific cases. EM models [13,22,55,67,69,72,79–91], on the other hand, employ the principles of radiative
transfer theory, with several input parameters, to model the scattering intensity of plants. Considering the high number of variables and the complex algorithms, EM models are computationally highly expensive and not useful for operational parameter estimation.

Even though different SAR image analysis techniques have been used to monitor rice fields, the assessment of phenological properties is still challenging and needs improvement. The available methodologies are still not fully capable of capturing all aspects of the phenological cycle (e.g. evolution of realistic plant morphology and environmental impacts) and being applicable in areas other than a particular test sites. Therefore, in this study the feasibility of high frequency (X- and C-band) SAR images are investigated by exploiting different temporal analysis and EM model based approaches to improve rice monitoring applications.

### 1.2 State of the Art

Rice fields have been monitored using SAR systems since late 80s to improve the management practices. Since then, the opportunities provided by the developments in the technology, different sensors, image analysis techniques, and frequencies have been exploited for the development and assessment of various approaches to monitor rice fields. This section summarizes the development in rice field monitoring methodologies and applications chronologically, starting from the first study in 1989 [13] to the most comprehensive study in 2016 [67]. Table 1.1 and Table 1.2 presents an up to date list of methodologies and main rice monitoring applications sorted by frequencies and SAR image analysis techniques, respectively.
After the invention of the SAR systems as a military surveillance tool in the 1950s, the first known study in rice crop monitoring was carried out in 1989 by Le Toan [13]. In this study, an airborne X-band SAR system (VARAN-S) was used to map rice fields by investigating the scattering behavior of rice fields in HH and VV channels, which were acquired non-simultaneously. In the same study, an EM model was exploited for the first time to simulate the backscattering intensity ($\sigma_0$) from rice fields. By being the first research in rice monitoring, it emphasized the feasibility of HH and VV channels in rice monitoring together with EM model simulations.

The launch of ERS-1 (European Remote Sensing Satellite-1) in 1991 made large scale rice monitoring possible from space. Following the ERS-1, different spaceborne SAR systems became operational within a short time, namely: JERS-1 (Japanese Remote Sensing Satellite-1) in 1992, ERS-2 in 1995, and RADARSAT-1 in 1996. The ERS-1/2 mission was able to provide backscattering information in VV polarization C-band with a repeat cycle of 35 days for a single satellite. JERS-1 and RADARSAT-1, on the other hand, were capable of providing HH polarization L-band data with 44 days of repeat cycle and C-band data with 24 days repeat cycle, respectively.

During the 1990s, ERS-1/2 [14–17, 80], JERS-1 [92], and RADARSAT-1 [18, 81] missions have led to the development of several methodologies to monitor rice fields. The main applications were the detection of rice fields [14, 15, 17, 80, 81, 92], temporal investigation of SAR observables [15, 18, 80, 81, 92] and correlation analysis against phenological parameters [14–16, 80, 81]. The first developed methodologies to detect rice fields were successful with classification accuracies higher than 89%. The methods used the low $\sigma_0$ values in early phases of the growth cycle to distinguish rice fields. The approaches that were developed to investigate the evolution of SAR observables emphasized the requirement of multiple SAR data due to the temporal variation in $\sigma_0$ values. Lastly, correlation analysis between $\sigma_0$ and phenological properties as height and yield provided good correlations. Apart from the mentioned researches, in 1997 Le Toan [80] proposed a new EM model as an improvement to the one published in [13]. The upgraded model simulates the backscattering intensity from rice fields by exploiting the first order radiative transfer equations and Monte Carlo simulations. In the model, rice fields are considered under flooded conditions and with their simplified plant morphologies, including the geometrical and dielectric properties of stalks and leaves. The simulations of the EM model achieved high accuracy with an average uncertainty of 2 dB throughout the growth cycle of rice plants.

Outcomes of the first rice monitoring research during the 1990s showed the feasibility of single-channel SAR systems with different frequencies. However, for operational rice monitoring applications, except rice field detection, the available systems were not effective due to lack of multipolarimetric data and long revisit periods of spaceborne systems. The methodologies developed during the 1990s were limited to their test sites and were incapable of explaining the effect of short term changes in backscattering signatures with rice phenological cycle. Considering the given gaps, new SAR systems and methodologies were needed for better rice monitoring applications.

During the 2000s new SAR systems became available additional to the ERS-1/2, JERS-1, and RADARSAT-1 missions, namely: ENVISAT ASAR, ALOS PALSAR, and TerraSAR-X. In 2002, ENVISAT ASAR, the successor of the ERS-1/2 mission, started to acquire dual-polarized data in C-band with a revisit period of 35 days. Later, in 2006 ALOS PALSAR began to provide fully polarimetric data in L-band with a revisit period of 46 days. Lastly, in 2008 TerraSAR-X, the first X-band SAR system in space, started to acquire dual-polarized data with a revisit period of 11 days and allowed for frequent large scale monitoring.

Data acquired by RADARSAT-1 [19–21, 23–26, 28, 29, 31, 82, 83, 96], JERS-1 [82], ENVISAT ASAR [27, 33–38], ALOS PALSAR [33, 85], and TerraSAR-X missions [32, 33], as well as ground
based systems, [22, 24, 30, 39, 74, 75, 97] were used to develop new methodologies. Similar to the 1990s, the applications were aiming to detect rice fields [19, 21, 23, 24, 26, 28, 31, 34, 35, 37, 38, 96], to investigate the evolution of SAR observables [20–22, 25, 27, 29, 30, 32–34, 39, 74, 75, 83–85, 97], and to analyze the relation between phenological parameters and SAR observables [22, 24, 25, 27, 33, 36, 74, 75, 82, 83, 85, 97]. Besides, the acquired data was also used to validate the new EM models, which can simulate the backscattering intensity from rice fields [22, 74, 82–85].

The studies conducted by Inoue [22], Ballester-Berman [75] and Lopez-Sanchez [32] can be seen as the milestones of rice monitoring research during the 2000s. Inoue [22] presented an extensive study by investigating the temporal relations of $\sigma^0$ for various frequencies (Ka-, Ku-, X-, C-, L-) and incidence angles with leaf area index, biomass, and canopy height parameters. Besides, Water Cloud Model, which was previously developed by Attema and Ulaby [98], was implemented to model the $\sigma^0$ from rice canopies using leaf area index and biomass parameters. As a result of the statistical analysis, L-band $\sigma^0$ was found to be highly correlated with biomass and C-band $\sigma^0$ values were correlated with leaf area index and plant height parameters. Besides, $\sigma^0$ of Ka-, Ku-, and X-bands showed strong correlations with panicle weight of plants. Water Cloud Model, on the other hand, was proven to be feasible only for C- and L-band SAR data. The research by Ballester-Berman [75] is the first study that uses polarimetric SAR interferometry for rice monitoring purposes. In this study, the feasibility of the model [99] is assessed for rice plants. The model describes the agricultural canopy as oriented scatterers of unknown height located on a ground surface. The polarimetric interferometric response is modeled by the contribution from volume and surface scattering from the canopy. The model was tested by indoor experiments for frequencies between 2-9 GHz and was proven to be useful when the absolute coherence values are higher than 0.3. The study by Lopez-Sanchez [32] is the first rice monitoring research that was carried out using X-band data from space. The study provided a detailed analysis by investigating the temporal trends of various polarimetric parameters based on the phenological cycle of rice plants. The results have presented the sensitivity of X-band backscattering signatures to phenological growth in rice plants and therefore the feasibility of TerraSAR-X mission in rice monitoring applications.

The research conducted in the 2000s, extended the rice monitoring applications of the 1990s significantly. The methodologies developed during the 2000s were able to present the short term temporal changes using multi-polarimetric SAR systems with lower revisit periods. However, new SAR systems brought new research questions about the feasibility of different image analysis techniques and possibility of monitoring algorithms, which are applicable out of their test sites.

During 2010s, additional to ENVISAT ASAR, ALOS PALSAR, and TerraSAR-X, three new SAR missions started to provide multi-polarimetric data, namely: RADARSAT-2, TanDEM-X, and COSMO-Skymed. RADARSAT-2, the successor of RADARSAT-1, began to provide fully polarimetric C-band data in 2008 with a revisit period of 24 days. In 2010 TanDEM-X was launched as TerraSAR-X’s twin satellite. Together with TerraSAR-X, they form the TANDEM-X formation which makes single-pass interferometric X-band data acquisition possible. COSMO-Skymed is the constellation of four satellites which were launched between 2007 and 2010, which are capable of providing copolar X-band data with a revisit period of 4 days.

Latest studies in the rice monitoring literature were conducted using the data acquired from ENVISAT ASAR [41, 62], ALOS PALSAR [93–95], RADARSAT-2 [42, 44, 45, 47–49, 51, 52, 55, 56, 58, 69–71, 79, 86–89], TANDEM-X [43, 46, 54, 57, 59–61, 63, 65, 67, 68, 72, 76–78, 89], and COSMO-Skymed [50, 63, 66]. The developed methodologies aimed to detect rice fields [41, 44, 52, 62, 71, 78], to investigate the temporal variation of SAR observables [40, 42, 43, 46–49, 51, 56, 60, 61, 63, 66, 88, 93–95], and to analyze the relation between plant phenology and SAR
observables [40, 48, 50, 51, 53–55, 63, 64, 67, 69, 70, 72, 76–79, 86, 87, 89]. For the first time in rice monitoring, the SAR data acquired during the 2010s was also employed for the estimation of growth stages [45, 46, 56–60, 65, 68, 72].

The researches presented by Inoue [50, 55], Erten [77], Lopez-Sanchez [46, 56] can be considered as the milestones of rice monitoring during 2010s. Each given research provided a significant contribution towards operational rice monitoring applications. The studies conducted by Inoue [50, 55] investigated the relation between phenological parameters and backscattering signatures using the X- and C-band data from COSMO-Skymed and RADARSAT-2, respectively. Besides, Water Cloud Model and a radiative transfer model was implemented to simulate the backscattering intensities. The results showed that while X-band $\sigma^0$ values were highly correlated with panicle dry weight, in C-band $\sigma^0$ values were correlated with leaf area index and leaf biomass parameters. The research conducted by Erten [77] investigated the feasibility of digital elevation model (DEM) differencing in estimating rice plant height using different polarimetric channels. In this research, the difference of two different DEMs that were generated before and during the cultivation period was calculated to see the effect of rice canopy as a vertical elevation. Even though the approach is promising, due to insufficient vertical baseline between TANDEM-X satellites, the estimations were not close to ground measured values. Towards growth stage estimation, the first studies were conducted by Lopez-Sanchez [46, 56] in X- and C-band. These studies investigated the sensitivity of backscattered signatures to the phenology of rice. Also, threshold based classification algorithms were proposed in a multi-dimensional SAR observable space. Later on, the methods suggested by Vicente-Guijbalba [57, 100], Debernardis [59], and Kucuk [68] improved the growth stage estimation algorithms using advanced methods such as Kalman filters, particle filters, and Support Vector Machines. The implementation of advanced methods both increased the number of estimated growth phases and the overall accuracy.

The most comprehensive study in rice monitoring is the research presented by Erten [67] which summarizes the feasibility of different algorithms and SAR image analysis techniques for rice plant height estimation. The algorithms include EM model inversion, DEM differencing and Pol-InSAR model inversion. The results of the presented algorithms had errors of less than 10 cm for rice plants that are at the end of their growth cycle. Comparing the study presented in 1989 by Le Toan [13] and the one in 2016 by Erten [67], the improvement in rice monitoring using SAR systems can be seen clearly. The research presented in this thesis uses PolSAR and Pol-InSAR image analysis methods to improve the plant morphology and growth stage estimation applications.

1.3 Research Objectives and Thesis Structure

This thesis contributes to rice monitoring literature by investigating the feasibility of plant morphology and growth stage estimations using temporal analysis of SAR observables and EM model inversion algorithms. The principles of agronomy, statistics, probabilistic inversion, and algorithmic optimization have been employed in this research, focusing on the following objectives to improve rice monitoring applications:

- Developing rice monitoring algorithms that are valid for the complete growth cycle
- Assessing rice plant morphology using different SAR image analysis techniques (e.g. PolSAR temporal analysis, Pol-InSAR) and EM model inversion
- Examining the feasibility of multi-polarimetric X- and C-band data on rice monitoring
- Providing rice monitoring algorithms having high-performance and low computation cost for easier implementation
Towards achieving the listed objectives, rice monitoring algorithms were developed using spaceborne PolSAR and Pol-InSAR data. PolSAR data was acquired in years 2009, 2013, 2014, and 2015 from the TerraSAR-X and in 2014 from the RADARSAT-2 satellites. Pol-InSAR data, on the other hand, was acquired only in 2015 from the TANDEM-X mission. TANDEM-X is a coherent system of twin satellites, called TerraSAR-X and TanDEM-X. It is capable of providing single-pass interferometric data within milliseconds, eliminating the temporal changes between acquisitions. Both satellites are capable of acquiring copolar (HH-VV) SAR data in X-band (31 mm wavelength) with a temporal resolution of 11 days. Unlike the satellites of the TANDEM-X, RADARSAT-2 is a single satellite mission, which is capable of providing fully polarimetric (HH-HV-VH-VV) SAR data in C-band (55 mm wavelength) with a temporal resolution of 24 days. Figure 1.1 presents the time plan for the PolSAR (TerraSAR-X, RADARSAT-2) and Pol-InSAR (TANDEM-X) acquisitions with corresponding incidence angles.

As shown on Figure 1.1, the SAR data was collected at two different test sites, Isla Major and Ipsala, which were chosen due to easily available ground measurements. Isla Major test site is located in southern part of Spain [N-37°7′53″ E-6°19′32″], with an approximately 380 km² area dedicated for rice cultivation purposes. The ground campaign was conducted in 2009 on six fields for a complete growth cycle, which starts with seeding and ends with harvesting. The field measurements aimed to track the evo...
Figure 1.3 – Temporal trends (mean and range) of crop morphology parameters obtained from field measurements in Ipsala (Turkey) test site, between 2013-2015

olution of four phenology descriptors, which were: growth stage, stalk height, the number of plants in a unit area, and the number of tillers for a plant. The Ipsala test site is located in the northwestern part of Turkey [N-40°47′59″ E-26°13′14″], with an approximate acreage of 190 km², mainly dedicated to rice cultivation. During the ground campaigns, the evolutions of various phenological parameters were measured, including growth stage, stalk height and diameter, leaf length and width, the number of plants in a unit area, number of tillers for a plant, and the number of leaves for a tiller. An areal photo of the rice fields are given in Figure 1.2 with a diagram of an average sized (0.013 km²) rice field. Considering the measurements collected from the Ipsala test site, Figure 1.3 summarizes the temporal variation of the phenological parameters for three consecutive years with the error lines representing the range of measured values from different fields. Due to the observed trends, while the parameters follow a consistent trend over the years, a high variation exists as a sign of phenological differences.

Figure 1.4 displays the simplified flow diagrams of the proposed algorithms for each chapter separately. The flowcharts are grouped based on the exploited ground and SAR data for integrity. Below, the overview of the thesis structure is provided with the research questions that are specific to each chapter.

Chapter 2. "A Metamodel-based Inversion for Determining Rice Growth Stage from SAR data", focuses on development and assessment of a growth stage determination algorithm in BBCH scale, using copolar TerraSAR-X data. The BBCH (Biologische Bundesanstalt, Bundessortenamt und Chemische Industrie) scale divides the growth cycle of cereals into 100 stages with phenological conditions [101]. This research aims to answer following research questions:

- Is it possible to develop a rice monitoring algorithm that is valid for different regions?
- How to consider sub-field phenological variations?
- What can be done to reduce the computation time of multi-dimensional EM models with complex algorithms?
Figure 1.4 – Summary flowcharts of the proposed algorithms given for each chapter, grouped according to the ground and SAR campaigns for different years and test sites.

In this research, as shown in Figure 1.4, two approaches are proposed to determine the growth stage of rice fields. The approaches are based on the temporal analysis of polarimetric parameters and the inversion of an EM model. This study is driven by the ideas and limitations observed in [46] for the temporal evolution of polarimetric parameters, [80, 82] for the plant morphology based EM model and [54] for the relation between phenological descriptors and backscattering intensity values. In the light of the previous research, Chapter 2 has following contributions to the literature:

• A stochastic inversion procedure for the EM model [80,82] is proposed. The method analyzes the multi-dimensional phenological relations in a parameter space to search for backscattering intensities that provide agronomically accurate estimations.
• A global sensitivity analysis is conducted for the EM model [80, 82].
• A useful tool is introduced to reduce the computation cost of EM models. The Polynomial Chaos Expansion (PCE) metamodel, proposed by [102], mimics the behavior of any analytical function by expanding high degree polynomials.

Chapter 3, "A Multi-Year Study on Rice Morphological Parameter Estimation with X-Band PolSAR Data", presents a detailed analysis on rice plant morphology estimation. In this study X-band copolar SAR data obtained from TerraSAR-X satellites from 2013 to 2015 were employed for the rice plant morphology estimations. The research tries to answer following questions:

• How does the accuracy of rice monitoring with the stochastic inversion of EM model changes with times?
• How does the accuracy of the plant morphology estimations vary according to growth phase?

Concerning the research questions, Chapter 3 employs the stochastic inversion of the PCE-driven EM model as shown in Figure 1.4. The coarse growth phase was taken a priori for algorithmic simplification. The research within Chapter 3 has following contributions to the literature:

• An estimation accuracy analysis is conducted for the feasibility of the stochastic inversion of EM model in X-band.
• First results on plant morphology based rice monitoring is presented. The concerning morphological parameters are determined as stalk height and diameter, leaf length and width.
Chapter 4. "Estimation of Rice Crop Height from X- and C-Band PolSAR by Metamodel based Optimization", aims to assess the performance of EM model stochastic inversion for different polarimetric channels and frequencies in estimating the height of rice plants with multipolarimetric SAR data. The following questions are acknowledged in Chapter 4:

- What are the effects of different channels and channel combinations on the plant height estimation accuracies?
- Which SAR frequency has the higher feasibility in estimation of rice plant height using stochastic inversion of EM model?
- What are the differences in plant height estimation accuracies for different periods of rice growth cycle?

Regarding the research questions, as shown in Figure 1.4, Chapter 4 presents rice plant height estimations that are obtained through stochastic inversion of the surrogate EM model using X- and C-band data. The results of the research contribute to the literature with following concepts:

- An in-depth analysis are presented on rice plant height estimation, which considers the effect of different polarimetric configurations.
- A multi-frequency comparison of plant height estimations is provided with copolar SAR data.

Chapter 5. "Integration of Coherent and Incoherent Inversions to Estimate Rice Crop Height using TanDEM-X Data" provides the rice plants height estimations using RvoG and PCE-driven EM model inversions. Apart from the findings of the Chapter 2, the research is also motivated by the ideas presented in [75, 103, 104] about the feasibility of Pol-InSAR for rice monitoring. The research presented in Chapter 5 aims to answer the following questions:

- What is the feasibility of Pol-InSAR in X-band for rice crop monitoring?
- How does the height estimation accuracy of the RVoG model inversion change during the rice growth cycle?
- Is it possible to provide better results with the EM model inversion by using height estimates from the RVoG inversion as an input?

In Chapter 5, as shown in Figure 1.4, RVoG and PCE-driven EM model inversions are implemented together to improve the rice plant height estimations. For this purpose the copolar SAR data from the science phase of TanDEM-X mission was employed which had large across track baseline. During the science phase, the large baselines allowed for increased sensitivity to the vertical distribution of scatterers. Considering the available dataset and the findings of the previous research, Chapter 5 has following contributions to the literature:

- An integrated rice crop height estimation algorithm is developed by combining inversion algorithms of RVoG and PCE-driven EM model. In the proposed approach, the RVoG based plant height estimation is used as an input to the PCE-driven EM model inversion. The provided plant height as an input eliminates the requirement of a priori growth phase.
- For the first time in literature, spaceborne Pol-InSAR data was employed to monitor rice plants for their complete growth period.

Chapter 6 concludes the thesis by providing general conclusions and discussions along with an overview of methodological strengths, weaknesses and opportunities.
Chapter 2

Determining Rice Growth Stage with X-Band SAR: A Metamodel Based Inversion

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Scientific Contributions

Yuzugullu built an integrated database for ground and SAR measurements
implemented the multi-dimensional EM model and the corresponding PCE metamodel
suggested to use stochastic approach for multi-dimensional EM model inversion
developed and implemented the rice growth stage monitoring algorithm
interpreted the analysis results, prepared the figures, and wrote the manuscript

Marelli wrote the “Polynomial Chaos Expansion and Global Sensitivity Analysis” subsection
assisted in interpretation of results and helped in writing the manuscript

Erten suggested to develop an inversion algorithm for a radiative transfer model
assisted in interpretation of results and helped in writing the manuscript

Sudret proposed to use PCE for computation effort reduction
assisted in interpretation of PCE results and helped in writing the manuscript

Hajnsek provided the SAR data and suggested to use temporal evolution of backscattering signatures
assisted in interpretation of results and helped in writing the manuscript
Abstract: Rice crops are important in global food economy and new techniques are being implemented for their effective management. These techniques rely mainly on the changes in phenological cycle, which can be investigated by remote sensing systems. High frequency and high spatial resolution Synthetic Aperture Radar (SAR) sensors have great potential in all-weather conditions for detecting temporal phenological changes. This study focuses on a novel approach for growth stage determination of rice fields from SAR data using a parameter space search algorithm. The method employs an inversion scheme for a morphology-based electromagnetic backscattering model. Since such morphology-based model is complicated and computationally expensive, a surrogate metamodel-based inversion algorithm is proposed for the growth stage estimation. The approach is designed to provide estimates of crop morphology and corresponding growth stage from a continuous growth scale. The accuracy of the proposed method is tested with ground measurements from Turkey and Spain using the images acquired by the TerraSAR-X (TSX) sensor during a full growth cycle of rice crops. The analysis shows good agreement for both datasets. The results of the proposed method emphasize the effectiveness of X-band PolSAR data for morphology-based growth stage determination of rice crops.

2.1 Introduction

Temperate climatic conditions with easy access to water sources provide optimum conditions for rice cultivation. In the history of agricultural practices, rice farming goes back to almost 8,000 BC. Currently, rice is the single most important source of income for the rural communities all around the world. According to the International Rice Research Institute (IRRI), worldwide rice production totaled 969 million tons in 2010 [2]. Frequent and efficient monitoring strategies are necessary for the optimization of economic competitiveness and the estimation of the associated environmental impacts (e.g. methane emissions). Concerning these issues, researchers have focused on finding sustainable monitoring methods for agricultural fields.

In the last decade, remote sensing techniques have frequently been used as a viable method to monitor agricultural areas. To this end, two main data sources are presented: optical and Synthetic Aperture Radar (SAR) systems. Optical systems measure reflected sunlight and provide spectral properties of their targets. Additionally, due to short wavelengths ($\lambda < 2500$ nm), they are mainly susceptible to atmospheric factors. On the other hand, SAR systems are superior compared to optical systems concerning their temporal coverage with their “all-weather” day and night imaging capability. Furthermore, they play a significant role in environmental monitoring with their sensitivity to the physical alterations in monitored objects. However, to provide a clear explanation of such changes one has to understand the relation between the target and the backscattered energy in SAR systems. This relation can be a complex function of the target and the sensor parameters including frequency, polarization setting, and incidence angle.

The selection of appropriate sensor parameters is crucial for agricultural monitoring. For instance with SAR systems, one should match the size of the structural parts of the crops with the available wavelength (frequency) of the system to identify the effects of morphological changes. Also, the use of different frequencies and incidence angles changes the scattering behavior and the attenuation of the waves inside the canopy [29]. Thus, in crop monitoring, high-frequency systems ($f > 5$ GHz) are expected to be more sensitive to the morphological changes than low-frequency systems.

Several studies monitoring paddy rice fields show that plant morphological structures have a high correlation with the backscattering behavior of high frequency electromagnetic (EM) waves [50, 55, 78, 105, 106]. There are currently two mainstream approaches to monitor crops, namely backward
and forward. The first class of approaches is based on the statistics of the polarimetric parameters [21, 22, 46, 49, 54–57, 77, 81, 107]. Among these, [22, 55] have completed the most comprehensive work to date by observing the full phenological cycle with different frequencies, polarizations and incidence angles. Such methods also depend on several factors including temporal variations in the structural density, type of crop or the use of seeds with different genotypes. In the literature, similar temporal trends have been observed for polarimetric descriptors during the phenological cycle, such as intensity, entropy, alpha and phase differences [22, 46]. The statistical classification methods in the literature are cost-effective and easy to implement. However, the high dynamic range of the polarimetric parameters makes it not trivial to develop widely applicable approaches that cover the full growth period in different locations. Consequently, current thresholding based statistical methods need to be adjusted for each new monitoring campaign depending on the region of the world they take place. Additionally, they usually require a full-time series for each new campaign. Therefore, most of the current statistical methods are not capable of explaining the growth cycle of rice crops in different areas while avoiding high training costs.

Unlike the statistical ones, the second class of approaches is based on the scattering behavior of an EM wave inside the canopy. This behavior can be explained by analytical relations between the crop physical structure (i.e. morphology) and the backscattering coefficients [80, 82, 83, 108, 109]. Such backscattering models take the plant morphology as input and provide the scattering properties of the EM wave (i.e. backscattering coefficients) as output [110]. Since they consider the geometrically simplified crop morphology, they usually have sophisticated mathematical algorithms. With such level of complexity, knowing the sensitivity of the model outputs on the input parameters is essential to understand the dynamics of the model. Global Sensitivity Analysis (GSA) provides the necessary quantitative tools to assess it properly [102,111]. However, the implementation of GSA can result in high computational costs due to the large number of model evaluations needed in standard sampling-based approaches [111]. An effective strategy to significantly reduce this computational burden is by using Polynomial Chaos Expansion (PCE), a surrogate modeling technique that has exceptional convergence properties for the estimation of Sobol’ indices for complex models [102]. It reduces the total computational cost to that of its training set, which is typically relatively small. Therefore, PCE makes GSA computationally efficient. Finally, after the assessment of the importance of model parameters, it is possible to develop an inversion scheme for the crop morphology from polarimetric observations.

An incoherent EM backscattering model [80] is chosen for this study. The model considers a simplified plant morphology with a higher number of unknowns than the number of measurables. For such an ill-posed problem, an analytical inversion approach is infeasible. Also, the presence of speckle noise in the measured intensity data makes pixel-sized inversion algorithms less efficient. In this paper, a parameter search space algorithm combined with a PCE surrogate of the full EM model is considered as a powerful option to handle these issues for the model inversion scheme.

This article proposes a new and effective method to determine the growth stage of flooded and broadcast sowed rice fields in large-scale cultivation areas using polarimetric SAR (PolSAR) data. Apart from the aforementioned growth phase determination methods for the rice fields, the proposed method focuses on the effect of the changes in crop morphology on the polarimetric backscattering intensities during the phenological cycle. It extends the a priori growth phase information with an EM backscattering model in a computationally efficient framework. The EM model inversion consists in a PCE-based parameter space search algorithm. Finally, the results are combined to determine the growth stage of the field from its morphology.
Chapter 2 Rice Plant Growth Stage Estimation with X-Band PolSAR

The paper provides the theory behind the proposed inversion approach in detail along with concise information about PCE metamodels and GSA in Section 2.2. Section 2.3 covers the test areas with the ground measurements and TerraSAR-X (TSX) campaigns. Section 2.4 presents the main results of GSA and growth stage estimation. Section 2.5 summarizes the work with an overall view on the proposed growth stage estimation approach in the context of precise agriculture.

### 2.2 Growth Stage Determination

Understanding the growth phases of the rice growth cycle is crucial in explaining their effect on the SAR system responses. The most common rice cultivation practice begins by flooding the fields several weeks before sowing. There are two main planting methods: transplanting and broadcasting. In transplanting, the seedlings are prepared and then transplanted to the fields to provide regular spacing between the plants. On the contrary, with broadcast sowing, the seeds are thrown to the flooded fields, resulting in spatial morphological heterogeneity [2].

Three significant growth periods can be identified in rice cultivation: vegetative, reproductive and maturative. The full cycle takes between 120-150 days depending on agricultural and environmental factors. In the literature, the rice growth cycle is defined by two distinct scales: International Rice Research Institute (IRRI) [2] and Biologische Bundesanstalt, Bundesbundesamt und CHemische Industrie (BBCH) [101]. The IRRI scale divides the growth cycle into five phases while the BBCH scale uses 100 stages between 0 and 99. A general overview of the growth cycle is presented in Figure 2.1 with sample morphologies. In this research IRRI scale is chosen as the a priori growth phase.

- **Vegetative Period:** The crops increase in height and structural density, depending on several factors as soil properties, temperature, and seeding density. The stalk orientation stays mostly vertical. Since the plants are structurally weak, the duration of this period strongly depends on the environmental conditions and the genotype of the crops.

- **Reproductive Period:** As the plants become stronger, they become less sensitive to the environmental stresses. Plant height and density continue to increase heterogeneously together with increasing wet biomass, which leads to varying orientation in leaves and stalks due to increasing weight. The flag leaf forms through the end of the period.

- **Maturative Period:** Excess water in the fields is drained, leading to a reduction in plant total biomass due to lower moisture content. Grains become more mature and heavier.

In this study, the growth stages of the fields are determined using the approach shown in Figure 2.2. This method uses three different inputs: PolSAR data, growth information, and the backscattering (EM) model. PolSAR data is used in two steps of the algorithm: feature clustering for BBCH assignment and parameter space search algorithm. Phenological data with a priori growth phase information is used for determining the growth boundaries and trends and training a
first PCE metamodel that predicts the BBCH scale based on the available morphological parameter (PCE\textsubscript{BBCH}). The backscattering model is then surrogated by an additional PCE metamodel for each of the various growth phases (PCE\textsubscript{EM}). Later, the outputs of the feature clustering, PCE\textsubscript{EM} and growth trends as natural limitations are integrated into the parameter search space algorithm. Finally, the growth stages are estimated using clustered PolSAR data and the PCE\textsubscript{BBCH}.

### 2.2.1 Backscattering Model

In this study, the canopy is modeled as uniformly distributed individual plants over a half space that represents the flooded ground used in broadcast seeding. The backscattering coefficients are estimated using the first order solution of the radiative transfer equation \[80\]. The chosen model provides a structural description of the plants including their simplified crop morphology (e.g. stalks, tillers, leaves, and panicles). The model also includes the backscattering enhancements and resulting wave clustering effects from the scatterers. The resulting backscattering intensities are estimated for different polarimetric channels by performing Monte Carlo (MC) simulations using Foldy Lax multiple scattering equations \[112\].

In the simulations, rice plants with vertically oriented stalks are placed randomly in a unit area \(A\), as in broadcast seeding. The locations of the plants are randomized automatically in each iteration of the MC simulation to provide spatial heterogeneity. Inside \(A\), there are \(n_s\) plants with \(n_t\) tillers with average height \(h_s\) and diameter \(d_s\). Each tiller has \(n_t\) leaves with length \(l_t\) and width \(w_l\) and \(n_p\) panicles with length \(l_p\) and width \(w_p\). The complex dielectric constants are \(\varepsilon_{s,t}\) for all plant structures (e.g. tillers, leaves and panicles) and \(\varepsilon_g\) for the underlying ground.

The current first order solution of the electromagnetic scattering problem considers four major scattering mechanisms \(P_n\), visualized in Figure 2.3:

1. Direct scattering from the scatterers
2. Scattering from the canopy followed by reflection from the ground
3. Reflection from the ground followed by scattering from the canopy
4. Reflection from the ground followed by scattering from the canopy, again followed by reflection from the ground

\[
E^s_i(r') = \frac{e^{ikr}}{r} (P_1 + P_2 + P_3 + P_4) E^p
\]

\[
= \sum_{N_s} \sum_{j} \left[ f^{1}_{qp}(\pi - \theta_i, \pi + \phi_i; \theta_i, \phi_i) e^{-\frac{z^2}{h}} e^{-\frac{z^2}{h}} e^{2i(k^2 x^2 + k^2 y^2 - k^2 z^2)}
\]

\[
+ R_q(\theta_i) f^{1}_{qp}(\pi - \theta_i, \pi + \phi_i; \theta_i, \phi_i) e^{+\frac{2z^2}{h}} e^{-\frac{z^2}{h}} e^{2i(k^2 x^2 + k^2 y^2 - k^2 z^2)}
\]

\[
+ f^{2}_{qp}(\pi - \theta_i, \pi + \phi_i; \pi - \theta_i, \phi_i) R_p(\theta_i) e^{-\frac{z^2}{h}} e^{+\frac{2z^2}{h}} e^{+\frac{z^2}{h}} e^{2i(k^2 x^2 + k^2 y^2 - k^2 z^2)}
\]

\[
+ R_q(\theta_i) f^{2}_{qp}(\pi - \theta_i, \pi + \phi_i; \pi - \theta_i, \phi_i) R_p(\theta_i) e^{+\frac{2z^2}{h}} e^{+\frac{z^2}{h}} e^{+\frac{z^2}{h}} e^{2i(k^2 x^2 + k^2 y^2 - k^2 z^2)} \right] E^p
\] (2.1)

The top surface of the canopy is indicated as \(z = 0\) and the underlying surface as \(z = -h\). It is possible to model the behaviour of an incident wave \(E^i\) in the direction \((\theta_i, \phi_i)\), of the incidence and
look angle, using (2.1). The model follows the finite cylinder approximation [113, 114] for stems, tillers and panicles and the physical optics approximation [115] for leaves. Additionally, the model variables are listed as: type of the morphological structure, \( t \); scattering matrix element where \( q \) and \( p \) are polarization channels (\( q, p \) for H, V) for scattered and incident waves, \( f_{q,p}^{\text{tiller}} \); propagation vector of the incident and scattered wave, \( k_{q,p}^{\text{tiller}} \); Fresnel reflection coefficients, \( R_q(\theta) \) and \( R_p(\theta) \). Lastly, the effect of the attenuation due to scatterers inside the canopy is considered by the \( M_{qp} \) term:

\[
M_{qp} = \frac{i2\pi n_s n_t k_0 h}{k_0 A h} (f_{q,p}^{\text{tiller}} + n_t(f_{q,p}^{\text{leaf}} + n_p(f_{q,p}^{\text{panicle}}))) \tag{2.2}
\]

where the angular brackets represent configurational average, \( h \) is the height of the canopy and \( k_0 \) is the free space wave number. Structural location vectors are given as: \( k_{x} = k_0 \sin \theta \cos \phi \), \( k_{y} = k_0 \sin \theta \sin \phi \), \( k_{z} = k_0 \cos \theta \). The backscattering coefficients for a polarimetric channel, \( qp \), are estimated from the ratio between the amplitudes of the scattered and incident electrical waves (2.3).

\[
\sigma_{qp}^o = \frac{4\pi r^2}{A_i} \frac{\langle |E_q|^2 \rangle}{|E_p|^2} \tag{2.3}
\]

where \( A_i \) is the illuminated area and \( r \) is the distance between the sensor and the target. For the MC simulation, the backscattering coefficients are averaged over 200 realizations.

2.2.2 Polynomial Chaos Expansion and Global Sensitivity Analysis

Sparse polynomial chaos expansions (PCE) are a well-known technique in the uncertainty quantification literature, and they are well suited to inversion problems. Compared to other surrogate modeling techniques such as Gaussian process modeling (a.k.a. Kriging, [116]) or support vector regression [117], they are particularly well suited for the solution of inverse problems. Indeed, their global approximation character combined with the strict relation they share with Sobol’ variance decomposition [102, 118], as well as and their built-in error estimators can be directly applied to assess the identifiability of parameters in inverse problems.

**Polynomial Chaos Expansion**

To reduce the high costs associated with the MC simulation of morphology-based scattering, the computational model can be substituted with a metamodel, a computationally inexpensive analytical approximation of the full computational model. Due to its versatility and relatively low training costs, sparse PCE [119] is an ideal candidate. PCE is a spectral decomposition technique that allows one to represent a finite-variance scalar-output function \( Y = \mathcal{M}(\xi) \) as:

\[
Y = \mathcal{M}(\xi) = \sum_{j=0}^{\infty} a_j \Psi_j(\xi) \tag{2.4}
\]

where \( \xi \in \mathbb{R}^M \) is the random vector of morphological parameters, \( a_j \in \mathbb{R} \) is a set of scalar coefficients and the \( \Psi_j(\xi) \in \mathbb{R} \) form a polynomial orthonormal basis with respect to the functional scalar product (expectation value):

\[
\langle g(\xi) h(\xi) \rangle = \int_{\mathcal{D}_{\xi}} g(\xi) h(\xi) f_{\xi}(\xi) d\xi \tag{2.5}
\]

where \( \mathcal{D}_{\xi} \) is the support of \( \xi \) and \( f_{\xi}(\xi) \) the probability density function (PDF) of the input random vector \( \xi \). Due to the linearity of Eq. (2.4), the \( a_j \) coefficients can be non-intrusively and efficiently calculated using compressive-sensing-based least-square minimization techniques (e.g. least angle
2.2 Methodology

regression-based selection [119]) from a training set of full model evaluations of \( \mathcal{M}(\xi) \). The size of the training set determines the maximal complexity and the accuracy of the resulting metamodel. PCE was implemented in MATLAB® within the UQLab framework [118, 120].

Global Sensitivity Analysis: Sobol’ indices

GSA allows one to quantify the effect of the variability of each of the input parameters in \( \xi \) on the variability of the model response \( \mathcal{M}(\xi) \). A widely accepted global sensitivity measure in the uncertainty quantification is given by the variance-decomposition-based Sobol’ indices [111].

The basic form of variance decomposition consists in representing a computational model \( \mathcal{M}(\xi) \) as a sum of functions depending only on increasingly larger subsets of the input vector \( \xi \) as follows:

\[
\mathcal{M}(\xi) = \mathcal{M}_0 + \sum_{i=1}^{M} \mathcal{M}_i(\xi_i) + \sum_{i<j} \mathcal{M}_{ij}(\xi_i, \xi_j) + \ldots + \mathcal{M}_{12...M}(\xi_1, \xi_2, \ldots, \xi_M) \tag{2.6}
\]

where the \( \mathcal{M}_{ij...s} \) are scalar functions depending on the subset of input variables \( \{\xi_i, \xi_j, \ldots, \xi_s\} \). In Sobol [111], it is demonstrated that such a decomposition exists for every finite-variance functional and that it is orthonormal, hence yielding unique coefficients. Sobol’ indices are defined as the ratio of the variance of each term \( D_{ij...s} \) in Eq. (2.6) to the total variance \( D \):

\[
S_{ij...s} = D_{ij...s} / D. \tag{2.7}
\]

It is demonstrated that a close relation exists between variance decomposition and PCE coefficients, which allows for the calculation of Sobol’ indices directly from the PCE coefficients \( a_j \) without the need for additional sampling [102]. Therefore, the total costs of the GSA reduce to the calculation of the PCE training set.

2.2.3 Feature Clustering for BBCH Assignment

Agricultural fields are known to have spatial morphological heterogeneity due to growth competition. This condition is observed mostly in fields with broadcast seeding practices. Therefore, this structural heterogeneity is also expected for all growth stages at any time \( t \) in a field. The definition of the BBCH scale takes this heterogeneity into account and states that BBCH growth stage assignment must be done with respect to the dominant morphology within the field [101]. In other words, the assigned BBCH value of a field has to represent at least 50% of all crops. Due to the same growth stage and similar morphology, crops are expected to have similar polarimetric scattering behaviors. Thus, to provide this requirement for the BBCH value assignment, the PolSAR data is clustered to obtain the smallest group with 50% of the samples using the well-known K-Means algorithm in the space of statistically independent PolSAR parameters (i.e. \( \sigma_{HH}, \sigma_{VV} \) and \( \rho \)). Details about the clustering methodology are given in [65].

2.2.4 Parameter Space Search Algorithm

The proposed solution is designed as a constrained optimization problem by considering the ill-posed condition of the scattering model. In the literature, there are two different ways to handle similar optimization problems: deterministic and distribution-based approaches. The former approach converges to a single optimum value whereas the latter converges to a distribution of values. In this case, because SAR data has high variance, mainly due to speckle noise, a method that converges to a single intensity value would be ineffective. Especially for deterministic methods, the
Chapter 2 Rice Plant Growth Stage Estimation with X-Band PolSAR

The presence of variance reduces the rate of convergence and increases the degree of classification error. On the other hand, distribution-based approaches are capable of handling problems with the different level of variances. The proposed parameter search space algorithm links the a priori IRRI growth phase (i.e. phase $S$) and the backscattering model. The proposed parameter space search approach follows the flow scheme given in Figure 2.4.

The method starts with the simulation of the parameter space using the growth-phase-specific PCE$_{EM}$. At this step, the growth phase, $S$, also determines the parametric range (min-max) of the morphological descriptors. The corresponding parameter space, $P^S$, can be visualized as a hyper-grid (2.8). For any $S$, the coordinate of a single point in the grid has the information to define a rice canopy with morphology and structural density. However, the biologically impossible structures present in the data cloud of the ground measurement database need to be eliminated. For this purpose, the $P^S$ is constrained using the convex-hull method based on the morphological growth information which was collected from the literature and ground campaigns.

$$P^{st} = \left[ \hat{h}^S, \hat{d}^S, \hat{n}_t^S, \hat{r}^S, \hat{w}_l^S, \hat{w}_p^S, \hat{n}_p^S \right]$$

After preparing the $P^S$, the PCE$_{EM}$ is used to simulate $P^S$ and obtain the corresponding observable spaces for each polarimetric channel backscattering intensities $O_{qp}^S$. The fitness function of the distribution-based optimization problem in a constrained parameter space is given by:

$$\min Z_\sigma = \frac{\left[ E(\sigma_{qp} - O_{qp}^S) \right]^2}{\text{Number of } qp \text{ combinations}}$$

In (2.9), the $\sigma_{qp}$ and $E(\bullet)$ represent the measured backscattering intensity and the expected value of the difference between measured and observable SAR intensities, respectively. In the proposed method there are two constraints on the $P^S$, which explain the relation between $P^S$ and $O_{qp}^S$.

**Backscattering intensity:** Each $O_{qp}^S$ covers a wide range of intensities based on the corresponding morphologies in the $P^S$. However, the intensity values obtained from the SAR data only cover a small range of $O_{qp}^S$. In order to consider the spatial heterogeneity of the field, the mean ($\mu_{\sigma_{qp}}$) and standard deviation ($\nu_{\sigma_{qp}}$) of the measured backscattering intensities are calculated for each data cluster of polarimetric channels. Each $O_{qp}^S$ is then bounded based on the intensity constraints (2.10).

$$C_{qp} = O_{qp}^S[\mu_{\sigma_{qp}} - 2\nu_{\sigma_{qp}}, \mu_{\sigma_{qp}} + 2\nu_{\sigma_{qp}}]$$

The confined observable space $C_{qp}$ has the same dimensionality as $O_{qp}^S$, but fewer samples. The link between the $O_{qp}^S$ and $P^S$ is used to select the corresponding morphologies from the $P^S$ for each polarimetric channel to obtain the constrained parameter spaces, $B_{qp}$. Thus, the morphological structures that are included in each $B_{qp}$ have a similar $\sigma_{qp}$ with respect to the measured $\sigma_{qp}$ values.
2.3 Datasets

TerraSAR-X | Turkey'14 & Spain'09

Morphological consistency: In PolSAR data a particular intensity value may correspond to different physical structures. This constraint resolves the ambiguity by taking the intersection of all $B_{qp}$ sets of each $N$ polarimetric channels as seen in (2.11).

$$I = \bigcap_{i=1}^{N} B_{qp}^i = B_{qp}^1 \cap B_{qp}^2 \cap B_{qp}^3 \cap \ldots$$

The resulting set $I$ includes the multidimensional parameter distributions for the 9 inputs in (2.8). The morphology vectors are kept intact to preserve the plant morphologies for the last step.

2.2.5 Assignment of Growth Stages by PCE$^{BBCH}$

The last step of the proposed approach considers the sample distribution of resulting morphologies that are included in set $I$. Since the BBCH stage is not physically measurable and strongly subjective, there is a need for a relation between morphological parameters and the BBCH stage. This link has a complex and non-linear behavior. Moreover, subjective decision criteria of the BBCH scale leads to a high degree of variation due to the variation in biophysical parameters. Therefore, PCE$^{BBCH}$ is trained by taking samples from the morphological measurements as input, $X$, on the corresponding BBCH stages as output, $Y$. This metamodel is then used to estimate the BBCH stages ($BBCH_{est}$) for the set of $I$. Finally, the growth stage of the field is determined by calculating the mode of the distribution of $BBCH_{est}$.

2.3 Ground Campaign and SAR Data

2.3.1 Test Area and Ground Measurements

This study was carried out in two independent rice cultivation sites located in Spain and Turkey. Figure 2.5 shows the location of the fields. Both sites are sowed by the broadcast technique over flooded ground. Figure 2.6 summarizes the timeline of the ground measurements and SAR acquisitions for both datasets with IRRI phases.

Isla Major, Spain: The site is located in the Isla Major region, South of Seville, centered at N $37^\circ7'53''$ and E $6^\circ19'32''$. The region has a flat topography and covers an area with an average radius of 20 km. The ground campaign was conducted in 2009 to measure the phenological stage, canopy height, plant and tiller density for the whole cultivation period (May - October). Figure 2.5 presents the location of the test area and the fields that were chosen for the ground measurements.
Chapter 2 Rice Plant Growth Stage Estimation with X-Band PolSAR

Figure 2.6 – Accordance plot of SAR acquisition and ground measurement dates (Day of Year) given with color coded IRRI stages for both test sites

Ipsala, Turkey: The site is located in the Thrace region, North West of Istanbul, centered at N 40°47′59″ and E 26°13′14″. The region has a flat topography and covers an area with an average radius of 15 km. The ground campaign was conducted in 2014 to measure the phenological stage, morphological parameters (stalk diameter and length, leaf width and length), plant, tiller and leaf density for the whole cultivation period (May - September). Figure 2.5 presents the location of the test area and the fields that were chosen for ground measurements.

2.3.2 SAR Dataset
In this study data from the TerraSAR-X (TSX) mission is used. It operates at a central frequency of 9.65 GHz with a wavelength of 31 mm. As an advantage to the other systems, TSX allows frequent monitoring of environmental changes with a temporal resolution of 11 days. Therefore, it is one of the best options on the market for agriculture monitoring purposes.

All data were acquired in descending strip map mode and processed by the German Aerospace Center to the standard product level 1b, i.e. single look complex (SLC) data (16-bit) with ~2 m pixel-size. Later, the data were co-registered by using bi-linear interpolation with an average root mean squared (RMS) accuracy of 0.1 pixels. Figure 2.6 presents the acquisition plan of the dual polarization (HH and VV) SAR data with a central incidence angle of $31^\circ$ for both test sites.

2.4 Results and Discussion
In this paper, a stack of HH/VV dual-polarization descending TSX images over rice fields located in Spain and Turkey was employed to check the effectiveness of the proposed methodology. This section presents the GSA analysis of the EM backscattering model and the accuracy assessments of the growth stage determination algorithm. Since the algorithm has a stepwise scheme, the accuracy analysis is provided separately for each step. The discussions about the analysis outcomes are given in their specific sub-sections.

Figure 2.7 presents the boundaries of 6 crop morphology parameters from the Ipsala 2014 campaign with their quantiles and max-min values for each growth phase, $S$. For the $P^S$, boundaries are further extended by 5% as a safety factor to consider morphological anomalies such as over or undergrowth conditions.

2.4.1 Accuracy Assessment: Backscattering Model
In this study, the theoretical backscattering model estimates the HH and VV backscattering intensities of the rice canopies, at a central frequency of 9.65 GHz and at an average incidence angle of $31^\circ$ to be consistent with the TSX beam. The effect of the variation in the incidence and look angle during the acquisitions is assumed as constant along the scene.

Before applying the proposed inversion-based classification, GSA was used to identify the parameters that most affect the backscattering coefficients; a step is known as model-reduction. During
2.4 Results and Discussion

Figure 2.7 – Variation of biophysical parameters in different growth phases. Data are obtained from 2014 Ipsala ground campaigns.

Table 2.1 – Calculated Sobol’ indices for the real and imaginary parts of the dielectric constant for plants and the underlying ground.

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<tr>
<td></td>
<td>HH</td>
<td>VV</td>
<td>HH</td>
<td>VV</td>
<td>HH</td>
</tr>
<tr>
<td>$h_{stalk}$</td>
<td>0.753</td>
<td>0.934</td>
<td>0.361</td>
<td>0.398</td>
<td>0.473</td>
</tr>
<tr>
<td>$\varepsilon_{r, stalk}$</td>
<td>0.009</td>
<td>0.008</td>
<td>0.007</td>
<td>0.006</td>
<td>0.006</td>
</tr>
<tr>
<td>$\varepsilon_{i, stalk}$</td>
<td>0.006</td>
<td>0.009</td>
<td>0.003</td>
<td>0.002</td>
<td>0.008</td>
</tr>
<tr>
<td>$\varepsilon_{leaf}$</td>
<td>0.007</td>
<td>0.004</td>
<td>0.005</td>
<td>0.003</td>
<td>0.101</td>
</tr>
<tr>
<td>$\varepsilon_{i, leaf}$</td>
<td>0.003</td>
<td>0.008</td>
<td>0.002</td>
<td>0.003</td>
<td>0.006</td>
</tr>
<tr>
<td>$\varepsilon_{panicle}$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.011</td>
</tr>
<tr>
<td>$\varepsilon_{i, panicle}$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.011</td>
</tr>
<tr>
<td>$\varepsilon_{ground}$</td>
<td>0.112</td>
<td>0.069</td>
<td>0.074</td>
<td>0.053</td>
<td>0.009</td>
</tr>
<tr>
<td>$\varepsilon_{i, ground}$</td>
<td>0.124</td>
<td>0.085</td>
<td>0.092</td>
<td>0.069</td>
<td>0.013</td>
</tr>
</tbody>
</table>

In this step, the sensitivity of the backscattering coefficients to environmental parameters such as plant and ground dielectric values have been evaluated. The results are reported in Table 2.1. The variability in both the real and imaginary parts of the dielectric constants within the given boundaries ([22.0+6.0i $\sim$ 30.0+10i] for the canopy and [60.0+15i $\sim$ 80.0+25.0i] for the ground) has a significantly low impact on the model response. Indeed, the corresponding Sobol’ indices are much lower than, e.g. those of the stalk height parameter. Therefore, the dielectric constants were kept constant during the analysis by setting them to values based on [82].

Table 2.2 summarizes the values of the parameters assumed to be constant during the simulations of the ground measured data for the estimation of backscattering intensities. The reported values of the parameters are determined either from the SAR settings or the existing literature [80]. Constant parameters represent the average properties of a rice canopy compared to environmental conditions.

Figure 2.8 shows the correlation between results of the theoretical morphology-based backscattering model from the simulation of the Ipsala ground measurements from 2014 and the acquired TSX data in dB. The results as mean and standard deviation of the estimated values are grouped into three available growth phases in two polarimetric channels, i.e. HH and VV. In the correspond-
Table 2.2 – Input parameters that are kept constant for the backscattering model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central frequency</td>
<td>9.65 GHz</td>
</tr>
<tr>
<td>Dielectric constant ($\epsilon_{s,l}$)</td>
<td>25+8j</td>
</tr>
<tr>
<td>Dielectric constant ($\epsilon_{g}$)</td>
<td>70+20j</td>
</tr>
<tr>
<td>Average incidence angle ($\theta$)</td>
<td>31°</td>
</tr>
<tr>
<td>Look angle</td>
<td>90°</td>
</tr>
<tr>
<td>Distance to target</td>
<td>514 km</td>
</tr>
<tr>
<td>Illuminated area x-size</td>
<td>2.58 m</td>
</tr>
<tr>
<td>Illuminated area y-size</td>
<td>1.79 m</td>
</tr>
<tr>
<td>Number of MC iterations</td>
<td>200</td>
</tr>
</tbody>
</table>

ing figure, each growth phase is represented by a different color and symbol. Good agreement is obtained between the SAR measurements and the model simulations for both polarimetric channels.

There is clearly a strong correlation between measured and estimated backscattering intensity values for both polarimetric channels. For the full dataset, the 2-D coefficient of correlation ($R^2$) and the root mean square error (RMSE) are calculated to be 87.1% and 2.02 dB for the HH channel and 84.6% and 1.91 dB for the VV channel. Additionally, when the growth phases are considered separately, for the HH channel the RMSE values of the first three stages are calculated as 2.69, 1.83 and 1.96 dB, respectively. For the VV channel, they are calculated as 2.21, 1.91 and 1.58. The implementation of the backscattering model does not include the underlying surface nor the morphological 3D orientation information. The underlying surface is assumed to be water all through the cultivation cycle with high dielectric constant. The 3D orientation of the morphological components is neglected because the model has been shown to provide reasonable accuracy even without their inclusion (see Figure 2.8). Including the rotational parameters for each plant would result in additional scatter of the EM response, comparable to the effect of the stochastic placement of the plants in the area described in Section 2.2.1.

2.4.2 PCE\textsubscript{EM} and Global Sensitivity Analysis

A PCE\textsubscript{EM} is generated by preparing a sample of size 2000 of the full model for each of the 5 growth stages identified previously, hence at a total training cost of 10000 model evaluations. Note that this is a 1-time cost: after the PCE\textsubscript{EM} is trained, no new full model evaluations are necessary to evaluate the PCE\textsubscript{EM} on new sets of morphological parameters. The PCE\textsubscript{EM} surrogates the mean and the variance of the forward backscattering model of the MC simulations in all polarimetric channels.

![Figure 2.8](https://example.com/image.png)

**Figure 2.8** – The TSX measured versus the theoretical backscattering model predicted HH and VV channel backscattering intensities with model prediction standard deviation as error bars from Ipsala 2014
2.4 Results and Discussion

Figure 2.9 – [Row 1&2] Relationship between backscattering model and PCE\textsubscript{EM} simulated $\sigma^0$ (in dB) values given for five growth stages with corresponding polynomial degree (P.Deg.), $R^2$, RMSE and LOO values. True value indicates the scattering model simulated values. [Row 3] GSA results given for five growth stages with corresponding Total Sobol’ indices for each input parameter.
In terms of computational costs, the evaluation of the $\text{PCE}_\text{EM}$ is comparatively inexpensive. In other words, while the original implementation of the backscattering model required approximately 22 hours to calculate the response to 2000 simulations on a computer with 24 GB RAM and 8 cores, the $\text{PCE}_\text{EM}$ needed only 0.04 seconds with a single core on the same hardware. Therefore, such an improvement allows increasing the size of the parameter and the observable spaces significantly, which in turn enhances the variation in the crop morphology input vectors.

Figure 2.9 shows the results of the accuracy and GSA of the $\text{PCE}_\text{EM}$. The figure is structured as an array with the first two rows visualizing the accuracy analysis and the last row visualizing the GSA results. Each column corresponds to a growth phase with all chosen crop morphological parameters. Accuracy analysis of the $\text{PCE}_\text{EM}$ are given with a corresponding polynomial degree (P.Deg.), $R^2$, RMSE and Leave-One-Out (LOO) error [119]. The results are discussed below.

**Early Vegetative:** For both polarimetric channels, the stage-specific $\text{PCE}_\text{EM}$ can approximate the backscattering coefficients perfectly. For HH and VV channels the $R^2$ values are calculated to be 99.4% and 98.3% respectively. The estimated RMSE values are 0.25 dB and 0.34 dB for HH and VV channels, respectively. The GSA of the EM model shows that stalk height is the primary source of the variance. Besides, the variation in stalk diameter is stronger in the HH channel.

**Late Vegetative:** During this stage, the significant growth in the plants increases the dynamic range of the intensity values in both polarimetric channels. This variance is also detected in the stage-specific $\text{PCE}_\text{EM}$ outputs. The results of the accuracy analysis show that $R^2$ and RMSE values are calculated to be 89.2% and 1.78 dB for HH, and 83.5% and 1.93 dB for VV channel. GSA shows that the major source of the variance in the model output originates from the stalk height, stalk diameters and the number of tillers. In addition, HH channel is slightly more sensitive to stalk density compared to VV channel.

**Early Reproductive:** As the plant enters this phase, head leaves and panicles are observed. The accuracy assessment of the $\text{PCE}_\text{EM}$ reports the $R^2$ and RMSE for the HH channel as 89.1% and 0.94 dB, and the VV channel as 80.0% and 0.97 dB. In terms of GSA, the model is observed to be sensitive to stalk height in both polarimetric channels. Additionally, the HH channel is sensitive to the changes in the number of tillers. On the other hand, the VV channel is found to be sensitive to the variation in panicle width and number of panicles.

**Late Reproductive:** For each polarimetric channel, the accuracy assessment of the stage-specific $\text{PCE}_\text{EM}$ provides $R^2$ and RMSE values as 81.9% and 0.95 dB for HH channel, and 89.9% and 0.56 dB for VV channel. For the GSA, the source of the variability is related to the changes in stalk height for both polarimetric channels. Also, the number of tillers and panicles are sources of variability for the HH and VV channels, respectively.

**Maturative:** During the last stage of the growth cycle, the accuracy of the stage-specific $\text{PCE}_\text{EM}$ is estimated for $R^2$ and RMSE values as 84.4% and 0.96 dB for HH, and 89.8% and 0.58 dB for VV channel. Moreover, the sources of the variation in the model outputs are found to be stalk height for HH and VV and the number of tillers for HH.

To sum up, growth-phase-specific $\text{PCE}_\text{EM}$ can estimate the outputs of the theoretical backscattering model with high accuracy. Minimum $R^2$ and maximum RMSE values for the full cycle are calculated to be 80.0% and 1.98 dB. Therefore, the replacement of the backscattering model with the surrogate $\text{PCE}_\text{EM}$ is acceptable. While the highest accuracy is observed in the early vegetative stage, the lowest accuracy is in the late vegetative stage. GSA shows that throughout the growth cycle model outputs in both polarimetric channels (HH and VV) are most sensitive to the stalk height. However, for the HH channel, the number of tillers and stalks become important starting from the late vegetative phase.
2.4 Results and Discussion

Table 2.3 – An average sample size of parameter space during each step of the search algorithm procedure.

<table>
<thead>
<tr>
<th>Process Step</th>
<th>Growth Phase</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P Space</td>
<td>48300</td>
<td>149290</td>
<td>204160</td>
<td>338328</td>
<td>181350</td>
</tr>
<tr>
<td></td>
<td>Pos. Morp.</td>
<td>7010</td>
<td>343800</td>
<td>47330</td>
<td>120780</td>
<td>26330</td>
</tr>
<tr>
<td>Cons. 1: B</td>
<td>2000-2500</td>
<td>25000-40000</td>
<td>8000-11000</td>
<td>17000-23000</td>
<td>4000-7000</td>
<td></td>
</tr>
<tr>
<td>Cons. 2: I</td>
<td>1500-2200</td>
<td>12000-30000</td>
<td>4000-10000</td>
<td>9000-20000</td>
<td>2000-6000</td>
<td></td>
</tr>
</tbody>
</table>

2.4.3 Structures of the Parameter and Observable Spaces

The proposed approach follows a search algorithm that depends on two multi-dimensional spaces, parameter $P$ and observable $O_{qp}$. The first space is built up based on the morphological parameters as a regular grid. In the current case, the increments of the grid were chosen as 1 cm for stalk height and leaf length, 1 mm for stalk diameter and leaf width, 1 unit for tiller and leaf number and finally 10 units for plant number. For each growth phase a different number of possible samples is obtained. Table 2.3 summarizes the remaining sample sizes throughout the analysis. The reason behind the different number of samples is due to the varying ranges (maximum and minimum values) of parameters as seen in Figure 2.7. Later, when the biologically unrealistic morphologies are eliminated in accordance to the crop morphology database, the sample sizes reduce to the values shown in row 3 of Table 2.3. Here it is observed that several morphologies in the parameter space are not biologically favored. In the next step, intensity and matching morphology constraints are implemented. Table 2.3 provides the average values from this study for the minimum and the maximum number of samples remaining after each constraint is applied. These values can change based on the variance of the data, which is either due to the structural heterogeneity of the region or due to the smoothing window. Finally, the remaining samples are used as an input to the $PCE_{BBCH}$.

2.4.4 Accuracy Assessment: $PCE_{BBCH}$

A random growth stage can correspond to several different plant morphologies. Besides, the variance of the crop morphology can affect the BBCH results. Therefore, this relation is achieved using a $PCE$ metamodel which relates ground measurements to their corresponding BBCH stages by $PCE_{BBCH}$ metamodel.

Figure 2.10 shows the results of the accuracy analysis of the $PCE_{BBCH}$. The plot is given with respect to the BBCH stages measured in the field versus the ones estimated by the $PCE_{BBCH}$. For the training, 200 randomly chosen ground measurements are taken into consideration from the 2014 Ipsala ground campaign. The coefficient of determination is calculated to be 94.0%. The overall RMSE value is found to be 5.80 stages, with lowest variance in the early vegetative stage and the highest in the maturative stage. This can be explained by the degree of the morphological complexity. In other words, as the structure gets more complicated, a lower accuracy for the $PCE_{BBCH}$ is observed. Lastly, the proposed scheme can provide a continuous growth trend in the BBCH scale.

![Figure 2.10 – Relation between ground measurement and $PCE_{BBCH}$ simulated BBCH values with corresponding $R^2$ for the training data.](image)
2.4.5 Accuracy Assessment: BBCH Assignment

The growth stage determination method proposed in this study makes the BBCH scale directly available for broadcast seeded rice monitoring by means of PolSAR. In other words, the phenological stage of a rice field of interest can be estimated by observing its polarimetric response and that of the surrounding area. Therefore, to prove the consistency of the approach, the PCE metamodel based inversion method is independently applied to each test field present in each TSX data from Isla Major and Ipsala.

The accuracy analysis by means of correlation plots of the proposed algorithm applied to all test fields of the available TSX data are shown in Figures 2.11 and 2.12 for the Isla Major and the Ipsala sites, respectively. The value of $R^2$ between ground measured and estimated BBCH is 94.1% for Isla Major and 84.1% for Ipsala test sites. Additionally, the RMSE deviation from the measured value is found to be 7.66 BBCH stages for Isla Major and 5.24 BBCH stages for Ipsala data. Unfortunately, the Ipsala data is not available for the full cycle. The analysis shows that, while the proposed algorithm tends to overestimate the earlier stages, it underestimates the later stages. This can be explained by crop morphology and subjective assignment of the BBCH stages. The inclusion of the PCE\textsubscript{BBCH} based growth stage assignment improves the overall accuracy. Field and full scaled growth maps are visualized in Figure 2.13 and Figure 2.14.

2.5 Overview and Summary

This paper has demonstrated that X-band HH/VV dual-polarization SAR data are suitable for the estimation of flooded and broadcast sowed rice field growth stages on a continuous scale, in terms of BBCH. This is due to the sensitivity of the X-band polarimetric descriptors to small scaled morphological changes. The validation of the proposed approach carried out at the field level provided an error of less than 10 BBCH stages. Additionally, the $R^2$ between the ground measurements and the algorithm estimation is found to be consistently higher than 80.0%.

Since the proposed methodology gives promising results, it may encourage agriculturists and local authorities to use SAR data for their monitoring purposes. To sum up, the main strengths, limitations and opportunities of the proposed methodology are:

2.5.1 Strengths

• The algorithm depends on the rice crop morphology. The proposed approach extends the usage of existing classification algorithms. The results of the existing classification algorithms can be used instead of the \textit{a priori} growth phase information as a coarse classifier. The proposed method introduces the PCE\textsubscript{EM}-based parameter search space approach, resulting in an estimate of the BBCH based on crop morphology.
2.5 Overview and Summary

• Several genotype variations are available for rice crops. The range of admissible morphological parameters (e.g. crop height vs. leave size) may therefore need to be extended should data on new/additional crop morphologies become available. The proposed method can easily be updated automatically with each new crop morphology dataset by appropriately extending the allowed morphological parameter space. Therefore, each new data set will contribute to the preservation of the plant morphological growth principles for different genotypes. The possibility to extend the base morphological data sets allows the proposed approach to be extended to include new morphologies.

• The proposed method allows for the detection of in-field heterogeneities to observe growth abnormalities. The included feature clustering approach handles polarimetrically similar regions of the field separately and therefore spatially localized problems (e.g. sickness or overgrowth) can be handled unless they have statistically a representative number of samples.

2.5.2 Limitations

• Even though the results are promising, some aspects were omitted in the chosen backscattering model such as the 3D orientation of the scatterers, the curvature of the leaves and panicles and the agronomical exceptions as extreme water loss from the plants. Besides, according to the Directorate of Trakya Agricultural Research Institute, the rice fields located in Turkey are kept flooded until 10-15 days before harvesting. Therefore, the current implementation of the model only considers the flooded conditions and misses the non-flooded periods.

• The performance of the morphology estimation strongly depends on the performance of the backscattering model and the environmental conditions. Since the proposed approach was developed for fields with flooded or strongly moist underlying surfaces, further studies are needed to assess its applicability for fields with dry or slightly moist soil.

2.5.3 Opportunities

• The chosen theoretical backscattering model can be replaced by any other morphology-based EM backscattering model. The alternative models may lead to higher accuracies with a higher number of parameters. However, the uncertainties of the inputs should also be taken into account. Therefore, it is possible to state that, for an improvement in the inversion accuracy, the alternative models should have lower variance in their outputs, which can be achieved by inclusion of the cross-polarimetric channels (HV and VH). Additionally, the proposed approach is also applicable to the monitoring of different crop types by simulating their morphology and the underlying ground information with the theoretical EM backscattering model.

• With the inclusion of the metamodels, the computational cost of the inversion algorithms decreases significantly. This may lead to development of new backscattering models with realistic morphology.

Future work will focus on the evaluation of the proposed methodology using different frequencies, crop types as well as incidence angles and polarization settings (e.g. combinations of dual-pol or quad-pol). Ongoing and future missions such as RADARSAT-2, Tandem-L and Sentinel-1 will be excellent opportunities for these evaluations.

Acknowledgment

This work has been supported by the Scientific and Technological Research Council of Turkey (TUBITAK) under project 113Y446 and by the German Aerospace Center (DLR) under project XTILAND1476. Additionally, the authors would like to thank the Federacion de Arroceros de Sevilla and the Directorate of Trakya Agricultural Research Institute for proving the ground measurements from Spain and Turkey, respectively.
Figure 2.13 — Phenological stage estimation results of the proposed algorithm obtained over two different region of interests (ROI) located in Ipsala 2014 dataset. The growth stages are given as estimated/measured BBCH stage.

Figure 2.14 — Growth maps with the phenological stage estimation with BBCH scale in two different areas exploiting their temporal behaviour. The date of the images are given as day of year (DoY).
Chapter 3

A Multi-Year Study on Rice Morphological Parameter Estimation with X-Band PolSAR Data

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Submitted to Applied Science

Scientific Contributions

Yuzugulu built a combined database for ground and SAR measurements
proposed to investigate the morphological estimation accuracy for rice plants
developed and implemented the rice morphology estimation algorithm
interpreted the analysis results, prepared the figures, and wrote the manuscript

Erten suggested to compare plant morphology estimation accuracies in X- and C-band
assisted in interpretation of results and helped in writing the manuscript

Hajnsek provided the SAR data
assisted in interpretation of results and helped in writing the manuscript
Abstract: Rice fields have been monitored with spaceborne Synthetic Aperture Radar (SAR) systems for decades. SAR is an essential source of data and allows for the estimation of plant properties such as canopy height, leaf area index, phenological phase, and yield. However, the information on detailed plant morphology in meter-scale resolution is necessary for the development of better management practices. This letter presents the results of the procedure that estimates the stalk height, leaf length and leaf width of rice fields from a copolar X-band TerraSAR-X time series data based on *a priori* phenological phase. The methodology includes a computationally efficient stochastic inversion algorithm of a metamodel that mimics a radiative transfer theory-driven electromagnetic scattering (EM) model. The EM model and its metamodel is employed to simulate the backscattering intensities from flooded rice fields based on their simplified physical structures. The results of the inversion procedure are found to be accurate for cultivation seasons from 2013 to 2015 with errors less than 13.5 cm for stalk height, 7 cm for leaf length, and 4 mm for leaf width parameters. The results of this research provided new perspectives on the use of EM models and computationally efficient metamodels for agriculture management practices.

3.1 Introduction

Rice is the main source of food and income for several highly populated countries. The increasing population and limited arable lands bring out the need for higher yields that depends on the development of better management practices. The traditional method monitoring by visual inspection is not possible for kilometer-square areas. For such large scales, remote sensing based methods are good alternatives. Among different data sources, information provided by Synthetic Aperture Radar (SAR) is advantageous with its sensitivity to geometric and dielectric properties of the objects and its availability in all light and weather conditions. Therefore, SAR is a valuable tool for monitoring the rice fields [121].

Understanding the phenological evolution of rice fields is important to develop effective management strategies. In the literature, several SAR data based algorithms have been developed to investigate the phenological evolution of rice fields including their canopy height, growth stage, leaf area index and yields. In SAR based rice monitoring, one way of monitoring the phenological cycle is the use of different SAR data analysis techniques including temporal trend analysis [22, 46], interferometric analysis [67, 77] and polarimetric interferometry analysis [75, 122]. The other approach employs EM models to simulate the polarimetric parameters from plant properties [67, 87, 89].

This letter presents the inversion results of the metamodel-driven EM model for the estimations of stalk height, leaf length, and leaf width parameters from copolar X-band TerraSAR-X time series data. The chosen EM model [80] uses the biophysical properties of rice plants to simulate the backscattering intensities ($\sigma_o$) with Monte-Carlo simulations. The computation costs related to multi-dimensional algorithm and the Monte-Carlo simulations were reduced by introducing metamodels, which mimics the EM model after trained for once. The stability of the inversion was tested over a dataset of three different cultivation periods (2013-2015), which includes data from rice fields under different agricultural practices and environmental conditions.

This research letter has four sections. It starts with the proposed methodology in Section 3.2 by providing the EM model, its metamodel, and the inversion procedure. Section 3.3 and 3.4 presents the SAR and ground data followed by the inversion analysis results. Finally, the overall summary is provided in Section 3.5.
3.2 Methodology

3.2.1 Theoretical Model and its Surrogate Model

In this study the EM model [80], \(M(\xi)\), is employed to simulate the backscattering intensities, \(\bar{\sigma}^o\), from a set of rice plant morphology parameters, \(\xi\), through Monte Carlo simulations for varying scatterer locations. The \(\xi\) set includes stalk dimensions (height and diameter), leaf dimensions (length and width), panicle dimensions (length and width), and their structural densities. The simulations are done for a unit area \(A\), having randomly placed non-overlapping cylindrical stalks with a specific height and diameter. Each stalk is modeled to have elliptical leaves with a fixed length and width. In this study, we assumed flooded ground and plant components with fixed complex dielectric constants for the complete growth cycle by relying on the sensitivity analysis of the EM model [123]. The \(M(\xi)\), given in (3.1), provides the relation between an incident \(\bar{E}^i\) and a scattered wave \(\bar{E}^s\) through the coherent sum of four different scattering mechanisms \(S_n\), as shown in Figure 3.2.

\[
\bar{\sigma}^o_{qq} = M(\xi) = \frac{4\pi r^2}{A} \frac{|<E_q^s>|^2}{|E_q^i|^2} = \left(\frac{e^{ikr}}{r} \left(\sum_{n=1}^{4} S_n \right)\right)^2
\]

(3.1)

In the EM model given in (3.1), \(q\) and \(p\) subscripts correspond to transmitted and received horizontal (H) and vertical (V) linear polarization channels. The parameters \(k\) and \(r\) represent the free-space wavenumber and the distance between the sensor and the target, respectively. The \(\bar{\sigma}^o_{qq}\) for the different polarimetric channels, \(qq\), are approximated from the ratio between \(E_q^s\) and \(E_q^i\).

The \(M(\xi)\) has high computation cost due to its multi-dimensional algorithm and Monte Carlo simulations. The computation costs of the algorithm were reduced using sparse Polynomial Chaos Expansion (PCE) metamodels. The PCE metamodels are spectral variance decompositions of the original model with low training cost and wide coverage in the parameter domain [119]. For the chosen \(M(\xi)\), its PCE metamodel, \(PCE_{EM}(\xi)\), is developed from the (3.2).

\[
M(\xi) \approx PCE_{EM}(\xi) = \sum_{j=0}^{\infty} a_j \Psi_j(\xi) \approx \sum_{j=0}^{N} a_j \Psi_j(\xi).
\]

(3.2)
In (3.2), \( a_j \in \mathbb{R} \) is a set of scalar coefficients and the \( \Psi_j(\xi) \in \mathbb{R} \) form a polynomial orthonormal basis [102]. For practical reasons and to avoid over fitting conditions, the metamodels were limited to \( N (=20) \) expansions. In this study, the PCE\(_{\text{EM}}\) metamodel, \( Y(\xi) \), was implemented with the UQLab toolbox [118].

### 3.2.2 Probabilistic Particle Swarm Optimization

The inversions of multi-dimensional EM models are ill-posed problems with the higher number of unknowns compared to the number of equations. For such problems, optimization algorithms are used to reach the optimum solution in the parameter space using different constraints. However, the optimization of multi-dimensional EM model inversions may result in multiple optimum solutions since different inputs can lead to similar outputs. The presence of multiple optimum solutions prevents the use of deterministic optimization algorithms that focus on a single solution. For the existence of multiple solutions, stochastic optimization algorithms can be considered as an alternative. In stochastic optimization, the procedure is initiated several times to obtain all local solutions in a given parameter space based on the defined set of rules.

In this study, the Particle Swarm Optimization (PSO) algorithm [124] is utilized, which is based on updating the position of the particles, i.e. possible solutions, until they converge to an optimum solution within a parameter space. In each iteration, the locations of the particles are updated according to the position of the particle with the best position. The iterations continue until the particles converge to a solution that agrees with the defined constraints. For the estimation of rice morphology parameters from copolar X-band SAR backscattering intensities, the PCE\(_{\text{EM}}\) metamodel is inverted with the stochastic PSO algorithm.

The fitness function for the PSO is given in (3.3) for HH and VV polarimetric channels and an arbitrary \( i^{th} \) iteration. The fitness function is defined to minimize the difference between measured \( \sigma_0^{\text{HH,VV}} \) and estimated \( \bar{\sigma}_0^{\text{HH,VV}} \) values. The consistency of the solutions for different polarimetric channels is provided by considering the same input vector for both polarimetric channels.

\[
\min C_i = \left( \sigma_0^{\text{HH}} - \bar{\sigma}_0^{\text{HH}} \right)^2 + \left( \sigma_0^{\text{VV}} - \bar{\sigma}_0^{\text{VV}} \right)^2 \quad i = 1...K
\tag{3.3}
\]

Optimization problems need constraints to simplify the problem by reducing the dimensional complexity. In PCE\(_{\text{EM}}\) metamodel inversion, three plant morphology dependent constraints were established that are based on the natural limitations excerpted from the available morphology data.

- **Positivity constraint** ensures positive and real morphological estimations for all iterations.
- **Min-Max constraint** limits the morphological estimations based on the phenological phase boundaries. Phenological phases are defined by the International Rice Research Institute (IRRI) [2]. The scale divides the growth cycle to five major phases. Figure 3.3 presents the boundaries obtained from ground data, for the chosen morphological parameters.
- **Natural limitations** provide non-linear relationships among rice morphology parameters during their development. These relations eliminates the solutions which might be impossible for a healthy plant, such as a 10-cm-tall stalk having two 50-cm-length leaves. This condition restricts the parameter space with a convex hull. Convex hull defines non-linear boundaries in a parameter space according the ground measurements that involve the agronomically possible solutions.

The stochastic PSO optimization provides distributions for each morphology parameter. For the accuracy analysis, the mean value of the resulting stochastic distributions is assigned as the estimated dimensions of the rice morphological parameters. For a single stochastic PSO optimization, a total number of 200 iterations was found to be sufficient for the optimization convergence which changes less than 0.1% regarding the mean of the estimated values.
3.3 Datasets

3.3.1 The Ipsala Test Site and Ground Data

The selected test area, Ipsala, is located in the North-West part of Turkey with its center at N 37°7’53” and E 6°19’32” coordinates. Ipsala is one of the biggest rice cultivation sites in Turkey with approximate acreage of 190 square kilometers. Based on the knowledge gathered from the Trakya Agriculture Research Institute (TARI), rice cultivation is done in the area by local farmers between May and September.

Field campaigns were conducted ±5 days of SAR acquisitions for crop morphology measurements. A total number of five broadcast seeded, and wet cultivated rice fields were selected by the expertise of the local researchers. To monitor the evolution of the plants, at each field seven parameters were monitored, namely: above water stalk height, stem diameter, leaf length and width, the number of plants per m², the number of tillers per plant, and the number of leaves per tiller. Figure 3.3 visualizes the distributions of some parameters for each IRRI growth stage using a box-whisker plot. In each parameter, a quasi-linear increase is observed until IRRI-3. From IRRI-3 on while most of the parameters tend to saturate, the stalk diameter starts to decrease.

3.3.2 SAR Data

During the study, the Ipsala test site is monitored with the data acquired from the TerraSAR-X satellite with an average incidence angle of 31°. The TerraSAR-X satellite has the central frequency of 9.65 GHz and temporal resolution of 11 days. The acquisition dates are given in Figure 3.4. The data were delivered in single look complex format and were spatially and temporally co-registered by bilinear interpolation.

Figure 3.3 – Temporal variations of the rice crop biophysical parameters from 2013-2014 Ipsala ground campaigns with respect to the growth stage as a Box-and-Whisker plot. Boxes present the quartiles while the whiskers present the ranges for IRRI growth stages (IRRI-1 [Early vegetative], IRRI-2 [Late vegetative], IRRI-3 [Early reproductive], IRRI-4 [Late reproductive], IRRI-5 [Maturative].
Figure 3.4 – The ground and SAR data collection dates for the cultivation period between 2013 and 2015. On the right side, the VV channel PolSAR intensity image is also provided from the June 30th, 2013. In the image, rice fields can be detected with their higher backscattering intensities.

3.4 Results and Discussions

In this section, we present the stochastic inversion results of the same PCE\_EM metamodel for the estimation of stalk height, leaf length and leaf width parameters from X-band co-polar SAR data on a dataset spanned over three cultivation periods. For the analysis, the noise in the TerraSAR-X data was reduced using 13×13 boxcar smoothing windows. The estimation accuracies of the chosen parameters are evaluated based on their correlation against the ground measured values. The results are reported with their R^2, and the RMSE values.

Table 3.1 provides the input parameters for the PCE\_EM metamodel evolutions that were assumed constant. The details of the EM model, its metamodel, their simulation accuracies and growth phase based global sensitivity analysis results of the PCE\_EM metamodel are provided in [123].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central frequency</td>
<td>9.65 GHz</td>
</tr>
<tr>
<td>Dielectric constant ((\epsilon_{s,l}))</td>
<td>25+8j</td>
</tr>
<tr>
<td>Dielectric constant ((\epsilon_{g}))</td>
<td>70+20j</td>
</tr>
<tr>
<td>Average incidence angle ((\theta))</td>
<td>31°</td>
</tr>
<tr>
<td>Distance to target</td>
<td>514 km</td>
</tr>
<tr>
<td>Illuminated area x-size</td>
<td>2.58 m</td>
</tr>
<tr>
<td>Illuminated area y-size</td>
<td>1.79 m</td>
</tr>
<tr>
<td>Number of MC iterations</td>
<td>200</td>
</tr>
</tbody>
</table>

The chosen EM model and the proposed stochastic inversion approach consider the simplified plant morphology. As observed in Figure 3.3, the evolution of chosen morphological parameters are related to the each other. In the proposed method these morphology based relations provide the base of the optimization constraints. As the stochastic inversion algorithm provides multi-dimensional parameter distributions, the mean values of the estimations are used for the calculation of R^2 and RMSE values.

The stochastic inversion results for stalk height, leaf length, and leaf width parameters are presented in Figure 3.5 and Table 3.2. The R^2 and RMSE were calculated against the estimated biophysical parameters are given for the cultivation periods from 2013 to 2015. The accuracy analyses were conducted using a total number of 93 different \(\sigma^o\) values (32 from 2013, 25 from 2014, and 36 from 2015) measured from different fields having different morphologies, agricultural practices and environmental conditions.
3.4 Results and Discussions

Figure 3.5 – The measured (stalk height, stalk diameter, leaf length and leaf width) versus the estimated parameters are given in a correlation scatter plot for X- and C-band inversion results with the reference line and $R^2$ values. Symbols are colored and shaped with respect to the ground measured IRRI growth phases (IRRI 1 [Early Vegetative] - ×, IRRI 2 [Late Vegetative] - ● and IRRI 3 [Early Reproductive] - ▲).

The global sensitivity analysis of the PCE$_{EM}$ metamodel was previously discussed in [123]. The analysis results emphasize the importance of stalk height, leaf length and structural density parameters (number of plant components in a unit area) throughout the growth cycle. The following deductions can be made from the stochastic inversion results.

**Stalk Height** estimations had the highest accuracy ($R^2 \geq 0.86$) considering the entire dataset of three cultivation periods. As presented in Figure 3.5, the stalk height estimation results are slightly over-estimated for rice canopies shorter than 0.6 m and under-estimated for the taller canopies. The performance of the algorithm for the 2015 dataset was calculated to be lower compared to the other years with an RMSE value of 13.5 cm. This situation can be related to the variance of the $\sigma^o$ values and the PCE$_{EM}$ metamodel simulations for the corresponding morphology parameter ranges in the parameter space. On the other hand, the estimation bias between the measured and estimated values shows an increasing spread with increasing stalk height. The variation in the bias can be interpreted by the presence of plants with varying physical structures and similar backscattering behaviors at later phases of the growth cycle. The RMSE values were calculated to be less than 13.5 cm, which are acceptable for the stalk height estimations calculated from copolar SAR data.

**Leaf Length** estimation accuracy is calculated to be lower than the stalk height estimation accuracy for the dataset of three cultivation periods. As shown in Figure 3.5, the leaf lengths are mainly over-estimated when they are shorter than 50 cm and under-estimated when they become longer. The stochastic inversion results of the PCE$_{EM}$ metamodel shows highly accurate results ($R^2 \geq 0.78$ and $\text{RMSE} \leq 7$ cm) for the evaluations from the complete dataset. From three different years, the lowest accuracy was obtained from the data acquired during 2015, as it was observed for the stalk height. Regarding the estimation bias, it is noted that the errors tend to increase with increasing leaf length. The increasing error with increasing leaf length can be explained by the presence of higher variance in the parameter space at later growth phases.

**Leaf Width** is morphologically related to the leaf length due to natural growth limitations. The accuracy analysis on leaf width estimations presented acceptable values with $R^2$ values higher than 0.61 and RMSE values lower than 3 mm. Similar to stalk height and leaf length parameters, the lowest accuracy was again obtained from the copolar SAR measurements of 2015. The estimation bias of the analysis vary between ±5 mm for the complete growth cycles of three years.

The stochastic inversion of the PCE$_{EM}$ metamodel provided successful estimations for stalk height and leaf length parameters for the cultivation periods of three years. However, from the chosen rice morphology parameters, leaf width estimations had lower accuracies with higher relative RMSE values. This situation is supported by the global sensitivity analysis results, which states

---

35
Table 3.2 – Accuracy analysis of the stochastic inversion of PCE\textsubscript{EM} metamodel given with the calculated $R^2$ and RMSE values for the years 2013, 2014, 2015 and the complete dataset

<table>
<thead>
<tr>
<th></th>
<th>Stalk Height</th>
<th>Leaf Length</th>
<th>Leaf Width</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$ RMSE</td>
<td>$R^2$ RMSE</td>
<td>$R^2$ RMSE</td>
</tr>
<tr>
<td>2013</td>
<td>0.921 0.108</td>
<td>0.804 0.069</td>
<td>0.646 0.003</td>
</tr>
<tr>
<td>2014</td>
<td>0.891 0.092</td>
<td>0.831 0.048</td>
<td>0.628 0.002</td>
</tr>
<tr>
<td>2015</td>
<td>0.868 0.135</td>
<td>0.776 0.055</td>
<td>0.613 0.003</td>
</tr>
<tr>
<td>Complete</td>
<td>0.894 0.116</td>
<td>0.848 0.057</td>
<td>0.717 0.003</td>
</tr>
</tbody>
</table>

the importance of stalk height and leaf length parameters on the PCE\textsubscript{EM} metamodel simulations, while mentions the lower effect of the leaf width [123].

The accuracy analysis exhibited in this study combines 93 different rice plant morphology and SAR measurements collected from the cultivation periods of 2013 to 2015. Concerning the presence of various environmental factors and agricultural practices, the results are considered to be representative for the wet-cultivated and broadcast seeded rice fields that are located in Ipsala (Turkey). Therefore, the results are encouraging for the development of new management practices, which can use the estimated morphology parameters to interpret the yield and the detailed growth stage.

3.5 Overview and Summary

In this research, a stochastic inversion method has been presented to invert a multi-dimensional PCE\textsubscript{EM} metamodel, trained from an EM model [80]. Apart from previous studies that estimates the stalk height, this study presents the estimations the stalk height, leaf length and leaf width parameters of rice plants over three cultivation cycles by considering the natural growth limitations.

We have tested the proposed inversion algorithm on a three-year cultivation period of ground, and copolar SAR datasets, which were acquired over broadcast seeded and flooded rice fields using the same PCE\textsubscript{EM} metamodel. We obtained significant correlations between the estimated and measured stalk height, leaf length and leaf width parameters using the proposed scheme. The results pointed out that the use of spaceborne X-band PolSAR data is significant for the development of new management practices. From the analysis, we calculated RMSE values less than 13.5 cm for stalk height, 6.9 cm for leaf length and 34 mm for leaf width parameters. We should mention that the overall performance of the approach relies on the EM model and the PCE\textsubscript{EM} metamodel.

The presented algorithm has several advantages such as coupling the agronomical growth rules with the EM models, inversion with stochastic optimization and most importantly being computationally efficient with the use of metamodels that are trained for once. In the presented study, the requirement of a priori knowledge of the growth phase and plant morphology information can be seen as a disadvantage. Considering the importance of rice and the existing research, related information can be found in the crop databases. Besides, in the literature, there are several different methodologies to determine the growth phase of rice plants [46, 57, 65].

In the future, studies are planned to improve the approach by substituting the a priori growth phase information with canopy height estimations that can be directly calculated from Pol-InSAR data. Besides, it is planned to extend the applicability of the inversion procedure to other crops.

Acknowledgments

The authors would like to thank for the support of Dr. Stefano Marelli and Prof. Dr. Bruno Sudret from the Chair of Risk, Safety & Uncertainty Quantification from ETH Zurich in setting up and providing help with the Polynomial Chaos Expansion metamodel and to the Directorate of Trakya Agricultural Research Institute with the ground campaigns.
Chapter 4

Estimation of Rice Crop Height from X- and C-Band PolSAR by Metamodel based Optimization

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Scientific Contributions

Yuzugullu built a combined database for ground and SAR measurements
proposed, developed and implemented the stochastic inversion for EM model
evaluated the plant height estimation performance for different frequencies and channels
interpreted the analysis results, prepared the figures, and wrote the manuscript

Erten proposed to investigate the feasibility of rice height estimation using EM model inversion
assisted in interpretation of results and helped in writing the manuscript

Hajnsek provided the SAR data and suggested to investigate performances in different frequencies
assisted in interpretation of results and helped in writing the manuscript
Abstract: Rice crops are important in global food economy and are monitored by precise agricultural methods, in which crop morphology in high spatial resolution becomes the point of interest. Synthetic Aperture Radar (SAR) technology is being used for such agricultural purposes. Using polarimetric SAR (PolSAR) data, plant morphology dependent electromagnetic scattering models can be used to approximate the backscattering behaviours of the crops. However, the inversion of such models for the morphology estimation is complex, ill-posed and computationally expensive. Here, a metamodel based probabilistic inversion algorithm is proposed to invert the morphology based scattering model for the crop biophysical parameter mainly focusing on the crop height estimation. The accuracy of the proposed approach is tested with ground measured biophysical parameters on rice fields in two different bands (X- and C-) and several channel combinations. Results show that in C-band the combination of the HH and VV channels has the highest overall accuracy through the crop growth cycle. Finally, the proposed metamodel based probabilistic biophysical parameter retrieval algorithm allows estimation of rice crop height using PolSAR data with high accuracy and low computation cost. This research provides a new perspective on the use of PolSAR data in modern precise agriculture studies.

4.1 Introduction

Rice is an important crop, whose cultivation is an important building blocks of several economies in the world. In the history of the agriculture, rice goes back to 8.000 BC and even today, it keeps it’s economical importance for the rural communities. Therefore, like many other crops, rice needs to be monitored frequently to optimize it’s competitiveness in the global food market. Because of these reasons, there is a wealth of knowledge about rice in the literature, including it’s morphology, phenology and the impacts of environmental factors on growth. Efficient monitoring techniques such as remote sensing exist for precise agricultural monitoring.

Remote sensing systems provide solutions over large areas. As an advantage, Synthetic Aperture Radar (SAR) systems provide day-and-night and all-weather operation capability and unlike other remote sensing systems, they are sensitive on the physical properties of the target in the 3D space. Thus, SAR becomes the perfect candidate for precise agriculture studies in terms of [125, 126] biophysical parameter estimation.

Considering the precise agriculture concept, the estimation of crop parameters by means of SAR includes various techniques such as polarimetry (PolSAR) [87, 127], interferometry (InSAR) [128, 129], differential interferometry (DInSAR) [77, 78], polarimetric interferometry (PolInSAR) [75, 130] and tomography (TOMO-SAR) [131]. In principle these methods, except PolSAR, allow estimation of crop parameters such as canopy height. Also, they do not require any a priori information. However, it is not always so trivial to acquire such SAR data. At this point by combining the knowledge of the agricultural and environmental principles with the fundamentals of the SAR polarimetry, it is possible to increase the accuracy of low cost analysis. In this case, it is possible to combine a priori information such as biological growth rules and boundaries of a specific crop, with PolSAR methods which focus on figuring out the interaction of the electromagnetic waves with the canopy. In this paper, polarimetric channel and frequency based comparisons are provided for a scattering model inversion algorithm, which estimates the observables from the measurements, to exploit the efficiency of PolSAR in estimation of the morphology by focusing on the stalk height.

The growth stage of agricultural crops can be coarsely determined using methods that employ single [22, 46, 56] or multiple [57, 72, 132] acquisitions. However, none of these methods are capable of explaining the crop morphology. To estimate the morphology, a deeper relation is required.
In the literature this explanation is covered by two different approaches: backward and forward. The backward approach [22, 50] shows the relation of the biophysical parameters and the backscattering coefficients under different frequency and incidence angles. On the other hand, the forward approach uses the scattering models [83, 84, 108, 113] to approximate the backscattering coefficients from a given complex plant morphology. Due to the under-determined character of such morphology based scattering models, analytical inversion is extremely challenging. Towards solving this issue, [87] has applied a genetic algorithm to estimate the height and density of paddy rice from RADARSAT-2 data. Apart from the methods present in the literature, this study focuses on the multi-dimensional distribution of the possible morphologies by following a probabilistic approach using the well-known Particle Swarm Optimization (PSO) [124].

Morphology based scattering models consider the real physical structure of the plants and therefore have complex algorithms. In this complexity, the importance of the parameters should be known, which is achieved by means of global sensitivity analysis (GSA). This allows understanding of the physics behind the scattering behaviour. The model proposed by [113] is a well-known example of such scattering models. For the chosen model, the GSA analysis has been done using Sobel’ indices using a high dimensional model representation (HDMR), in terms of the polynomial chaos expansion (PCE) metamodel. It showed that canopy height and the vertical structural density are the most important biophysical parameters for the model output [123]. As a forward step, in this paper we focus on the height estimation accuracy of the complex scattering model under different frequencies and channel combinations by taking coarse growth phase information as a priori.

The paper is structured in four main sections. The proposed methodology as shown in Figure 4.1 is explained including the details of the scattering model and the metamodel in Section 4.2. Section 4.3 provides a brief explanation of the ground and the SAR data, and the results of the frequency and the polarimetric channel comparisons are presented in Section 4.4.

4.2 Methodology

4.2.1 Theoretical Model and the PCE Metamodel

Temporal changes in the SAR backscattering signature of a rice canopy is closely related to variations in the biophysical properties (e.g. stalk, leaf and panicle structure) and the water content of the canopy in time. This section focuses on the HDMR of a morphology based incoherent theoretical scattering model with the PCE metamodel.

The model used in this study to simulate the rice canopy is one of the more complex ones in the literature, which considers complete plant structure. To start with, it considers the complete plant morphology by allowing for the inclusion of the location of the scatterers and their quantitative densities. Moreover, it also takes into account the backscattering enhancement and the clustering effects of the scatterers [80]. Thus, the final backscattering coefficients for different polarimetric channels are calculated by Monte Carlo (MC) simulations over a group of dielectric cylinders and elliptical disks over a dielectric half space [112].
The model simulates a unit illuminated area, \( A \). Inside \( A \), the plants are randomly placed and made sure that none of them are overlapping. In area \( A \), there are \( n_s \) plants with \( n_t \) stalks with a height of \( h_s \) and a diameter of \( d_s \). Each stalk has \( n_l \) leaves with a length of \( l_l \) and a width of \( w_l \). Last but not the least in the list of plant structures, there are \( n_p \) panicles with a length of \( h_p \) and a diameter of \( d_p \). In addition, complex dielectric constants \( (\epsilon_{s,l}) \) include the effect of the moisture content. Finally, flooded ground is characterized by the complex dielectric constant \( \epsilon_g \).

The corresponding backscattering algorithm considers four independent scattering mechanisms \( (S_n) \), visualized in Fig. 4.2.

- \( S_1 \): Direct scattering from the scatterers
- \( S_2 \): Scattering from the canopy followed by reflection from the ground
- \( S_3 \): Reflection from the ground followed by scattering from the canopy
- \( S_4 \): Reflection from the ground followed by scattering from the canopy and followed by reflection from the ground

The sum of these four scattering mechanisms relate the incident \( (i) \) wave \( \vec{E}^i \) to the scattered \( (s) \) wave \( \vec{E}^s \) as in (4.1).

\[
E_q^s(r) = \frac{e^{i k r}}{r} (S_1 + S_2 + S_3 + S_4) \vec{E}^i_p \tag{4.1}
\]

In (4.1) \( q \) and \( p \) correspond to transmitted and received polarization channels respectively. Lastly, the backscattering coefficients for the different channels, \( q_p \), are approximated from the ratio between \( E_q^s \) and \( E_p^i \) while the wave travels through the distance between the sensor and the target, \( r \), as given in (4.2).

\[
\sigma_{qp}^o = \frac{4 \pi r^2 \langle |E_q^s|^2 \rangle}{A |E_p^i|^2} \tag{4.2}
\]

The chosen complex morphology based scattering model is computationally expensive due to the included MC simulations, requiring long computation times. In this paper, this issue is handled by introducing HDMR methods. Such high dimensional representations substitute any mathematical model to an input-output metamodel by applying a polynomial expansion. Such that, for a function, \( f \), with input vector, \( x \), the expansion is written as in (4.3).

\[
f(x) = f_0 + \sum_{i=1}^{n} f_i(x_i) + \sum_{i<j} f_{ij}(x_i, x_j) + \ldots + f_{12\ldots n}(x_1, x_2, \ldots, x_n) \tag{4.3}
\]

The metamodels are the response surface of a surrogate model with unknown coefficients. Since they are polynomial expansions, their coefficients can be estimated by means of optimization algorithms. Fortunately, when they are compared to the original model, they provide significantly similar behaviour. With their polynomial based algorithm, they are memory efficient and computationally inexpensive. It should be mentioned that using such models as a substitute to the complex
models boosts the efficiency up to $10^4$ times. In this study, PCE, developed by [119], was implemented in MATLAB® using the Uncertainty Quantification Laboratory (UQLab) toolbox [120]. In this way it reduces the computational cost of the approach by handling the multi-dimensionality of the retrieval problem.

### 4.2.2 Probabilistic PSO

Agricultural crops are biophysically complex structures through their growth cycle. Inverting the complex mathematical relation between the morphology and an electromagnetic wave traveling inside the canopy creates an under-determined problem. In such problems the number of unknowns (i.e. morphological parameters) are higher than the number of equations (i.e. polarimetric backscattering intensities). Selecting optimization algorithms is a good tool to overcome this shortcoming. Using optimization, the extrema (e.g. minima and maxima) points of the model can be determined empirically. However, use of data with high variation may reduce their accuracy by leading to a local extrema. To reduce this uncertainty, a probabilistic approach is preferred, which considers a constrained region in the parameter space and provides a set of solutions that includes the function extrema as well. In the probabilistic methods, multiple initiations have been done aiming the same output to have an idea of the distribution of the solution.

In the literature there are several optimization methods to handle multi-variate problems. Methods like genetic algorithm (GA), artificial neural networks (NN) and evolution strategy (ES) are some examples for flexible and intelligent algorithms. However, due to the complex logic behind, they require numerous adjustments. In this study, to keep the inversion approach simple and effective, PSO is considered. The PSO algorithm optimizes a problem by iteratively improving the solution using a population of candidates based on the initial velocity and position of each particle. During an iteration, each particle is affected by the particle that has the best position in the search-space. Thus, the particles continuously moves to find the local/global extremes inside the boundaries [124].

In this study the fitness function for the PSO algorithm is developed using the PCE metamodel of the morphology based backscattering model. As the PCE metamodel mimics the scattering model, morphology vector $X$, given in (4.4) is taken as an input and the backscattering intensities, $\sigma_{qp}$ is produced as output.

$$X = [h_s, d_s, n_s, l_t, w_l, n_l, d_p, n_p] \quad (4.4)$$

The PSO algorithm is used to minimize the output of the fitness function by varying the $X$ vector in every $i^{th}$ initiation. The full-polarization fitness function of the corresponding optimization problem for the $i^{th}$ iteration is given in (4.5). The structure of the designed fitness function is flexible and it can be modified for different channel combinations (e.g. single-, dual- or quad-polarization). In other words, based on the preferred polarimetric channels, unused components of the fitness function can be eliminated from the linear equation. The idea behind using multiple polarimetric channels in the same fitness function is to consider the same morphological structure and therefore to fix the parameter space. In (4.5), $\sigma_{qp}$ and $\bar{\sigma}_{qp}$ correspond to measured and PCE estimated backscattering intensities in several $qp$ (HH, HV, VV) channels respectively.

$$\min C_i = (\sigma_{HH} - \bar{\sigma}_{HH})^2 + (\sigma_{HV} - \bar{\sigma}_{HV})^2 + (\sigma_{VV} - \bar{\sigma}_{VV})^2 \quad (4.5)$$

Almost all of the optimization algorithms require boundary conditions, also called constraints, to reduce the complexity of the problem and to avoid the presence of misleading results. In this study, constraints are chosen based on the biophysical principles of the agricultural crops. The PSO algorithm, used in this paper, considers three given constraints.
• **Positivity constraint:** In the physical world with the biological growth rules, a plant dimension cannot be negative. Therefore, this constraint forces the optimizer to keep the sizes of the all morphological parameters positive under all conditions.

• **Min-Max constraint:** Based on the coarse growth phase of the crop, the biophysical parameters have specific minimum and maximum values. The ranges are given in Fig. 4.5. For this constraint, the growth boundaries are extended by 10% to take the extreme conditions into account.

• **Morphological constraint:** Within a crop type, each biophysical parameter evolves in accordance with the others following biological growth rules. Because of this, some crop morphologies are biophysically impossible to observe under healthy conditions. Such as, it is not possible to observe a rice plant with 2 m height and 1 leaf with 10 cm in length. Thus, they are eliminated using the convex hull obtained from the ground based morphology dataset. By this, biophysically possible morphologies are obtained.

Such constraints bound the optimizer, thus reduce the computational cost. Additionally, the use of morphological growth boundaries increases the accuracy of the analysis. The optimization procedure is stopped after the percent change in the elements of the morphological vector is less than 1%. In this study the PSO algorithm has been initialized 200 times to generate representative parameter distributions. Lastly, the mode of the resulting distribution is used as the extrema point.

### 4.3 Datasets

#### 4.3.1 The Ipsala Test Site and Ground Data

The investigated area is near the Lake Gala National Park in the Thrace region, north west of Istanbul, Turkey. It is centred at N 37°7'53" and E 6°19'32" and has a flat topography. It is one of the major rice cultivation areas in Turkey with an area of 20 km×30 km. In the region single season rice cultivation is done from late April to early October. The Meriç (Evros or Maritsa) river flows close to the rice fields and provides the majority of the fresh water requirement of the irrigation districts. Fig. 4.3. visualizes the location of the test site and the fields with example photos from a test field.

The ground surveys were conducted synchronous to the SAR data acquisitions to measure the rice crop morphology through the full growth cycle. A total of five test fields were selected from the area of interest, which were geo-referenced by a GPS before the campaign. At each test site a total of 7 bio-physical parameters were monitored: stalk height above water surface, stalk diameter, leaf length and width, number of plants per m², number of tiller per plant and number of leaves per tiller. Additionally, the growth stages are reported in terms of the BBCH, which increases from 1 to 99 during the phenological cycle. Fig. 4.4. visualizes the temporal trend of the BBCH stage.

Fig. 4.5. shows the temporal changes in bio-physical parameters as a function of the BBCH. For each parameter, a quasi-linear increase is observed until mid-late reproductive stage. Later, while most of the morphological parameters tend to stabilize, the stalk diameter starts to decrease due to reduced water content. The differences within descriptors at a specific growth stage can also be related to the differences in the environment.

#### 4.3.2 SAR Data

The Ipsala test site was observed with the TerraSAR-X (TSX) and RADARSAT-2 (RS2) in 2014. The acquisition dates of the TSX and RS2 data are shown in Fig. 4.4. The TSX data were acquired by the German Aerospace Center (DLR) and the RS2 by the Canadian Space Agency. The data is delivered in single look complex (SLC) format and co-registered by using bi-linear interpolation.
4.3 Datasets | TerraSAR-X & RADARSAT-2 | Turkey’14

Figure 4.3 – The location of the test area (Ipsala, Turkey). The test fields for the ground measurement are framed in the figure. Photos at the left represent red framed rice fields in given dates.

TSX and RS2 systems have two major differences. Firstly, TSX operates in the central frequency of 9.65 GHz, while RS2 operates in the 5.35 GHz. Due to this difference, TSX is more sensitive to small scaled biophysical changes. Also, the penetration depth inside the canopy increases with decreasing frequency. Therefore, RS2 interacts more with the lower parts of the canopy. Secondly, TSX and RS2 have temporal resolution of 11 and 24 days, respectively. Such that, TSX allows more frequent monitoring than the RS2 system.

Figure 4.4 – Acquisition dates for SAR data in 2014, given with the temporal variation of the BBCH stages for test fields.
4.4 Results and Discussions

This paper presents two important comparisons for the estimation of biophysical parameters using a proposed probabilistic inversion approach. The first comparison considers the effect of frequency (Section 4.4.1) between X- and C-band SAR data. The second comparison takes the possible polarimetric channel combinations into account (Section 4.4.2). For the second comparison, quad-pol RS2 data are used. The accuracy of comparisons are not only evaluated over the correctness of the estimation but also the convergence rate of the optimization based algorithm.

This rate of convergence can be quantified using three basic statistical parameters, which tests the similarities between resulting set of solution and its relationship to the delta function. The first parameter, range, is the difference between the maximum and the minimum value of the distribution. Higher range means that distribution is widely spread. In terms of convergence, it means that the algorithm has a comparable lower rate of convergence. The second parameter is absolute value of the one minus the ratio between the mean and the median of the resulting distribution. As this value gets closer to zero, skewness of the distribution reduces and convergence increases. The third and the last parameter is the standard deviation of the resulting distribution, which is sign of a higher convergence rate with its lower value.

A PCE metamodel representing a theoretical electromagnetic backscattering model is used for the forward approach which simulates from the biophysical parameters to obtain backscattering coefficients. The parameters given in Table 4.1 were assumed constant during the evaluations, either due to low degree of sensitivity of the backscattering model to the parameter or because they are system parameters [82].

Based on the constant parameters shown in Table 4.1, simulations for the available ground data are completed. The accuracy analysis of the simulations are provided in Table 4.2. Interpreting the results, simulations for the individual band showed that co-polar X-band channels has a slightly higher accuracy than C-band. Additionally, X-band HH channel and C-band VV channel provided

![Figure 4.5 – Temporal variations of the rice crop biophysical parameters from 2014 Ipsala ground campaign with respect to the growth stage as a Box-and-Whisker plot. Box presents the information for the quartiles while the whiskers present minimum and maximum values.](image)
4.4 Results and Discussions

Table 4.1 – Input parameters that are kept constant for the simulations given for both tested frequencies.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>X-Band value</th>
<th>C-Band value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central frequency [GHz]</td>
<td>9.65</td>
<td>5.35</td>
</tr>
<tr>
<td>Dielectric constant, plant</td>
<td>25.7+8j [80]</td>
<td></td>
</tr>
<tr>
<td>Dielectric constant, ground</td>
<td>74+21j [80]</td>
<td></td>
</tr>
<tr>
<td>Average incidence angle [deg]</td>
<td>31</td>
<td>29</td>
</tr>
<tr>
<td>Distance to target [km]</td>
<td>514</td>
<td>798</td>
</tr>
<tr>
<td>Illuminated area x-size [m]</td>
<td>2.6</td>
<td>7.6</td>
</tr>
<tr>
<td>Illuminated area y-size [m]</td>
<td>1.8</td>
<td>5.2</td>
</tr>
<tr>
<td>Number of realizations</td>
<td>250</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.2 – The measured SAR versus the estimated theoretical backscattering intensities given by $R^2$ and RMSE values for different channels

<table>
<thead>
<tr>
<th>Channel</th>
<th>$R^2$</th>
<th>RMSE [dB]</th>
</tr>
</thead>
<tbody>
<tr>
<td>TSX</td>
<td>HH</td>
<td>0.871</td>
</tr>
<tr>
<td></td>
<td>VV</td>
<td>0.846</td>
</tr>
<tr>
<td>X-Band</td>
<td>HH</td>
<td>0.813</td>
</tr>
<tr>
<td></td>
<td>VV</td>
<td>0.831</td>
</tr>
<tr>
<td>RS2</td>
<td>HH</td>
<td>0.782</td>
</tr>
<tr>
<td></td>
<td>HV</td>
<td>0.782</td>
</tr>
<tr>
<td>C-Band</td>
<td>VV</td>
<td>0.831</td>
</tr>
</tbody>
</table>

higher $R^2$ (coefficient of determination) and lower RMSE (root mean square error) values. The lowest accuracy was observed in C-band cross-polarization channel, HV.

The chosen backscattering metamodel is strongly affected by the changes that take place in bio-physical parameters. Global sensitivity analysis based on the PCE variance decomposition showed that the majority of the uncertainty in the metamodel output is due to the canopy height and the vertical density of the scatterers. Additionally, starting from the late reproductive stage, the density of the panicles significantly contributes to the metamodel output. [123].

The scattering metamodel and the proposed probabilistic inversion algorithm considers complete morphological structure. Therefore, each height value is supported with a full physical structure including stalk density, leaf length and width, panicle length and diameter and density descriptors as number of plants per m$^2$ and number of tiller, leaves and panicles per plant. Consequently, the results need to be analysed by taking this information into account.

The following sub-sections present the estimation accuracy of the height parameter, which has the highest uncertainty among the model input parameters, in the scattering metamodel. The results were obtained using the proposed probabilistic inversion algorithm over the metamodel using the PSO given for different frequencies (4.4.1) and different polarization combinations (4.4.2).

4.4.1 Estimation Accuracy: X-Band and C-Band

As shown in Fig. 4.6, the probabilistic inversion of the scattering algorithm for height estimation are calculated for three distinct times that have different coarse growth phases. The first group of results belong to the early vegetative and the following two groups correspond to late vegetative and early reproductive stages respectively. In order to have a viable study, similar resolutions in TSX and RS2 data and HH-VV channel combination fitness function are used for the optimization analysis. For this, $13 \times 13$ and $11 \times 11$ window sizes are used for TSX and RS2, respectively. The results are presented over five independent test fields. The color scale in Fig. 4.6 represents the detection probability of the canopy height with the black line representing the value of the field-averaged ground measurement.
Chapter 4 Rice Plant Height Estimation using X- and C-Band PolSAR

Figure 4.6 – Height estimation accuracy distribution plots for 3 different dates and for 5 spatially independent Test Areas (TA). T and R correspond to TerraSAR-X and RADARSAT-2. Number of iterations = 200

Table 4.3 – Field average convergence rate values X- and C-band data in the early vegetative phase.

<table>
<thead>
<tr>
<th></th>
<th>X-band</th>
<th>C-band</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range [m]</td>
<td>0.19 ± 0.02</td>
<td>0.15 ± 0.03</td>
</tr>
<tr>
<td>abs(1-(Mean/Median))</td>
<td>0.15 ± 0.01</td>
<td>0.05 ± 0.03</td>
</tr>
<tr>
<td>Standard Deviation [m]</td>
<td>0.071 ± 0.015</td>
<td>0.042 ± 0.007</td>
</tr>
</tbody>
</table>

During the early vegetative stage, the probabilistic inversion algorithm for each frequency has consistent results. In this stage, stalk height varies between 5 cm and 30 cm. There is no obvious over or under estimation trend for the full test fields. The majority of the deviation of the estimation from the ground measurement varies in the range of ± 10 cm. Besides, as shown in Table 4.3, the proposed algorithm has better rate of convergence in C-band compared to X-band. This may originate from the sensitivity of X-band to smaller scaled morphological changes, in which the growth of plant structures affect X-band backscattering behaviour stronger than C-band.

Table 4.4 – Field average convergence rate values X- and C-band data in the late vegetative phase.

<table>
<thead>
<tr>
<th></th>
<th>X-band</th>
<th>C-band</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range [m]</td>
<td>0.80 ± 0.06</td>
<td>0.83 ± 0.07</td>
</tr>
<tr>
<td>abs(1-(Mean/Median))</td>
<td>0.06 ± 0.03</td>
<td>0.05 ± 0.03</td>
</tr>
<tr>
<td>Standard Deviation [m]</td>
<td>0.151 ± 0.012</td>
<td>0.134 ± 0.017</td>
</tr>
</tbody>
</table>

After the early vegetative stage, the plant goes into the late vegetative phase. During this stage, the plant height evolves from 15 cm to 110 cm, while the backscattering intensities increase 10 dB in average for each individual channel (e.g. HH, HV and VV). Moreover, as shown in Fig. 4.5, this phase has the largest available morphological parameter space. Therefore, as shown in Table 4.4, the convergence rate for different morphological parameters are reduced in both frequencies, which causes a higher deviation in the inversion results. Additionally, in this stage the scattering algorithm tends to under estimate for X-band and over estimate for C-band. This condition has both model-based and physical reasons. From the model point of view, variation in the model parameters changes the value of the optimum solution. Besides, the difference in the data calibration methods for the TSX and RS2 data may effect this situation. The other important issue is the frequency. Since
the frequency is important for the interaction with the target, it may cause under or over estimated results. Thus, based on these two reasons, small degree of deviation ($\leq 10$ cm) is accepted.

<table>
<thead>
<tr>
<th>Table 4.5 – Field average convergence rate values X- and C-band data in the early reproductive phase.</th>
</tr>
</thead>
<tbody>
<tr>
<td>X-band</td>
</tr>
<tr>
<td>Range [m]</td>
</tr>
<tr>
<td>abs(1-(Mean/Median))</td>
</tr>
<tr>
<td>Standard Deviation [m]</td>
</tr>
</tbody>
</table>

Finally, the last case of the frequency comparison analysis belongs to the early reproductive stage. During this stage, the canopy height increases from 75 cm to 120 cm. Moreover, by initiation of the ears and the panicles slows down the decreasing trend of the backscattering intensities and turns them to an increasing trend. In terms of the convergence rate of the metamodel, given in Table 4.5, an antipodean situation is observed due to given morphological reasons with respect to the late vegetative stage.

In overall, under the same conditions for the incidence angle and the local resolution, the convergence rate of C-band is observed to be higher than X-band in the vegetative stage of the rice fields. However, in the early reproductive stage, the degree of convergence increases significantly for X-band, while it decreases for C-band due to small scaled changes in the plant morphology. In addition, since the model is not capable of perfectly explaining the backscattering behaviour, the amount of deviation in the mode of the distribution resulting from the ground measurement values can be considered acceptable for any industrial monitoring applications.

4.4.2 Estimation Accuracy: single-, dual- and quad-pol

The estimation accuracy analyses for the different channels have been carried out using 7 cases corresponding to different single polarimetric (HH, HV and VV) or multiple polarimetric channels (HH&HV, HV&VV, HH&VV and HH&HV&VV). In this section of the study the probabilistic inversion algorithm for the biophysical parameter retrieval is applied over the fully polarimetric RS2 data, which was acquired through the full growth cycle of rice crops in total of 5 acquisitions.

The results of the probabilistic inversion are presented in Fig. 4.7 for each fitness function and test field. The color scale used in Fig. 4.7 is based on the observance probability of the results, with the black line emphasizing the ground measured value. The outcomes are thoroughly analysed in Fig. 4.8. The analysis covers the standard deviation and the bias between the mean of the distribution and the ground measured value. A summary presenting the distance with the mean of the results and the optimum solution, point (0,0), is given in Table 4.6. The channel comparison over the optimization procedure is discussed for each growth phase (e.g. early vegetative, late vegetative, early reproductive, late reproductive and maturative) separately to provide a clear view about the effect of the distinct morphological differences.

**Early Vegetative (St.1)** - The highest height retrieval accuracy is observed with the single channel fitness function of the HH polarization, while the lowest is observed with the VV channel. From the optimization with dual-polarization configurations, all options have provided similar distributions. However, the quad-polarization fitness function has resulted in a lower accuracy compared to dual-polarization fitness functions. Therefore, the probabilistic retrieval of the height parameter in the first phase of the growth can be achieved solely using the HH intensity. This condition is supported by the plant morphology. The reason is that the stalks are mostly under water with all the leaves above the water surface. This results in weaker interaction of electromagnetic waves with the vertical structures. Thus, the canopy height is underestimated more for the VV channel.
Figure 4.7 – Height estimation accuracy distribution plots for 7 different polarization channel combinations, 5 different dates for 5 spatially independent test areas. Number of runs for the PSO = 200. The x-axis is sorted with respect to the increasing height. (a) Single Pol: HH, (b) Single Pol: HV, (c) Single Pol: VV, (d) Dual Pol: HH& HV, (e) Dual Pol: HV& VV, (f) Dual Pol: HH& VV, (g) Quad Pol: HH& HV & VV
4.4 Results and Discussions

Figure 4.8 – Stage average of standard deviations versus scene average of mean bias values are given with error bars representing the corresponding standard deviations.

Late Vegetative (St.2) - In order to decide upon the estimation quality of the stalk height retrieval algorithm in the second stage, the growth boundaries should be remembered. Due to the wide range of possible solutions, the results tend to have a higher variance around the optimum solution as observed in ground measurements. Vertical structures of the canopy are formed during the late vegetative phase of the growth. Thus, the results with the VV including fitness functions have higher accuracy. The highest accuracies are observed in the VV, HV&VV based fitness functions. However, in contrast to the early vegetative phase of the growth, the lowest accuracy was observed in the single-polarization HH function due to strong attenuation from the leaves.

Early Reproductive (St.3) - The early reproductive stage can be described as a growth-wise saturation stage for the plant height. The rate of increase for the canopy height slows down significantly in this phase. However, the plant wet biomass continues to increase. Since the physical structure of the canopy is continuing to be mainly vertical, VV channel fitness function continues to have the highest accuracy. Besides, the height retrieval from the fitness function of the HV channel in combination with VV, has the lowest accuracy.

Late Reproductive (St.4) - In the late reproductive stage of the growth cycle, the plant reaches its maximum wet biomass and structural density. Therefore, in this dense structural environment none of the single-polarization based fitness functions have high accuracy. Besides, the HV channel is significantly different from the ground value compared to the rest of the cases. In this growth phase, the fitness functions of the HV&VV, HH&VV and HH&HV&VV combinations showed the highest accuracies.

Maturative (St.5) - As the rice field reaches the end of its growth cycle, the water content decreases and the vertical structure becomes easily observable again. This condition is also observed in the probabilistic retrieval of the stalk height parameter. The fitness function that takes the VV channel into account has the highest accuracy compared to the others. On the other hand, the function for the HH&VV channel combination has the lowest accuracy.
Table 4.6 – Euclidean distance [cm] between the mean of the analysis result and the ground measurement. Lower distance indicates higher accuracy.

<table>
<thead>
<tr>
<th>Polarization</th>
<th>St.1</th>
<th>St.2</th>
<th>St.3</th>
<th>St.4</th>
<th>St.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH</td>
<td>2.97</td>
<td>17.81</td>
<td>4.95</td>
<td>6.80</td>
<td>5.57</td>
</tr>
<tr>
<td>HV</td>
<td>3.64</td>
<td>14.60</td>
<td>5.16</td>
<td>11.32</td>
<td>7.72</td>
</tr>
<tr>
<td>VV</td>
<td>5.05</td>
<td>12.02</td>
<td>3.67</td>
<td>8.88</td>
<td>3.72</td>
</tr>
<tr>
<td>HH, HV</td>
<td>3.21</td>
<td>16.04</td>
<td>4.86</td>
<td>8.41</td>
<td>7.06</td>
</tr>
<tr>
<td>HV, VV</td>
<td>3.09</td>
<td>11.94</td>
<td>7.59</td>
<td>4.96</td>
<td>6.02</td>
</tr>
<tr>
<td>HH, VV</td>
<td>3.31</td>
<td>13.82</td>
<td>5.49</td>
<td>4.48</td>
<td>8.27</td>
</tr>
<tr>
<td>HH, HV, VV</td>
<td>4.22</td>
<td>15.43</td>
<td>4.38</td>
<td>4.84</td>
<td>6.91</td>
</tr>
</tbody>
</table>

The extensive analysis of the proposed probabilistic inversion of a morphology based electromagnetic scattering model approach shows that there is no single fitness function present for the retrieval of the stalk height in rice fields. From the set of single channel fitness functions, the function of the VV channel shows superiority in most of the growth phases. However, a solution obtained through a single channel fitness function (e.g. HH, HV and VV) may result in a stronger deviation from the optimum solution with respect to the function of the polarimetric channel combinations. Therefore to provide the morphological consistency in the 3D space, the channel combinations with at least 2 channels should be preferred. So, until the maturation stage, the fitness function for the HH&VV combination has lower average standard deviation and lower bias between the solution and the ground measurement, based on the Table 4.6.

The observed deviation in the results mainly occurs from three reasons. The first reason is in the accuracy of the scattering model in explaining the scattering mechanisms. Since the model cannot consider the environmental impacts and has simplifying assumptions about the plant morphology, it would be mathematically impossible to expect perfect inversion results. The second reason is the presence of the speckle noise. Even with spatial smoothing, presence of the noise in the SAR data affects the backscattering intensities. The third and the least significant reason is the accuracy of the PCE metamodel in fitting to the backscattering model. Considering all the reasons, the majority of the deviation originates from the first reason, the forward approach accuracy of the backscattering model. It can be solved by using an alternative scattering model, which needs to be able to provide a better explanation to the scattering behaviour of the rice canopy.

The drawbacks of the proposed approach lie in two important points. The first point is the requirement of a pre-classification for the decision of the coarse growth phase and the second one is the requirement of the biological growth boundaries for the rice crops. It needs to be mentioned that first issue has already been studied in the literature and several statistical methods have already been proposed such as in [65, 72, 130, 132]. For the second case, the morphological information about all major crops, including rice, are available in the literature to avoid impossible structures such as plants with 2 m stalk height and 2 cm stalk diameter.

4.5 Conclusion and Future Work

In this paper, a probabilistic inversion method for a scattering model has been proposed, applied and tested for biophysical parameter retrieval such as stalk height of rice crops from polarimetric SAR data. The proposed probabilistic inversion scheme is designed to be computationally efficient using HDMR methods, specifically a PCE metamodel. The approach requires a pre-classification step for the coarse growth phase and the biological growth boundaries of the rice crops. In this method, unlike the previous ones, the biophysical parameters of the targets are estimated in terms of their probability distributions for a specific polarimetric backscattering intensity. In other words,
the retrieval algorithm is developed to estimate the multi-variate distribution of the possible plant structures that correspond to a measured backscattering intensity under different conditions like different frequencies and polarimetric channels.

The accuracy of the proposed methodology was tested in rice fields for two different frequencies (X- and C-band) and 7 different cases of polarimetric channel combinations. In terms of the frequency comparison, inversion outcome in X-band provided higher accuracy than C-band with higher sensitivity to morphological variations. This higher sensitivity in X-band can be explained by the small scaled developments in the plant morphology compared to the wavelength. Additionally the channel combination comparison in C-band pointed out that, due to vertical structure of the canopies, use of VV channel or the combination of the HH&VV channels has higher overall height estimation accuracy through the growth cycle.

Since the scattering model considers the physical changes in 3D space including all components of the plant morphology, the applicability of the proposed approach is expected to be valid for different locations. However, the performance of the probabilistic inversion algorithm mainly depends on the accuracy of the forward scattering model in explaining the scattering behaviour. Lower accuracy of the forward electromagnetic scattering model may lead to stronger deviations from the real value of the biophysical parameter. It is also possible to apply the given approach for the determination of full plant morphology such as canopy density and corresponding dimensionality of the leaves or panicles. However, following the outcomes of the global sensitivity analysis the research is focused on the stalk height, which is the most significant parameter for the polarimetric backscattering intensity in rice crops.

Finally, the novel approach presented in this study emphasizes the use of PolSAR for biophysical parameter estimation using a metamodel based and therefore computationally inexpensive morphology based electromagnetic scattering model. Using such metamodels allows use of computationally expensive algorithms in industrial applications for much lower costs.

In the future, it is planned to broaden the use of the proposed algorithm on different crops under the concept of the precision agriculture. Moreover, the improvement of the probabilistic retrieval algorithm and HDMR methods to eliminate the pre-classification step will be a subject of future research.

**Acknowledgments**

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Chapter 5

Assessment of rice canopy height by combining coherent and incoherent model inversions

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IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing

Scientific Contributions

Yuzugullu  
- built a combined database for ground and SAR measurements
- developed and implemented the EM model stochastic optimization algorithm
- modified and implemented the RVoG model inversion algorithm
- evaluated the plant height estimation performances of different approaches
- interpreted the analysis results, prepared the figures, and wrote the manuscript

Erten  
- helped in interpretation of results and in writing the manuscript

Hajnsek  
- provided the SAR data
- suggested to investigate rice plant height estimation using copolar Pol-InSAR data
- assisted in interpretation of results and helped in writing the manuscript
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 (>1km) 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 integrates the previous two algorithms.

The validation analysis were carried out using the Pol-InSAR and ground measurement data acquired between May and September in 2015 over rice fields located in Ipsala, Turkey. The results of the presented height estimation algorithms demonstrated the advantage of Pol-InSAR data with the integrated height estimation approach provided canopy height with errors less than 20 cm for the complete growth cycle.

5.1 Introduction

Rice is the main source of food for several highly populated countries and has an increasing demand due to the increasing population. Researchers aim to improve the production yield for the development of new management systems by monitoring the phenological evolution of rice [2]. From various phenological properties, canopy height is an important parameter for the biomass estimation and detection of growth irregularities. Considering the traditional way of monitoring by visual inspection requires great manpower for kilometer-square scaled areas, remote sensing systems can provide regional to global scaled information on a systematic way.

Among different remote sensing data sources, Synthetic Aperture Radar (SAR) has been used to observe rice fields since the end of 1980s [13]. Since then, SAR based methodologies has become popular in rice monitoring with their sensitivity to changes in physical and dielectric properties of plants. In the meantime, different SAR image analysis techniques have been exploited for rice monitoring: multi-polarimetric SAR (PolSAR) [55,89], interferometric SAR (InSAR) [77,78], and multi-polarimetric interferometric SAR (Pol-InSAR) [67, 122].

The methods that exploit PolSAR data investigate the polarization dependent interaction between plants and electromagnetic waves using two main group of approaches, namely: temporal trend analysis and electromagnetic scattering (EM) models. The first group focuses on explaining the temporal changes in polarimetric observables [22,106,133]. 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 [69,80,82,83,109] are not preferred for operational purposes due to their high computation costs. This issue was recently solved by using metamodels [134].

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 interferometric acquisition geometry provides a vertical sensitivity for a particular polarization and allows for the calculation of digital elevation models [7]. Pol-InSAR permits the characterization of the scattering contributions in vertical coordinate by coherently combining multiple PolSAR data with interferometry [10].

Pol-InSAR data has been employed to assess canopy height of rice fields [122]. Using Pol-InSAR, phenological monitoring applications are challenging particularly with spaceborne Pol-InSAR data due to rapid changes in plant morphologies and the right sensitivity to height. Recently,
5.2 Methodology

In this paper we present three different model inversion based approaches (Figure 5.1) 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 their integrated approach.

The TanDEM-X mission provides a pair of copolar SAR data through bistatic acquisition. In this study the Pol-InSAR data was acquired in HH and VV polarization channels. It is possible to express the data with scattering vectors $\hat{k}_1$ and $\hat{k}_2$ in the Pauli basis as formulated in (5.1).

$$\hat{k}_i = \frac{1}{\sqrt{2}} \left[ S^\alpha_{hh} + S^\alpha_{vv}, S^\alpha_{hh} - S^\alpha_{vv} \right] \quad i = 1, 2, \quad (5.1)$$
In (5.1), \( S_{\text{HH}}^i \) and \( S_{\text{VV}}^i \) stand for the complex scattering matrices of the \( i^{th} \) SAR acquisition. For the distributed targets, \( \hat{k}_1 \) and \( \hat{k}_2 \) can be given with the coherency matrix, \([T_4]\),

\[
[T_4] = \left[ \begin{array}{c} \hat{k}_1 \\ \hat{k}_2 \end{array} \right] = \left[ \begin{array}{cc} \hat{k}_1 \hat{k}_2^* & \hat{k}_2 \hat{k}_1^* \end{array} \right],
\]

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

\[
\bar{\gamma} = \frac{\langle \hat{\omega}^\dagger [\Omega_{12}] \hat{\omega} \rangle}{\sqrt{\langle \hat{\omega}^\dagger [T_{11}] \hat{\omega} \rangle \langle \hat{\omega}^\dagger [T_{22}] \hat{\omega} \rangle}},
\]

where \( \hat{\omega} \) vectors are the unitary vectors for polarization combinations and \( \langle . \rangle \) represents the spatial multilooking. The value of the \( \bar{\gamma} \) depends on several sensor and object related factors such as temporal difference, acquisition geometry, signal to noise ratio, data quantization and vertical distribution of scatterers within the volume (\( \gamma_{\text{vol}} \)). Further information about the Pol-InSAR image analysis technique can be found in [10] and [135].

Besides the \( \bar{\gamma} \) value, the Pol-InSAR data also allows for the calculation of backscattering intensities (\( \sigma^o \)), which are employed in the EM model inversion. The \( \sigma^o_{\text{HH}} \) and \( \sigma^o_{\text{VV}} \) values are calculated from the expressions given in (5.4).

\[
\sigma^o_{\text{HH}} = 10 \log_{10} (|S_{\text{HH}}^o S_{\text{HH}}^T|), \quad \sigma^o_{\text{VV}} = 10 \log_{10} (|S_{\text{VV}}^o S_{\text{VV}}^T|).
\]

### 5.2.1 Approach 1: RVoG Model Inversion

The RVoG model inversion, shown by red lines in Figure 5.1, is used to estimate canopy height from the \( \bar{\gamma}_{\text{vol}} \) value by implementing the procedure detailed in [135]. Before proceeding with the model inversion, the effect of decorrelation sources are needed to be reduced on the \( \bar{\gamma} \) value. For this purpose the data was pre-processed with range common band filtering [136], flat earth phase removal and signal to noise ratio (SNR) correction [137].

The RVoG model [12], describes a canopy with two layers (a vegetation volume and ground surface) to simulate the Pol-InSAR coherence (\( \gamma \)) using the formula given in (5.5). The volume layer is described with a thickness \( h_V \) and contains randomly oriented particles, while \( z = z_0 \) represents the vertical location of the ground component.

\[
\gamma = e^{j\phi_0} \cdot \frac{\gamma_{\text{vol}} + \mu(\hat{\omega})}{1 + \mu(\hat{\omega})},
\]

In (5.5), \( \phi_0 \) 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 by,

\[
\gamma_{\text{vol}} = \frac{2\beta}{\cos(\theta) \left( e^{2\beta(\cos(\theta) \tan(\theta))} - 1 \right)} \cdot e^{\left( \frac{2\beta}{\cos(\theta)} \right) j \kappa_2} - 1.
\]

In (5.6), \( \theta \), \( \beta \) and \( \kappa_2 \) 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 \( \kappa_2 \), is calculated as shown in (5.7) using baseline \( B \), wavelength \( \lambda \), and range \( R \) parameters.

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5.2 Methodology

Figure 5.2 – (a) Absolute coherence distribution of Pol-InSAR data taken from an example rice field (b) Example: The range of possible $\gamma_{vol}$ values for a given observed coherence region over a complex plane (c) Example: Distribution of the plant height estimated with RVoG model inversion with 942 samples

\[
\kappa_z = \frac{4\pi \Delta B}{\lambda \sin \theta} \tag{5.7}
\]

In rice canopies, plants are expected to have similar growth rates under normal conditions. However, factors like different sowing practices and the presence of weed may result in structural heterogeneity, leading to spatially varying extinctions. As shown in Figure 5.2(a), the $\bar{\gamma}$ distribution involves the effect of such variations. The proposed RVoG model inversion exploits the $\bar{\gamma}$ distribution by modifying the last step of the well-known three-step inversion procedure to provide the height of the rice canopy [135].

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 multi-looked 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 0.1 and 10 dB/m with 0.1 dB/m increments. In the proposed methodology, the estimated canopy height is considered to be valid when the estimated $\gamma_{vol}$ is higher than the $\gamma$ of minimum ground contribution ($m_G$), as shown in Figure 5.2(b) with the green color.

The inversion of $\gamma_{vol}$ from a single resolution cell provides a range of $h_V$ values for given range of $\beta$ values. The estimated $h_V$ ranges are aggregated for all resolution cells. The inversion result is reported with the most likely value of the $h_V$ distribution and its standard deviation as shown in Figure 5.2(c) with the green shading.

5.2.2 Approach 2: EM Model Inversion

The EM model inversion, shown by green lines in Figure 5.1, is implemented to estimate the average morphological properties of plants in a canopy from the measured $\sigma_{HH}^0$ and $\sigma_{VV}^0$ values, by considering a priori plant phenology descriptors. The EM model [80], $M(\xi)$, is employed to simulate the $\sigma_{HH}^0$ and $\sigma_{VV}^0$ values from 18 different plant morphology parameters, $\xi$, through Monte Carlo simulations.

The inversion of $M(\xi)$ is an ill-posed problem as the number of inputs are higher than the number of equations. Therefore, the inversion of the $M(\xi)$ has multiple $\xi$ vectors as solutions. In this study, we propose a stochastic optimization approach for the inversion of the $M(\xi)$ algorithm, which aims to find all $\xi$ vectors through several initiations of the procedure. Considering the stochastic optimization, the inversion of the multi-dimensional $M(\xi)$ is computationally expensive with complex algorithms and the Monte Carlo simulations. In this study, we overcome the computation cost issue using metamodels.
EM model: The chosen EM model [80], \( \mathcal{M}(\xi) \), is used to simulate \( \sigma_{\text{HH}}^o \) and \( \sigma_{\text{VV}}^o \) 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 [113, 114] for stalks and panicles, and physical optics approximation [115] 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 \( \mathcal{M}(\xi) \) provides a relation between incident, \( \vec{E}^i \), and scattered wave, \( \vec{E}^s \) using the coherent combination of four scattering mechanisms, \( S_n \) namely, (i) direct scattering from canopy, (ii) scattering from the canopy followed by reflection from the water, (iii) reflection from the water followed by scattering from the canopy, (iv) 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 (5.8),

\[
\sigma_{\text{HH}}^o = \mathcal{M}(\xi) = \frac{4\pi r^2}{A} \left( \frac{|E_{\text{HH}}^s|^2}{|E_{\text{HH}}^i|^2} \right) = \left\{ \left| \frac{e^{ikr}}{r} \left( \sum_{n=1}^{4} S_n \right) \right|^2 \right\}, \tag{5.8}
\]

In equation (5.8), \( k \), \( r \), and \( q \) are defined as free-space wavenumber, the distance between the receiving antenna and the target, and linear polarization channels, respectively. The \( \sigma_{o}^o \) values for a 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 \( \mathcal{M}(\xi) \) simulations is reduced by substituting the \( \mathcal{M}(\xi) \) with its Polynomial Chaos Expansion (PCE) metamodel [102]. The PCE metamodels can mimic any mathematical model to an input-output analytical approximation. Such that for the \( \mathcal{M}(\xi) \) with multi-dimensional input set \( \xi \in \mathbb{R}^M \) and \( \sigma_{o}^o \) as output, the PCE metamodel, PCE\(_{\text{EM}}\), is defined as:

\[
\mathcal{M}(\xi) \approx \text{PCE}_{\text{EM}}(\xi) = \sum_{j=0}^{\infty} a_j \Psi_j(\xi). \tag{5.9}
\]

In (5.9), \( a_j \in \mathbb{R} \) 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\(_{\text{EM}}\) is implemented using the Uncertainty Quantification Laboratory (UQLab) toolbox [120] in MATLAB. The toolbox is used to calculate the \( a_j \) and \( \Psi_j(\xi) \) terms using least-square minimization techniques [119] from a training set of full model evaluations of \( \mathcal{M}(\xi) \) for once. Compared to the \( \mathcal{M}(\xi) \), the PCE\(_{\text{EM}}(\xi) \) requires significantly lower computational effort. For 10000 simulations the computation time was up to 10\(^4\) times lower [72].

Parameter space search algorithm: The PCE\(_{\text{EM}}\) is inverted by comparing the measured and estimated backscattering intensities. The presented approach employs a multi-dimensional parameter space \( \mathbb{P} \), \textit{a priori} growth phase and a set of simplifying constraints. The \( \mathbb{P} \), is defined as a multi-dimensional 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.

\[
\mathbb{P} = \{ \text{tiller}(h, d, n, \epsilon_{r,i}), \text{leaf}(l, w, n, \epsilon_{r,i}), \text{flag}(l, w, \epsilon_{r,i}), \text{panicle}(l, d, n, \epsilon_{r,i}), \text{ground}(\epsilon_{r,i}) \} \tag{5.10}
\]

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
5.3 Datasets

5.3.1 The 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″. Figure 5.3 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 (TARI) during the cultivation periods (May-September) of 2013-2015. With these campaigns, more than 400 measurements were collected for morphology parameters, i.e. stalk diameter and height, leaf length and width, and the number of stalks, tillers, leaves.

Figure 5.3 – Location of the study area with HH and VV interferograms calculated on 11.08.2015. The test fields of the ground campaigns are also marked.

in the from 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 $\sigma_{\text{HH}}^0$ and $\sigma_{\text{VV}}^0$ values are searched for in the $\mathcal{P}$ by employing two different constraints. The implemented limitations ensure positivity in morphological solutions, the consistency between measured and estimated backscattering intensities, and coherence of $\xi$ vectors for HH and VV channels.

The first constraint eliminates the $\xi$ vectors based on the $\bar{\sigma}_{\text{HH}}^0$ and $\bar{\sigma}_{\text{VV}}^0$ values. To this aim, the PCE$_{\text{EM}}$ is employed to simulate the $\sigma_{\text{HH}}^0$ and $\sigma_{\text{VV}}^0$ from each point in $\mathcal{P}$ grid. The simulated $\sigma^0$ values, which stay in the range defined by mean with standard deviation of the measured $\sigma^0$ values for a field, are assigned to parameter space subsets $\mathcal{B}_{\text{HH}}$ and $\mathcal{B}_{\text{VV}}$.

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 $\mathcal{B}_{\text{HH}}$ and $\mathcal{B}_{\text{VV}}$ subsets and determines the unique set of candidate rice plant morphologies for all parameters included in $\mathcal{P}$. From the intersection set, the information regarding the possible range of rice plant height is determined.

5.2.3 Approach 3: The Integrated EM and RVoG Inversion

The third approach employs both $\bar{\sigma}_{\text{HH}}^0$, $\sigma_{\text{HH}}^0$ and $\sigma_{\text{VV}}^0$ values to obtain the rice plant height. As shown in Fig. 5.1 with the blue line, the a priori growth stage limitation in the parameter space of PCE$_{\text{EM}}$ inversion is substituted with the canopy height range provided by the RVoG model inversion. The integrated RVoG and PCE$_{\text{EM}}$ 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 $\mathcal{P}$ for stalk height of the whole field including the natural limitations. Lastly, PCE$_{\text{EM}}$ inversion provides the canopy height estimations.
Chapter 5 Rice Plant Height Estimation with X-Band Pol-InSAR

Figure 5.4 – 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. [P1] early vegetative, [P2] late vegetative, [P3] early reproductive, [P4] late reproductive, and [P5] maturative.

Figure 5.5 – Observed frequency of plant height based on IRRI growth phases is given for the wetland-rice. Data was obtained from the ground campaigns of 2013 to 2015 over 400 sample points.

Figure 5.4 presents the temporal trend of the measured canopy height for five spatially independent test fields [2].

Figure 5.5 shows the growth phase based rice canopy height distributions, which are useful in understanding the plant height boundaries. Correspondingly, Figure 5.6 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.

5.3.2 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 (DLR) to provide level 1b (Single Look Complex, SLC) data. Later, the SLC data were co-registered 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 15x15 box-car filter.
5.4 Results and Discussions

Figure 5.6 – Temporal variations of the rice plant biophysical parameters obtained from the ground campaigns of 2013 and 2015 over 404 sample points given as a Box-and-Whisker plot. Box presents the information for the quartiles while the whiskers present minimum and maximum values. [P1] early vegetative, [P2] late vegetative, [P3] early reproductive, [P4] late reproductive, and [P5] maturative

The copolar Pol-InSAR time series data was acquired with 30.7° degree 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 Figure 5.4.

5.4 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\textsubscript{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.

5.4.1 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 [104, 138]. In Cloude et al., [135], it was stated that the optimum configuration is achieved with a \( \kappa_z h_v/2 \) between 1 and 1.25 for a vegetative canopy. In the available data, \( \kappa_z h_v/2 \) 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. 5.7.

In the first analysis, Fig. 5.7 (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 to estimate the height of the canopies taller than 36 cm.

The second analysis, Fig. 5.7 (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 box plots, given in Figure 5.7 (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 was 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 and structural heterogeneity of the plants in the field. For a detailed explanation on the data variance and the accurate inversion possibility, we investigated the behavior of the $\bar{\gamma}$ for five major growth phases with respect to 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. Additionally, the presence of double bounce between the canopy and the underlying surface, and also the speckle noise due to the underlying water surface lowers the estimation accuracy. Presence of this behavior leads to a strongly over-estimated canopy heights.

**Late Vegetative:** During the beginning of this growth phase, the effect of insufficient $\kappa_z$ becomes sounds. Through the end, $\bar{\gamma}$ values lies 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 canopy and the underlying water, and the presence of speckle noise continue to exist. It is noted that the low variance in the $\bar{\gamma}$ during 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 $\kappa_z$, 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 increasing structural heterogeneity on the top layer 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 under-estimation 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 sources of spatial structural heterogeneity.
5.4 Results and Discussions

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central frequency</td>
<td>9.65 GHz</td>
</tr>
<tr>
<td>Vegetation dielectric constant</td>
<td>25+8j [82]</td>
</tr>
<tr>
<td>Ground dielectric constant</td>
<td>70+24j [82]</td>
</tr>
<tr>
<td>Average incidence angle (\theta)</td>
<td>31°</td>
</tr>
<tr>
<td>Distance to target</td>
<td>514 km</td>
</tr>
<tr>
<td>Illuminated area x-size</td>
<td>2.58 m</td>
</tr>
<tr>
<td>Illuminated area y-size</td>
<td>1.79 m</td>
</tr>
<tr>
<td>Number of MC iterations</td>
<td>250</td>
</tr>
</tbody>
</table>

**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 \(\kappa_z\) 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.

### 5.4.2 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 5.1 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 metamodel, which was trained on an experimental set of 5000 samples, calculated in 110 hours with the EM model. Figure 5.8 visualizes the accuracy of PCE\(_{EM}\) for 15000 validation samples, calculated in 3 seconds with the UQLab toolbox. The polarimetric channel specific PCE\(_{EM}\) 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.

![Figure 5.8](image_url)  
**Figure 5.8** – Scatter plot for HH and VV channel of the EM versus PCE metamodel simulated validation set backscattering intensities

\[63\]
5.4.3 Inversion Results of the Models

Until this point, the applicability of the proposed RVoG model and PCE\textsubscript{EM} 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 (5.11). Both of the given accuracy quantification parameters are calculated concerning canopy height above the water surface.

\begin{equation}
\text{RME} = \left( \frac{h_{\text{estimated}} - h_{\text{measured}}}{h_{\text{measured}}} \right) \\
\text{NV} = \frac{h_{\text{estimated error}}}{h_{\text{measured}}} 
\end{equation}  \hspace{1cm} (5.11)

The first parameter, RME, explains the relative difference between measured and estimated canopy height. When RME is interpreted, the positive results indicate over-estimation and the negative values indicate under-estimations. 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 estimated canopy height.

In this study, the canopy height estimation accuracy analysis is conducted over 35 measurements 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. 5.9), evolution of coherence region over the complex plane (Fig. 5.10), scatter plots of accuracy analysis (Fig. 5.11) and the RME and NV values in Table 5.2.

| Table 5.2 – Results of the accuracy analysis for each growth phase with RME and NV using: RVoG model inversion, PCE\textsubscript{EM} inversion and RVoG model inversion constrained PCE\textsubscript{EM} inversion. |
|----------------|----------------|----------------|----------------|
|                | RVoG            | PCE\textsubscript{EM} | RVoG+PCE\textsubscript{EM} |
| Early Veg.     | RME 5.38        | NV 2.03          | N/A             |
|                |                  |                  |                  |
| Late Veg.      | RME 0.41        | NV 0.59          |                  |
|                |                  |                  |                  |
| Early Rep.     | RME 0.17        | NV 0.35          |                  |
|                |                  |                  |                  |
| Late Rep.      | RME -0.21       | NV 0.22          |                  |
|                |                  |                  |                  |
| Mat.           | RME -0.33       | NV 0.17          |                  |
|                |                  |                  |                  |
5.4 Results and Discussions

**Figure 5.10** – Evolution of coherence loci calculated at the central pixel of a chosen field for the five major growth phases and measured canopy heights.

**Figure 5.11** – Scatter plot of accuracy analysis results given estimated versus measured values with three different algorithms - (a) RVoG model inversion (b) PCE\textsubscript{EM} inversion (c) RVoG model inversion constrained PCE\textsubscript{EM} inversion - for growth phases and observed height ranges for early vegetative (blue), late vegetative (green), early reproductive (red), late reproductive (orange) and maturative (purple).

**Early Vegetative Phase [n=6]** - As shown in Fig. 5.9(a), a rice canopy can be described by sprouts having small leaves in a flooded field. In this stage of the phenological evolution, the points within the coherence region converges to a single point while neglecting the effect of polarization. The main reason of this behavior is interpreted with the surface scattering.

(a) RVoG \textit{[RME=5.38, RVE=2.03]}: The inversion results in a strong over-estimation 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) PCE\textsubscript{EM} \textit{[RME=0.06, RVE=1.01]}: The application of the PCE\textsubscript{EM} metamodel inversion has provided successful results with low RME values. In the estimations, there is no clear over or under-estimation condition for the mean values. However, due to growth phase bounded morphological limitations, the resulting distributions have high variances.

(c) RVoG & PCE\textsubscript{EM} \textit{[RME=NA, RVE=NA]}: The combination of two methods are not possible due to non-overlapping height ranges by the results of the RVoG and the PCE\textsubscript{EM} algorithms.

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

**Late Vegetative Phase [n=10]** - As visualized in Fig. 5.9(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 co-presence of a volume and surface scattering.
(a) RVoG \[ \text{RME} = 0.43, \text{RVE} = 0.59 \]: The RVoG model assumptions continue to mislead in 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 over-estimate 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) PCE\textsubscript{EM} \[ \text{RME} = 0.07, \text{RVE} = 1.45 \]: As shown in Fig. 5.5, 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 & PCE\textsubscript{EM} \[ \text{RME} = 0.28, \text{RVE} = 0.40 \]: Considering the RVoG model inversion results, the RVoG model inversion constrained PCE\textsubscript{EM} metamodel inversion achieved a lower NV than the PCE\textsubscript{EM} metamodel inversion. The results have improved to 0.11 in RME and 0.19 in NV compared to the RVoG model inversion itself.

**Overview:** In the late vegetative phase, due to the insufficient \( \kappa_z \), the RVoG model inversion continues to over-estimate the rice canopy height until the canopies are taller than 50 cm. Backscattering intensity based PCE\textsubscript{EM} 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. 5.9(c), complete the significant part of their morphological development during this phase by becoming structurally denser. This phase is essential with 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 minimum and maximum ground contribution points compared to the late vegetative phase.

(a) RVoG \[ \text{RME} = 0.17, \text{RVE} = 0.35 \]: The structurally dense rice canopies start to satisfy the RVoG model inversion 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 over-estimation conditions can be explained by the double-bounce effect between the canopy and the underlying surface [139].

(b) PCE\textsubscript{EM} \[ \text{RME} = -0.03, \text{RVE} = 0.43 \]: The rice plants in this growth phase have higher morphological similarity within the field (Fig. 5.6) due to reduced growth rate. By including the effect of the flag leaves in the PCE\textsubscript{EM}, the accuracy of the inversion approach increases by resulting a lower RME compared to each vegetative phases. However, as the PCE\textsubscript{EM} inversion considers all possible solutions in a given range, the results continue to present high NV values.

(c) RVoG & PCE\textsubscript{EM} \[ \text{RME} = 0.12, \text{RVE} = 0.16 \]: The results of the combined approach had lower NV values compared to RVoG model and PCE\textsubscript{EM} 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.

**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, PCE\textsubscript{EM} was also able to provide a high accuracy while the resulting distributions with lower NV values. The suggested RVoG and PCE\textsubscript{EM} combined approach increased the estimation accuracy with lower NV and higher RME values than both standalone inversions.
5.4 Results and Discussions

**Late Reproductive Phase** \([n=6]\)  - Rice plants (Fig. 5.9(d)) develop their panicles in the top layer of the canopy. The flooded condition of the fields is reduced from the mid-late 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.

(a) \(RVoG\) \([RME=-0.21, RVE=0.22]\): The over-estimation behavior of the inversion changes to under-estimation 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) \(PCE_{EM}\) \([RME=-0.06, RVE=0.46]\): 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 5.2, 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. 5.5.

(c) \(RVoG \& PCE_{EM}\) \([RME=-0.19, RVE=0.12]\): 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.

**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 (Fig. ?(c)), farmers stop flooding the rice fields. In a short time, this leads to a reduction in the moisture content of the plants, resulting in a lower dielectric constant, and osmotic pressure in the plant structure. With lower osmotic pressure, plant structures could not 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 decrease to lower value than the late reproductive step.

(a) \(RVoG\) \([RME=-0.38, RVE=0.17]\): The canopy height above ground suffers from a strong under-estimation during this growth phase. It is known that drier plants allow deeper penetration of the electromagnetic waves inside the vegetative canopy, which lowers the location of the volume phase center inside the canopy. The under-estimated results might be related to the changing structural density as well. Moreover, with the structurally developed morphology and structural density in fields, the growth rate differences between plants decreases, which can be observed by focusing on the decreasing NV values.

(b) \(PCE_{EM}\) \([RME=-0.06, RVE=0.43]\): 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.

(c) \(RVoG \& PCE_{EM}\) \([RME=NA, RVE=NA]\): As the overlapping resulting 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 of the rice canopies using Pol-InSAR dataset.
Chapter 5 Rice Plant Height Estimation with X-Band Pol-InSAR

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 under-estimation of the rice canopy height range, which prevented the application of the combined approach. However, similarly to the early vegetative phase, if the a priori growth phase information exists, the $PCE_{EM}$ metamodel inversion should be considered for the plant height estimation.

As a result of the detailed investigation, it is observed that the accuracies of the canopy height estimation algorithms change during the phenological cycle. Considering a system with a fixed baseline, Fig. 5.12 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. However, today the systems with varying baselines are available, which can make the detection of smaller volumes likely.

5.5 Conclusion 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 $\kappa_z$ 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 $PCE_{EM}$ 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 RVoG model and $PCE_{EM}$ 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

- 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 sub-field morphological heterogeneity, the proposed approach handles the structural
5.5 Conclusions

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.

- The implemented PCE$_{\text{EM}}$ 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.

- The PCE$_{\text{EM}}$ 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 [65], it would be possible to monitor subfield morphological growth irregularities, particularly for fields with statistically a representative number of resolution cells.

Limitations

- 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 early 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.

- 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$_{\text{EM}}$ metamodel inversion needs the corresponding growth phase as a priori information to select the morphological growth boundaries.

- The performance of the PCE$_{\text{EM}}$ 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 in the areas with dry soil conditions.

- 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 misinterpretation 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. Additionally, in the current implementation of the RVoG model inversion the effect of the double-bounce between the ground and the plant was not considered. This may cause a shift in the scattering phase center and influence the estimated canopy height at different stages of the phenological cycle [122, 139].

Opportunities

- Considering that rice yields are closely related to canopy heights and densities, the large phase science phase of the TanDEM-X mission presented a good possibility of spaceborne rice yield estimations.

- By providing a suitable across-track baseline, the integrated stochastic approach allows for the estimation of the simplified plant morphology. An ideal Pol-InSAR data may eliminate the requirement of a priori growth phase information for the PCE$_{\text{EM}}$ metamodel inversion.
• The suggested PCE$\text{EM}$ 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 [80]. 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.

• 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 integrated 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.

Future work is dedicated to the evaluation of the proposed methodology using different incidence angles, baselines as well as major plant types.

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Chapter 6
Summary and Conclusion

This thesis focuses on the estimation of rice plant morphology and growth stage using an EM model inversion. For this purpose, different SAR image analysis techniques such as multi-polarimetric SAR and polarimetric SAR interferometry, have been employed. The algorithms are developed and validated using detailed ground measurements that were conducted between 2013 and 2015 from the Ipsala test site located in Turkey.

This research presents the first implementation of stochastic inversion to an EM model, which considers agronomical, environmental, and modeling uncertainties. The study also contributes to the literature by introducing the use of surrogate models as an alternative for models that require high computation effort. This chapter synthesizes the dissertation with the main conclusions of the previous sections and concludes the thesis by providing investigation suggestions for the future of remote sensing based rice field monitoring.

The temporal evolution of backscattering signatures in X-band SAR data is a non-monotonic function of time and growth stage. Therefore, some backscattering signatures can be measured in different stages of the growth. The proposed rice monitoring procedure proposes a method developed from copolar Pol-InSAR data. In 2015, TANDEM-X mission had a science phase to acquire large baseline bi-static interferometric acquisitions with height of ambiguity less than 5 meters. This mission allowed for the estimation of plant heights that are higher than 40 cm. RVoG model is used to predict height ranges of rice plants, which are later used as a constraint in the stochastic inversion.

In the inversion approach developed in the study, the IRRI growth stages are used to organize the ground measured data to define the boundaries of the multi-dimensional parameter space of morphological descriptors. The chosen EM model with Monte Carlo simulations [82] is employed for simulating the backscattering intensities from a multi-dimensional parameter space. The performance of the EM model is assessed for each available polarimetric channel in X- and C-band for backscattering intensities. The accuracy analysis between model estimates and satellite measurements reached $R^2$ values higher than 0.78 and RMSE values less than 2.85 dB.

The integration of the Monte Carlo simulations into the multi-dimensional EM model leads to high computation effort. Towards solving this issue, the scattering model is substituted with its surrogate model, which was obtained through PCE algorithm [119]. The PCE metamodel was trained to mimic the behavior of the multi-dimensional EM model within the parameter space. The PCE-driven EM model reached $R^2$ higher than 0.86 and RMSE less than 5.3 dB.

The importance of the input parameters on the PCE-driven EM model simulations is investigated by conducting a global sensitivity analysis on a previously defined parameter space. The results showed that the stalk height and structural density parameters had a considerable influence over the estimated backscattering intensities.

The proposed EM model inversion algorithm focuses on handling the effects of morphological variance within rice fields. In SAR based monitoring approaches, the information contained within a resolution cell represents an average of the scattering returns from hundreds of plants with different
morphologies. Different growth rates between those plants introduce a structural heterogeneity within fields. This heterogeneity can be observed in SAR images as parametric variance. The plant morphology based EM models become advantageous against other techniques on investigating this morphological variability. This thesis presents a new perspective to EM model inversion that aims to estimate the plant morphology as stalk height, stalk diameter, leaf length, and leaf width. The proposed approach uses a stochastic inversion, which searches the parameter space for the plant morphologies that have similar scattering returns to the measured backscattering signature.

The success of the stochastic inversion algorithm depends on three conditions. The first condition is that high computation effort requirement is provided by employing a PCE metamodel. The other two conditions are provided as optimization constraints which are based on backscattering intensity and agronomical relations to limit the multi-dimensional parameter space. The measured intensity based constraint eliminates the plant morphologies that return different intensities. The agronomy based constraint removes the unlikely plant morphologies from the multi-dimensional parameter space using a convex-hull, which was defined using the data obtained from the ground measurements. The samples that are members of the complex-hull are considered to be agronomically possible morphologies for the measured backscattering intensity value.

A detailed growth scale called BBCH classifies the crops according to their quantitative measures: number of leaves, tillers, and formation of flowers, panicles, and grains. Considering that there might be variations in plant morphology at a specific stage, the BBCH scale does not provide a direct link between growth stages and the morphologies. However, the stochastic inversion of the EM model provides estimations on the morphological measures of rice plants. The missing link is provided using high-degree polynomial relations generated by PCE metamodels.

The results obtained from the stochastic inversion of the PCE-driven EM model with a priori IRRI growth phase showed accurate estimates of the crop height with absolute errors less than 15 cm. The integration of the EM model and the RVoG model inversion algorithms, on the other hand, reduced the errors in plant height estimations to values less than 10 cm. The proposed rice morphology estimation algorithms achieved R² values higher than 0.6 between measured and estimated stalk diameter, leaf length, and leaf width. Lastly, in the BBCH stage estimations with the multi-dimensional non-linear relation provided by the PCE metamodel managed to have errors less than 10% compared to the measured values.

The objectives of this research were accomplished by presenting a morphology based rice monitoring algorithm that is valid for multi-frequency and multi-polarimetric SAR image analysis techniques. As planned, the implementation of PCE surrogate model has reduced the computation effort significantly. Regarding the site independence, the algorithm was tested on different locations and presented promising results. The improvements in rice field monitoring for plant morphology and growth stage are expected to encourage agriculturists, local authorities, and insurance companies to use SAR data with different image analysis techniques. The major strengths, opportunities, and limitations of this dissertation are discussed below.
Strengths

- The proposed stochastic inversion algorithm employs a multi-dimensional EM model. The EM model is capable of simulating the backscattering intensity from each single morphological formation of the rice plants during the full growth cycle. The accurate estimation of the plant morphology makes the proposed approach stronger against existing algorithms.
- Multi-dimensional EM models mostly have high computation effort, which becomes more significant with Monte Carlo simulations. Surrogate models like PCE metamodel help to reduce the computation effort of the algorithms considerably. PCE algorithm reduced the computation time of 2000 simulations with the EM model [80] from 22 hours to 0.04 seconds.
- In the literature, rice monitoring algorithms either focuses on a rice morphology parameter (e.g. plant height, biomass, leaf area index) or the growth stage. This thesis provides a connection between two growth descriptors using PCE metamodels for interpretation of infield irregularities and problems possible by exploiting the variation of PolSAR parameters.
- The proposed stochastic inversion algorithm requires a multi-dimensional parameter space that is based on the morphological characteristics of rice plants. For applications in different monitoring sites, the multi-dimensional parameter space can be expanded by including additional morphological data, aiming to update the growth constraints.
- In rice monitoring, agronomically sound morphology estimations are essential for high accuracy. The multi-dimensional parameter space, where each node of the space represents a biologically likely plant structure, can provide the required conditions.

Limitations

- The performance of the stochastic inversion algorithm depends on the accuracy of the EM model. The chosen EM model [80] considers a rather simplified rice plant morphology than a fully realistic crop structure. The EM model can only estimate the backscattering intensities without the phase information. Therefore, the accuracy of the overall approach can be improved by incorporating a coherent EM model.
- The copolar Pol-InSAR based plant height estimations with different models (e.g. RVoG, OVoG) can be employed in the proposed algorithm as a substitute for the IRRI stage determination. However, the model based pre-classification brings two new issues. The first problem is the height of ambiguity based on the baseline between antennas. The current interferometric systems, except the science phases of current missions as TanDEM-X, do not have large enough baselines for sufficient height of ambiguity. The second issue is based on the key assumption of the RVoG model, which considers the canopy with randomly oriented scatterers. The rice canopy has an oriented structure. However, dual-pol SAR data is insufficient for inversion due to the higher number of variables present in the OVoG model.

Opportunities

- The stochastic inversion algorithm can be implemented both in the small and large scaled monitoring applications. In both cases, the proposed method is capable of estimating the possible distribution of biophysical parameters and the BBCH growth stages.
- The proposed probabilistic BBCH stage determination approach has a flexible algorithm. It can be modified to invert any morphology based EM model. Therefore, it is possible to improve the overall accuracy or introduce different parameters to the estimation process.
- In this study, a multi-dimensional EM model is used to estimate the growth state of rice fields with PCE metamodels. This improvement can encourage researchers to develop new EM models for agricultural monitoring purposes.
Perspectives and Future Work

This research presents a unique set of improvements to rice crop monitoring applications using satellite-based multi-frequency and multi-polarimetric SAR image analysis techniques. The stochastic inversion of the EM model allows for estimation of simplified plant morphology and growth stage of rice fields both at IRRI and BBCH scales. The estimations can be used to assess the growth irregularities in field scale applications. The study also presents an advancement in phenological monitoring by integrating the inversion algorithms of RVoG and EM models.

The approaches presented in this thesis offers substantial opportunities for future rice monitoring studies. Firstly, since rice is a major staple crop, the compatibility of the proposed approach should be expanded to make it applicable for multi-frequency SAR data. New satellite missions will allow the use of stochastic inversion approach with the SAR systems such as Sentinel-1 A&B and COSMO Skymed. Secondly, considering the current growth principles, agronomically sound rice monitoring systems should be developed for satellite based SAR data. In this frame, the morphological parameter space needs to be updated to consider different rice species. As a final aim, a rice morphology database can be implemented and incorporated into an automated PolSAR/Pol-InSAR based precision agriculture monitoring system. Furthermore, the EM model can be updated to monitor different staple crops like wheat and corn by considering the ground contributions.
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