Detecting Rice Crop Establishment Methods Using Sentinel-1 Multi Temporal Imagery in Nueva Ecija, Philippines

VIDYA NAHDHIYATUL FIKRIYAH
[February, 2018]

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ABSTRACT

Rice is a major staple food, and monitoring its production and management requires detailed spatial and temporal information. However, conventional methods for obtaining this information are often time-consuming and labour intensive. Remote sensing data have been used to monitor rice crop condition effectively and efficiently compared to the existing methods. Among several sources of remote sensing data, Synthetic Aperture Radar (SAR) images have an advantage over optical images due to their all-weather observation capability. Rice is cultivated under different management practices, including two different crop establishment methods: transplanting (TP) and direct seeding (DS). The choice of crop establishment method affects water use, the presence of weeds, and even the yield, and hence information on which crop establishment method used is useful for decision making and extension work. However, only a few studies have looked at this issue.

The launch of Sentinel-1 provides a new opportunity to observe the rice crop, based on 20m spatial resolution, C-band, dual polarization imagery with a 12-day revisit time. This study aims to detect the difference in backscatter between TP and DS rice using multi-temporal Sentinel-1 imagery in Nueva Ecija, the Philippines. Multi-temporal Sentinel-1 images throughout the rice growing seasons (dry and wet, from late 2016 to end of 2017) were processed to generate backscatter values. Field observation data were collected across the study area, based on crop establishment information from previous farmer surveys, and were used to extract average backscatter values per field per observation date. The period and polarizations for best discriminating TP and DS rice were investigated and tested by Mann-Whitney U tests. Discrimination rules for the dry and wet season were generated using a decision tree algorithm applied to the backscatter values from different times in the season and different polarizations, and the accuracy of the trees was assessed.

The results show that the backscattering from TP and DS rice were significantly different in the early growing season, specifically during land preparation, crop establishment, and tillering-stem elongation stages. VV and VH polarizations, and the VV/VH band ratio all showed differences in backscatter. The rules set by decision tree obtained high accuracy in the dry season, which is when farmers commonly use both TP and DS, with overall accuracies of 72% and 78% (without and with relative elevation as an additional data, respectively). However, the discrimination in the wet season, when the majority of farmers use TP, produced a considerably low accuracy. We concluded that multi-temporal Sentinel-1 imagery could detect TP and DS rice in the dry season when both establishment methods are commonly used. More ancillary data could improve the discrimination in both seasons, though the value in the wet season is limited by the very low occurrence of DS. Further study in sites where both dry and wet direct seeding are practised should also be explored.

Keywords: Sentinel-1, transplanting, direct seeding, decision tree

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ACRONYMS

CART	: Classification and Regression Tree
CE	: Crop establishment
CEM	: Crop establishment methods
CHIRPS	: Climate Hazard Group InfraRed Precipitation with Station data
DDS	: Dry direct seeding
DEM SRTM	: Digital Elevation Model
DS	: Direct seeding
DT	: Decision tree
FLD	: Flooding
HE-FLW	: Heading and flowering
HVS	: Harvesting
IRRI	: International Rice Research Institute
LP	: Land preparation
MT	: Maturity
SAR	: Synthetic Aperture Radar
SRTM	: Shuttle Radar Topographic Mission
TL-SE	: Tillering and stem elongation
TP	: Transplanting
UPRIIS	: Upper Pampanga River Integrated Irrigation System
WDS	: Wet direct seeding

1. INTRODUCTION

1.1. Background

1.1.1. The importance of crop establishment method

Rice has significant importance for food security and environmental issues. As a major staple food for more than half of the world's population (Chauhan et al., 2015), it has high water demand relative to other crops and affects climate change through methane emissions. Therefore, there is a strong demand for reliable, regular, and spatially explicit information on the rice crop to support decision making for better crop and environmental management. However, existing rice information systems that are based on survey and statistical methods may not be sufficient to accommodate these information needs, and there is scope for further research on methods to deliver reliable and timely information (Xiao et al., 2006; Gumma et al., 2014; Nelson et al., 2014).

According to FAO (2014), Asia produces and consumes over 85% of the world's rice, and over 652 million tons were produced in 2011. The major rice-growing countries of Asia cover a large geographic area with wide variation in climatic conditions, meaning that rice is grown in different environments or ecosystems. IRRI (2007a) defines four main rice ecosystems or environments: irrigated, rainfed lowland, rainfed upland and flood-prone/deep-water). Within these, there are different cropping intensities (one, two or three crops grown per year on the same plot), different planting, sowing and harvesting periods, as well as different crop establishment methods (Nelson et al., 2014; Setiyono et al., 2017).

In general, rice is established by two different methods: transplanting (TP) and direct seeding (DS) (Chauhan et al., 2015). Direct seeding is a technique where the seeds are directly broadcast onto the soil surface and is commonly practised in rainfed and deep-water ecosystems, but also in irrigated systems. DS has the advantages of reduced labour costs, faster maturity, and better water use, but the crop is less resistant to weed problems (Sangeetha and Baskar, 2015). DS can be classified into wet direct seeding (WDS) and dry direct seeding (DDS) (Pandey et al., 2000). In WDS, pre-germinated seeds are broadcast into the mud or puddled field, while in DDS, seeds are sown in dry prepared soil followed by harrowing at the onset of the rainy season (Singh et al., 2008). On the other hand, TP is primarily performed in irrigated, and rainfed lowland ecosystems (Singh et al., 2008). This involves the replanting of rice seedlings into puddled fields after a few weeks of growth in a nursery bed. This requires nursery bed preparation followed by transplanting which results in more labour and time needed to establish the crop (Sangeetha and Baskar, 2015). TP provides benefits for a farmer in terms of lower seed density and weed control hence potentially producing a higher yield compared to DS (Singh et al., 2011). TP can be done manually by transplanting in rows or by a mechanical transplanter. DS can also be done manually by broadcasting or throwing the seeds, or in certain areas (mainly the US and Australia) mechanically by a drum seeder which results in a more even distribution of seeds.

The growth of a rice plant is divided into three main phases: vegetative, reproductive, and ripening (De Datta, 1981). These phases can be subdivided into ten growth stages: four in the vegetative phase, from (0) germination, (1) seedling, (2) tillering, to (3) stem elongation; three in the reproductive phase from (4) panicle initiation/booting, (5) flowering, to (6) heading, and; three in the ripening phase, from (7) milk grain stage, (8) dough grain stage, to (9) mature grain (IRRI, 2007a). In tropical regions, a medium duration (120 days) variety will have a vegetative phase of around 60 days followed by another 30 days in the reproductive phase and 30 days in the ripening phase (Yoshida, 1981). This duration will vary depending on the rice variety, environment, and climate condition (Yoshida, 1981; Kuenzer and Knauer, 2013;). For example, low temperature can lengthen the duration of the vegetative phase, while water availability can affect the duration of the reproductive phase (Vergara, 1992). With regards to the establishment methods, Yoshida (1981) indicated that DS rice starts the tillering phase earlier than TP rice since growth is not disturbed by transplanting shock. This means that DS rice can mature earlier (by 7 to 10 days) than TP rice (Pandey et al., 2000; Farooq et al., 2011; Sudhir-Yadav et al., 2014). Moreover, prior to rice establishment, field is prepared, cleared, and flooded. Land preparation, flooding, crop establishment, three phases of rice growth, and harvesting are events in the rice growing season.

Figure 1.1 shows the phases and stages of the rice crop as well as land preparation and harvest.

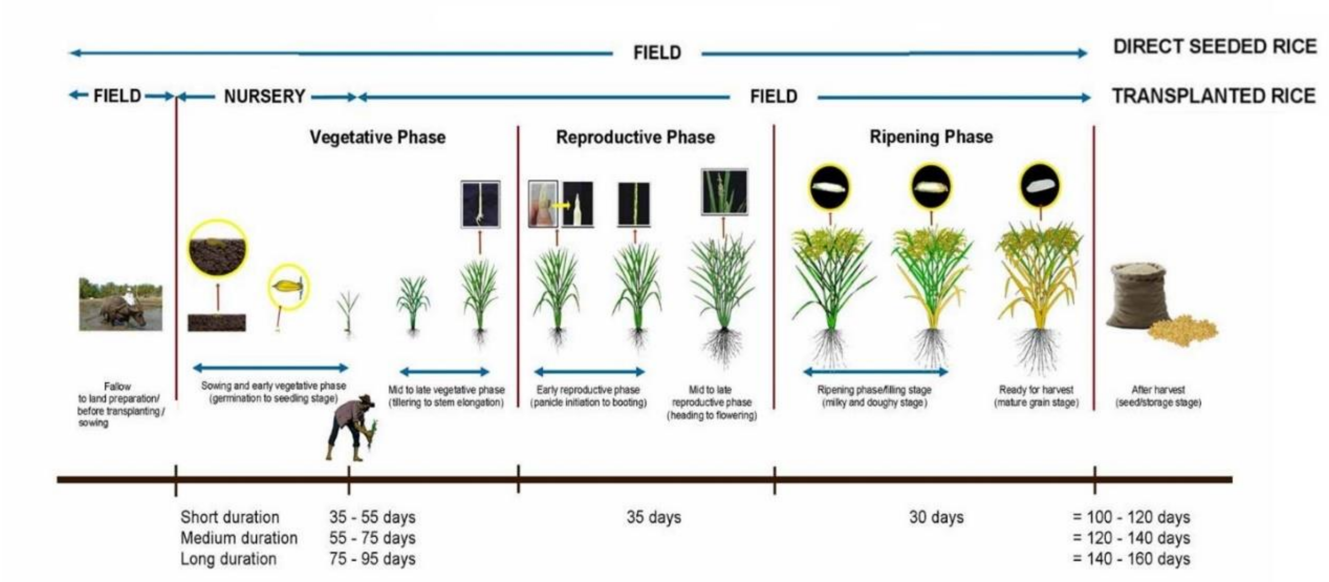

Figure 1.1 Growth duration of direct seeded and transplanted rice.

(source: http://www.knowledgebank.irri.org/step-by-step-production/pre-planting/crop-calendar)

In terms of the difference that can be observed in the field, the difference between DS and TP occurs between germination and the early vegetative phase: DS rice is wet or dry sown into the field and left to germinate; TP rice is germinated in the nursery bed and transplanted as seedlings into the flooded field. As the vegetative phase continues, the canopy will close making the difference in seed or seedling distribution harder to see.

Rice is managed under different water regimes, and this depends on its position in the toposequence. Toposequence refers to a particular topographic sequence in the landscape which is associated with soil and local hydrological properties (IRRI, 1996). The top toposequence fields are drought-prone; they do not preserve standing water as a large amount of runoff may deepen the groundwater table, and the coarse-textured soil makes the soil drier (Boling et al., 2008). The fields in the mid-toposequence are well-drained, while the fields in the bottom toposequence are poorly drained (IRRI, 2006; Singh et al., 2008). A wide variation of rice ecosystems occurs across the toposequence. Upland rice is in the top of toposequence, rainfed fields (upland and lowland) and irrigated fields appear in the mid-toposequence, while flood-prone fields are in the bottom sequence (near the riverbank). Figure 1.2, taken from IRRI (2007b) and Kirk et al., (2014), shows a schematic distribution of rice ecosystems in different toposequences. In terms of the crop establishment methods, although TP and DS can be practised in any sequence, DS is mainly unsuitable for fields with poor levelling and drainage, unless there is a pumping system, hence TP is more common in such fields where water can stagnate for a long time (Pandey et al., 2000).

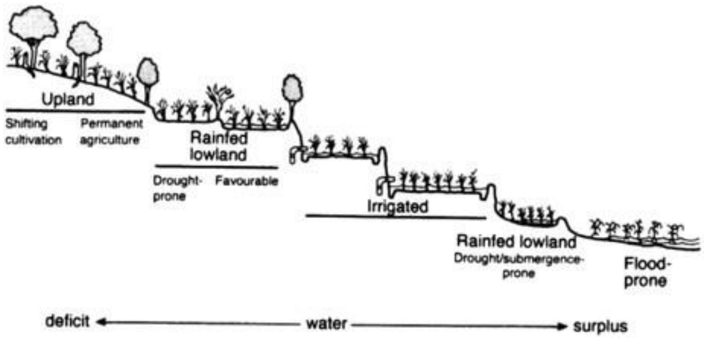

Figure 1.2 Rice ecosystem distribution on each toposequence
(source: IRRI (2007b) and Kirk et al., (2014))

Several studies have shown that crop establishment method is correlated with water use, weed, and disease incidence which can influence the canopy structure, growth duration, growth rate and yield (Singh et al., 2011; Chauhan et al., 2015; Setiyono et al., 2017). As such, Setiyono et al., (2017) suggested taking crop establishment method, as one of rice cropping system characteristics, into consideration for the improvement of rice detection algorithms in various rice environment conditions. Gumma et al., (2015) highlighted that spatial information of establishment methods is a means to track farming practices which can be used to support agricultural planning. In addition, a recent study by Zhi et al., (2017) pointed out a significantly higher accuracy for rice phenology estimation when considering TP and DS rice separately, due to their differences in the morphological structure at the vegetative phase.

1.1.2. Synthetic Aperture Radar remote sensing for crop detection and mapping

Mapping and monitoring the rice crop using remote sensing techniques have been widely conducted, and have included different sensors (optical and radar), resolutions (spatial, spectral and temporal), area coverages (local to global), purposes, and methods (Dong and Xiao, 2016).

However, observation in tropical and subtropical regions, where rice is mostly grown is challenging due to frequent cloud cover, especially during the monsoon season when most rice cultivated (Gumma et al., 2014). Consequently, an optical satellite with a very short revisit time is required in order to monitor and capture the different phenological stages in the rice growth (Nguyen et al., 2015). Even then, obtaining sufficient cloud-free images is a challenge.

As an alternative, Synthetic Aperture Radar (SAR) has advantages over optical imagery, due to its independence from sunlight and weather conditions which can overcome the cloud cover problem (Lee et al., 2009). SAR is an imaging radar that employs microwaves to detect objects. Objects are identified by the amount or intensity of energy reflected back to the SAR sensor, which is called backscatter (dB). Several properties of objects can be distinguished from the difference in backscatter (Lee et al., 2009), and review studies have summarised various SAR applications in rice crop using different bands, polarizations, and techniques (Kuenzer and Knauer, 2013; Mosleh et al., 2015; McNairn and Shang, 2016). Nelson et al., (2014) developed a rule-based classification for mapping rice area and estimated rice crop detection parameters based on temporal characteristics using COSMO SkyMed and TerraSAR-X imagery (X-band, HH-polarized images). Nguyen, Gruber, & Wagner, (2016) presented the use of HH polarization from C-band Envisat ASAR (Advanced Synthetic Aperture Radar) to analyse the temporal variation in backscatter to classify crop seasonality. Furthermore, Setiyono et al., (2017) explored X-band (COSMO SkyMed and TerraSAR-X) and C-band (Sentinel-1) imagery and then generated an automated image processing and rule-based classification to classify rice area, seasonality and leaf area index (LAI) as inputs to a crop growth simulation model to estimate yield.

SAR sensors can vary in the wavelength, incidence angle, and polarization configurations. In a number of studies utilizing SAR image, X, C and L bands have been used to extract rice crop information (Inoue et al., 2002; Suga & Konishi, 2008). The selection of wavelength affects the depth of penetration and which part of the crop interacts with SAR signal (Mcnairn & Brisco, 2004). Furthermore, Mcnairn & Brisco (2004) explained that X-band interacts more with the upper canopy while longer wavelengths (L-band) can get a response from the lower part of the canopy. C-band has been used to extract the backscatter from low biomass crops without much soil interference (Mcnairn et al., 2009b). The capability of C-band has also been proven by Inoue et al., (2014) showing a good correlation with rice canopy variables (LAI and biomass) throughout the season. Moreover, Lopez-Sanchez et al. (2014) observed the high performance of C-band to retrieve rice phenology stage information.

Polarization can determine the richness of information from the target and is classified into co-polarization (VV or HH) and cross-polarization (VH or HV). Le Toan et al., (1989) indicated that high backscatter in VV could be explained by the vertical orientation of the leaves. In a crop field, a co-polarized signal may detect the vertical structure such as the change in growth stages, while cross-polarization is more sensitive to volume scattering within the canopies and multiple scattering (Mcnairn & Brisco, 2004). Moreover, Inoue et al., (2014) identified that VH polarization in C-band is highly correlated with canopy biophysical variables in rice, such as LAI. The uses of the polarization ratio (VH/VV ratio for example) has also been studied, and it has been reported that surface roughness has a positive correlation with VH/VV ratio (Sarabandi et al., 1991) and VV/HH ratio (Mcnairn and Brisco, 2004).

Rice exhibits a particular temporal pattern of SAR intensity and demonstrates various scattering behaviours due to the interaction between the SAR signal with the rice canopy, the underlying soil, and the water content in both the leaves and the soil (Kuenzer and Knauer, 2013). The temporal variability in the rice SAR signature can be seen as a function of growth time, where there is a large dynamic range correlated to the growth stages of rice canopy (Inoue et al., 2002; Choudhury and Chakraborty, 2006). The canopy structure of agricultural crops and the properties in soil surface give a particular response to the SAR backscatter (Bouman, 1995; Kuenzer and Knauer, 2013). The changes in the vegetation cover and structure (such as height, size, shape, and leaves orientation), the dielectric properties of the vegetation and soil, as well as the soil roughness can alter the SAR backscatter signature (Mcnairn and Brisco, 2004; Kuenzer and Knauer, 2013). As discussed by McNairn and Shang, (2016), the dielectric constant (water moisture) of the object would give strong backscatter values. However, backscatter would be very low in the case of flooded soil, while dry soil gives weak scatter (Kasischke et al., 2014).

The interaction between SAR scattering and the vegetation-soil- water can be explained by three main scattering mechanisms: the direct-volume scattering from the rice canopy, the surface scattering from the ground, and the multiple scattering from the interaction between the rice canopy and the ground surface (double-bounce) (Bouvet and Le Toan, 2011; Koppe et al., 2013). In the case of rice fields, the low backscatter is observed at the start of the growing season due to the specular effect in the flooded field (Bouvet and Le Toan, 2011). The double-bounce effect and volume scattering contribute to the backscatter significantly as the rice grows due to the interaction between the water surface and the plant stem (tillers); until reach the peak in the reproductive phase (Choudhury and Chakraborty, 2006; Bouvet and Le Toan, 2011). The backscatter remains constant during the reproductive phase because there is no significant difference in crop biomass, height, and density (Le Toan et al., 1997). Decreasing backscatter is observed after the ripening phase and until harvesting, as a response to the drying plant and the drained field (Le Toan et al., 1997; Torbick et al., 2017).

Regarding crop establishment methods, several studies have investigated the difference in backscatter during the rice growing period. Gumma et al., (2015) demonstrated the use of C-band (HH polarization) with a 25-day revisit period to distinguish TP and DS rice, showing that backscatter of early TP and DS rice are distinct during the establishment time. Moreover, with full polarimetric C-band data, Zhi et al., (2017) showed that the double bounce effect by the stalk and the underlying surface are higher in DS rice during the tillering stage, while in TP this effect is lower due to the more space between plants. However, these studies had a limitation on the number of polarization and image availability. They mainly focused on the observation during the rice growth, but have not looked at the field condition before planting, such as during the land preparation. They also have not explored the factors of environment, such as rainfall and topography in explaining the farmer's preferences for crop establishment methods.

Obtaining remote sensing-based information on the type of crop establishment method, therefore, can be useful for better understanding of management practices. Since the yield and problems confronted in the field may vary between TP and DS rice, some uses of information on the establishment methods can be mentioned. The more accurate in the yield estimation, detection of high-risk location with the disease, water use management, and losses prediction are examples among other uses that can contribute to the agriculturally related planning.

Le Toan et al., (1997) indicated that the flooding/transplanting period, growth duration (vegetative, reproductive, and ripening), and fallow period are important to characterize the temporal dynamics of rice. This rice growth duration is related to the duration of each phenological stage. Nguyen et al., (2015) monitored rice phenology using ENVISAT ASAR WSM data to extract rice seasonality. In another study, the backscatter signature in X-band SAR image was used to monitor the rice phenology stages, showing the sensitivity of the flooded area and successfully obtained a high agreement with the ground measurement (Lopez-Sanchez et al., 2012).

As the characteristics of TP and DS methods have been mentioned above, a comparison table summarizing the differences between TP and DS is presented in Table 1.1, including potential remote sensing-based information to detect the difference in crop establishment methods.

Table 1.1 Comparison of crop establishment methods
(source: Yoshida, 1981; Pandey et al., 2000; Singh et al., 2008; Nelson et al., 2014; Sangeetha & Baskar, 2015)

Relevant field, crop and water management factors	Transplanting	Wet direct seeding	Dry direct seeding	Potential for detection by remote sensing or other spatial information
Seedbed condition	Puddled- flooded soil	Puddled- wet (saturated) soil	Dry soil (no puddled and unsaturated)	Soil surface roughness and soil saturation
Commonly practised location	Irrigated and rainfed areas	Irrigated areas	Rainfed areas	Existing maps of irrigation systems
Land preparation	Flooding before transplanting (2-5 cm)	Field is drained before seeding (saturated soil)	Soil without standing water, dry tillage	Soil surface roughness and soil saturation
Water management	Maintaining the water level between 5-10cm as rice growth	Maintain low water level (2-5 cm) for 21 days after sowing	Use early rainfall, maintain low water level (2-5 cm) for 21 days after sowing	Water presence/soil saturation
Growth duration	Transplanting after 15-21 days old, transplanting shock effect, longer in maturity (about 1 week)	Pre-germinated seed (after soaked in 24 hours, have 2-3 cm length), faster in maturity (7-10 days)	Harvested 10-15 days earlier than transplanted	The rate of growth in an early season. Difference in temporal signature of rice crop phenology
Toposequence	More suitable in the medium-low toposequence	More suitable in the top- medium toposequence	More suitable in the top- medium toposequence	Relative elevation from Digital Elevation Model
Advantages	Resistant to weed, less seed needed	Less labour to establish	Less labour to establish, favourable in dry areas	Presence of weed species in canopy
Disadvantages	More labour needed to establish the crop	More seed needed, weed problem	More seed needed, weed problem	Presence of weed species in canopy

Therefore, in this study, to discriminate the crop establishment methods using SAR multi-temporal imagery, the backscatter characteristics throughout the rice growing season, from the land preparation, flooding, and subsequent phenological stages are explored. Particularly, the condition at the start of the growing season is expected to help in discrimination. Since the condition of the field and the rice growth stages are detectable (spatial and temporally) through remote sensing according to the mentioned studies above. Based on the reviewed literature, Figure 1.3 represents the expected differences in temporal backscatter between TP, WDS, and DDS rice, indicating where the best opportunities are for remote sensing-based discrimination between them. The reason for the expected signature is as follows: High dB of WDS in land preparation due to saturated soil; high dB of TP in crop establishment because TP rice is planted with seedlings; high dB of WDS in vegetative due to the tiller and plant density, dB of DDS is higher than WDS because of the weed infestations, while dB of TP is low corresponding to the shock effect. There is no difference highlighted from reproductive to harvesting time.

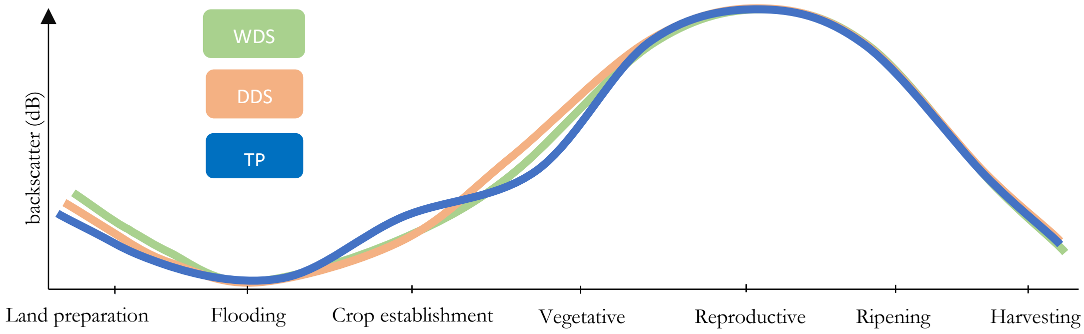

Figure 1.3 Conceptual temporal backscatter (dB) profile of TP (transplanting), WDS (wet direct seeding), and DDS (dry direct seeding) in different phenological stages based on reviewed literature

The next sections cover the classification methods to consider and the available SAR data for detecting and discriminating between rice crop establishment practices.

1.1.3. Classification methods for crop detection and mapping

Some factors should be considered in selecting a suitable classification method. Lu and Weng, (2007) mentioned some of those factors, such as the user's need, image spatial resolution, sources of data, image pre-processing and classification algorithm available, and the time constraint.

Various classification methods have been applied to remote sensing data which are generally divided into supervised and unsupervised methods, depending on the use of representative training data for each predefined classes (Tso and Mather, 2009). The supervised methods also vary in the algorithm. For example, Maximum Likelihood Classifier (MLC), was the first rigorous and widely applied technique (Richards and Jia, 2006). However, the performance of this classifier depends on the assumption of normally distributed data. To obtain high accuracy, a large number of training data is required to meet the normality assumption (Tso and Mather, 2009; Khoi and Munthali, 2012) which can be costly and time-consuming in both data collection and processing. Consequently, when a constant size of training data is used in classifying high-dimensional data (spectral bands), the classifier performance can decrease due to the 'Hughes phenomenon' (Salehi et al., 2017).

More advanced algorithm classifiers which are independent of data distribution, have also been introduced such as Artificial Neural Network (ANN), Support Vector Machines (SVM), fuzzy algorithms, and Decision Trees (DT), showing improvement in accuracy compared to conventional methods (Tso and Mather, 2009). Among others, the DT classifier is faster in processing time and easier to analyse (Pooja and Lecturer, 2011). It is a multistage classification, where a set of hierarchical decision rules is designed to assign pixels into the best class (Richards and Jia, 2006). Additional advantages of the DT classifier are its flexibility in handling data of different classes and type (categorical and numeric) and the ability to handle nonlinear relationships in the inputs (Pal & Mather, 2003; Mcnairn et al., 2009). However, DT has a tendency of overfitting and has poor performance when applied to large sets of input features (Salehi et al., 2017). Gumma et al. (2014) applied DT for mapping seasonal cropland using MODIS data. Nguyen, Gruber, & Wagner (2016) also presented the use of this technique in classifying rice cultivated area using Sentinel-1 multi-temporal images and obtained a very high classification accuracy (87.2%).

1.1.4. Overview of Sentinel-1 imagery

The Sentinel-1 mission was launched under the Copernicus joint initiative of the European Commission (EC) and the European Space Agency (ESA). It is operated by two constellation satellites: Sentinel-1A (launched in April 2014) and Sentinel-1B (launched in April 2016). It provides freely accessible SAR data with a single (VV or HH) and dual polarizations (VV+VH and HH+HV) capability in C-band and four modes of imaging acquisitions (Strip map, Interferometric Wide Swatch, Extra Wide Swatch, and Wave mode) in several resolutions and spatial extents (ESA, 2013). Three level of images are available: Level 0, Level 1 in Single Look Complex (SLC) or Ground Range Detected (GRD), and Level 2 for the ocean. Flying at the 693km height and 98.18° inclination, Sentinel-1 captures images globally with a 12-day revisit time for each satellite and is used for large area monitoring with applications in disaster mapping, geology, agriculture, and forestry (Velotto et al., 2016). As Sentinel-1A and Sentinel-1B fly 180° apart from each other in the same orbital plane, the visit time gap can be reduced to 6 days or fewer in the more northern and southern latitudes, depending on the observation scenario (acquisition plan). When compared to previous SAR satellites platforms (ERS-1, ERS-2, and ENVISAT), Sentinel-1 offers improvement in terms of spatial resolution, revisit time, area coverage, and dissemination of data (ESA, 2013).

1.2. Conceptual framework

Figure 1.4 shows the conceptual framework of this study. The geographical boundary of the system is the Nueva Ecija Province of the Philippines which includes several municipalities and villages. The elements consist of the land environment and people in the villages who manage the land and particularly the rice fields. The land environment is characterized by altitude, soil, and water which vary in spatial and temporal aspects. Rice fields, as part of the land, are classified as upland, irrigated, rainfed lowland, and flood-prone based on the hydrology condition and altitude. Rice is planted and harvested within the crop calendar. Two major rice field ecosystems are irrigated and rainfed rice fields which have their own characteristics of soil and water availability that affect the choice of crop establishment method. TP and WDS are commonly practised in the irrigated rice field, while DDS is more common in rainfed rice fields. Each method of crop establishment has different requirement of soil (dry, puddled, flooded soil), seed, water, and labour that can result in a difference in growth duration. Outside of the system, there is dual polarization Sentinel-1 SAR imagery in every 12 days. The knowledge gap is how the different crop establishment methods can be detected by the SAR signal. The accuracy and validation of this detection will be conducted by using the data from fieldwork.

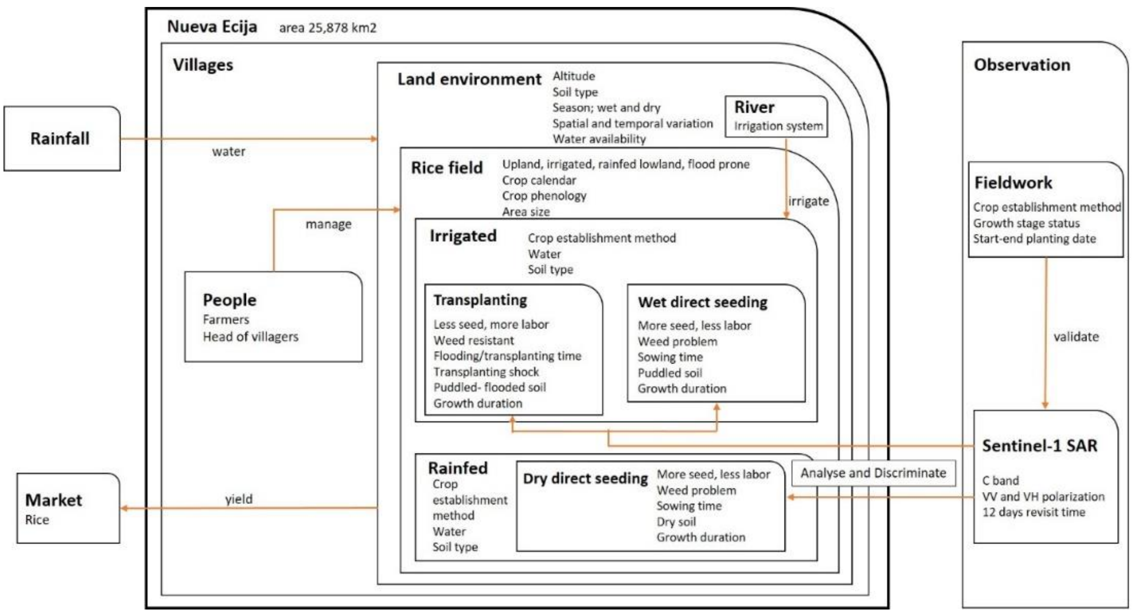

Figure 1.4 The crop establishment methods under rice field system (conceptual framework)

1.3. Problem statement

The availability of accurate and timely crop information is fundamental for the food security purpose. In particular, the crop establishment method is essential information to support the crop management since it influences the canopy structure, growth rate and yields (Singh et al., 2011).

Mapping and monitoring in tropical rice growing regions are challenging due to persistent cloud cover. Previous studies have proven that SAR images are useful for improving the accuracy in detecting and monitoring of rice crops since SAR can provide information independent of cloud conditions (McNairn and Shang, 2016). Most of these studies were mainly focused on crop type classification and area calculation (Panigrahy et al., 2012), crop monitoring (Suga and Konishi, 2008), yield estimation (Shao et al., 2001; Doraiswamy et al., 2004), and crop seasonal analysis (Gumma et al., 2014) .

The launch of Sentinel-1 brings more opportunities in crop detection and monitoring with the advantages of higher spatial and temporal resolutions, as well as the characteristic of C-band and dual polarization capability. The short revisit time allows capturing and discriminating the change in the crop growth phase more accurately (Nguyen et al., 2016). In addition, C-band with dual polarization can provide more information to distinguish the condition of the rice crop (Mcnairn & Brisco, 2004; Inoue, Sakaiya, & Wang, 2014).

Every classification technique has its advantages and disadvantages. As some classification techniques have been mentioned before, the performance of a more advanced classifier can be identified. Decision Tree (DT) algorithm will be employed to set the thresholds and rules in discriminating crop establishment method in this study.

Although many studies have utilized SAR data for rice crop applications, our above literature review shows that there are very few studies which have focused on the crop establishment method. In particular, using the higher temporal resolution images with VV, VH, and the VV/VH ratio, since the backscatter ratio of VV/VH has not been much exploited yet.

Therefore, considering the importance of crop establishment method for rice production and the potential of detecting it using Sentinel-1 data, this study aims to discriminate the crop establishment method using multi-temporal Sentinel-1 imagery. We try to understand how SAR backscatter signal responds to different crop establishment methods in different seasons. Different polarizations and the band ratio will be used with a time series of Sentinel-1A images, and the classification will be based on differences in the temporal backscatter signatures during the rice growing season. Moreover, Decision Tree (DT) will be employed to generate the discrimination rules.

1.4. Research objectives

The general objective of this study is to discriminate crop establishment method using Sentinel-1 multi-temporal imagery in the Nueva Ecija Province, of the Philippines. This aim will be achieved through the specific objectives as follows.

1. To analyse the multi-temporal signatures to extract the backscatter values characteristics in different crop establishment methods.
2. To identify the polarizations in multi-temporal Sentinel-1 imagery that best discriminates crop establishment methods.
3. To determine classification thresholds and rules for classifying transplanted and direct seeded rice based on backscatter values and ancillary data.

1.5. Research questions

Several research questions were made to address the specifics objectives.

1. Are there any significant differences in backscatter values between transplanted rice and direct seeded rice?
2. Among different polarizations (VV, VH, and VV/VH ratio), which polarizations can significantly discriminate the crop establishment method?
3. Can transplanted and direct seeded rice be accurately classified using a decision tree method based on the backscatter values and ancillary data?

1.6. Hypotheses

1. H0: There are no significant differences in backscatter value between transplanted and direct seeded rice
   H1: Backscatter values of transplanted rice are significantly different from direct seeded rice during the early growing season.
2. H0: VH polarization can significantly discriminate the crop establishment method
   H1: VV, VH, and VV/VH ratio polarizations can significantly discriminate the crop establishment method
3. H0: Transplanted and direct seeded rice cannot be classified by decision tree method
   H1: Transplanted and direct seeded rice can be classified by decision tree method

1.7. Expected research outputs

The expected output of this study is an MSc thesis which mainly focuses on the analysis of SAR backscatter characteristics of different crop establishment methods, and whether they can be discriminated by using multi-temporal Sentinel-1 images. The polarization(s) and the event(s) in the rice growing season, including the crop growth stage(s) for best discrimination of crop establishment methods will be identified, followed by classification rules. We will derive recommendations for further research on the use of SAR data for mapping crop establishment methods and the rice management practices in the Philippines.

2. STUDY AREA AND DATA

The study takes place in Nueva Ecija Province (Figure 2.1), located in Central Luzon, Philippines which covers an area of 25,878 km². The location geographically lies between 15°10'00" N to 16°7'56" N and 120°26'50" E to 121°22'26" E. The province is divided into 28 municipalities and four cities with the capital being Palayan City.

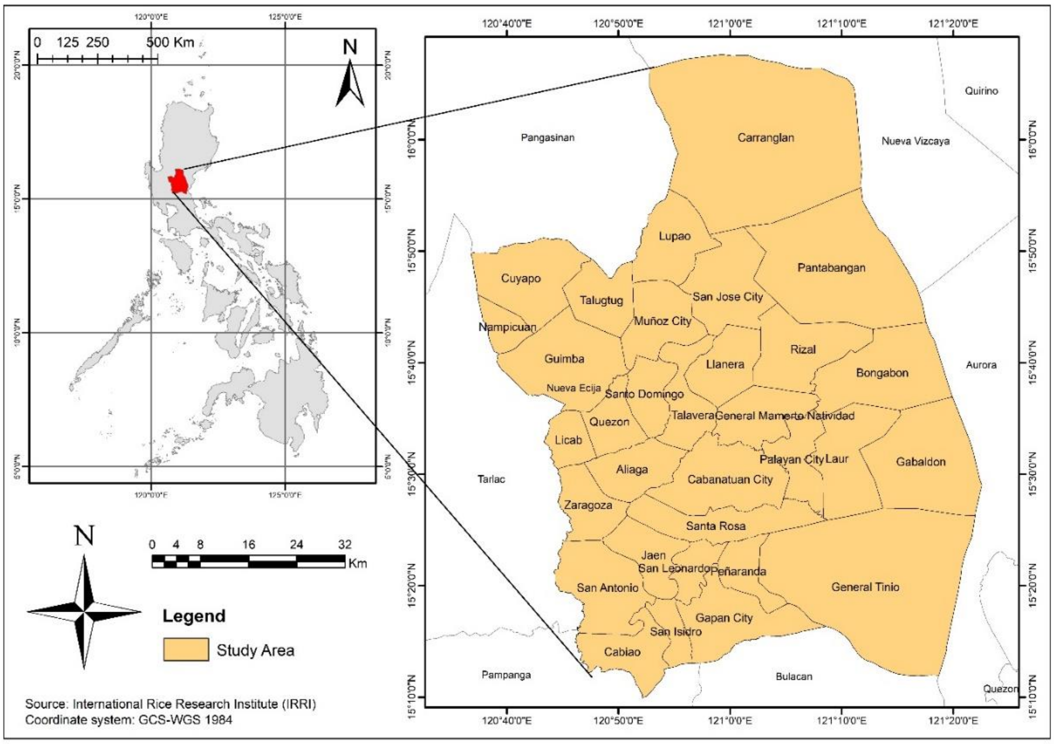

Figure 2.1 The location of the study in Nueva Ecija Province, Central Luzon, Philippines

The area is characterised by mostly flat terrain in the southwest near the Pampanga border and rolling upland in the northeast close to the mountain of Sierra Madre (Departement of Tourism Philippines, 2009). Figure 2.2 shows the elevation (m) of Nueva Ecija extracted from the Digital Elevation Model (DEM) of Shuttle Radar Topographic Mission (SRTM) 30m.

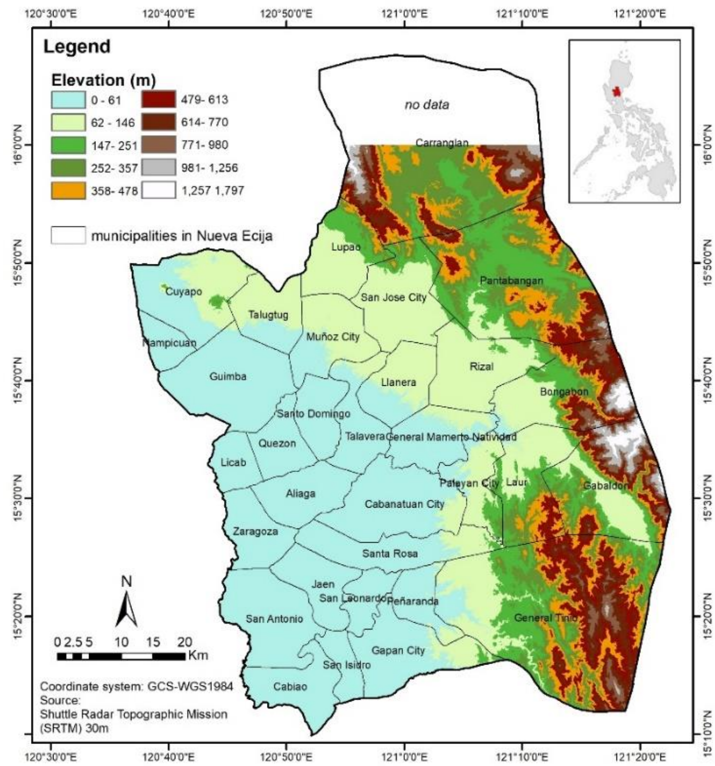

Figure 2.2 Elevation (m) of Nueva Ecija extracted from DEM SRTM 30 m

A tropical climate consists of the dry season (December to April) and wet season (May to November) are found in this area (Departement of Tourism Philippines, 2009). The mean temperature is 27.1°C while the average annual rainfall is 1,781 mm with maximum rainfall occurring in July and August (Asilo et al., 2014; Bordey et al., 2016). Figure 2.3 shows the average monthly rainfall and temperature in Nueva Ecija between 1991 and 2015.

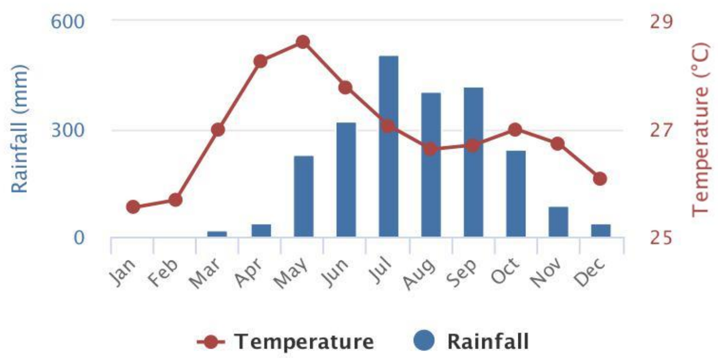

Figure 2.3 Monthly rainfall and temperature averages in Nueva Ecija.
Data were taken from Cabanatuan station (15°28'48" N, 120°58'12" E) in 1991-2015. (source: The World Bank Group, 2017)

The Philippines is one of the top ten rice producing countries in the world, with an average annual paddy production of more than 30 million tons in 2006-2010 (GRiSP, 2013). Among the provinces in the Philippines, Nueva Ecija is the largest rice producer and has contributed to approximately 8% of total rice production from 1990 until 2013 (Bordey et al., 2016). Most of the rice fields in Nueva Ecija are irrigated lowlands (78%) covering 138,157 ha, while the rainfed rice fields occupy an area of 38,387 ha (22%); the water for irrigated fields is supplied from the Upper Pampanga River Integrated Irrigation System (UPRIIS)

(Asilo et al., 2014; Nelson et al., 2014). Concerning the crop establishment methods in irrigated or rainfed fields, transplanting is commonly practised in the wet season, whereas direct seeding is applied more in the dry season (Asilo et al., 2014), though both methods can be found in both seasons. Generally, planting time in the dry season is from December to April, whereas in wet season planting occurs in June to October (Bordey et al., 2016). Figure 2.4, modified from Asilo et al., (2014) presents the cropping systems and crop calendars in Nueva Ecija.

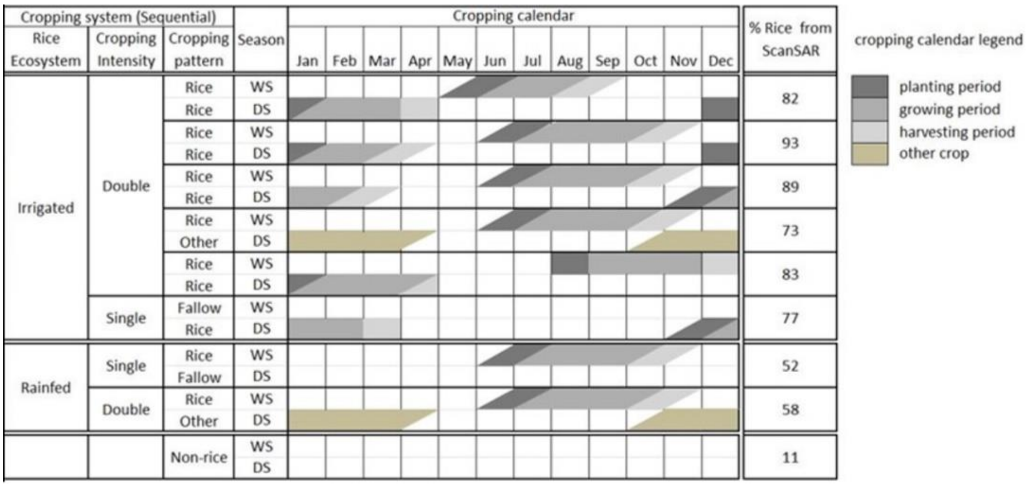

Figure 2.4 Cropping system and crop calendar in Nueva Ecija, Central Luzon
(modified from Asilo et al., 2014)

2.1. Data

This study benefited from a number of existing datasets in addition to the data collected during the fieldwork and multi-temporal remote sensing data. The following sections provide a brief description of each dataset.

2.1.1. Existing household and rice farm survey dataset

A survey dataset about rice farming production in Central Luzon (MISTIG data survey) was available from the International Rice Research Institute (IRRI). This survey was conducted in the dry season (2013) and the wet season (2014) under the "management information system for the rice monitoring and impact evaluation" project (http://ricestat.irri.org/mistig). A three-stage sampling was used to select the municipalities, the villages, and the households to be surveyed. Fifteen municipalities were randomly chosen in four provinces (Bulacan, Nueva Ecija, Pampanga, and Tarlac), each having at least 2,000 ha of rice area. Four villages were then randomly selected from each municipality. Systematic sampling was used to select twenty farm households in each village, with the village hall as the reference point and ten households as the skip factor. On average, 200 farmers were interviewed in each village.

For this study, MISTIG data survey which contained GPS coordinates of farmer's households with their farmland characteristics was used to select the municipalities, villages, and the farmers to be interviewed during the fieldwork.

2.1.2. Water release schedule data

Data of water release time for the Upper Pampanga River Integrated Irrigation System (UPRIIS) was provided by the National Irrigation Administration of the Philippines. UPRIIS is the largest national irrigation system which provides irrigation water to the Central Luzon region, including Nueva Ecija. The irrigation service is divided into five area divisions (Figure 2.5). Irrigation water is supplied by several dams: Tayabo, Pantabangan, Aulo, Atate, Penaranda, as well as the Talavera river and Cumabol creek. Water is released for an area depending on the schedule. But, generally, in the dry season, irrigation starts in

November- December and ends in March- April. For the wet season, water is released in May- July until September- November. For this study, the water release schedule was available for the dry and wet seasons (2016-2017) and was used to help in analysing the backscatter profiles.

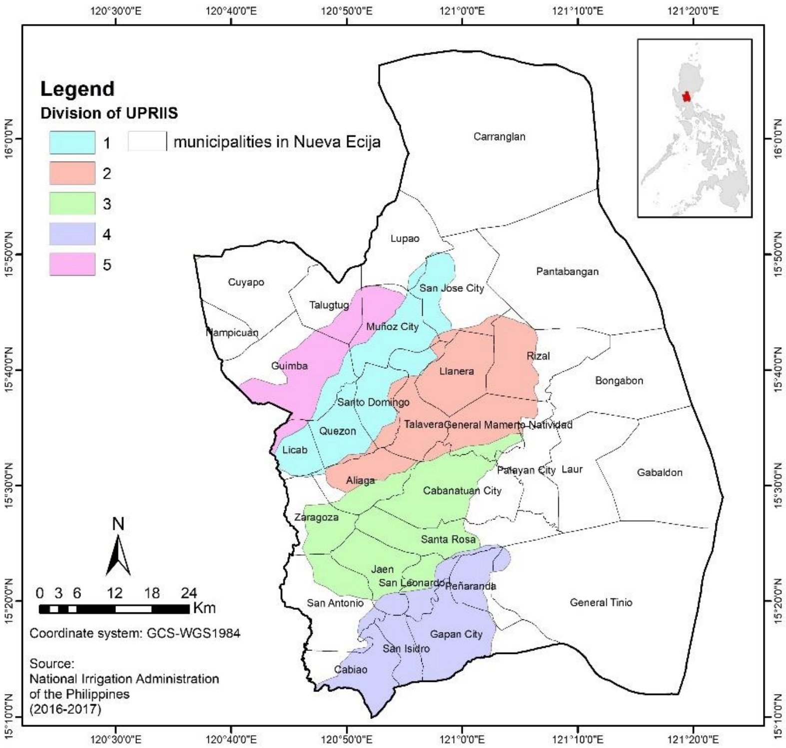

Figure 2.5 Divisions of the Upper Pampanga River Integrated Irrigation System (UPRIIS) in Nueva Ecija

2.1.3. Shuttle Radar Topographic Mission (SRTM) data

The Digital Elevation Model information was derived from SRTM with 1-arc (30m) resolution. Two scenes of January 2015 were downloaded freely from https://earthexplorer.usgs.gov to cover the whole study area. This data was used to generate the relative elevation as a proxy for position in the toposequence.

2.1.4. CHIRPS rainfall data

The CHIRPS (Climate Hazard Group InfraRed Precipitation with Station data) dataset is an interpolated meteorological dataset based on observation and monitoring of high-resolution Infrared Cold Cloud Duration (CCD) satellite images (Funk et al., 2015). CCD is an estimation method that measures the amount of rainfall based on the time of cloud presence (Tucker and Sear, 2001). CHIRPS dataset provides satellite-based total rainfall estimation (mm) in 0.05^0 resolution which is calibrated by station data and is available for daily, pentadal, decadal and monthly rainfall estimation. Funk et al., (2015) successfully demonstrated the use of the developed algorithm of CHIRPS to support the hydrological condition analysis in regional and global areas, such as temperature anomaly and drought.

For this study, decadal (10 days) rainfall totals were acquired from the CHIRPS website (ftp://chg-ftpout.geog.ucsb.edu/pub/org/chg/products/CHIRPS-2.0). These data were used to help in interpreting the backscatter signature. Figure 2.6 shows the CHIRPS-rainfall estimation for both, dry and wet seasons (November 2016- October 2017) in the study area.

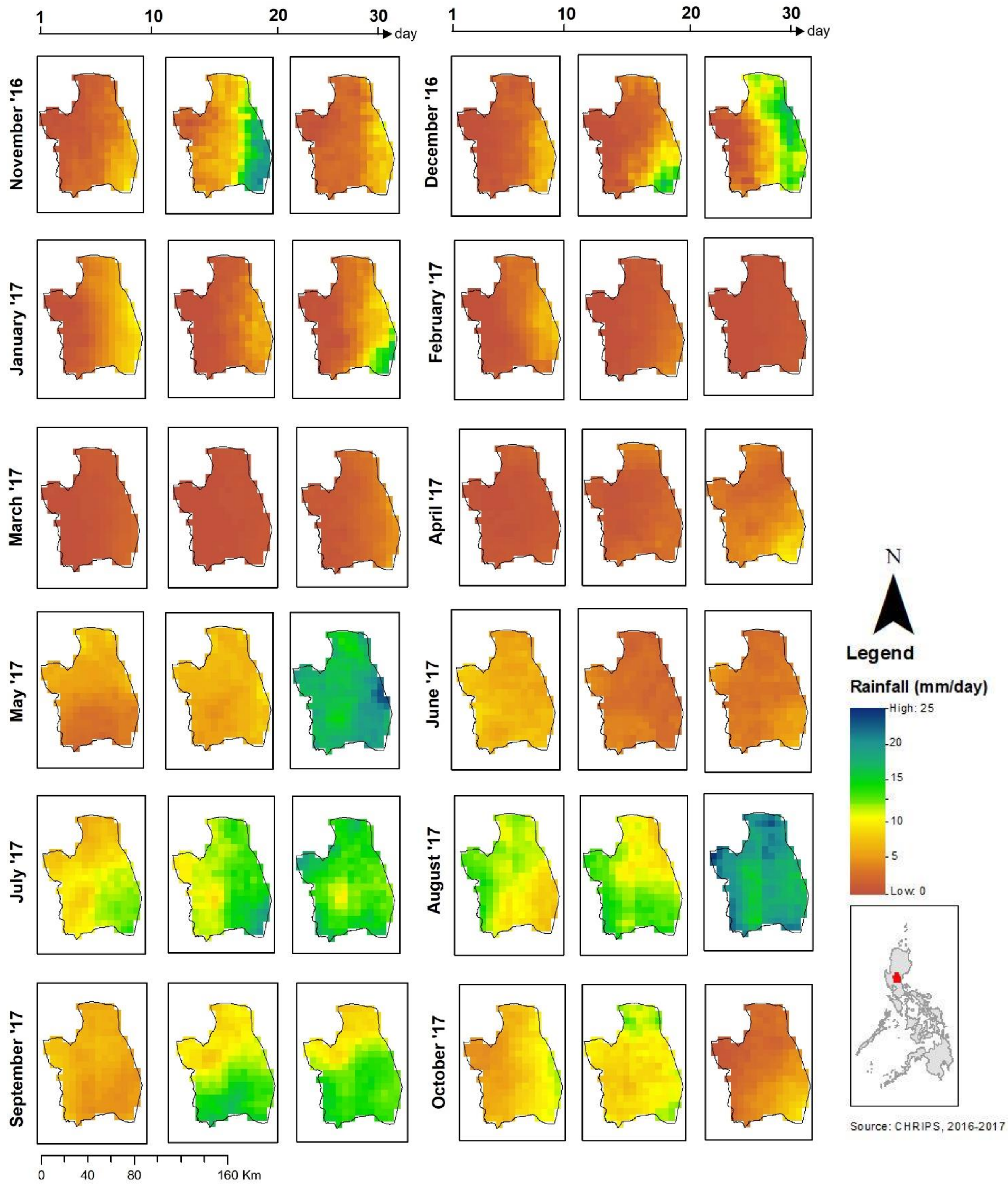

Figure 2.6 CHIRPS decadal data of rainfall from November 2016 to October 2017 in the study area.
Figure shows the high amount of rainfall for the months of November- December (dry season) and July- August (wet season) (source: CHIRPS, 2017)

2.1.5. Field data

Field data was collected, and interviews were conducted during the fieldwork. In total, 73 farmers were interviewed, and 91 plots were observed. Data of crop management practice were obtained from farmer interview, and the GPS (geographic) coordinates of rice fields were taken from the field measurements. This data was used to create the multi-temporal backscatter signatures and to extract the backscatter characteristics of every crop establishment method. The sampling scheme and fieldwork procedure are described in chapter three, while the results of fieldwork are explained further in chapter four.

2.1.6. Sentinel-1 images

Sentinel-1 consists of two satellite constellations: Sentinel-1A (launched in 2014) and Sentinel-1B (launched in 2016). The launch of Sentinel-1B reduces the revisit time from 12 days to 6 days depending on the observation scenario over a given location. Multi-temporal Sentinel-1 images with 20 m resolution were acquired in Interferometric Wide swath (IW) mode as Level-1 Ground Range Detected (GRD) products. IW mode consists of 3 sub-swathes that sum up to a swath of around 250km and is the primary operational mode for Sentinel-1 for land observation (ESA, 2013). The GRD product provides intensity values that are focused, multi-looked and projected to the ground range; hence the pixel resolution and pixel spacing will be approximately square (ESA, 2013; Torbick et al., 2017). Level-1 images are available in segmented slices to ease the data distribution, and each slice is a stand-alone image (ESA, 2013).

Dual polarization (VV and VH) images were available in the study area. Based on the crop calendar in Nueva Ecija taken from Asilo et al., (2014) (Figure 2.4), a total of 38 images of Sentinel-1A within the period of November 2016 to October 2017 were downloaded from ESA Copernicus Open Access Hub website (https://scihub.copernicus.eu/dhus/#/home). The images were used to obtain the backscatter of crop establishment methods in the dry and wet season. Mean backscatter of pixels within the rice fields polygons were extracted to create the temporal signatures of TP and DS rice. For some acquisition dates, slice assembly was conducted to cover the study area completely. Sentinel-1 B images were not used since the acquisition time gap, and orbit differences between Sentinel-1 A and B over the study area were only 2-3 days and also considering the time was required for doubling the amount of image processing. The detailed specifications of images used for this study are shown in Table 2.1, and the Sentinel-1A scenes coverage are shown in Figure 2.7.

Table 2.1 Specification of Sentinel-1 images used in the study (ESA, 2013)

Parameter	Specification
Satellite	Sentinel-1 A
Orbit	Sun-synchronous (descending pass)
Height, inclination	693 km, 98.18º
Wavelength/frequency	C (3.75 – 7.5 cm)/ 5.405 GHz
Repeat cycle	12 days
Polarization	Dual polarization (VV and VH)
Incident angle	30°-46°
Mode	Interferometric Wide swatch (IW)
Level data	Level-1 Ground Range Detected (GRD)
Resolution	20 m
Acquisition date	November 2016- October 2017

	Date	Slice number	Date	Slice number	Date	Slice number	Date	Slice number
	1/Nov/16	3 and 4	5/Feb/17	3	12/May/17	3	28/Aug/17	3
	13/Nov/16	3 and 4	17/Feb/17	3	24/May/17	3	9/Sep/17	3
	25/Nov/16	3 and 4	1/Mar/17	3	5/Jun/17	3	21/Sep/17	3
	7/Dec/16	3 and 4	13/Mar/17	3	29/Jun/17	3	3/Oct/17	3
	19/Dec/16	3 and 4	25/Mar/17	3	11/Jul/17	3	15/Oct/17	3
	31/Dec/16	3 and 4	6/Apr/17	3	23/Jul/17	3	27/Oct/17	3
	12/Jan/17	3 and 4	18/Apr/17	3	4/Aug/17	3		
	24/Jan/17	3 and 4	30/Apr/17	3	16/Aug/17	3		
Total number of images	38 images							

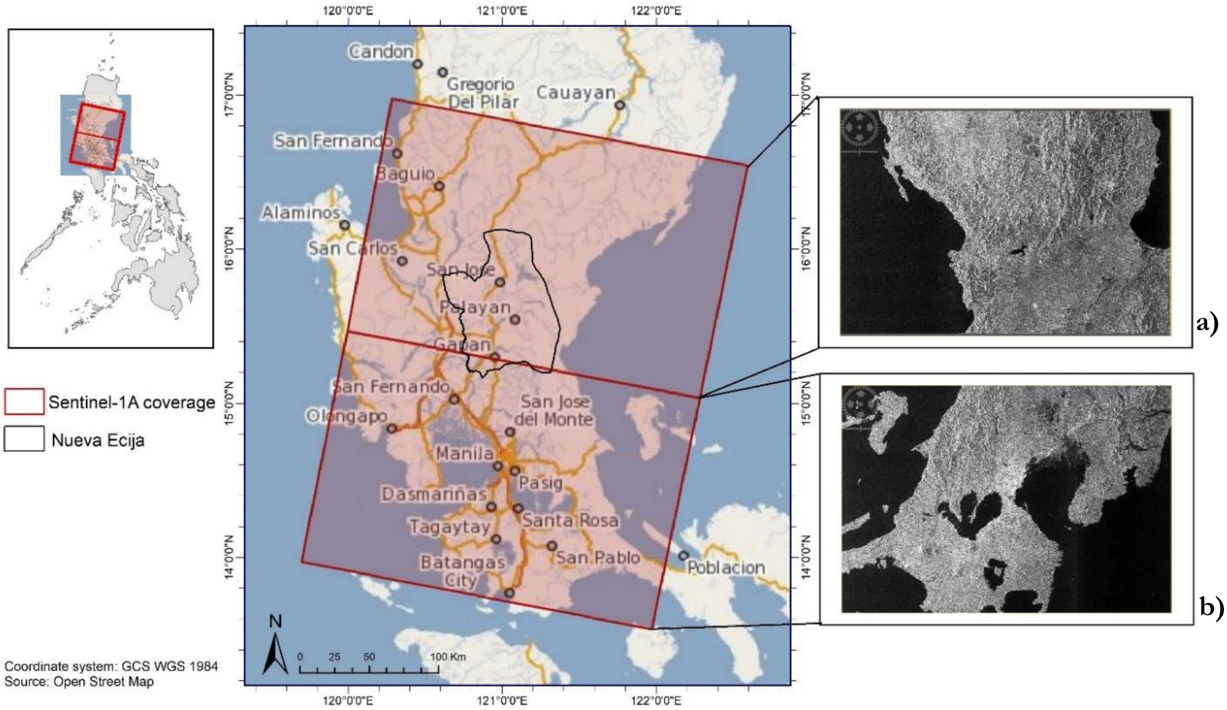

Figure 2.7 Sentinel-1A images coverage, with the examples of raw Sentinel-1 images. Images were acquired on 1 November 2016 with VV polarization.

From Nov '16 to Jan '17, two slices: number 3 (a) and number 4 (b) are needed to cover the study area completely. The figure shows that area directions in the raw images are reversed.

2.2. Software

The following software was used in this study:

- SNAP (Sentinel Application Toolbox) 5.0: Sentinel-1 images pre-processing
- ENVI Classic 5.3, with additional spectral extraction tool (developed by Natural Resources Department, ITC): backscatter value extraction by polygons
- ArcGIS 10.4.1: plot data management, polygon buffering, data visualization
- R 3.4.3 and R studio 1.0.143: decision tree (with package 'tree' version 1.0-37) and data visualization
- IBM SPSS Statistic 24: significance tests
- Microsoft Excel 2016: data management, minor data calculation and graph making

3. METHODS

This chapter describes the research steps used to achieve the study aim, including field data collection, image pre-processing, multi-temporal signature plotting, significance testing, and discrimination rules setting. The overview of the research methodology is presented in Figure 3.1.

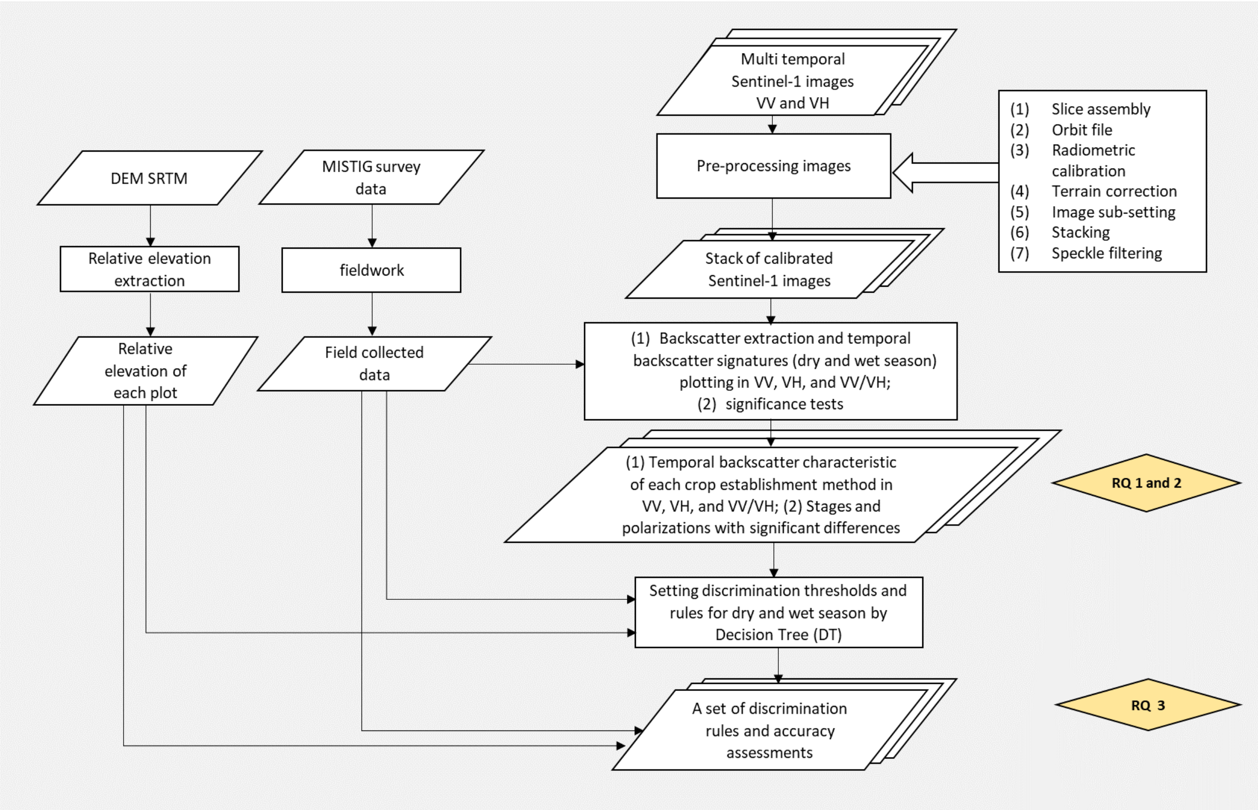

Figure 3.1 Flowchart of the research methodology

3.1. Field data collection

The fieldwork was carried out between 24th September and 10th October 2017. The main purpose was to collect specific information from farmers about rice crop management practice during the dry and wet season (2016-2017) and to identify the rice field boundaries and record their coordinates in the study area.

Purposive sampling was applied to collect information from farmers with a certain crop establishment method. The selection of municipalities, villages, and farmers was based on IRRI-MISTIG data (by using MISTIG information on the percentage of farmers using each crop establishment method in the municipality and their plot sizes) (Table 3.1). Accordingly, the villages in the municipality of Aliaga, Bongabon, Santa Rosa, and Talugtug were selected due to the reported crop establishment methods. Only farmers with a minimum 0.5 ha field were selected, considering the number of pixels within the field can be used for the backscatter extraction (only six to seven pixels can be extracted within 0.5 ha field). The number of farmers visited per village depended on the number of households surveyed by IRRI-MISTIG and variability in the crop establishment methods, with some adjustments considering accessibility, farmer availability and time restriction. In general, six to eight farmers were visited in each village.

Table 3.1 Cultivated area and crop establishment methods by municipality in Nueva Ecija during the wet and dry seasons

(source: IRRI-MISTIG data, 2015). The highlights represent the selected municipalities for field data collection.

		Wet season		Dry season		Wet & dry season	
	Cultivated area (ha)	Rice area (ha)	% area transplanted	Rice area (ha)	% area transplanted	Rice area (ha)	% area transplanted
Aliaga	104	101	92	92	56	193	75
Bongabon	88	74	69	32	30	106	57
Guimba	123	117	100	87	98	204	99
Llanera	110	107	91	90	92	198	92
Munoz City	97	87	100	82	100	170	100
Santa Rosa	156	155	95	149	57	304	76
Talavera	114	107	100	107	98	214	99
Talugtug	107	97	97	35	100	133	97
Nueva Ecija (total)	899	845	94	676	79	1521	87

Two activities were conducted during the fieldwork (Figure 3.2). First, the selected farmers were interviewed with a set of questionnaires, about their crop management practices in the dry and wet season (2016-2017). The questions included the time for land preparation, flooding, crop establishment, harvesting, as well as the crop establishment method and yield (Appendix I). Second, plot observations and measurements were conducted after the interview, collecting the coordinates of rice field boundaries, soil condition, seedbed location, photograph, and a sketch of the plot (Appendix 1). Coordinates of rice fields were used to create the plot polygons that would be linked to the SAR images. As TP rice is first raised in the seedbed, the backscatter of this area will be different from the main field, and thus needs to be removed during the backscatter extraction. Every plot measurement was linked to the corresponding questionnaire using a unique ID. The coordinates of fields with regular shape were only recorded at the corners, while for the fields with irregular shapes, GPS tracking system was used (model Garmin GPSMAP 62sc). Any objects inside or surrounding the field that could interfere the backscatter, such as trees or pump houses, were also noted. Other information related to the crop establishment method was also collected, such as the establishment cost to get a better understanding of the farmer's preference in his management practice.

All the acquired information was used to explain the backscatter characteristics of the different rice crop establishment methods, and to further discriminate them as the objectives of this study. Table 3.2 shows the list of equipment used during the fieldwork.

Figure 3.2 Activities conducted during the fieldwork: farmers interview (left) and the plots coordinates measurement (right).

Table 3.2 Equipment used in the fieldwork

Equipment	Function
GPS (Garmin GPSMAP 62sc)	To record the location and area of rice fields for training and validation purposes
Questionnaire sets and observation sheet	A list of questions related to the rice field and management practice, to get the information from the farmers and rice field condition
Camera	To take pictures of rice fields samples

3.2. Image pre-processing

Pre-processing of 38 multi-temporal Sentinel-1 IW Level-1 GRD images was executed automatically in the SNAP Toolbox. The process included the following steps:

(1) Slice assembly: A pair of images with the same acquisition date (slice 3 and 4) were merged into one image. There were eight images in total (acquired in November 2016- January 2017) that needed to be combined to cover the whole Nueva Ecija area. Subsequent dates were covered by just one slice.
(2) Apply orbit file: This process was to update the orbit information provided in the SAR metadata for accurate satellite position. The restituted orbit option was selected as this information is available real-time while the precise orbit can only be obtained after 20 days from the image acquisition time.
(3) Radiometric calibration: As it is a required process for SAR quantitative analysis, images were calibrated, converting the intensity values into sigma nought ($\sigma°$) to represent the true SAR backscatter of the objects. This step is also to ensure the comparability between SAR images (Tso and Mather, 1999).
(4) Terrain correction: Range-Doppler Terrain correction was applied to remove the distortion caused by topography and to register the images from the sensor geometry into geographic projection-WGS 1984 using DEM of SRTM 3 secs ($\pm$90m)
(5) Image sub-setting: Cropping the images to only cover the study area. This step was for computational efficiency purpose, reducing both memory requirements and processing time.
(6) Image stacking: To compile the images with the same polarization for the input in the next process. Two stacks, VV and VH images were created. In each stack, a total of 30 images were listed in the ascending order.
(7) Multi-temporal speckle filtering: Speckle is a granular noise in SAR images caused by random interference, and it degrades the quality of images (Argenti et al., 2013). Multi-temporal filtering is a spatial and temporal filter which minimises the short-term change of backscatter caused by a SAR sensor; therefore, any change in the backscatter is assumed due to the change in the object properties in the environment (Nelson et al., 2014; Nguyen & Wagner, 2017). Filtering of multi-temporal images also has an advantage over a single image filtering in maintaining the spatial pattern, especially for objects with relatively stable boundaries (such as agricultural fields), by using a larger number of pixels (in different time-images) to estimate the spatial average value (Quegan and Yu, 2001).

Refined Lee filtering was applied for this study. It is operated by adjusting the size of sliding window based on K-Nearest Neighbour algorithm and calculating the local mean and variance within the window (Yommy et al., 2015). It can effectively reduce the noise, but still preserves edge boundaries (Argenti et al., 2013). According to Lavreniuk et al., (2017), the Refined Lee filter, could yield the highest classification accuracy for crop mapping compared to other filtering methods in the SNAP Toolbox. This filtering was applied to the VV and VH stacks. An example of visual comparison between the original image, single time filtered, and a multi-temporal filtered image is shown in Figure 3.3. The filtered

VV and VH images were then used as input for the backscatter extraction in the subsequent step. It should be noted that the backscatter coefficients up to this stage were still in linear scaling (not in decibel/ dB).

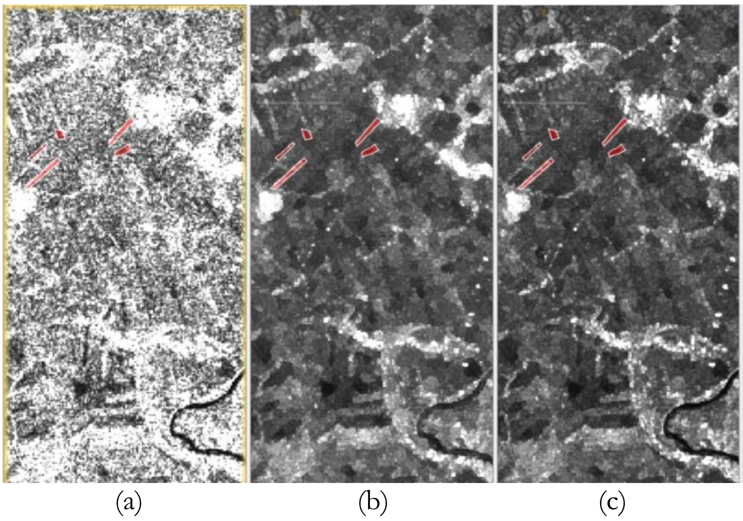

Figure 3.3 Comparison of filtering methods. Image date is 3 October 2017, VV polarized image

(a) original image (b) single date-filtered image, and (c) multi temporal-filtered image (using Refined Lee). Figures show that the edges are better defined in the multi temporal-filtered image. Red polygons are rice fields.

3.3. Backscatter value extraction

The GPS (geographic) coordinates of the rice fields were converted into polygons and were given the ID linked to the questionnaires. In total, there were 91 rice field polygons. To get the pure pixels (pixels falling totally within the rice fields) from the rice fields and to avoid the disturbance from unwanted objects (bunds, seedbed, trees, houses, and adjacent fields with different practice), they were masked out, and a 20m-negative buffer was implemented (for 44 out of 91 polygons). However, the buffering could not be applied to very narrow rice fields (47 polygons). Hence, possible noise due to the interference from the surrounding fields in these polygons was unavoidable.

Backscatter extraction was performed using a spectral extraction tool developed at the NRS Department in ENVI software, with the stacked images (VV and VH) and the two groups of polygons as the inputs. In this case, the means of pixel's values within each polygon were obtained. Figure 3.4 shows the example of a comparison of the polygons (before and after negative buffering) and the extracted mean value (DN) are shown in Table 3.3. For the comparison of all 44 polygons can be seen in Appendix III.

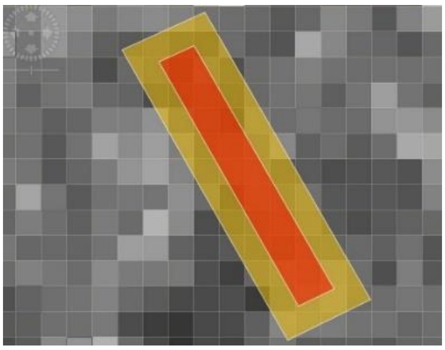

Figure 3.4 Comparison of rice field polygons before and after negative buffering (yellow and red, respectively) over the 3 October 2017 image- VV polarization

Table 3.3 Example of the extracted mean value (DN) difference between before and after the negative buffer

	Before negative buffering	After negative buffering	Difference
Value in VV	0.1024	0.09907	3.37%
Value in VH	0.0322	0.029	11.1%

For the subsequent analysis, the extracted backscatter values (DN) were grouped based on the crop establishment methods and the seasons.

3.4. Phenological stages estimation and multitemporal backscatter signature plotting

Analysis of the temporal backscatter signature was based on the change in the backscatter values throughout all events in the rice growing season, which is started from the land management (from the land preparation, flooding, and crop establishment), the subsequent phenological stages (from the vegetative, reproductive, to ripening phase) until harvesting. The rice growth stages were based on the IRRI (2007) classification. The time of land preparation, flooding, crop establishment, harvesting, as well as the age of seedling and rice maturity duration were obtained from the farmer questionnaires. However, the time of tillering and stem elongation (as the last stage of vegetative phase), the heading and flowering (as the last stage of reproductive phase), and the maturity (as the last stage of ripening phase) (Figure 1.1), were estimated from the maturity of the variety. The longer maturity duration would give the longer duration in the vegetative stage, while the duration in the reproductive, and ripening stage would be about the same (35 days and 30 days respectively) (IRRI, 2007a). For example, rice with 100 days maturity will only spend 35 days in the vegetative phase, while rice with a longer duration (120 days) will spend 55 days in the vegetative phase (IRRI, 2007a).

The estimation time of growth stages also depended on the crop establishment methods. For TP, the estimation time for each growth stage was reduced by the age of seedling, because the vegetative phase has already started in the nursery. On the other hand, as indicated in the Yoshida (1981) DS rice may have earlier tillering stage than TP. Therefore, the estimation time for the tillering and stem elongation was also adjusted. Hence, in this study, it was assumed that the duration in the vegetative stage of DS rice was ten days shorter (Pandey et al., 2000; Farooq et al., 2011; Sudhir-Yadav et al., 2014).

Since the Sentinel-1 images were acquired by date (not by growth stage or event), an adjustment was needed to plot the right backscatter values for the different events. In this study, the matching method was adopted from the study by Asilo et al., (2014). In general, the backscatter values of an event were obtained from the closest time with the image acquisition date. Although for the harvest, the images after the harvest date were used to represent the clear field. The benefit of this approach is to avoid the mixed backscatter values for an event caused by the different crop calendar. Since the management practice varies from farmer to farmer, one image can capture backscatter from the different stage of rice even with the same crop establishment method. However, this approach has difficulty in plotting for the different events which took place in the same week, and consequently different events might have the same backscatter values. For example, the flooding may occur just a few days after the land preparation. Since the revisit time of Sentinel-1A is 12 days, the backscatter for land preparation and flooding might be extracted from the same image.

In the next step, the backscatter values (VV and VH) in both seasons were converted from the linear scaling (DN) to decibel scaling (dB); the ratio of VV/VH was also calculated using the formula as follows (Veci, 2015).

$$\text{Backscatter coefficients of VV or VH (dB)} = 10 * \log_{10} (\text{DN})$$

$$\text{Ratio of VV/VH} = 10 * \log_{10} (\text{DN of VV/DN of VH})$$

After the value conversion, boxplots of VV, VH, and VV/VH ratio in both seasons which plotted the minimum, first quartile, second quartile (median), third quartile, and maximum values were all studied to identify the pattern of backscatter signatures of each establishment method. Furthermore, the signatures with and without the assumption of the early tillering stage in DS were also plotted.

3.5. Significant differences tests

Prior to the significance test, the distribution of the samples was tested through Shapiro-Wilk test. This test, along with the visual test (Q-Q plots, boxplots, and histogram) was preferable and more powerful compared to other tests (Kolmogorov Smirnov and Lilliefors test) to detect the normality in data (Razali and Wah, 2011; Ghasemi and Zahediasl, 2012). The null hypothesis stated that data is normally distributed. The level of confidence was set at 95%, meaning that data is not normal (H0 is rejected) when the p-value<0.05.

Significance tests were performed to answer the question of which event or rice growth stage and which polarization can discriminate the crop establishment classes. The distribution value of two independent groups can be compared using a t-test, but this test needs an assumption of normally distributed data which is not usually achieved in some situations (Rojewski et al., 2012). As a result, a comparable technique to the t-test, the Mann-Whitney U test, was selected, concerning the data distribution and the number of classes. It is a non-parametric test which compares two independent groups by their medians instead of their means, like in the t-test (McCrum-Gardner, 2008), which makes the test more robust under the non-normality condition (Sawilowsky, 1990). This study used 95% (α=0.05) as the level of confidence; therefore the significant difference between TP and DS was considered in p-value<0.05.

The significance difference test also represented the separability of classes. Events and polarizations with the lowest p-value indicated the high potential for the crop establishment methods to be discriminated.

3.6. Relative elevation identification as a proxy for position in the toposequence

Watershed boundaries were created as an approach to identify the relative elevation as a proxy for position in the toposequence. The SRTM DEM was used as the basis for the watershed interpretation and delineation. Watershed boundaries were identified following the elevation and stream orders (Strahler method); the higher the order of the stream, the larger the accumulation flow (Singh et al., 2013). The watershed boundaries were generated once the largest accumulation locations (outlets) were determined. All of the steps were performed using hydrological tools ArcGIS 10.4. The relative elevation of each rice plot was then calculated by subtracting the elevation of the plots from the elevation of the outlets of the watershed in which the plot lay.

Figure 3.5 shows the generated stream overlaid on the Google Earth and the watershed boundaries in the study area.

a) b)

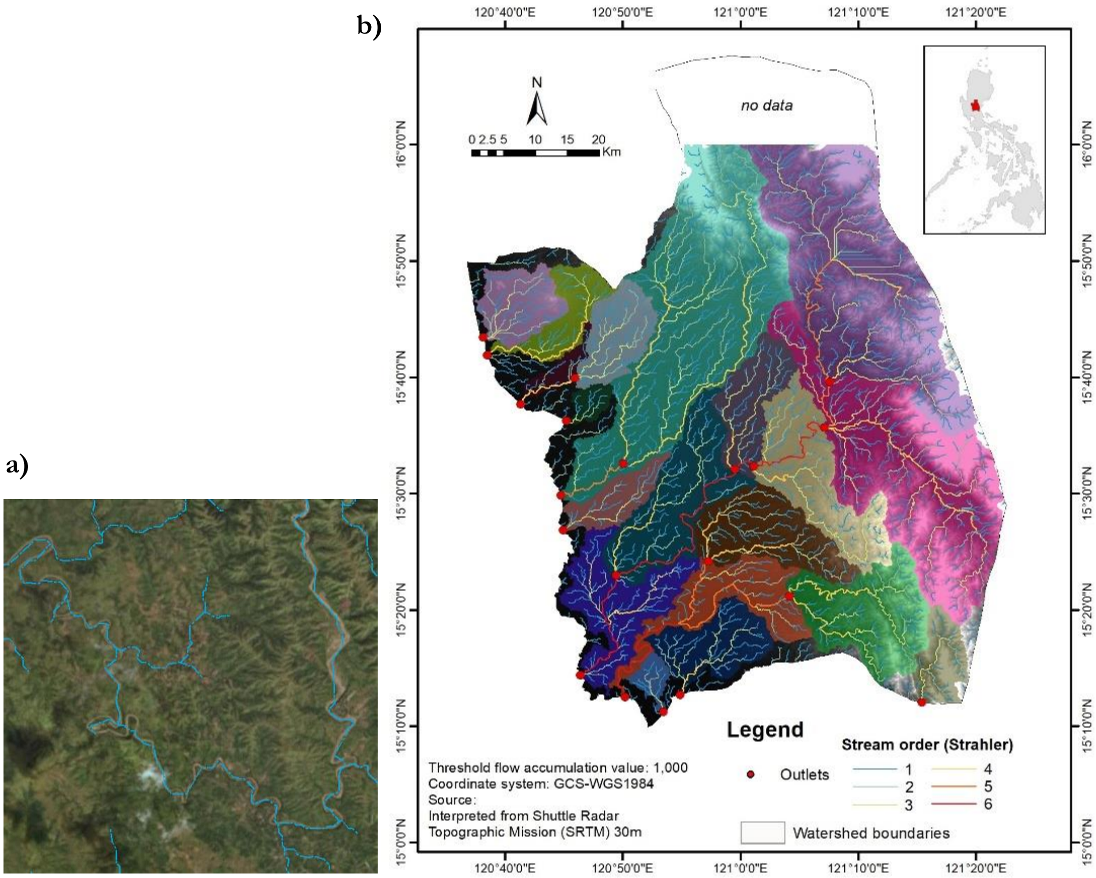

Figure 3.5 (a) Stream generated from SRTM over the Google Earth image. (b) Different watershed boundaries are shown by different colours.

Watershed boundaries were interpreted from DEM SRTM 30 m. Stream orders represent the stream size, where the higher the stream order, the larger the accumulation flow.

3.7. Classification thresholds and rules setting

A decision tree classifier (DT) is operated by a chain of simple sequential decisions which is constructed by the root that contains all data; the branches as the decision; the internal nodes as the testing place; and the leaves as terminal nodes (Pal and Mather, 2003). In DT design, data are classified by partitioning them hierarchically into a leaf (class) based on the testing result until all the decisions generate a tree, and this tree would continue splitting and growing until a certain terminal condition is achieved (Steinberg, 2009). An example of DT construction is shown in Figure 3.6.

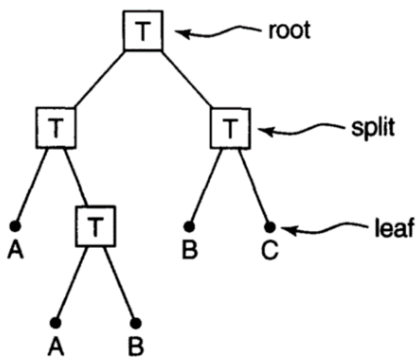

Figure 3.6 A Decision Tree construction

The T box is a node where the testing applied to split data into the leaves or terminal nodes (source: Friedl and Brodley, 1997).

Several DT algorithms have been introduced, such as CART (Classification and Regression Trees), C4.5, C5.0, ID3 (Iterative Dichotomizer 3), CHAID (Chi-squared Automatic Interaction Detector), and QUEST (Quick, Unbiased, Efficient and Statistical Tree Algorithm (Tso and Mather, 2009). Among others, CART, introduced by Breiman et al., (1984), is a popular binary-based approach to classify (for categorical data) or to predict data (for continuous data) (Steinberg and Colla, 1995; Song and Lu, 2015). It constructs the tree by determining the best variable to split and the best thresholds based on some impurity measures, which are gini, entropy, and deviance (Breiman et al., 1984). The advantages of using CART are its flexibility in handling unbalanced training data, where CART will adjust and re-weight the class frequencies in every node relative to class frequency in the training data, and its ability to handle missing values (Steinberg, 2009).

Prior to the model fitting, a pair of training (70%) and validation datasets (30%) was prepared from both seasons. Considering the characteristic of TP and WDS rice from the reviewed studies (Pandey et al., 2000; Farooq et al., 2011; Sudhir-Yadav et al., 2014), we proceed the analysis of backscatter with the assumption of the early tillering stage in WDS.

In this study, CART was applied to generate the thresholds and classification rules for discriminating between crop establishment methods in both seasons. The 'tree' package version 1.0-37 in the R statistical computing environment was used. This package is one of the several packages in R that implements CART and offers an option to control the tree size (Brian and Ripley, 2016). For the tree features (independent variables), only backscatter coefficients from the significantly different events were used, with relative elevation as additional data. To improve the performance in DT classification, a step called pruning is necessary by removing nodes that do not provide additional information (reducing the cost complexity in the model) (Steinbert, D., 2009; Song and Lu, 2015). This step was performed after composing the first decision tree.

To evaluate the performance of the DT model, several indicators were selected: (1) overall accuracy, (2) Kappa coefficient, and (3) ROC curve. These are common accuracy measures that have been widely used in previous remote sensing studies (Nishii and Tanaka, 1999; Liu et al., 2007; Rozenstein and Karnieli, 2011). A confusion matrix gives a simple cross-tabulation, comparing the class predicted by the model with the actual class, to derive the overall accuracy and the Kappa coefficient (Foody, 2004). The overall accuracy, considered as a simple indicator of accuracy, is calculated by the total number of correctly classified samples divided by a total number of reference samples (Congalton, 1991).

Kappa coefficient is also widely used as accuracy measurement which represents the agreement between classified and actual class in non-diagonal elements into account (Lu and Weng, 2007). In this study, the Kappa coefficient was interpreted as follows: poor (kappa <0.4), moderate (kappa 0.41-0.6), good (kappa 0.61-0.75), excellent (0.7- 0.80), and almost perfect (kappa > 0.80) (Richards and Jia, 2006).

Receiver Operating Characteristic (ROC) curve is one of the well-known measures of the goodness of fit of machine learning algorithm (Foody, 2004). The prediction accuracy of the model then can be assessed by the AUC (Area Under Curve) through comparison of sensitivity (true positive rate) and the specificity (false negative rate), referring to the miss-classification cost by the model (Bradley, 1997). The AUC value ranges from 0.5 to 1.0, where 1.0 means there is a perfect separation of two groups (Zweig and Campbell, 1993).

4. RESULTS

The following sections cover the main findings of the research, including those obtained from the field data, the temporal signatures of different crop establishment methods, results of statistical tests and the discrimination rules for both seasons.

4.1. Field data

In total, 73 farmers were interviewed, and 91 rice plots were visited and measured across 11 villages in four municipalities (Table 4.1). Rice was cultivated in 61 of the plots during the dry season and in 90 plots during the wet season (Table 4.2). The sample plots covered the western and eastern part of Nueva Ecija (Figure 4.1) where most of the rice fields are located (PRISM, 2017).

Table 4.1 Number of farmers interviewed and plots collected during the fieldwork.
On average six farmers and eight plots were visited per village.

No	Municipality	Village	Visited farmers	Plots
1	Bongabon	Macabaclay	7	10
2		Pesa	6	8
3		Vega	10	13
4		Calanaan	5	5
5	Talugtug	Villa Rosario	10	11
6		Alula	5	6
7		Cabiangan	6	7
8	Santa Rosa	Berang	6	7
9		San Isidro	6	10
10	Aliaga	Pantoc	6	8
11		San Felipe	6	6
		Total	73	91

Table 4.2 Number of rice and non-rice plots visited during the fieldwork

	Dry Season	Wet Season
Rice	61	90
Non-rice	30	1
Total	91	91

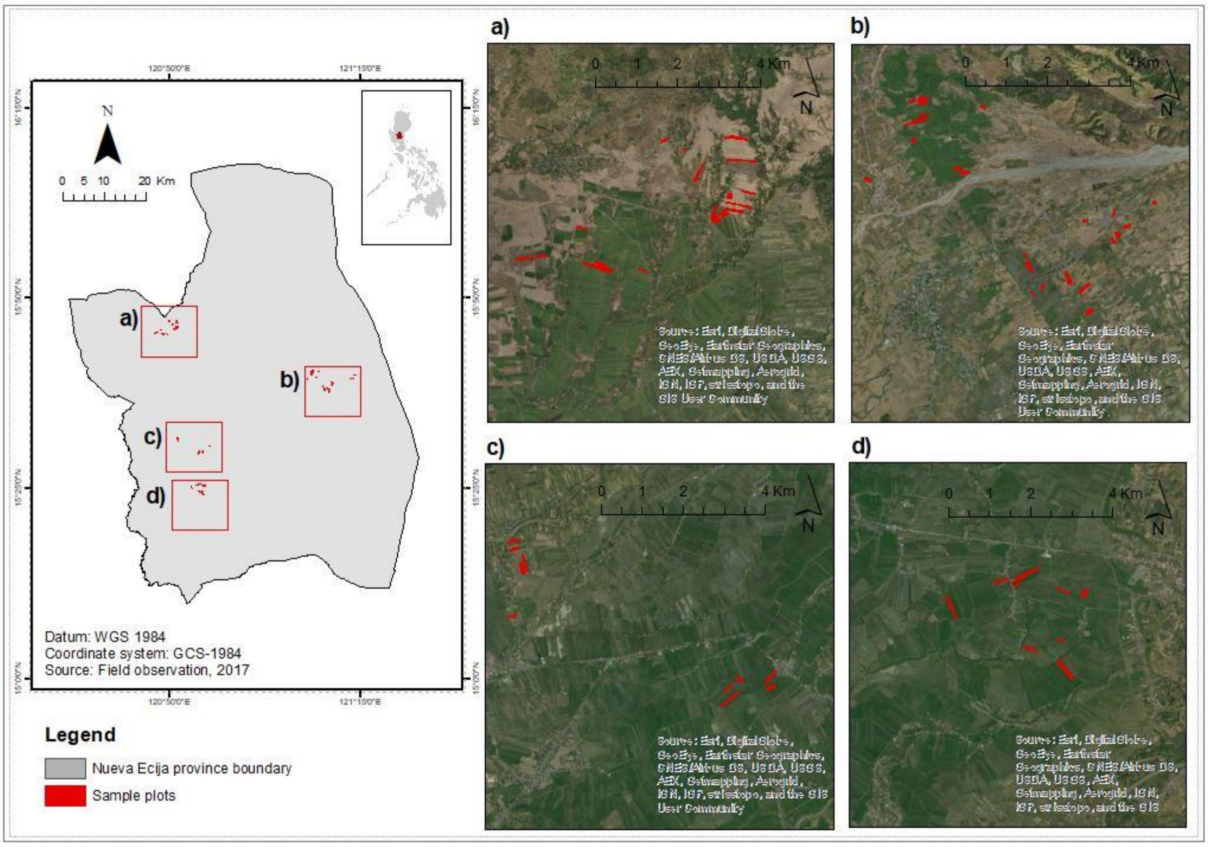

Figure 4.1 Rice plots distribution. Location of the plots in the municipalities of (a) Talugtug, (b) Bongabon, (c) Aliaga, and (d) Santa Rosa, respectively.

Some plots had regular shapes, but some plots were irregular. Plot locations were recorded by waypoints and tracking function in GPS (Garmin GPSMAP 62sc) with ±3m accuracy.

Regarding the crop establishment methods, the distribution of different practices in the dry and wet season can be summarized in Table 4.3. In the dry season, there was an almost balanced number of farmers practising TP and WDS. However, in the wet season, the TP was by far the most practised method, while DDS was not popular in either dry or wet season.

Table 4.3 Number of plots practising Transplanting (TP), wet direct seeding (WDS), and dry direct seeding (DDS) in both seasons.

	Dry season	Wet season
TP	29 (47%)	74 (82%)
WDS	31 (51%)	14 (16%)
DDS	1 (2%)	2 (2%)
Total	61	90

Table 4.4 provides the comparison between the collected field data and the existing survey data in Nueva Ecija (MISTIG). As can be seen from this table the proportions of TP and DS plots from the fieldwork had a similar trend with MISTIG data, with DS was common in the dry season and TP being more widely practised in the wet season. However, a high difference of proportion appeared in Bongabon and Santa Rosa municipality. This difference occurred because of a change in practice (as MISTIG data was taken in 2013-2014) which was confirmed by the farmers during the interviews. This result confirms that in general, the collected samples are in line with the existing survey data, and therefore can represent the distribution of the crop establishment practice in the study area.

Table 4.4 Comparison of field data (2016/2017) to MISTIG (2013/2014) based on the crop establishment methods in dry and wet season.

TP and DS stand for transplanting and direct seeding, respectively. The red boxes represent the large difference between field data and MISTIG.

Municipality	Crop establishment method	Dry Season		Wet Season	
		MISTIG	Field	MISTIG	Field
Bongabon	TP	9 (28%)	2 (13%)	48 (58%)	29 (80%)
	DS	23 (72%)	14 (87%)	35 (42%)	7 (20%)
Talugtug	TP	27 (100%)	18 (100%)	76 (93%)	23 (96%)
	DS	0 (0%)	0 (0%)	6 (7%)	1 (4%)
Santa Rosa	TP	29 (57%)	5 (29%)	46 (88%)	10 (63%)
	DS	22 (43%)	12 (71%)	6 (12%)	6 (37%)
Aliaga	TP	10 (31%)	4 (40%)	34 (79%)	12 (86%)
	DS	22 (69%)	6 (60)	9 (21%)	2 (14%)
	Total number of samples	142	61	260	90

Information related to rice crop management practice in the dry and wet season (2016- 2017) based on farmers interviews are summarized in Figures 4.2-4.5. Survey responses at the time of land preparation, flooding, crop establishment, and harvesting were used as a guide to understanding the relationship between the backscatter response and field conditions. As shown in Figure 4.2, most farmers started the land preparation (land clearing) in the first week of December during the dry season, while during the wet season, the land preparation time varied between the first week of June until the second week of July.

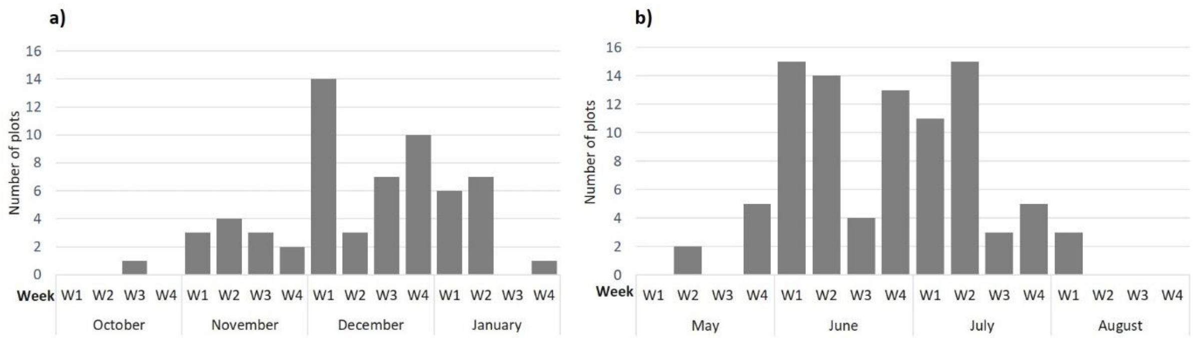

Figure 4.2 Land preparation time in the dry season (a) and wet season (b)

The flooding time in Figure 4.3 shows a similar trend as the land preparation time where the majority of flooding started between the first week of December and second week of January during the dry season. In the wet season, flooding happened from the first week of June to last week of July. Based on the farmers' reports flooding was usually performed just after the land preparation in the same week and continuously occurred for one or two weeks. This information looks consistent with the UPRIIS data, where water was released mostly in December and June for the dry and wet season, respectively.

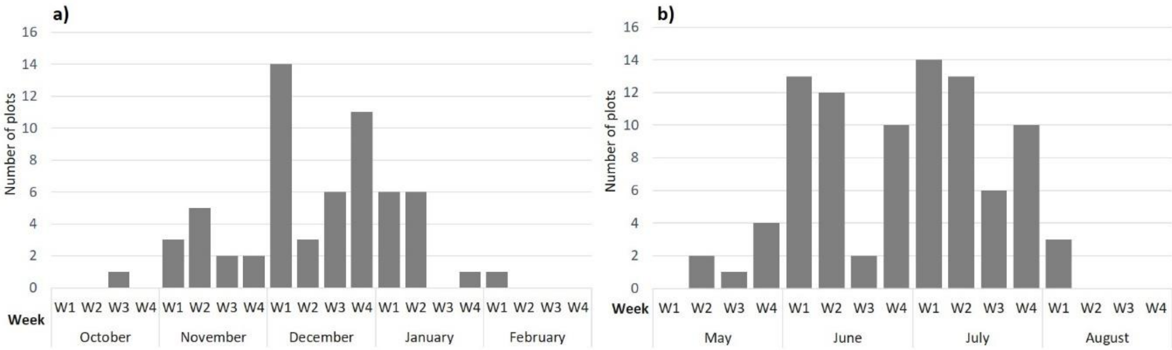

Figure 4.3 Flooding time in the dry season (a) and wet season (b)

Crop establishment occurred between the first week of December and the third week of January in the dry season, whereas in the wet season the peak time of establishment was in the fourth week of July (Figure4.4). The timing was around three to four weeks after the land preparation and flooding. Most farmers established the crop manually in both seasons. For TP rice, on average, the age of seedling in the dry season was 23 days and in the wet season was 27 days.

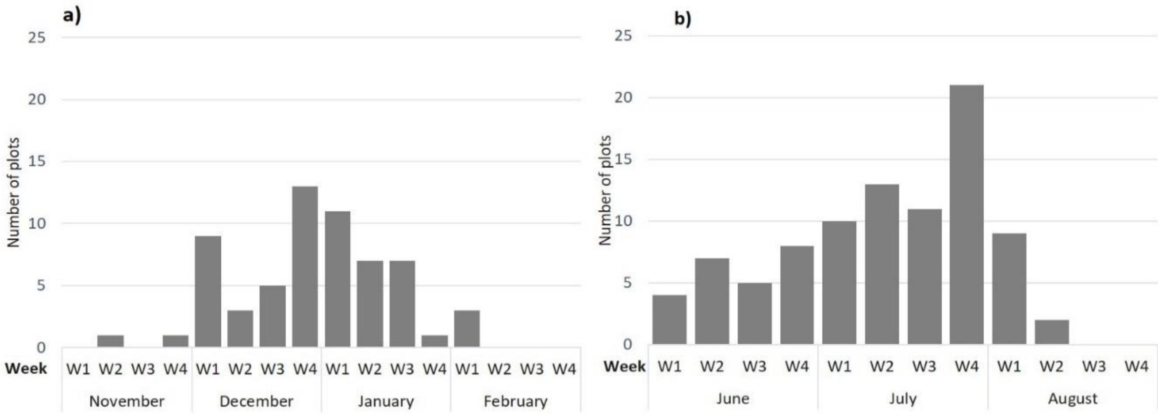

Figure 4.4 Crop establishment time in the dry season (a) and wet season (b)

Rice varieties with short maturity duration (90-120 days), such as NSIC (National Seed Industry Council) Rc216 (Tubigan 17), Rc222 (Tubigan 18), and Hybrid SL8 varieties were more commonly planted by farmers. Figure 4.5 shows that in the dry season, most farmers harvested the crop in the first week of April, while in the wet season, the harvesting time ranged from the last week of September to the first week of November. Almost all farmers did mechanical harvesting whether in dry or in the wet season. Mechanical harvesting was preferred especially in wet season for its efficiency and speed, so the damage and losses caused by the typhoon can be prevented. Only a few farmers practised ratooning (leaving the stubble to regrown for a small additional yield) after the harvest.

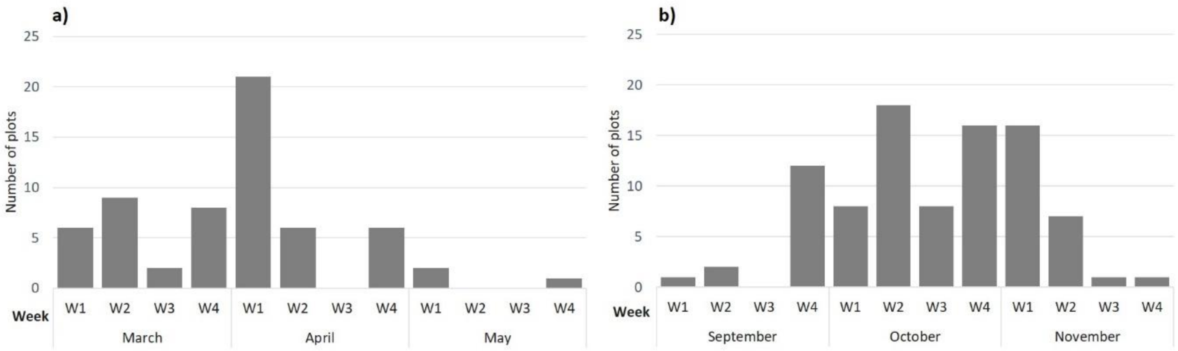

Figure 4.5 Harvesting time in the dry season (a) and wet season (b)

4.2. Temporal signature of rice in dry and wet season

The following figures demonstrate the temporal backscatter signature of rice in the dry season (Figure 4.6a) and wet season (Figure 4.6b) regardless of the crop establishment method. As can be seen, the VV and VH polarizations exhibit similar patterns in the dry and the wet season, although in VV the rate of change in backscatter looked larger in the wet season. This suggests that each polarization can present the rice backscatter behaviour consistently, regardless of the season. The lowest backscatter coefficients were shown in the flooding for both season and both polarizations.

In VV, the backscatter values increase from the crop establishment and reach the peak in the tillering-stem elongation stage, then decrease at the heading-flowering stage. At the maturity stage and harvesting, the backscatter signature, however, shows irregularities in dry and wet seasons.

For the VH polarization, the patterns appear the same for both seasons. As the rice growth, the backscatter gradually increased to the highest point in the maturity stage. It can also be seen from the Figures 4.6, that the deviation values of land preparation and flooding are large, meaning that the field condition in those events are highly varied.

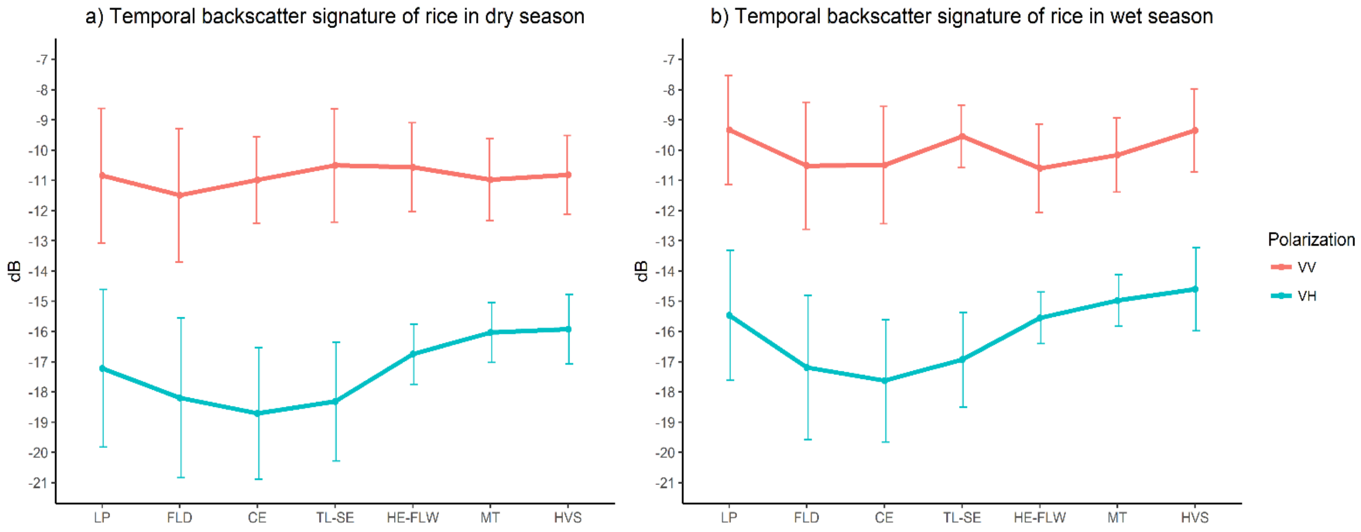

Figure 4.6 Temporal backscatter signature of rice in the dry season (a) and wet season (b) for VV and VH polarization. Graphs show the mean and standard deviation of backscatter (dB) during the rice growing season. *n* in the dry season: 61, and *n* in the wet season: 90. LP: land preparation, FLD: flooding, CE: crop establishment, TL-SE: tillering-stem elongation, HE-FLW: heading- flowering, MT: maturity, and HVS: harvesting

The sub-sections below provide the results of temporal signatures for the crop establishment methods, statistical tests, and the discrimination rules. As indicated in Table 4.3 very few samples were collected for DDS rice. Therefore, the analysis in the next steps will only consider TP and WDS rice.

4.3. Temporal backscatter signature of TP and WDS rice with assumption of early tillering in WDS

To identify the backscatter characteristics of TP and WDS rice, boxplots providing the backscatter distribution for each event and the temporal signatures are shown in Figure 4.7 (dry season) and Figure 4.8 (wet season). Here, the signature with the assumption of early tillering in WDS is first shown.

As shown in Figure 4.7 (a-c), in the dry season, the backscatter (dB) of TP and WDS appeared similar during the heading-flowering to the harvesting time. However, there were variations of median and range of dB during the land preparation until tillering-stem elongation stage (the early growing season). For TP rice, the lowest dB point was observed at the flooding; then it increased from the crop establishment until reached the maximum point at the heading-flowering and maturity stage (VV and VH respectively). Although in VH, a decline was seen in at the tillering-stem elongation stage.

On the other hand, although WDS rice had the same lowest dB point as TP (at the flooding), the dB showed relatively no change and even lower in the crop establishment (in VV and VH, respectively). The dB appeared significantly higher at the tillering-stem elongation stage in VV. Unlike TP rice, dB of WDS was consistently higher in VH. Moreover, from the VV/VH ratio graph, the distribution of dB values between TP and WDS rice were observed similar at most of the events in the rice growing season, except at the land preparation, crop establishment, and the tillering-stem elongation stage.

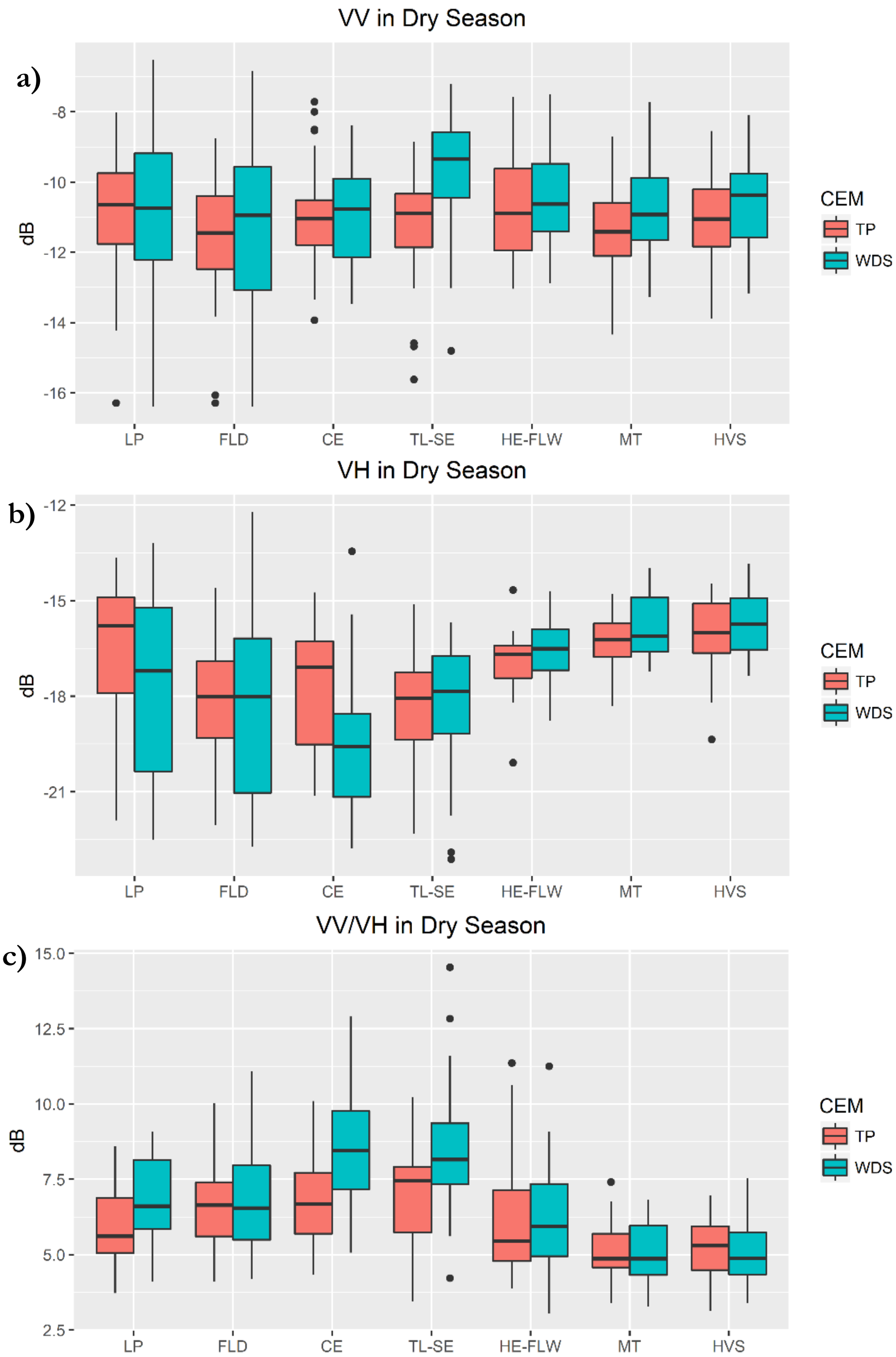

Figure 4.7 Temporal backscatter signature of TP (Transplanted rice) and WDS (Wet Direct Seeded rice) in the dry season, in VV (a), VH (b), and the ratio of VV/VH (c).

Graphs show the backscatter coefficient (dB) for different events in the rice growing season. LP: land preparation, FLD: flooding, CE: crop establishment, TL-SE: tillering-stem elongation, HE-FLW: heading- flowering, MT: maturity, and HVS: harvesting

For the wet season, as presented in Figure 4.8 (a-c), TP and WDS rice showed the same increasing trend during the heading-flowering to the harvesting time. The distribution of backscatter between the groups was mostly similar even during the early growing season. Some differences still could be noticed in the tillering-stem elongation stage in VV and in the land preparation in VV/VH ratio. In comparison to the dry season, in the wet season the backscatter behaviours of all polarizations were similar from heading-flowering to harvesting, however, the backscatter difference of VH was not visible at the crop establishment.

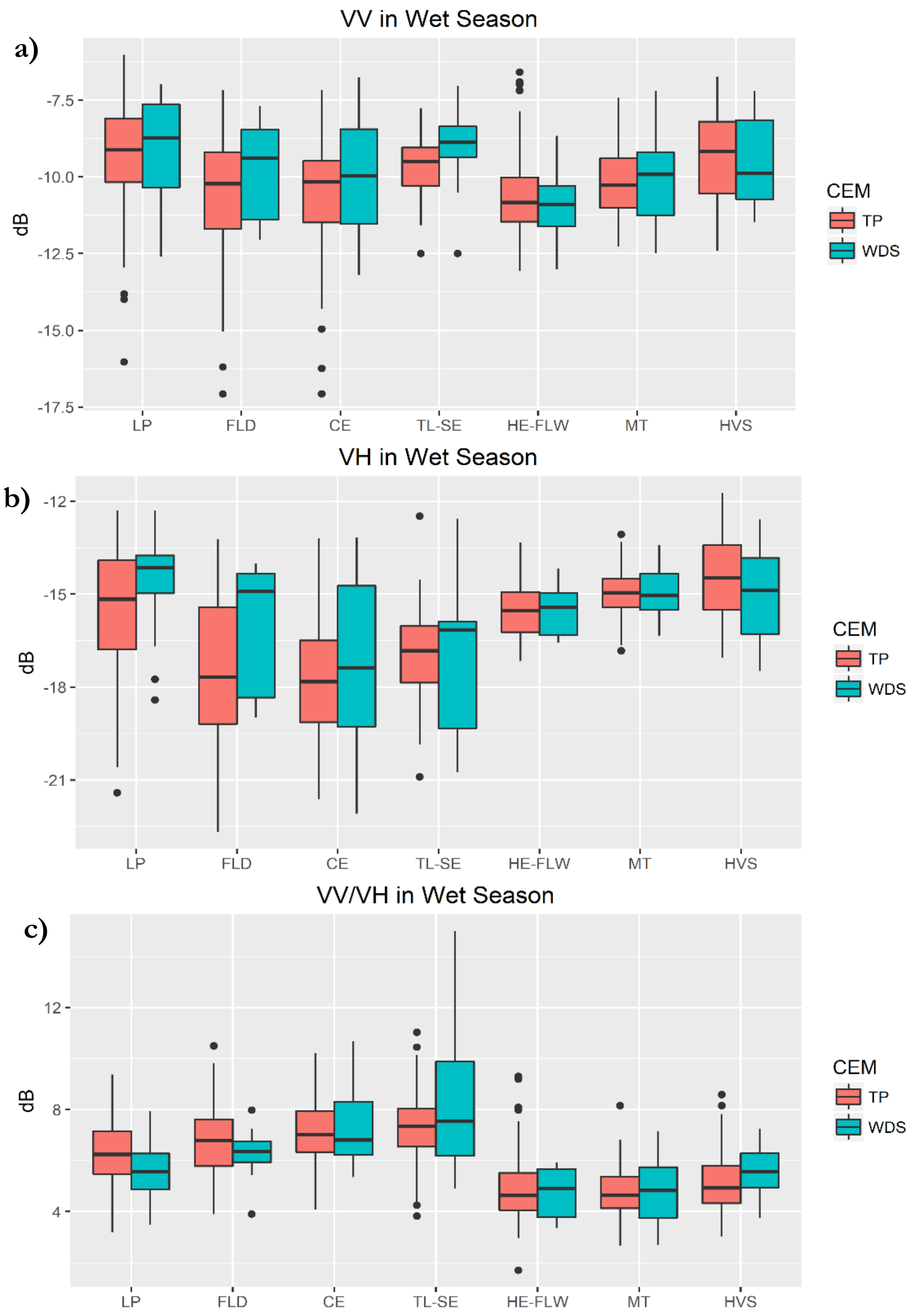

Figure 4.8 Temporal backscatter signature of TP (Transplanted rice) and WDS (Wet Direct Seeded rice) in the wet season, in VV (a), VH (b), and the ratio of VV/VH (c).
Graphs show the backscatter coefficient (dB) for different events in the rice growing season. LP: land preparation, FLD: flooding, CE: crop establishment, TL-SE: tillering-stem elongation, HE-FLW: heading- flowering, MT: maturity, and HVS: harvesting

4.4. Temporal backscatter signature of TP and WDS rice without the assumption of early tillering in the WDS

Figures 4.9 and 4.10 plot the backscatter distribution of TP and WDS rice at different events in the dry and wet season respectively without the assumption of the early tillering stage in WDS.

As can be seen in Figure 4.9 (a-c), the behaviour of WDS rice in the dry season compared to the previous graphs (with the assumption in WDS), shows a greater increased in backscatter than TP at the tillering-stem elongation in VV and VV/VH ratio, but not in VH polarization.

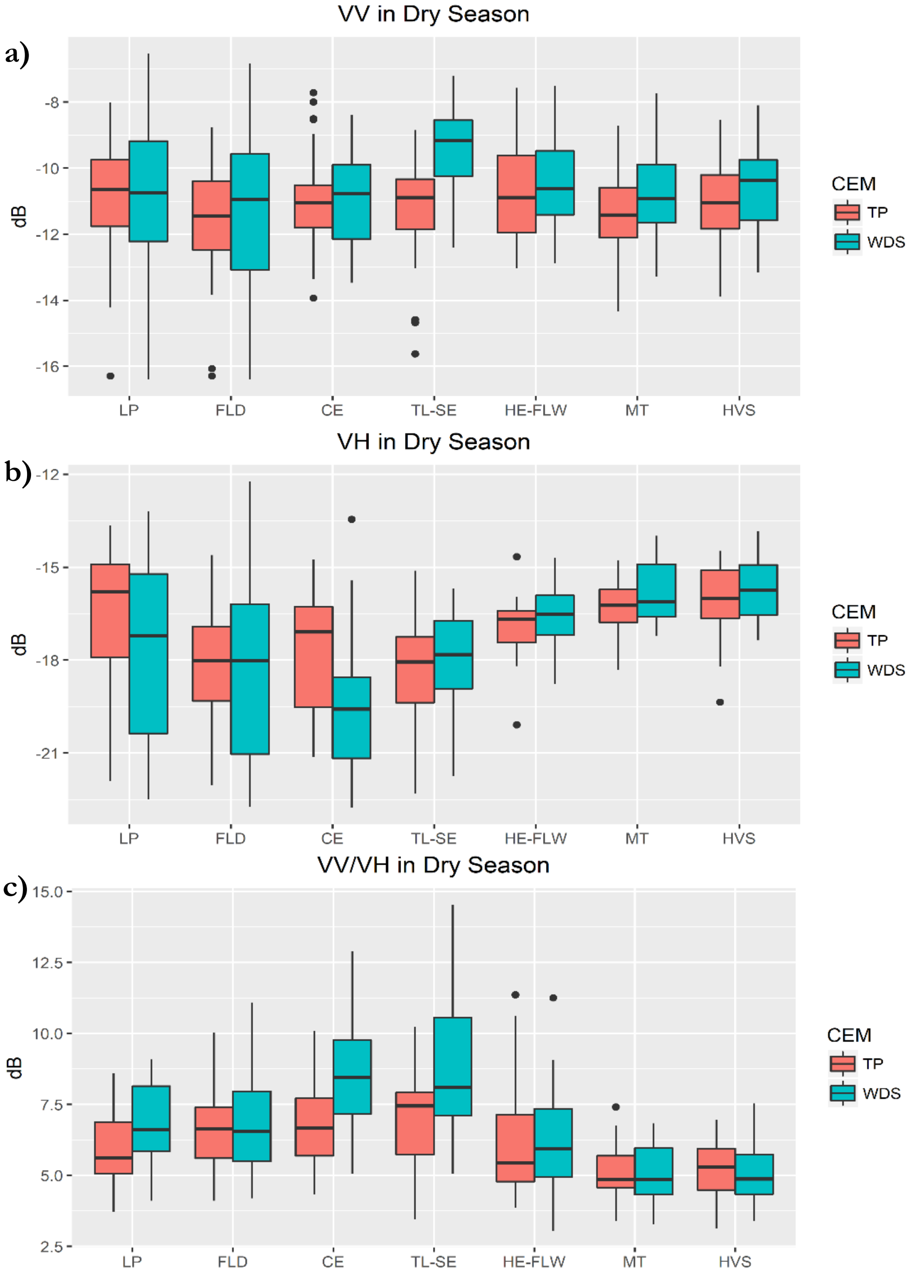

Figure 4.9 Temporal backscatter signature of TP (Transplanted rice) and WDS (Wet Direct Seeded rice) in the dry season (without assumption in WDS), in VV (a), VH (b), and the ratio of VV/VH (c).
Graphs show the backscatter coefficient (dB) for different events in the rice growing season. LP: land preparation, FLD: flooding, CE: crop establishment, TL-SE: tillering-stem elongation, HE-FLW: heading- flowering, MT: maturity, and HVS: harvesting

In the case of the wet season (Figure 4.10 a-c), the large backscatter differences between WDS and TP were only visible at the tillering-stem elongation stage in VV and VH when compared to the graphs with the early tillering assumption in WDS.

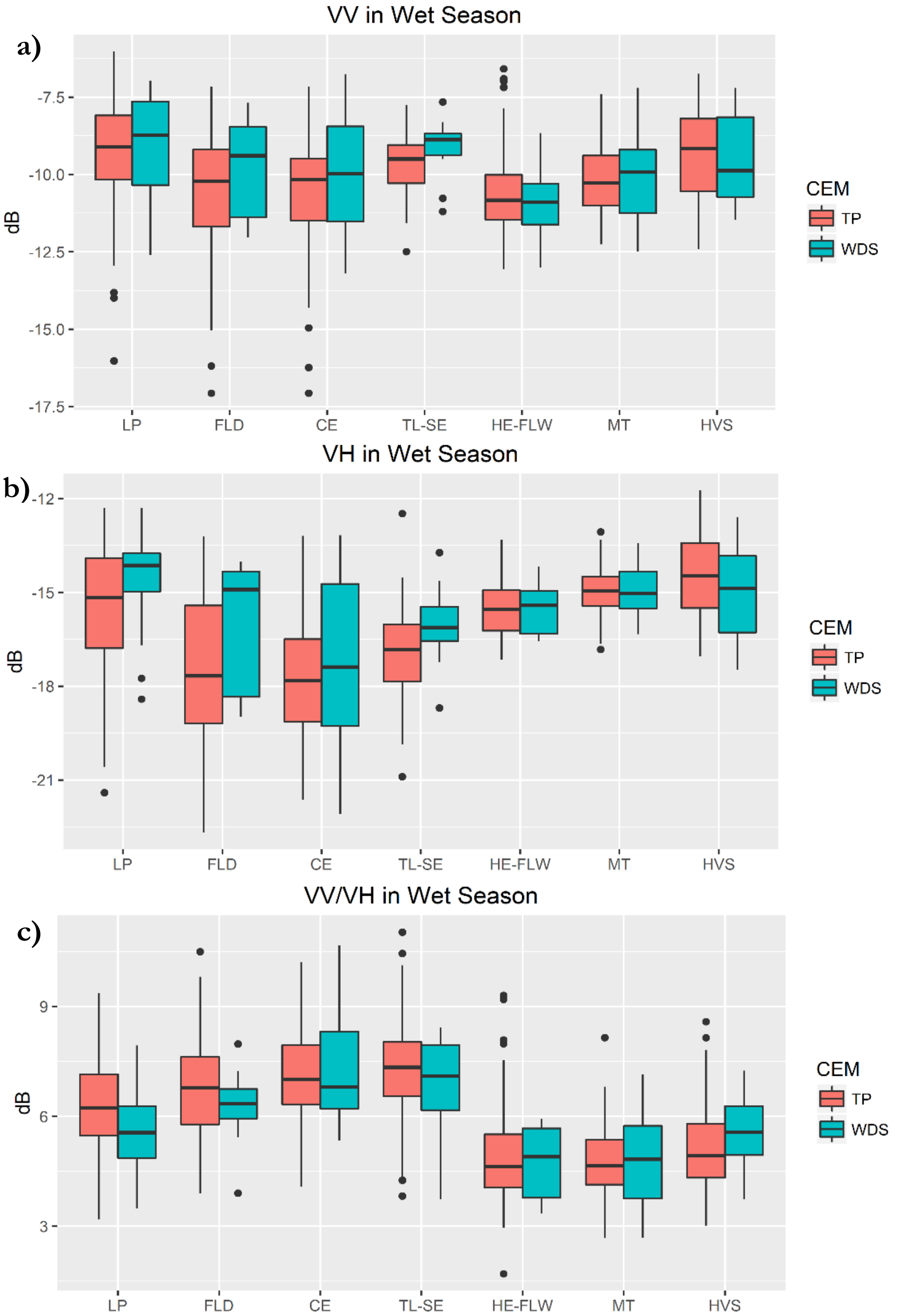

Figure 4.10 Temporal backscatter signature of TP (Transplanted rice) and WDS (Wet Direct Seeded rice) in the wet season (without assumption in WDS), in VV (a), VH (b), and the ratio of VV/VH (c).
Graphs show the backscatter coefficient (dB) for different events in the rice growing season. LP: land preparation, FLD: flooding, CE: crop establishment, TL-SE: tillering-stem elongation, HE-FLW: heading- flowering, MT: maturity, and HVS: harvesting

4.5. Relative elevation of plots practising TP and WDS

Figure 4.11 shows the distribution of the relative elevation of TP and WDS plots. Plots with low relative elevation practising WDS in the dry season, whereas the small number of WDS plots in the wet season showed high variation in relative elevation.

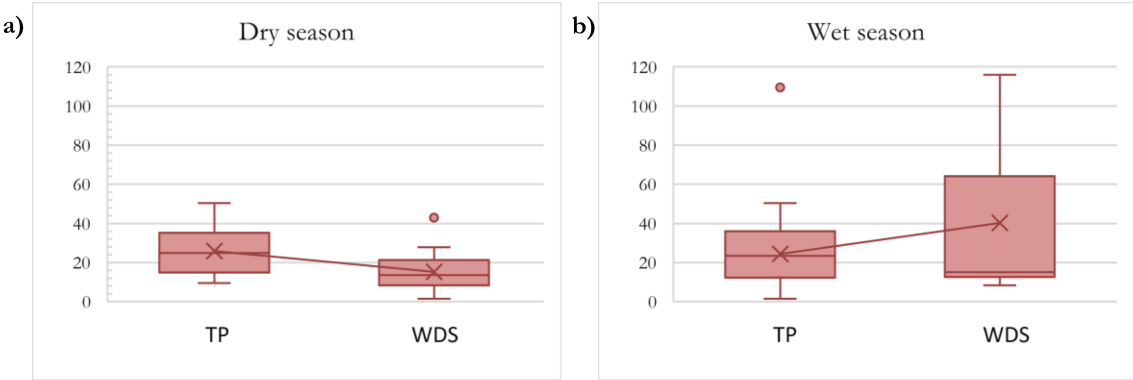

Figure 4.11 Relative elevations (m) of plots practising different crop establishment methods (CEM): Transplanting (TP) and Wet Direct Seeding (WDS) in the dry (a) and wet (b) season.
For the dry season, *n*TP=29; *n*WDS=31. For the wet season, *n*TP=74, *n*WDS=14. Source: SRTM 30m

4.6. Statistical tests (Mann- Whitney U test)

The Mann- Whitney U test was used to assess whether there were significant differences between TP and WDS. Table 4.5 provides p-values for the dry and wet season, comparing also the results between data with and without the assumption of early tillering in the WDS.

Table 4.5 p- values between transplanted (TP) and wet direct seeded rice (WDS) from Mann-Whitney U test.
The highlights correspond to events with the sig. difference (p<0.05 and α= 95%)

With assumption in Wet Direct Seeding				Without assumption in Wet Direct Seeding			
Dry Season				Dry Season			
	VV	VH	VV/VH		VV	VH	VV/VH
LP	0.837	0.136	0.009	**LP**	0.837	0.136	0.009
FLD	0.758	0.814	0.649	**FLD**	0.758	0.814	0.649
CE	0.769	0.001	0.000	**CE**	0.769	0.001	0.000
TL-SE	0.000	0.725	0.002	**TL-SE**	0.000	0.41	0.006
HE-FLW	0.48	0.233	0.872	**HE-FLW**	0.48	0.233	0.872
MT	0.175	0.317	0.965	**MT**	0.175	0.317	0.965
HVS	0.205	0.239	0.649	**HVS**	0.205	0.239	0.649
Wet Season				Wet Season			
	VV	VH	VV/VH		VV	VH	VV/VH
LP	0.631	0.105	0.052	**LP**	0.631	0.105	0.052
FLD	0.175	0.07	0.232	**FLD**	0.175	0.07	0.232
CE	0.615	0.553	0.933	**CE**	0.615	0.553	0.933
TL-SE	0.04	0.739	0.473	**TL-SE**	0.060	0.023	0.452
HE-FLW	0.523	0.8	0.765	**HE-FLW**	0.523	0.8	0.765
MT	0.952	0.969	0.986	**MT**	0.952	0.969	0.986
HVS	0.63	0.201	0.189	**HVS**	0.63	0.201	0.189

n in the dry season, TP: 29, WDS: 31; *n* in the wet season, TP: 74, WDS: 14. LP: land preparation, FLD: flooding, CE: crop establishment, TL-SE: tillering-stem elongation, HE-FLW: heading- flowering, MT: maturity, and HVS: harvesting

As Table 4.5 shows, in general, there are more significant differences ($p< 0.05$) between TP and WDS in the dry season compared to the wet season. In the dry season, the backscatter difference at crop establishment (VH) and tillering-stem elongation stage (VV) were significant. In addition, the dB signal at the land preparation, crop establishment, and tillering-stem elongation stage from VV/VH ratio were also significantly different. This pattern was consistently found for all data (with and without the early tillering assumption in the WDS). Unexpectedly, in the wet season, the difference was only significant at the tillering-stem elongation stage, although it occurred at the different polarization depending on the assumption in WDS. The tests resulted in statistically different in VV when using the assumption. However, when the early tillering was not assumed, the significant difference was found in VH.

Table 4.6 presents the result of the Mann-Whitney U test, showing that the relative elevation between TP and WDS plots in the dry season was statistically different.

Table 4.6 p- values of relative elevation between plots practising transplanting (TP) and wet direct seeding (WDS) from Mann-Whitney U test.

The sig. difference was set at $p<0.05$ and $\alpha= 95\%$.
For dry season, n=60. For wet season, n=84

	p-value
Dry season	0.000
Wet season	0.418

4.7. Discrimination thresholds and rules setting

The thresholds and rules setting to discriminate TP and WDS rice were performed in R using the ‘tree’ package version 1.0-37. Different approaches to select the features were used for the rules in the dry and wet season, considering the results of the statistical tests in the previous step (Tables 4.5 and 4.6).

4.7.1. Dry season

For the rules in the dry season, only events with significant differences based on the results of the Mann-Whitney U tests were selected as the predictor features. Although the ratio of VV/VH gave more significantly different events (Table 4.5), other polarizations were also used, based on the expectation that they may provide complementary information for the discrimination. The relative elevation was also added in the second run of model fitting. Hence, for the first run, five features were considered for the tree model as follows:

- VV at tillering-stem elongation (TLSE_VV)
- VH at crop establishment (CE_VH)
- VV/VH ratio at land preparation (LP_VV_VH)
- VV/VH ratio at crop establishment (CE_VV_VH)
- VV/VH ratio at tillering-stem elongation (TLSE_VV_VH)

The order of the features was set by the CART algorithm which calculated the impurity index of each feature. Figure 4.12 shows the decision tree construction of the first run, and as can be seen, only four features (with five leaves) appeared, since the CE_VH feature was not used.

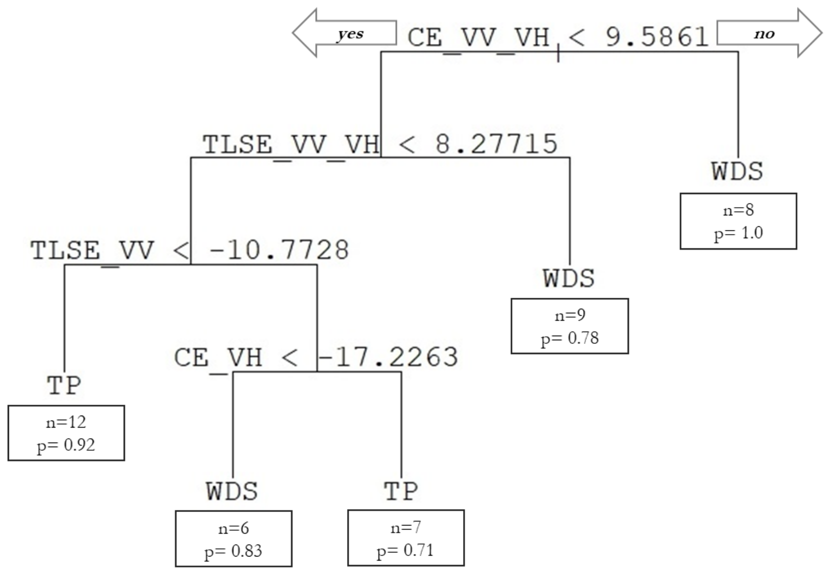

Figure 4.12 Decision tree for discriminating TP (Transplanting) and WDS (Wet Direct Seeding) with backscatter as features

The classification accuracies for the first tree model are shown in Table 4.7, showing the values for overall accuracy (OA), producer accuracy (PA), user accuracy (UA), Kappa coefficient, and area under the curve (AUC). In general, the first tree model produced high overall accuracies (OA=72%, Kappa=0.44, AUC=0.75). It could predict more than half of the TP class (PA=56%) and almost all of the WDS class (PA=89%). The Kappa value is interpreted as moderate based on Richards and Jia (2006).

Table 4.7 Confusion matrix and accuracy values obtained from decision tree with backscatter as features.
TP: transplanting, WDS: wet direct seeding, PA: producer accuracy, UA: user accuracy, OA: overall accuracy

	Reference				
Prediction	**TP**	**WDS**	**Total**	**PA (%)**	**UA (%)**
TP	5	1	6	56	83
WDS	4	8	12	89	67
Total	9	9	18		
OA (%)	72.22				
Kappa	0.44				
AUC	0.75				

Relative elevation was included for the second run of fitting the model. Figure 4.13 displays the decision tree generated from the backscatter and relative elevation as the features, showing that only three features were used to predict the class of TP and WDS rice.

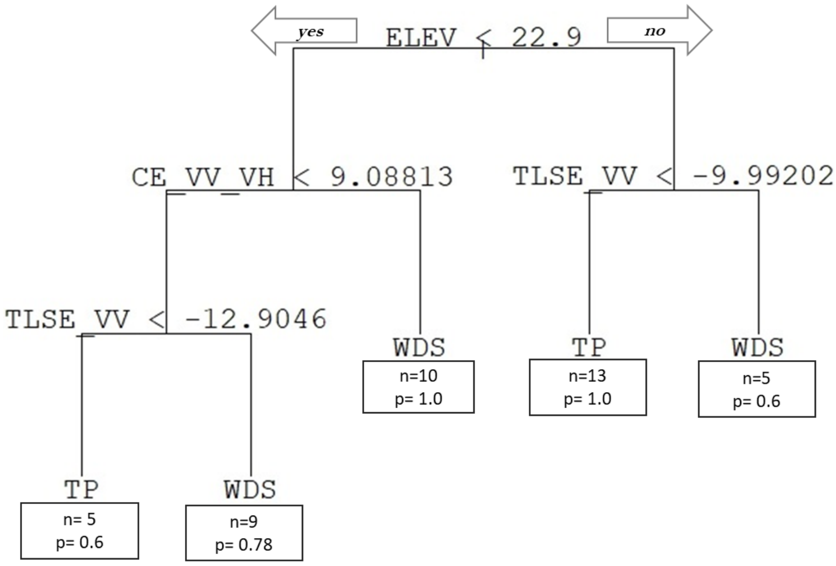

Figure 4.13 Decision tree for discriminating TP (Transplanting) and WDS (Wet Direct Seeding) with backscatter and relative elevation as features

The accuracy for the second tree is shown in Table 4.8. This decision tree with relative elevation as the additional data gave higher accuracy values (OA=78%, Kappa=0.56, AUC=0.86), indicating the better performance of the model to predict the TP or WDS classes. This second model could completely predict the WDS class (PA=100%), but it could only predict half of TP class (PA=56%). According to Richards and Jia (2006), the Kappa value is interpreted as moderate.

Table 4.8 Confusion matrix and accuracy values obtained from decision tree with backscatter and relative elevation as features in the dry season.

TP: transplanting, WDS: wet direct seeding, PA: producer accuracy, UA: user accuracy, OA: overall accuracy

	Reference				
Prediction	**TP**	**WDS**	**Total**	**PA (%)**	**UA (%)**
TP	5	0	5	56	100
WDS	4	9	13	100	67
Total	9	9	18		
OA (%)	77.78				
Kappa	0.56				
AUC	0.86				

The accuracy values from the two models are summarized in Table 4.9. Overall, the tree algorithm performed well under a different number of features. However, it is apparent that the accuracy values, Kappa, and AUC were increased after involving the relative elevation.

Table 4.9 Comparison of classification accuracy values between the decision tree with backscatter (dB) and relative elevation as features in the dry season

features	dB	dB+ relative elevation
Overall Accuracy (%)	72.22	77.78
Kappa	0.44	0.56
AUC	0.75	0.86

4.7.2. Wet season

For the wet season, since the Mann-Whitney tests (Table 4.5) did not show many significant differences, we tried to include the same events as in the dry season. However, the relative elevation was not added since the difference was not significant in the wet season.

Figure 4.14 displays the decision tree with only backscatter values as the features, and Table 4.12 shows the accuracy values obtained by this decision tree. TLSE_VV and TLSE_VV_VH and LP_VV_VH became the selected features in the tree model.

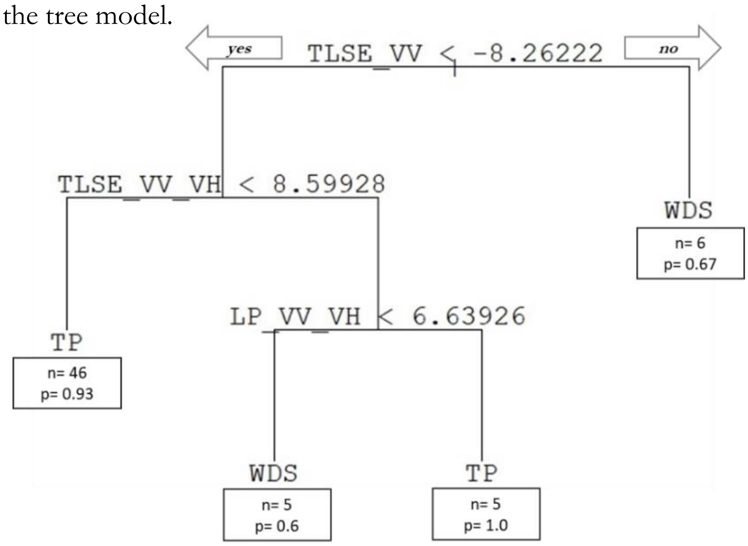

Figure 4.14 Decision tree for discriminating TP (Transplanting) and WDS (Wet Direct Seeding) in wet season with backscatter as features

Table 4.10, shows that the tree resulted in 73% of overall accuracy. The producer accuracy for TP was 82% but for WDS was only 20%, meaning that many WDS points were misclassified to TP class. Even though this model resulted in high overall accuracy, the Kappa and AUC values were very low (0.062 and 0.53 respectively). Using the range value by Richards and Jia, (2006), the Kappa value was interpreted as poor.

Table 4.10 Confusion matrix and classification accuracy value obtained from the decision tree with backscatter as features in the wet season.
TP: transplanting, WDS: wet direct seeding, PA: producer accuracy, UA: user accuracy, OA: overall accuracy

	Reference				
Prediction	**TP**	**WDS**	**Total**	**PA (%)**	**UA (%)**
TP	18	3	21	82	86
WDS	4	1	5	25	20
Total	22	4	26		
OA (%)	73.08				
Kappa	0.062				
AUC	0.53				

5. DISCUSSION

5.1. The temporal signatures of transplanted and wet direct seeded rice, with stages and polarizations to discriminate them

From the reviewed literature, very few studies have addressed the question of backscatter response from TP and DS rice. While some studies presented the backscatter difference of TP and WDS rice using RISAT-1 (Gumma et al., 2015) and RADARSAT-2 (Zhi et al., 2017), these studies suffered from low temporal resolution, a limited number of polarizations, and limited image availability. Since the backscatter response of TP and DS rice is still poorly understood, this research attempted to broaden the current knowledge through the use of the Sentinel-1 images, which are freely accessible, dual-polarized images with high temporal resolution.

On average, we found that along with the rice growth, the temporal backscatter of rice consistently increased as the canopy closure increased. Interestingly, the peak was identified at a different stage for VV and VH, although the patterns were similar for both seasons. Backscatter in VV reached a peak at the vegetative phase, while in VH the peak was observed within the reproductive-ripening phase. This result is in agreement with the observation by Oh et al., (2009) and Nguyen et al., (2016) who identified value saturation at the reproductive phase and the canopy attenuation at the ripening phase in VV polarization. This is also most probably caused by the double bounce effect in VV which is more dominant during the vegetative phase, while VH is less sensitive to contact with the underlying water and is more affected by the increase in biomass (more canopy closure/ increase leaf coverage) (McNairn and Brisco, 2004). In general, this implies that rice growth can be well detected by using Sentinel-1 images. However, contrary to much literature, the backscatter remained high at the harvesting time. This discrepancy could be related to the harvesting method. The harvesting was done mostly by mechanical harvesting (Figure 5.1a), where usually a large quantity of crop residues (stubles) are left in the field (Figure 5.1b), and thus contributes to the high backscatter values. Mechanical harvesting, using specialised small combine harvesters has only recently been introduced in Central Luzon (and in other parts of Asia), and it is possible that previous studies focussed on areas where manual harvesting with much lower stubble or residue was dominant.

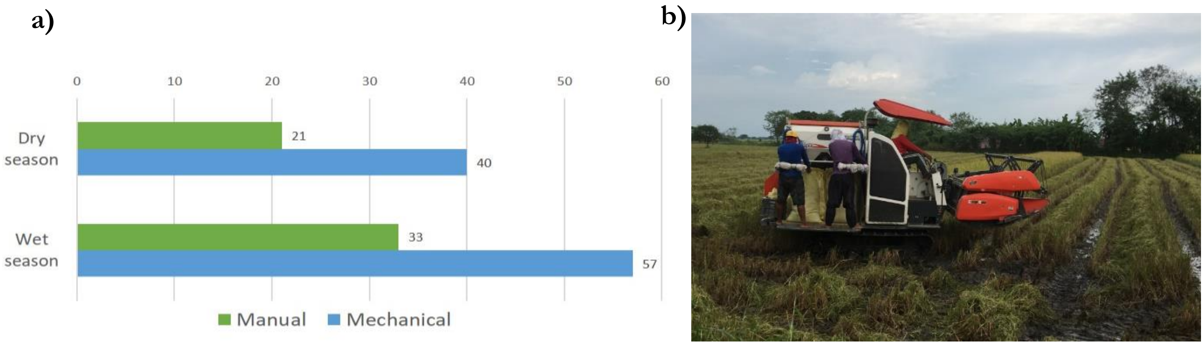

Figure 5.1 (a) Harvesting method in the dry and wet season (2016-2017); (b) a much higher stubble is left in the field after the mechanical harvesting than in manual harvesting.

This study showed a notable backscatter response (VV and VH) from TP rice; as an increased dB at the crop establishment and a decreased dB at the tillering-stem elongation stage. This suggests the contribution from the seedlings that makes higher dB of TP than WDS at the crop establishment. The transplantation shock in TP can slow the tillering process (Pandey et al., 2000) which may result in a slight decrease of dB after transplantating. By contrast, WDS rice had a lower dB at crop establishment and a higher dB at the tillering-stem elongation stage. These findings can be explained by some factors. As WDS rice is broadcasted by seed, the backscatter is still mainly from the soil which contributes to the low values (surface scattering is dominant). Further, since a WDS rice is in the field for all of its growing time, the growth process (in particular tillering) can continue without any delay or transplanting shock (Yoshida, 1981). The larger amount of seed used per hectare in WDS may produce higher plant density, hence more tillers per unit area and thus more double-bounce scattering occur. At the tillering-stem elongation stage, the canopy is not completely established yet, thus there are still gaps for the SAR signal to penetrate and create the double scatterings with the underlying water surface. This result is supported by Lopez-Sanchez et al., (2014) that the double bounce in C-band dominates dB during the late vegetative stage, whereas with the shorter wavelength in X-band this effect is visible in the early vegetative stage. Another factor might be from the weed infestations in WDS. The observed high dB at the tillering stage could be related to weed presence, as they typically emerge almost at the same time as rice (Bordey et al., 2016). There were no major changes and differences between TP and WDS during the heading-flowering and maturity stage, as a result of the absence of water and a smoother canopy surface as the leaves completely layer the field as explained by Le Toan et al., (1997).

In short, the temporal patterns of TP and WDS concurs well with the expected temporal signature (Figure 1.2). Despite the observed dB characteristics in land preparation showed a different response in the dry season (dB of WDS were much lower than TP), in the wet season, dB of WDS rice was higher than TP rice as expectation. The high dB at land preparation might result from the moisture content that makes soil saturated and increased the dielectric properties.

Another interesting aspect is, when the short tillering stage in WDS was not assumed, the backscatter of WDS rice at the tillering stage was dramatically higher than TP rice (especially in VV), which can indicate that tillering was still in process. This is a possible case since the growth duration may vary depending also on the variety, nutrient, and weather conditions (Yoshida, 1981). Therefore, we can still see the differences in backscatter between TP and WDS rice at this stage with or without the assumption, which implies a good possibility to discriminate them.

In response to research questions one and two, the significance tests (Mann-Whitney U) indicated that in the dry season, TP rice was significantly different to WDS rice at the land preparation (VV/VH ratio), crop establishment (VH and VV/VH ratio), and tillering-stem elongation stage (VV and VV/VH). This result is the same as the data without the early tillering assumption in WDS, meaning that the differences between TP and WDS in those three events were not occurred by chance.

However, the tests of the wet season did not give satisfactory results, as the difference was observed only at tillering-stem elongation in VV. It is most likely that the low number of observations of WDS and the large gap of the sample with TP (nWDS=14, nTP =74) which gave the negative response in the tests. While the difference was not significant at the alpha level of 95% ($p<0.05$), there is still pronounced difference at the land preparation ($p=0.052$ in VV/VH ratio), indicating that we can still expect differences between TP and WDS at that time.

A significant difference was observed at crop establishment in the dry season, but this was not found in the wet season. This inconsistency in the wet season may relate to the high-water availability in the field. As shown in Figure 5.2, high rainfall (>100mm) in the wet season occurred in May, July, and August, the same time as most of the crop was established (Figure 4.4). This high-water availability resulted in saturated or flooded fields, and separating TS from WDS becomes challenging. Further, it should be noted that TP and WDS are more proportionally practised in the dry season, while in the wet season almost all farmers practise

TP (Table 4.4). This implies that a good classification result for the dry season is much more important than for the wet season.

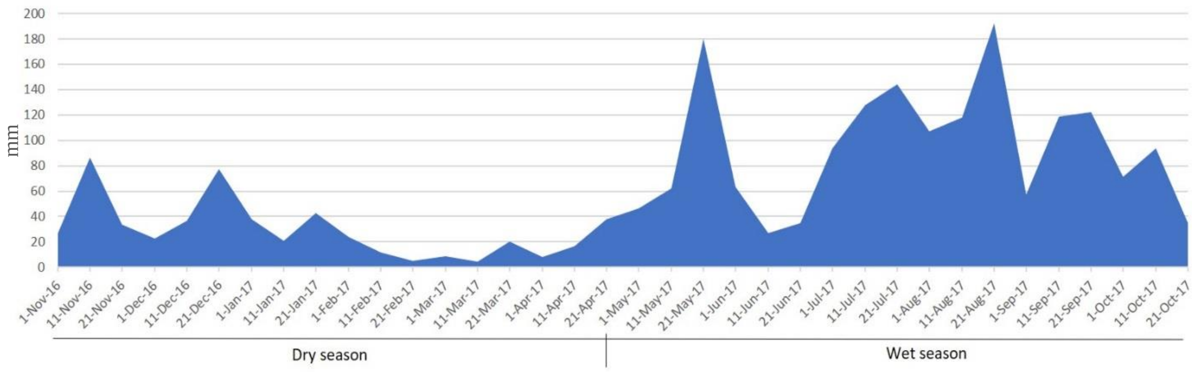

Figure 5.2 Average rainfall (mm) in Nueva Ecija during the rice growing season in 2016-2017.
source: decadal CHIRPS data (2017)

In summary, this study revealed that TP and WDS rice could be discriminated by backscatter information from VV, VH, and the VV/VH ratio at certain events in the rice growing season. During the early growing season, particularly at the land preparation, crop establishment, and tillering-stem elongation stage, the differences in backscatter between TP and WDS rice were significant. These findings are in line with those obtained by Gumma et al., (2015) where TP and DS rice showed distinct backscatter at the transplantation time (HH polarization) and at the tillering stage (by full-polarized images) (Zhi et al., 2017). Therefore, by these findings, the H0 of the first and second hypotheses are rejected.

5.2. Backscatter extractions, the thresholds and rules set by the DT

With respect to the backscatter extraction, as explained in the method section, some narrow polygons could not be buffered which can contribute to the error in the backscatter value and uncertainty in assigning the values to the right class. We tried to calculate the dB difference between before and after the negative buffer, which resulted in differences of 0.41 dB in VV and 0.45 dB in VH (appendix III). Considering that the mean differences of TP and WDS rice were approximately 1 to 2 dB (Appendix IIA-B), the possible error introduced by unbuffered polygons can be ignored, and the extracted backscatters from those polygons were considered acceptable. This is also supported by the results of the significance tests. The Mann-Whitney tests showed the same pattern as in Table 4.5 when using the non-negative buffered polygons (Appendix IV).

The discrimination rules generated by the DT showed that in the dry season, the overall accuracy of the tree using backscatter only was acceptable (OA= 72%, Kappa= 0.4, AUC= 0.75). Involving relative elevation as the additional feature could increase the overall accuracy by 8.3%, as well as the Kappa and AUC value (Table 4.8). The tree structures seem to be consistent with the significance levels (Table 4.5). The DT calculates the impurity index as the splitting criteria to produce the most homogenous/ pure terminal nodes (Rokach and Maimon, 2005; Murphy, 2012), and this can be regarded as an approach to measure classes separability as in the significant difference test. Further, Hansen et al., (2000) explained that DT sets the thresholds in a multi-dimensional space which best define the separation boundaries between classes. The relative elevation was in the first rank (p=0.00), followed by VV/VH at crop establishment (p=0.00) and VV at tillering-stem elongation stage (p=0.00). When adding the relative elevation, three events were not selected as features (VV/VH ratio at land preparation, VH at crop establishment, and VV/VH ratio at tillering-stem elongation), meaning that those events did not give additional information for the whole tree due to the lower significance values. Interestingly, although plots of WDS were mainly at the lower relative elevation (Figure 4.11), class of WDS was split into two parts in the decision tree, higher and lower than 22.9m (Figure 4.13). This difference addresses the variability of plots in the relative elevation, which is confirmed by Pandey et al., (2000) that WDS plots exist and are possible to do in any toposequence.

Regarding the rule for the wet season, although the overall accuracy was acceptable (OA=73%), Kappa and AUC value were very low (0.062 and 0.53 respectively). The model could predict TP rice well (PA= 82%) but not WDS rice (PA= 25%). Again, this low accuracy might be explained by the low observation number in WDS (*n* training=10, *n* validation=4).

In general, it was found that the DT algorithm could successfully generate the discrimination rules leading to acceptable accuracy. However, apart from the simple and the straightforward decision structure, this technique is considered as a 'greedy algorithm' meaning that the tree can continuously grow until it finds the highest purity index for the leaves (Alkhalid et al., 2013). Therefore, checking and optimization of the tree is recommended to avoid over-fitting the model. We also observed the changes in the structure when including different features. Some studies have highlighted this sensitivity aspect, where small changes in training data can highly affect the tree structure, and hence may not be an appropriate approach for data with high variability (Murphy, 2012).

5.3. Sentinel-1 images, field data, and ancillary data

The backscatter value of rice is dynamic depending on its growth stage (Le Toan et al., 1997). Consequently, images with a short revisit time are required to optimally detect changes in the backscatter over time. In this study, Sentinel-1 images were adequate to monitor and capture the different stages of rice based on evidence from previous literature and observations made in this study. Yet, extracting the backscatter values for the events with the short gap compared to the image acquisition was still challenging. The capability of C-band was also useful to extract the information not only from the canopy but also from the underlying surface before canopy closure (McNairn and Brisco, 2004) which means that more factors can be considered to interpret the backscatter signatures during the early rice growth stages.

The field data presented in this study were considered to have a good distribution and proportionally in line with previous survey data (Table 4.4). Nevertheless, the unexpected change in management practice was still an issue during the data collection, leading to a low number of sample in both DDS and WDS, especially in the wet season. We also observed during the fieldwork that the trend of management practice in a village was similar (for example, almost all farmers cultivate non-rice in the dry season), therefore selecting more villages would help to increase the needed samples for the future work. Other relevant factors should be considered as well in the sampling, such as variation in elevation, irrigation system availability, and rainfall to get more variation in the data and insight of the practice. Interviewing all farmers at a place (village office) was more efficient rather than visiting them one by one. Although this is not always possible, this method is encouraged for future surveys in the area but requires good relations and communication with the village heads.

The SRTM DEM provided information on relative elevation. Since its resolution was similar to Sentinel-1 (30m and 20m respectively) and the sample plots were located close to each other, the difference between the resolutions was considered acceptable. Unfortunately, the coarse resolution of the CHIRPS rainfall data (0.05^0 or approximately 5km) limited its performance in the discrimination rules of DT. It was not detailed enough to capture the variability across the study area and therefore did not contribute to increasing the discrimination accuracy (Appendix V).

5.4. Crop establishment methods in Nueva Ecija

The interviews revealed several factors that affect farmer's preference for crop establishment methods. The response from farmers supported that cost (labour, seed, and fertilizer) is a major consideration. About PhP 4,000-7,000 (EUR 64- 112) and 15-20 labourers are required to transplant a one-hectare field. In contrast, direct seeding (wet or dry) only needs about PhP 800 (EUR 13) per hectare, and 1-4 labourers to broadcast the seed, though farmers mentioned that more seeds are needed in direct seeding (35-40 kg for TP, and ±80 kg for WDS for a hectare field). In terms of the yield, TP produced more than WDS or DDS and with the reduction in labour cost, was also considerately more cost-effective.

It also important to highlight the factor of rainfall as a reason on the low number of WDS in the wet season. TP was more preferred in the wet season since the soil was more frequently flooded (due to heavy rain), so planting with seedlings was more favourable in such wet conditions for better germination. This is supported also by the information that the age of seedling used for the wet season is longer than for the dry season, due to the longer and more stable root. For DDS, although its use was promoted in Central Luzon in 2012-13, as a means to reduce labour cost and water shortages, the interviews also revealed that farmers were reluctant to practise it due to weed, rat, and bird problems, which increased the cost for herbicide, and those that implement DDS, rapidly changed back to TP or WDS due to the above problems.

Our findings show the inconsistency in the relative elevation, where contrary to literature, in our case WDS were mainly found in the lower sequence. This can be correlated to the more extensive weeding in WDS. Weed control by flooding and the labour shortages encouraged more direct seeding to be adopted in irrigated and rainfed lowland fields (McLean et al., 2002). Other factors could be from the large variability across the villages and adaptation by farmers to the water availability along the toposequence, as mentioned by Homma et al., (2007).

Furthermore, it seems that in our case, the availability of irrigation system does not affect the establishment method. As can be seen in Figure 5.3, almost all plots (TP and WDS) were located under the irrigation system. Although Bongabon was not under the system, water could still be accessed from the Pantabangan dam which means that either TP or WDS can be practised.

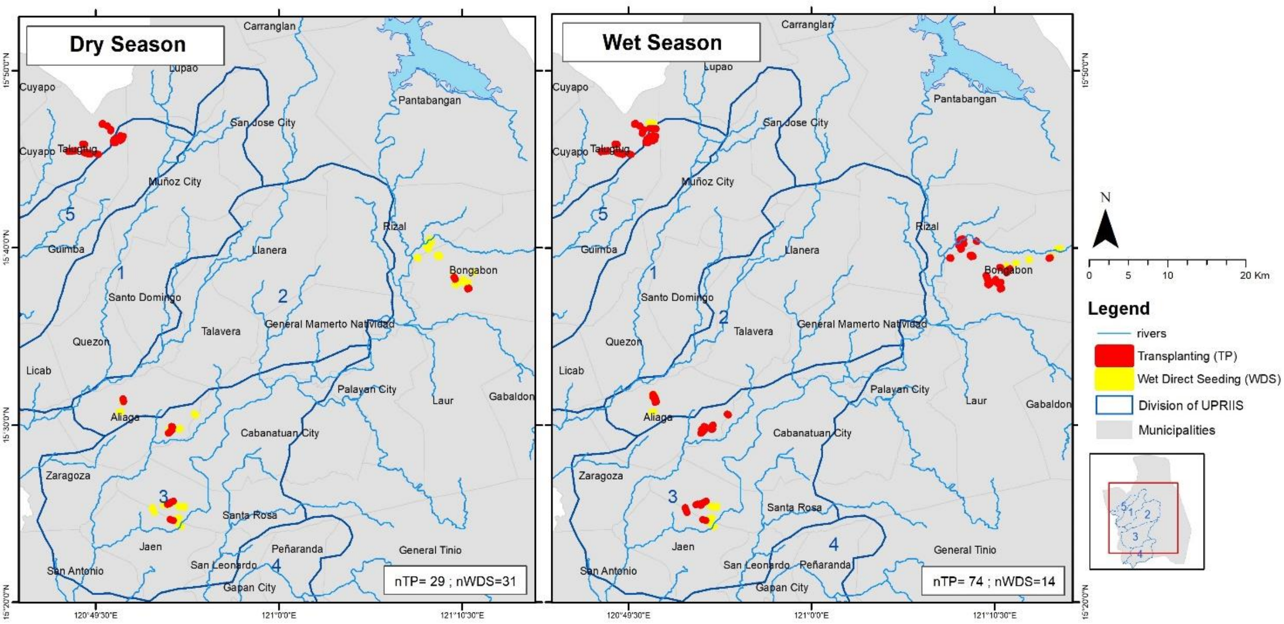

Figure 5.3 Distribution of crop establishment methods relative to the location of the Upper Pampanga River Integrated Irrigation System (UPRIIS)

5.5. Limitation and recommendation

The difference in rules and the accuracies indicates that it is much easier to discriminate TP and WDS in the dry season. Therefore, distinguishing TP and WDS rice in the wet season remains an issue, considering the abundant water availability in the field and the low number of samples. However, given the very small area of WDS rice in the wet season, it is more important to have a good classifier in the dry season where TP and WDS are almost evenly practised. Also, it should be taken into account that farmer may change their management practice, not only in terms of the rice establishment method but also the type of crop. This dynamic management practice has an implication on the mapping process in the future, which suggests that regular monitoring should be implemented (as is done in the PRISM project).

In this study, only SAR backscatter values and relative elevation that were taken into account. In line with the suggestion by Gumma et al., (2015), other factors can probably help the discrimination process, such as wind and weed presence. Particular consideration of the soil texture may also support the practise preference relative to water stagnancy (Pandey et al., 2000). It is noted from the findings of this study, that there were relatively high gradients of dB in particular events of the rice growing season, from flooding to crop establishment for TP rice, and from crop establishment to tillering- stem elongation stage for WDS rice, which were not considered yet as features for discrimination. Moreover, since crop establishment time is one of the critical time in distinguishing TP and WDS rice, better time estimation for this stage is needed. Therefore, methods of detecting establishment date from Asilo et al., (2014) can be further studied and potentially used. The comparison and implementation of different classification method are also encouraged to get better accuracy results. Random forest, a classifier that is based on an ensemble of many individual classification trees, could be employed to address the low accuracy of DT when there is high diversity in training data (Deschamps et al., 2012) as experienced in this study for the wet season.

The area under DS is expected to expand in the future. Despite the barriers in DS mentioned before, the prospect of this method is risen, since it is widely promoted due to environmental issues, especially for water conservation and reducing methane emissions (IRRI, 2018). The wet land preparation (puddling and tilling) and raising nurseries in TP requires a high amount of water. Through the adaptation of DS, water supply can be cut by the dry land preparation. Even in irrigated fields, where water is much available, farmers may adopt DS to reduce the labour cost and the water use (Bouman et al., 2007). Thus, knowledge sharing related to establishment methods is highly encouraged (IRRI, 2018) in which this study and further studies can bring benefits in the future.

6. CONCLUSION

Several specific conclusions with respect to the three research questions are presented as follows.

1. ***Are there any significant differences in backscatter values between transplanted rice and direct seeded rice?***

The results showed that there were significant differences in backscatter between transplanted (TP) and wet direct seeded rice (WDS) in the early growing season, specifically during land preparation, the crop establishment and tillering-stem elongation stage. The Mann-Whitney tests revealed the strong differences at those events, where the p-value ranged from 0.00 to 0.009 in the dry season. However, a significant difference could only be detected at the tillering-stem elongation stage in the wet season ($p=0.04$).

2. ***Among different polarizations (VV, VH, and VV/VH ratio), which polarizations can significantly discriminate the crop establishment method?***

VV, VH, and VV/VH ratio could significantly discriminate the TP and WDS rice, although the discriminations occurred at the different events in the rice growing season. VV was statistically different at the tillering-stem elongation stage. VH was significantly different at the crop establishment. Whereas VV/VH ratio showed significant differences in the land preparation, crop establishment, and tillering-stem elongation stage. The VV/VH ratio could produce more significant differences between TP and WDS rice compared to VV and VH polarization.

3. ***Can the transplanted and direct seeded rice be accurately classified using decision tree method based on the backscatter values and ancillary data?***

High accuracy of discriminating TP and WDS in dry season could be obtained by the decision tree with CART algorithm. The involvement of relative elevation could improve the accuracy, Kappa, and AUC values (OA=78%, Kappa=0.56, AUC=0.86) for the dry season. However, the discrimination for the wet season could only yield low accuracy (OA=73%, Kappa= 0.062, AUC=0.53). The relative elevation was not relevant to the discrimination rules in the wet season.

To conclude, this study identified the differences in backscatter between transplanted (TP) and wet direct seeded rice (WDS) using multi-temporal Sentinel-1 imagery in Nueva Ecija. From the findings of this study, polarization analysis at the early rice growing season could be used to discriminate TP and WDS rice. Moreover, the Sentinel-1 imagery was found to be adequate to capture the changes in backscatter throughout the rice growth period. We also demonstrated the use of a DT algorithm to discriminate TP and WDS rice by their backscatter values, incorporating additional data. The discrimination rules set by the decision tree could generate high accuracies for the dry season where both TP and WDS are widely practised. However, discriminating TP and WDS rice in the wet season remains a challenge, in which more ancillary data are expected to improve the discrimination in the wet season.

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8. APPENDICES

Appendix I- Questionnaire

QUESTIONNAIRE FOR RICE CROP MANAGEMENT IN CENTRAL LUZON

This survey aims to obtain information related to rice crop management. We will ask you questions about one or more of your rice plots, and we would like to visit those plots with you after the questions. The plots should have been planted with rice at least once between November 2016 and now. The plot should be reasonably close to your home (no more than 15 min travel) and ideally larger than 0.5 hectares. Do you have one or more plots that match these criteria?

1	Date and time		
2	Interviewer	V/S/K	
3	Interview No.		
4	Farmer's name		
5	Location of farmer's household	Village:	X:
		Municipality:	Y:
		HHID:	
6	How many plots do you have?	_plots	

A. Farmer interview sheet [one sheet per plot, maximum of three plots per farmer]

0	HHID				
1	What is the size of the plot (ha)	____ha			
2	How many crops did you grown between Nov 2016 and now?	_crops			
	Questions (ask them crop by crop)	1st crop	2nd crop	3rd crop	Notes/codes
3	What crop				Can be R(ice), M(aize), (O)nion, B(ean) or F(allow) etc.
4	Water source for this crop If irrigated, when did irrigation start? If rainfed, when did rainfall start?				IR or RF Month and week (1, 2, 3, 4) Month and week (1, 2, 3, 4)
5	At the start of the season, was there too much, too little or sufficient water?				Too much water [TM], too little water [TL], sufficient [S].
6	Was part of the plot used as a seedbed for this crop (rice only)?				
7	What was the crop establishment method (rice only)				TP, DDS, WDS
8	What was the age of seedlings (transplanted rice only)				Number of days old
9	What was the method of crop establishment				Manual or mechanical
10	Date of land preparation (clearing)				Month and week (1, 2, 3, 4)
11	Date of flooding (rice only)				Month and week (1, 2, 3, 4)
12	Date of establishment of crop				Month and week (1, 2, 3, 4)
13	Date of flowering				Month and week (1, 2, 3, 4)
14	Date of harvest (current crop can be expected harvest date)				Month and week (1, 2, 3, 4)
15	What was the method of harvesting				Manual or mechanical
16	Did you ratoon the rice (rice only)				Yes or no
17	What was the yield including those paid for rent and taken away as payment for harvesting (current crop can be expected yield)				Make a note if this is in cavans and ask how many kg per cavan, this varies by the farmer (Cavan: mass unit → ± 50 kg) Also note the unit for the yield of other crops.
18	Notes:				

B. Plot data sheet [one sheet per plot, maximum of three plots per farmer]

0	HHID		
1	Date and time		
2	Measurements	S/V/K	
3	Plot No.		
4	Corner Coordinates	X1: X2: X3: X4:	Y1: Y2: Y3: Y4:
5	Field length and width (m)	L:	W:
6	Field size (ha)	field measurement: ha	
7	Soil condition	Dry/Wet/Flooding with ….. cm water level	
8	Plant height (cm), 3 reps	(a) (b) (c) (d) average: cm	
9	Rice plant age	days	
10	Sketch *If part of the field was used as a seed bed, mark the approximate location. Take photos of the field and the surrounding area (N,E,S and W). Draw sketch facing to the north*		
11	Notes:		

Appendix IIA-

Dynamic range in dB of transplanted and wet direct-seeded rice in VV (a), VH (b), and VV/VH (c) in the dry season. The highlights correspond to the events with potentially have a high difference. LP: land preparation, FLD: flooding, CE: crop establishment, TL-SE: tillering-stem elongation, HE-FLW: heading- flowering, MT: maturity, and HVS: harvesting

a) VV

	Transplanted rice (dB)					**Wet direct seeded rice (dB)**				
	min	**max**	**range**	**mean**	**std**	**min**	**max**	**range**	**mean**	**std**
LP	-16.30	-8.02	8.28	-10.80	1.88	-16.40	-6.52	9.88	-10.89	2.54
FLD	-16.30	-8.76	7.53	-11.59	1.81	-16.40	-6.83	9.57	-11.41	2.55
CE	-13.94	-7.71	6.22	-10.99	1.59	-13.47	-8.39	5.09	-10.98	1.30
TL-SE	-15.62	-8.85	6.77	-11.30	1.64	-14.81	-7.20	7.61	-9.76	1.79
HE-FLW	-13.04	-7.57	5.47	-10.70	1.53	-12.88	-7.51	5.38	-10.44	1.42
MT	-14.35	-8.72	5.63	-11.21	1.25	-13.28	-7.73	5.55	-10.76	1.44
HVS	-13.90	-8.55	5.35	-11.01	1.27	-13.17	-8.10	5.07	-10.64	1.33

b) VH

	Transplanted rice (dB)					**Wet direct seeded rice (dB)**				
	min	**max**	**range**	**mean**	**std**	**min**	**max**	**range**	**mean**	**std**
LP	-21.90	-13.66	8.24	-16.67	2.34	-22.50	-13.19	9.31	-17.74	2.79
FLD	-22.04	-14.61	7.44	-18.14	1.96	-22.73	-12.22	10.51	-18.25	3.09
CE	-21.13	-14.75	6.38	-17.75	1.96	-22.77	-13.45	9.31	-19.61	2.12
TL-SE	-22.32	-15.11	7.21	-18.29	1.76	-23.11	-15.69	7.42	-18.33	2.05
HE-FLW	-20.09	-14.66	5.42	-16.92	0.95	-18.77	-14.70	4.06	-16.59	0.96
MT	-18.32	-14.79	3.53	-16.27	0.85	-17.23	-13.98	3.24	-15.82	1.02
HVS	-19.35	-14.47	4.88	-16.15	1.16	-17.36	-13.84	3.52	-15.72	1.04

c) VV/VH

	Transplanted rice (dB)					**Wet direct seeded rice (dB)**				
	min	**max**	**range**	**mean**	**std**	**min**	**max**	**range**	**mean**	**std**
LP	3.72	8.59	4.87	5.88	1.28	4.11	9.08	4.97	6.85	1.36
FLD	4.10	10.04	5.93	6.55	1.40	4.19	11.09	6.91	6.84	1.73
CE	4.33	10.09	5.76	6.77	1.56	5.06	12.90	7.84	8.63	2.01
TL-SE	3.45	10.23	6.78	6.99	1.52	4.22	14.54	10.33	8.57	2.09
HE-FLW	3.86	11.36	7.50	6.22	1.93	3.03	11.26	8.23	6.15	1.76
MT	3.40	7.41	4.01	5.06	0.98	3.28	6.83	3.55	5.07	1.02
HVS	3.14	6.95	3.81	5.14	1.00	3.39	7.53	4.13	5.08	0.97

Appendix IIB-

Dynamic range in dB of transplanted and wet direct-seeded rice in VV (a), VH (b), and VV/VH (c) in the wet season. The highlights correspond to the events with potentially have a high difference. LP: land preparation, FLD: flooding, CE: crop establishment, TL-SE: tillering-stem elongation, HE-FLW: heading- flowering, MT: maturity, and HVS: harvesting

a) VV

	Transplanted rice (dB)					Wet direct seeded rice (dB)				
	min	max	range	mean	std	min	max	range	mean	std
LP	-16.03	-6.77	9.26	-9.88	2.16	-12.61	-6.99	5.62	-9.25	1.55
FLD	-17.07	-7.36	9.71	-11.67	2.47	-15.05	-7.36	7.69	-10.25	2.14
CE	-17.07	-8.44	8.63	-11.00	2.07	-13.20	-6.77	6.43	-9.95	1.53
TL-SE	-12.50	-8.44	4.06	-9.58	0.89	-12.50	-7.04	5.46	-9.21	1.04
HE-FLW	-12.88	-6.59	6.29	-10.41	1.56	-13.01	-7.18	5.83	-10.49	1.45
MT	-12.27	-7.41	4.86	-9.97	1.33	-12.49	-7.21	5.28	-9.93	1.57
HVS	-11.65	-6.99	4.66	-9.08	1.47	-11.65	-6.99	4.66	-9.22	1.47

b) VH

	Transplanted rice (dB)					Wet direct seeded rice (dB)				
	min	max	range	mean	std	min	max	range	mean	std
LP	-21.41	-12.30	9.11	-16.44	2.71	-19.86	-12.31	7.55	-15.53	2.24
FLD	-22.68	-13.23	9.45	-18.70	2.54	-22.68	-13.23	9.45	-16.97	2.61
CE	-21.63	-15.89	5.74	-18.52	1.50	-22.09	-13.18	8.91	-17.62	2.33
TL-SE	-20.89	-14.84	6.05	-17.37	1.35	-20.75	-12.56	8.19	-17.10	1.81
HE-FLW	-17.15	-13.51	3.64	-15.62	0.87	-16.57	-13.51	3.06	-15.52	0.77
MT	-16.25	-13.08	3.18	-14.67	0.87	-16.34	-13.40	2.94	-14.72	0.81
HVS	-16.43	-12.49	3.94	-14.33	1.19	-17.48	-12.49	4.99	-14.60	1.33

c) VV/VH

	Transplanted rice (dB)					Wet direct seeded rice (dB)				
	min	max	range	mean	std	min	max	range	mean	std
LP	3.19	9.37	6.18	6.57	1.35	3.49	9.37	5.88	6.28	1.34
FLD	4.52	9.81	5.29	7.04	1.37	3.90	9.81	5.90	6.71	1.13
CE	4.55	10.22	5.66	7.52	1.39	5.34	10.65	5.31	7.68	1.44
TL-SE	5.78	11.02	5.24	7.82	1.20	4.89	14.97	10.08	8.05	2.12
HE-FLW	3.31	9.18	5.87	5.26	1.57	3.34	9.18	5.84	5.10	1.45
MT	2.67	8.15	5.48	4.64	1.14	2.69	7.15	4.46	4.78	1.25
HVS	3.52	8.15	4.63	5.19	1.13	3.74	7.24	3.50	5.39	0.93

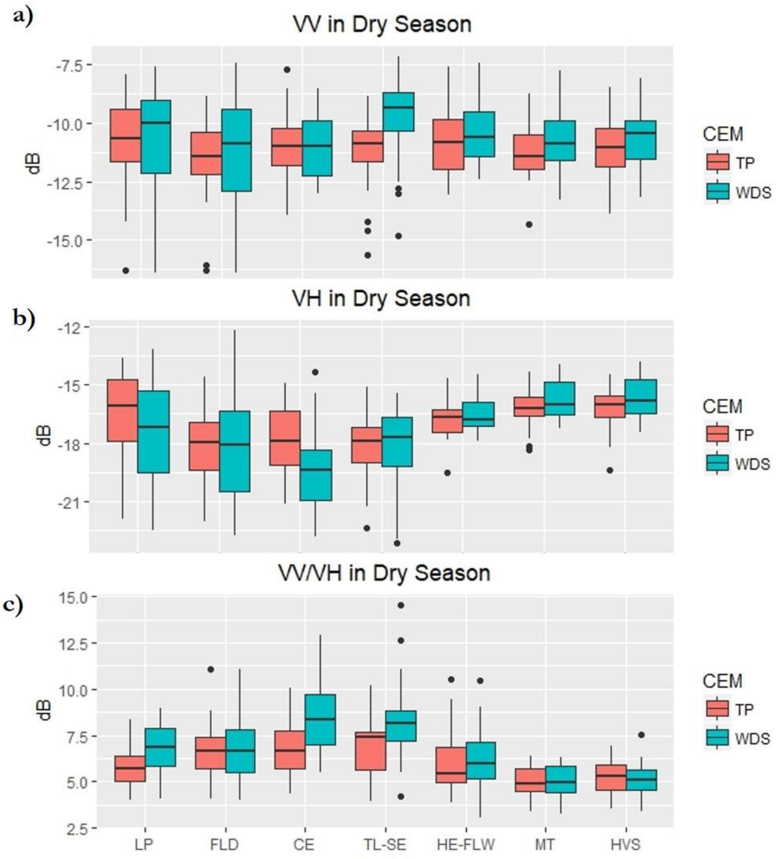
Appendix III- Difference in backscatter (dB) of polygons between before and after negative buffering (VV and VH)

Polygon	1-Nov-16	13-Nov-16	25-Nov-16	7-Dec-16	19-Dec-16	31-Dec-16	12-Jan-17	24-Jan-17	5-Feb-17	17-Feb-17	1-Mar-17	13-Mar-17	25-Mar-17	6-Apr-17	18-Apr-17	30-Apr-17	12-May-17	24-May-17	5-Jun-17	29-Jun-17	11-Jul-17	23-Jul-17	4-Aug-17	16-Aug-17	28-Aug-17	9-Sep-17	21-Sep-17	3-Oct-17	15-Oct-17	27-Oct-17	average
	dB difference																														
1	0.20	0.15	0.03	0.25	0.43	0.36	0.15	0.39	0.73	0.09	0.23	0.02	0.18	0.14	0.19	0.21	0.50	0.39	0.15	0.30	0.42	0.53	0.34	0.68	0.28	0.16	0.12	0.37	0.23	0.02	0.27
2	0.12	0.81	0.01	0.12	0.31	0.08	0.18	0.18	0.15	0.11	0.07	0.27	0.34	0.28	0.14	0.18	0.18	0.39	1.03	0.14	0.38	0.09	0.06	0.14	0.55	0.35	0.38	0.84	0.09	0.07	0.27
3	0.26	0.62	0.69	0.54	0.59	0.58	0.20	0.24	0.16	0.48	0.40	0.27	0.62	0.37	0.52	0.03	0.16	0.68	0.23	0.29	0.50	0.25	0.14	0.56	0.63	0.64	0.56	0.06	0.02	0.15	0.38
4	0.51	0.74	0.67	0.59	0.31	0.28	0.74	0.53	0.10	0.15	0.07	0.45	0.16	0.39	0.05	0.23	0.07	0.67	0.50	0.79	0.66	0.04	1.98	0.25	0.02	0.19	0.19	0.02	0.41	0.40	0.41
5	0.82	0.91	0.29	0.41	0.57	1.97	1.07	0.75	0.74	0.26	0.36	0.62	1.22	0.84	0.34	1.00	0.16	0.06	0.28	0.20	0.81	0.73	0.79	0.06	0.46	0.08	0.14	0.58	0.01	0.96	0.58
6	0.01	0.07	0.42	0.14	0.46	0.32	0.00	0.10	0.06	0.00	0.53	0.30	0.61	0.20	0.42	0.19	0.55	0.23	0.08	0.03	0.07	0.00	0.15	0.55	0.01	0.26	0.66	0.50	0.47	0.22	0.25
7	0.49	0.30	0.70	0.70	1.20	0.37	0.62	0.06	0.74	0.60	0.74	0.31	0.58	1.09	0.44	1.17	0.38	0.96	1.02	0.89	0.53	1.56	0.73	0.08	1.88	2.12	0.03	0.64	0.69	0.89	0.75
8	0.37	0.57	0.06	0.44	0.09	0.86	0.44	0.60	0.06	0.35	1.35	0.65	0.78	0.16	0.55	0.14	0.04	0.35	0.81	1.14	0.16	0.56	0.25	1.04	0.54	1.25	0.98	0.43	0.19	0.60	0.53
9	0.19	0.55	0.41	0.32	1.26	0.74	0.27	0.75	0.91	0.26	0.12	0.06	0.15	0.03	0.92	0.36	0.02	0.26	1.42	0.82	1.38	0.57	0.58	0.61	0.84	0.31	0.00	0.80	0.04	0.34	0.51
10	0.65	0.21	0.66	0.54	0.57	0.16	0.32	0.03	0.09	0.42	0.20	0.33	0.53	0.87	0.57	0.36	0.68	0.69	0.31	0.61	0.45	0.24	0.64	0.95	0.28	1.23	0.11	0.44	0.52	0.75	0.48
11	0.24	0.21	0.07	0.18	0.14	0.67	0.34	0.20	0.06	0.06	0.06	0.10	0.07	0.38	0.04	0.11	0.03	0.19	0.12	0.13	0.19	0.08	0.01	0.06	0.05	0.16	0.21	0.07	0.31	0.03	0.15
12	0.51	0.36	0.28	0.28	0.18	0.91	0.33	1.22	0.12	0.01	0.27	0.20	0.11	0.01	0.06	0.12	0.11	0.24	0.10	0.64	1.07	0.34	0.14	0.15	0.17	0.29	0.36	0.51	0.38	0.09	0.32
13	0.06	0.43	0.07	0.25	0.10	0.36	0.07	0.63	0.35	0.50	0.16	0.02	0.11	1.09	0.16	0.21	0.24	0.09	0.03	0.20	0.39	0.20	0.03	0.25	0.23	0.29	0.52	0.29	0.47	0.07	0.26
14	0.33	0.15	0.20	0.36	0.32	0.44	0.43	0.20	0.94	0.21	0.41	0.40	0.57	0.40	0.04	0.05	0.30	0.09	0.34	0.23	0.05	0.28	0.04	0.11	0.04	0.14	0.14	0.05	0.02	0.58	0.26
15	0.34	0.25	0.05	0.02	0.37	0.45	0.09	0.44	0.32	0.49	0.38	0.26	0.58	0.04	0.52	0.16	0.07	0.41	0.45	0.13	0.94	0.10	0.22	0.17	0.20	0.56	0.23	0.32	0.09	0.76	0.31
16	0.61	0.37	1.03	1.19	1.00	0.48	0.06	2.07	0.38	0.67	0.30	0.60	0.14	0.00	0.44	0.18	1.01	1.71	0.54	1.15	2.03	1.05	0.90	0.81	0.10	1.37	0.54	0.44	0.88	1.31	0.78
17	0.40	0.23	0.54	0.38	0.35	0.02	0.18	0.08	0.39	0.28	0.66	0.01	0.64	0.50	0.13	0.21	0.24	0.06	0.08	0.06	0.50	0.19	0.53	0.18	0.11	0.24	0.27	0.44	0.13	0.57	0.29
18	0.34	0.30	0.66	1.28	0.05	0.05	0.28	0.03	0.27	0.25	0.31	0.36	0.64	0.20	0.02	0.96	0.38	0.97	0.39	0.13	0.50	0.61	0.02	1.07	0.10	0.84	0.38	0.02	0.23	0.56	0.41
19	0.08	0.07	0.27	0.90	0.10	0.70	0.04	0.26	0.13	0.04	0.48	0.26	0.10	0.16	0.09	0.25	0.24	0.48	0.13	0.04	0.00	0.21	0.14	0.39	0.25	0.03	0.08	0.14	0.18	0.29	0.22
20	0.09	0.40	0.01	0.30	0.47	0.55	0.67	0.38	0.04	0.06	0.03	0.04	0.02	0.12	0.10	0.47	0.45	0.22	0.01	0.14	0.47	0.10	0.22	0.07	0.10	0.25	0.23	0.16	0.16	0.00	0.21
21	0.14	1.15	0.79	0.17	0.19	0.18	0.46	0.40	0.25	0.36	0.02	0.33	0.08	1.17	0.38	1.45	0.51	0.07	0.22	0.52	1.15	0.28	0.17	0.86	0.39	0.01	0.01	1.36	0.27	0.14	0.45
22	1.30	1.16	0.39	0.10	1.15	0.45	0.55	0.41	0.49	1.01	0.24	0.20	0.35	0.06	0.30	0.21	0.01	0.18	0.62	0.71	0.06	1.08	0.07	0.21	1.06	0.92	0.64	0.22	0.19	0.19	0.48
23	0.01	0.39	0.59	0.39	0.02	0.09	0.38	0.84	0.37	0.03	0.09	0.10	0.14	0.11	0.08	0.36	0.06	0.15	0.24	0.08	0.29	0.78	0.31	0.01	0.85	0.66	0.14	0.16	0.41	0.53	0.29
24	0.11	0.14	0.18	0.16	0.18	0.06	0.55	0.10	0.93	0.14	0.48	0.58	0.31	0.07	0.09	0.05	0.54	0.13	0.18	0.13	0.13	0.17	0.37	0.28	0.35	0.10	0.22	0.21	1.23	0.32	0.28
25	0.11	1.20	0.15	0.97	0.56	1.00	0.49	0.47	0.04	0.75	0.26	0.68	1.47	0.06	0.24	0.20	0.55	0.08	0.02	1.46	0.87	1.09	0.38	0.13	0.07	0.33	0.40	0.43	0.45	0.49	0.51
26	0.05	0.16	0.46	0.24	0.75	0.05	0.92	0.17	0.86	1.16	0.19	0.54	0.27	0.72	0.13	0.28	0.43	0.09	0.13	0.10	0.21	0.18	0.03	0.43	0.13	0.43	0.75	0.43	0.05	1.87	0.41
27	0.83	0.37	0.46	0.28	0.32	0.06	0.00	1.04	0.25	0.20	0.55	0.45	0.64	0.08	0.56	0.37	0.36	0.17	0.21	0.25	0.14	0.22	0.05	0.60	0.18	0.09	0.11	0.56	0.73	0.01	0.34
28	0.19	0.53	0.71	0.09	0.46	0.09	0.19	0.92	0.37	0.02	0.04	0.46	0.21	0.13	1.14	0.46	0.45	0.08	0.03	0.21	0.01	0.15	0.25	0.43	0.57	0.16	0.16	0.87	0.78	0.75	0.36
29	0.04	0.13	0.13	0.35	0.26	0.14	0.36	0.16	0.00	0.07	0.12	0.76	0.43	0.12	0.29	0.52	0.17	0.26	0.03	0.37	0.28	0.62	0.12	0.39	0.16	0.53	0.09	0.57	0.24	0.00	0.26
30	0.55	0.54	0.17	0.16	0.45	2.12	0.53	0.89	0.45	0.18	0.52	0.40	0.43	0.09	0.19	0.37	0.70	0.45	0.39	0.65	0.38	0.02	0.73	1.39	0.20	0.00	0.12	0.69	0.25	0.61	0.49
31	0.08	0.10	0.09	0.15	0.09	0.47	0.02	0.30	0.26	0.20	0.22	0.12	0.11	0.17	0.11	0.13	0.20	0.02	0.57	0.10	0.12	0.32	0.19	0.16	0.14	0.11	0.14	0.16	0.06	0.22	0.17
32	0.27	0.24	0.06	0.06	0.21	0.24	0.40	0.34	0.01	0.28	0.32	0.88	0.05	0.12	0.33	0.15	0.06	0.02	0.01	0.11	0.63	0.14	0.41	0.00	0.20	0.13	0.23	0.05	0.04	0.18	0.21
33	0.40	0.12	0.08	0.05	0.01	1.16	0.58	0.08	0.03	0.15	0.42	0.43	0.43	0.01	0.24	0.00	0.02	0.01	0.18	0.24	0.07	0.60	0.04	0.18	0.17	0.02	0.05	0.06	0.32	0.22	0.21
34	0.01	1.78	0.51	0.47	0.20	0.16	0.58	1.66	0.68	0.16	0.43	0.66	0.57	0.45	0.81	0.30	0.52	0.64	0.64	0.21	1.36	1.01	0.00	0.45	0.16	0.68	0.48	1.07	0.56	0.24	0.58
35	0.01	0.05	0.41	0.70	0.85	0.30	0.23	0.06	0.86	0.82	1.30	0.16	0.05	0.06	0.55	0.01	0.56	0.14	0.33	0.33	0.54	3.93	0.73	0.21	0.02	1.01	1.00	0.30	0.21	1.03	0.56
36	0.20	0.54	0.65	0.92	0.44	0.69	0.00	0.17	0.32	0.11	0.34	0.17	0.16	0.21	0.02	0.09	0.15	0.24	0.01	0.02	0.15	0.00	0.37	0.08	0.10	0.39	0.32	0.03	0.18	0.00	0.24
37	0.35	0.68	0.96	0.13	0.38	0.09	0.01	0.27	0.94	0.28	0.42	0.23	0.06	0.25	0.12	0.32	0.08	0.34	0.44	0.65	0.03	0.19	0.11	0.47	0.05	0.60	0.16	0.64	0.72	0.22	0.34
38	0.18	0.93	0.94	0.23	1.34	0.83	0.99	0.43	0.89	0.25	0.02	0.26	0.16	1.59	0.23	0.76	0.00	0.46	1.02	1.54	0.12	0.17	2.76	0.34	0.34	1.14	0.00	0.15	0.40	0.56	0.63
39	0.63	0.71	1.07	1.86	0.57	1.84	0.72	0.46	0.35	0.38	1.22	0.60	0.87	0.65	0.52	0.54	0.19	0.02	2.24	0.91	0.66	0.96	1.27	0.97	1.40	1.24	0.68	0.36	0.63	0.56	0.84
40	0.52	0.03	0.54	0.89	0.80	0.64	0.10	0.18	0.01	0.37	0.03	0.16	0.23	0.22	0.06	0.13	0.25	0.23	0.35	0.66	0.06	0.13	0.37	0.24	0.29	0.34	0.14	0.40	0.27	0.14	0.29
41	0.79	0.17	1.75	1.50	0.91	0.21	0.85	0.02	2.43	0.34	1.37	0.78	1.43	0.32	0.94	0.35	0.19	1.05	0.23	1.43	0.30	2.52	0.34	0.28	2.17	2.49	2.71	1.37	0.20	2.05	1.05
42	0.14	0.22	1.91	0.22	0.20	0.14	0.15	0.10	0.11	0.20	0.13	0.12	0.02	0.38	0.02	0.13	0.12	0.19	0.13	0.40	0.52	0.02	0.12	0.44	0.22	0.40	0.73	0.29	0.35	0.09	0.27
43	0.30	0.88	0.52	0.41	0.19	0.15	0.13	0.81	0.54	0.34	0.43	0.40	0.51	1.00	0.47	0.37	0.27	0.57	0.13	0.03	0.72	0.28	0.54	0.14	0.52	0.41	0.37	0.58	1.26	0.32	0.45
44	0.64	0.48	0.78	1.13	0.63	2.11	0.69	0.66	0.11	0.79	0.25	0.27	0.68	0.45	0.62	0.25	0.12	0.09	0.89	0.63	1.25	0.47	0.22	0.15	0.20	0.83	1.04	0.26	0.35	0.22	0.58
																												dB	Average difference		0.41

Polygon	1-Nov-16	13-Nov-16	25-Nov-16	7-Dec-16	19-Dec-16	31-Dec-16	12-Jan-17	24-Jan-17	5-Feb-17	17-Feb-17	1-Mar-17	13-Mar-17	25-Mar-17	6-Apr-17	18-Apr-17	30-Apr-17	12-May-17	24-May-17	5-Jun-17	29-Jun-17	11-Jul-17	23-Jul-17	4-Aug-17	16-Aug-17	28-Aug-17	9-Sep-17	21-Sep-17	3-Oct-17	15-Oct-17	27-Oct-17	average
	dB difference																														
1	0.33	0.31	0.19	0.14	0.33	0.20	0.56	0.02	0.15	0.22	0.46	0.04	0.33	1.14	0.20	0.48	0.05	0.66	0.36	0.47	0.14	0.38	1.21	0.12	0.12	0.37	0.37	0.53	0.79	0.52	0.37
2	0.62	0.95	0.43	0.20	0.11	0.56	0.19	0.27	0.71	0.17	0.03	0.26	0.33	0.10	0.13	0.07	0.21	0.48	0.26	0.00	0.46	0.07	0.37	0.05	0.22	0.08	0.13	0.24	1.10	0.73	0.32
3	0.77	0.78	0.48	1.03	0.36	1.27	0.02	0.44	0.43	0.36	0.77	0.67	0.41	0.73	0.03	0.05	1.26	0.12	0.14	0.85	0.50	0.64	0.85	0.30	0.24	0.51	0.37	0.28	0.89	0.00	0.52
4	0.83	0.37	0.18	0.56	0.24	0.37	0.13	0.39	0.19	0.45	0.50	0.47	0.68	0.25	0.49	0.92	0.36	0.50	0.35	1.72	0.76	1.04	2.73	0.87	0.44	0.45	0.09	0.16	0.64	0.92	0.60
5	1.13	0.51	0.20	0.78	0.21	0.35	1.00	0.47	0.67	1.55	0.22	0.22	0.84	0.91	0.72	0.73	0.00	0.28	0.16	0.01	0.67	0.73	0.60	0.79	0.88	0.43	0.89	1.28	0.63	0.32	0.61
6	0.02	0.28	0.09	0.37	0.13	0.01	0.10	0.15	0.04	0.34	0.19	0.32	0.04	0.08	0.69	0.12	0.19	0.46	0.37	0.02	0.09	0.69	0.77	0.34	0.35	0.26	0.61	0.17	0.64	0.01	0.27
7	0.43	0.60	1.78	0.36	0.29	0.05	0.46	0.51	0.54	0.03	0.88	0.10	0.24	0.27	0.45	1.45	0.02	1.00	0.15	0.29	0.37	0.68	0.21	0.04	1.52	0.11	0.90	0.08	0.20	0.03	0.47
8	0.44	0.10	0.44	0.27	0.48	0.78	0.20	0.14	0.51	0.68	0.31	0.56	0.43	0.57	0.64	0.42	1.19	0.64	0.45	0.29	0.10	0.51	0.63	0.58	1.32	0.34	0.05	0.04	0.50	0.60	0.47
9	0.75	0.52	0.22	0.14	0.26	1.22	0.94	0.56	2.74	0.96	0.10	0.12	1.64	0.83	0.91	0.22	0.03	0.30	0.60	0.77	0.33	0.52	1.04	0.47	0.72	0.23	0.43	0.28	0.08	0.53	0.62
10	0.56	1.25	0.18	0.64	0.36	0.87	0.21	0.02	0.60	0.81	0.74	0.60	1.71	1.14	0.19	0.96	1.08	0.21	0.42	0.27	0.50	0.45	0.28	0.02	0.69	0.15	0.11	0.41	0.16	0.53	0.54
11	0.44	0.09	0.05	0.16	0.07	0.27	0.15	0.02	0.15	0.05	0.06	0.18	0.06	0.05	0.06	0.33	0.26	0.16	0.22	0.00	0.27	0.03	0.24	0.13	0.06	0.40	0.01	0.29	0.23	0.12	0.15
12	0.24	0.06	0.11	0.03	0.71	0.94	0.79	0.99	1.08	0.61	0.27	0.10	0.55	0.08	0.07	0.18	0.09	0.14	0.25	0.48	1.06	0.74	0.14	0.09	0.20	0.34	0.20	0.29	0.02	0.02	0.36
13	0.90	0.34	0.42	0.43	0.56	0.15	0.51	0.43	1.32	0.78	0.50	0.19	0.39	0.49	0.24	0.30	0.22	0.97	0.22	0.30	0.62	0.59	0.68	0.67	0.55	0.46	0.60	0.08	0.44	0.54	0.50
14	0.16	0.30	0.32	0.30	0.40	0.02	0.00	0.07	0.78	0.21	0.14	0.10	0.05	0.15	0.10	0.20	0.24	0.34	0.23	0.20	0.46	0.29	0.64	0.28	0.01	0.67	0.24	0.05	0.25	0.04	0.24
15	0.10	0.02	0.12	1.67	0.29	0.65	0.48	0.06	0.01	0.09	0.30	0.00	0.02	0.16	0.47	0.55	0.52	0.04	0.05	0.30	0.41	0.17	0.06	0.43	0.05	0.27	0.02	0.18	0.17	0.08	0.26
16	0.07	0.50	0.96	1.95	1.79	0.23	0.57	0.65	1.44	0.51	1.08	0.62	0.67	0.14	0.11	2.21	0.78	1.01	0.47	1.10	0.16	0.38	0.91	0.09	1.05	0.25	0.36	0.28	0.04	0.28	0.69
17	0.13	0.12	0.57	0.84	0.32	0.79	0.58	0.28	0.26	0.05	0.26	0.36	1.01	0.44	0.56	0.38	0.56	0.26	0.33	0.23	0.46	0.94	0.15	0.53	0.94	0.51	0.22	0.06	0.49	0.19	0.43
18	0.64	0.14	0.36	1.01	0.36	1.05	1.12	0.68	0.04	0.66	0.53	0.56	1.04	0.26	0.21	1.28	0.69	1.20	0.36	0.79	0.67	1.99	0.23	0.50	1.89	0.31	0.86	0.13	0.47	0.74	0.69
19	0.29	0.07	0.17	0.49	0.60	0.67	0.34	0.04	0.28	0.49	0.35	0.16	0.44	0.04	0.20	0.24	0.03	0.61	0.43	0.09	0.32	0.17	0.27	0.30	0.32	0.20	0.44	0.46	0.32	0.09	0.30
20	0.01	0.03	0.15	0.57	0.48	0.31	0.58	0.74	0.51	0.55	0.33	0.45	0.15	0.45	0.41	0.09	0.19	0.04	0.10	0.06	0.40	0.45	0.00	0.33	0.18	0.29	0.15	0.30	0.24	0.05	0.29
21	1.46	0.85	0.16	1.84	0.37	0.24	0.31	2.06	0.37	0.09	1.16	0.45	0.44	1.86	0.59	0.49	0.60	1.16	2.15	0.74	0.98	0.30	0.27	0.12	0.75	0.28	0.21	0.41	0.39	0.16	0.71
22	0.13	0.70	1.02	0.92	1.33	0.54	0.27	0.31	0.55	0.05	0.19	0.16	0.14	0.04	0.42	0.62	0.17	1.22	0.16	0.61	0.97	2.08	0.83	0.28	0.66	0.36	0.06	0.11	0.00	0.12	0.50
23	0.56	0.88	0.92	0.17	0.23	0.13	0.01	0.31	0.51	0.17	0.16	0.75	0.14	0.29	0.31	0.30	0.11	0.20	0.13	0.33	0.30	1.42	0.64	0.36	0.41	0.13	0.05	0.27	0.12	0.13	0.35
24	0.46	0.01	0.20	0.09	0.07	0.12	0.11	0.31	0.11	0.18	0.67	0.63	0.15	0.24	0.03	0.10	0.38	0.07	0.26	0.65	0.34	0.00	0.36	0.02	0.21	0.07	0.15	0.16	0.36	0.03	0.22
25	0.20	0.33	0.11	0.38	0.17	0.52	0.07	0.39	0.53	0.41	0.42	0.67	0.27	0.66	1.31	0.14	0.19	0.01	0.19	0.96	1.68	0.01	0.29	1.46	0.28	0.45	1.64	1.01	0.47	0.24	0.52
26	0.33	0.70	0.02	0.17	0.49	0.23	0.16	0.08	0.10	0.17	0.51	0.31	0.60	0.32	1.13	0.22	0.01	0.03	2.84	0.90	0.37	1.12	0.96	0.73	0.42	0.63	0.05	0.46	0.14	0.24	0.48
27	0.28	0.42	0.29	0.38	0.50	0.58	0.15	0.20	0.28	0.07	0.01	0.10	0.08	0.30	0.43	0.23	0.56	0.54	0.25	0.14	0.02	0.43	0.51	0.43	0.26	0.27	0.19	0.13	0.03	0.23	0.28
28	0.03	0.24	0.21	0.02	0.25	0.50	0.28	0.71	0.09	0.16	0.08	0.16	0.63	0.26	0.18	0.59	0.82	0.21	0.08	0.16	0.34	0.56	0.37	0.08	0.14	1.09	0.13	0.36	0.58	0.68	0.33
29	0.21	0.27	0.16	0.21	0.02	0.56	0.15	0.07	0.14	0.31	0.17	0.56	0.23	0.12	0.03	0.90	0.27	0.09	0.24	0.46	0.04	0.92	0.05	0.28	0.04	0.04	0.02	0.34	0.31	0.15	0.25
30	0.09	1.29	0.13	0.38	0.72	1.62	0.46	0.43	0.35	0.02	0.07	0.37	0.22	0.33	0.08	0.14	0.58	0.32	0.54	0.54	0.12	0.65	1.12	0.25	0.46	0.41	0.27	0.32	0.83	0.11	0.44
31	0.01	0.09	0.21	0.07	0.05	0.29	0.17	0.59	0.57	0.21	0.20	0.11	0.01	0.02	0.23	0.04	0.10	0.05	0.21	0.04	0.18	0.24	0.05	0.16	0.26	0.00	0.08	0.05	0.04	0.02	0.14
32	0.37	0.15	0.10	0.15	0.51	0.02	0.49	1.20	0.41	0.24	0.09	0.70	0.08	0.40	0.28	0.03	0.60	0.41	0.03	0.14	0.04	0.39	0.33	0.70	0.32	0.24	0.74	0.03	0.16	0.07	0.31
33	0.13	0.07	0.19	0.13	0.22	1.14	0.30	0.19	0.17	0.14	0.15	0.14	0.16	0.35	0.04	0.16	0.01	0.08	0.18	0.02	0.23	1.12	0.42	0.26	0.12	0.05	0.18	0.05	0.04	0.02	0.22
34	1.14	0.23	0.08	2.15	0.54	0.10	1.60	1.63	2.37	0.50	0.95	0.01	0.03	0.23	0.56	0.73	0.80	0.42	0.99	1.01	0.05	0.87	1.55	0.06	0.29	0.46	0.77	0.19	0.72	0.16	0.71
35	0.84	0.20	0.23	0.97	2.69	2.95	1.40	0.88	0.88	0.90	0.26	0.82	0.53	0.36	0.80	0.04	0.14	0.15	0.13	0.40	0.51	2.41	0.88	0.57	0.56	0.36	0.62	0.51	0.01	0.97	0.77
36	0.23	0.64	0.59	0.53	0.69	1.20	0.46	0.43	0.70	0.00	0.07	0.15	0.27	0.30	0.37	0.04	0.07	0.52	0.34	0.34	0.16	0.15	0.11	0.06	0.19	0.02	0.19	0.28	0.06	0.01	0.30
37	0.94	0.33	0.83	0.51	0.88	1.06	0.09	0.52	0.36	0.24	0.04	0.12	0.16	0.40	0.29	0.74	0.59	0.13	0.09	0.94	0.47	0.49	0.12	0.32	0.29	0.34	0.41	0.81	0.70	0.47	0.46
38	1.36	0.73	1.77	2.66	1.91	1.11	0.48	0.22	1.37	1.40	0.91	0.93	2.09	0.01	0.40	0.54	0.34	0.43	0.04	0.65	0.27	0.53	0.98	0.62	1.02	2.04	0.29	0.28	0.10	0.47	0.87
39	0.03	0.36	2.18	1.90	0.59	0.87	1.14	0.68	0.53	0.56	0.19	0.18	1.05	0.09	0.31	0.11	0.67	0.29	2.03	1.10	0.55	0.41	0.18	0.21	0.19	1.00	0.32	0.09	0.09	0.04	0.60
40	0.04	0.15	0.09	1.50	0.30	1.08	0.74	0.89	0.50	0.94	0.49	0.12	0.49	0.46	0.39	0.15	0.18	0.52	0.25	0.38	0.89	1.12	0.69	0.27	0.47	0.26	0.01	0.47	0.10	0.27	0.47
41	0.45	0.49	2.13	1.29	0.52	0.84	1.47	0.12	1.84	0.99	0.20	1.08	0.19	1.35	0.51	0.37	1.12	0.62	2.38	0.31	0.46	0.73	0.68	1.60	0.10	2.10	0.14	2.42	0.32	1.12	0.95
42	0.07	0.27	1.90	0.68	0.27	0.34	0.78	0.26	0.56	0.36	0.12	0.38	0.17	0.10	0.34	0.07	0.17	0.20	0.21	0.52	0.55	0.06	0.21	0.03	0.03	0.27	0.14	0.16	0.00	0.68	0.33
43	0.10	0.28	0.40	0.31	1.03	0.57	0.73	0.25	0.75	0.18	0.43	0.15	0.20	0.29	0.29	0.13	0.06	0.45	0.22	0.25	0.76	0.16	0.21	0.09	0.37	0.70	0.06	0.19	0.45	0.23	0.34
44	0.09	0.30	1.29	0.22	0.12	0.05	0.03	0.56	0.38	0.42	0.35	0.02	1.17	0.26	0.38	0.70	0.31	0.03	1.08	0.14	0.19	0.10	1.22	1.22	0.27	0.59	0.70	0.48	0.82	0.73	0.47
																												dB	Average difference		0.45

Backscatter difference (dB) of polygons between before and after negative buffering in VV (top) and VH (bottom). Tables show that the mean dB difference in VV is 0.41 dB, and in VH is 0.45 dB

Appendix IV- Temporal backscatter signatures using the non-negative buffered polygons, with the result of Mann-Whitney tests (in the dry season)



Appendix IV-A. Temporal backscatter signature of TP (Transplanted rice) and WDS (Wet Direct Seeded rice) in the dry season (using the non-negative buffered polygons), in VV (a), VH (b), and the ratio of VV/VH (c).
Graphs show the backscatter coefficient (dB) for different events in the rice growing season. LP: land preparation, FLD: flooding, CE: crop establishment, TL-SE: tillering-stem elongation, HE-FLW: heading- flowering, MT: maturity, and HVS: harvesting

Appendix IV-B. p- values between transplanted (TP) and wet direct seeded rice (WDS) from Mann-Whitney U test (with the non-negative buffered polygons) in the dry season
The highlights correspond to events with the sig. difference ($p<0.05$ and $\alpha = 95\%$)

Dry Season

	VV	VH	VV/VH
LP	0.83	0.153	0.008
FLD	0.75	0.923	0.807
CE	0.762	0.001	0.001
TL-SE	0.000	0.769	0.002
HE-FLW	0.473	0.186	0.739
MT	0.171	0.234	0.784
HVS	0.201	0.201	0.539

Appendix V- Accuracy values, Kappa, and AUC values of decision tree using different features in the dry and wet season

Dry season

features	dB	dB+ rainfall	dB+ relative elevation	dB+ rainfall+ relative elevation
OA (%)	72	72	78	61
Kappa	0.44	0.44	0.56	0.22
AUC	0.75	0.72	0.86	0.71

Wet season

features	dB	dB+ rainfall	dB+ relative elevation	dB+ rainfall+ relative elevation
OA (%)	73	81	69.23	65
Kappa	0.06	-0.07	0.02	-0.02
AUC	0.53	0.47	0.45	0.48