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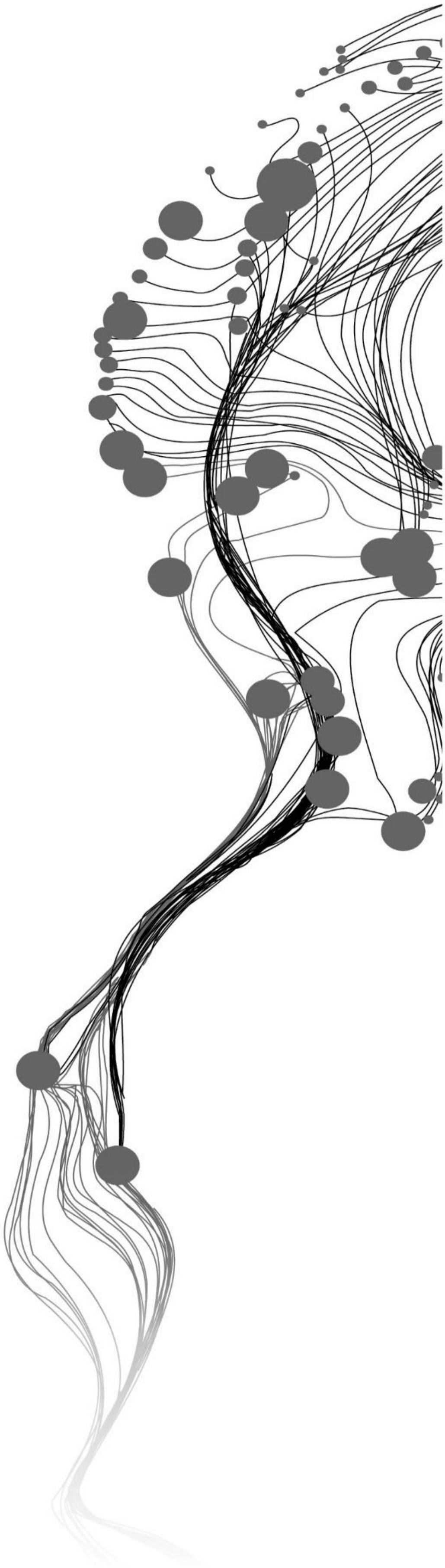

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Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-Information Science and Earth Observation.
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ABSTRACT

Rice is one of the most important staple foods, and more than 3.5 billion people consume rice worldwide, with Asia being the largest producing and consuming region. Paddy rice is cultivated on flooded soil (which can be irrigated or rainfed) and consumes a significant amount of water. It is estimated that 34-43% of the total world's irrigation water or 24-30% of the total world's freshwater withdrawal is used to irrigate lowland rice. Having an understanding of the different rice water sources is not just useful for water management but also for water conservation planning, for example, to help farmers to cope with the common problem of water scarcity.

In this research, a simple but robust method was used to distinguish the rice fields with different water sources (canal irrigated, rainfed and water pump supplemented) in Central Luzon, Philippines. Firstly, multi-temporal Sentinel-1A images with 20m spatial resolution were used to create the time series of whole rice growing events and stages (land preparation, crop establishment, panicle formation, flowering and harvest) during the wet season (April to October 2017). Secondly, information about rice fields with different water sources: canal irrigated (IR), rainfed (RF) and water pump supplemented (WP) were obtained in the field through interview. For this, a total of 99 farmers were interviewed, and 116 rice fields (IR=60, WP=46 and RF=10) were observed during fieldwork conducted between September 24 and October 10, 2018, and a database was developed.

The backscatter coefficients of the rice fields with different water sources were extracted from VV and VH of Sentinel-1A. The image acquisition dates were matched with the observed dates of key rice growing events, such as land preparation and stages such as flowering. One-way ANOVA was employed to examine whether there were significant differences between rice fields with different water sources during key rice-growing events and stages in VV, VH and VV-VH. The backscatter coefficients during land preparation and crop establishment of VH and land preparation of VV-VH exhibited a significant difference between rice fields with different water sources. To identify the threshold and set of rules, data was divided into training (70%) and test data (30%). A decision tree algorithm was used to establish thresholds and sets of rules to differentiate rice fields with different water sources using training data. Ten different rules were developed in the decision tree using the rice growing events and stages of VV and VH with different probabilities.

The thresholds and rules set by decision tree obtained the overall accuracy of 74.29% (kappa=0.51) with user accuracy for IR and WP were 71.43% and 78.57% respectively, and producer accuracy for IR and WP were 83.33% and 78.57%, respectively. Due to the low number of field observations, decision tree was unable to distinguish pure rainfed rice fields resulting zero user and producer accuracies. However, decision tree gave the satisfactory class accuracies while differentiating other classes IR and WP and also the satisfactory overall accuracy. The study revealed the possibility of using multi-temporal Sentinel-1A imageries and decision tree classification to distinguish the rice fields with different water sources. The proposed method can be used in tropical and sub-tropical regions provided that there is sufficient and accurate field observations and multi-temporal remote sensing data at high spatial resolution similar to Sentinel-1A.

Keywords: Sentinel-1A, backscatter coefficient, polarisation, rice ecosystem, ANOVA, decision tree

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LIST OF ACRONYMS AND ABBREVIATIONS

ALOS	Advanced Land Observing Satellite
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
ASAR	Advanced Synthetic Aperture Radar
BMMA	Biased maximum margin analysis
CART	Classification and Regression Tree
CE	Crop establishment
CLLS	Central Luzon Loop Survey
DEM	Digital Elevation Model
DN	Digital Number
ENVISAT	Environmental Satellite
ERS	European Remote-Sensing Satellite
ESA	European Space Agency
EWS	Extra Wide Swath mode
F	Flowering
GADM	Database of Global Administrative Areas
GRD	Ground Range Detected
GRiSP	Global Rice Science Partnership
Ha	Harvest
HH	Horizontal transmit and Horizontal receive
HV	Horizontal transmit and Vertical receive
IR	Canal irrigated rice fields
IRRI	International Rice Research Institute
IWS	Interferometric Wide Swath mode
LP	Land preparation
MIS	Management Information System

MISTIG	Metrics and Indicators for Tracking in GRiSP
MLC	Maximum Likelihood Classification
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
NIA	National Irrigation Administration
PAGASA	Philippine Atmospheric, Geophysical and Astronomical Services Administration
PALSAR	Phased Array type L-band Synthetic Aperture Radar
PF	Panicle formation
PhilFSIS	Philippines Food Security Information System
RF	Rainfed rice fields
RWS	Rice water sources
SAR	Synthetic Apearture Radar
SLC	Single Look Complex
SM	Stripmap Mode
SPOT	Satellite for observation of Earth
SRTM	Shuttle Radar Topographic Mission
SVM	Support Vector Machine
UPRIIS	Upper Pampanga River Integrated Irrigation System
VH	Vertical transmit and Horizontal receive
VV	Vertical transmit and Vertical receive
WP	Water pump supplemented rice fields

1. INTRODUCTION

1.1. Background

Rice is one of the most important cereal crops from a food security perspective. It is one of the staple food for a large number of people on earth since nearly half of the world's population depends on rice (GRiSP, 2013a). However, the rise in population growth and stable or increasing rates of rice consumption requires more rice production to fulfil the food requirements. In this regard, efficient and timely monitoring and mapping of paddy rice agriculture have prime importance for providing information on agricultural productivity, environmental sustainability, food security and greenhouse gas emissions (Wang, Zhou, Jia, & Yu, 2017).

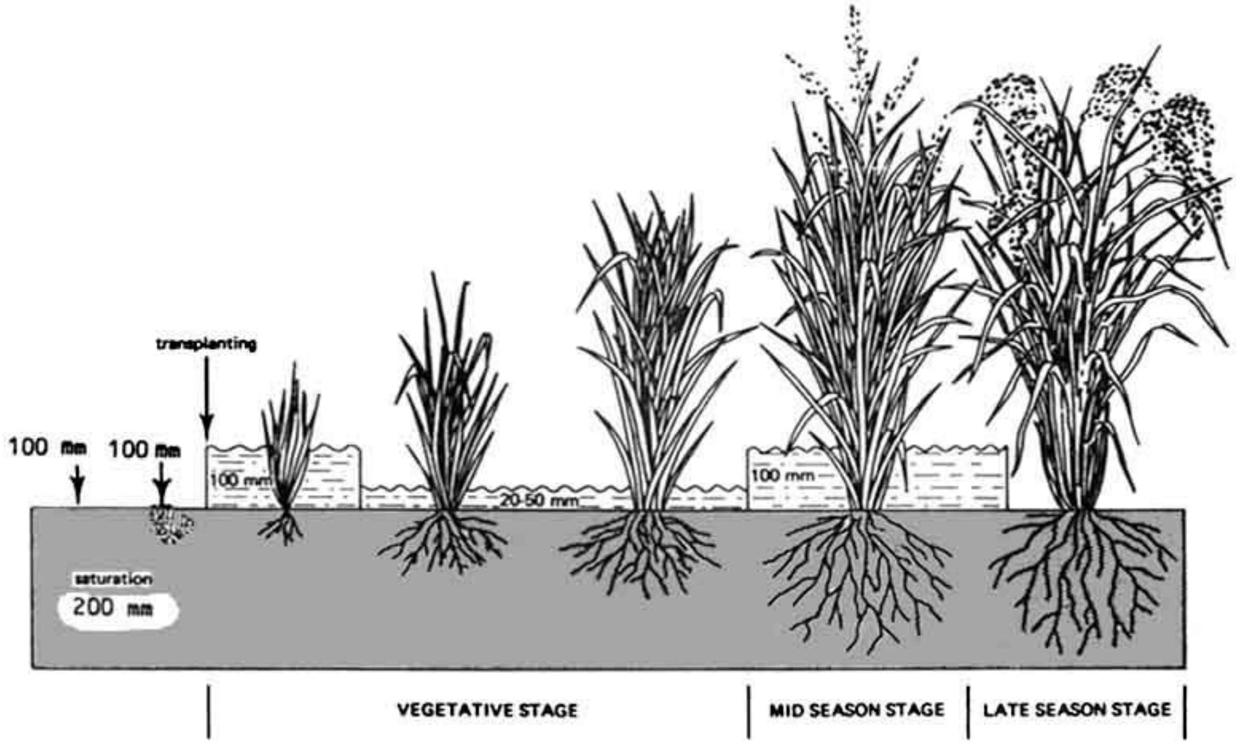
Paddy rice grows on flooded soil (which can be irrigated or rainfed). The International Rice Research Institute (IRRI) classified rice ecosystems, also known as cultural types (Chakraborty, Panigrahy, & Sharma, 1997) into four categories: irrigated, rainfed lowland, upland and deep water (GRiSP, 2013a). Irrigated and rainfed lowland rice is grown in fields with small levees or dykes. Irrigated rice fields are bunded and receive water from surface or groundwater sources as well as from rainfall and runoff. Rainfed lowlands are bunded fields entirely dependent upon local rainfall and runoff for water supply whereas rainfed uplands are un-bunded fields that completely depend on rainfall only. Deepwater rice lies in low-lying areas and depressions where maximum water depth can reach three meters. Rainfed rice growing environments are perhaps one of the most vulnerable rice ecosystems to water stress such as drought and floods and are characterised by uncertainties, particularly with regard to the timing, duration, and intensity of rainfall (Gumma et al., 2015). 75% of the world's rice production comes from irrigated rice fields which account for half of the world's rice land, and more than 80% of the freshwater use in developing countries is diverted for irrigation (Kamthonkiat, Honda, Turral, Tripathi, & Wuwongse, 2005).

Irrigated rice systems generally achieve higher yields than any of the rainfed systems, with upland and deep water having the lowest yields. Irrigation system change broadly and include six different categories (Bouman, Lampayan, & Tuong, 2007):

- Individual pump irrigation from a shallow tube well with a depth about 15m
- Small to medium scale community-based pump irrigation from deep well with a depth of 200-300m
- Small to medium scale community-based surface irrigation where water is diverted from pond to reservoirs
- Small to medium scale community-based surface irrigation where water is directly diverted from the river
- Large-scale surface irrigation where water is diverted form reservoir or lakes
- Conjunctive groundwater – surface-water irrigation scheme which can be from small to large scale

Rice requires about 2-3 times more water than other cereals such as maize or wheat (Bouman & Tuong, 2001). Water required by a rice crop in a given period of time depends upon the field condition if the growth is normal. The various factors like state of the soil, quantity, and type of fertilizer given, quality of water used and the climatic conditions determine the amount of water required for rice (Azwan, Zawawi, & Puasa, 2010). The water requirement of the rice plants varies with the rice growing events and stages. Different approaches have been used regarding the depth of water in rice fields, for example, in some cases, 100 mm of water is established after transplanting and maintained throughout the growing season. However, in common practices, the water layer is reduced to 20-50 mm during the end of the vegetation phase by draining excess water and brought back to 100 mm during the mid-season stage (flowering) as shown in Figure 1 (Brouwer, Prins, & Heibloem, 1989). Different levels of water should be maintained in different growing stages in order to reduce the moisture stress. Further, it is also very important to measure or to estimate the rate of water use for determination of irrigation water requirement (Azwan et al., 2010).

The availability of water is decreasing in many areas due to excessive water extraction from reservoirs and aquifers and increasing demands from other sectors. The decrease in water may threaten traditional ways of growing rice under irrigated conditions (Alberto et al., 2009). The increase in water demand in the agriculture sector, as well as other non-agriculture sectors, exhibits an increased demand for urgent improvement in water management for agriculture (Alberto et al., 2009 & 2011). According to Mekonnen & Hoekstra (2016), the demand for water in agriculture sector is mainly driven by the expansion of irrigated agricultural systems. However, an efficient irrigation system can minimise the water stress in agricultural ecosystem whereas ineffective system can result in farmers at the end of irrigation system receiving little to no water. In addition, well managed, favourable rainfed rice fields can also achieve yields approaching that of irrigated systems, with less pressure on water resources. Better estimates of the irrigated and rainfed area can help support better investments in water management for improved production. Therefore, an accurate and up-to-date assessment of the area of rice that is irrigated and rainfed is an important piece of information for improved rice water management and eventual rice productivity.



Phase	**Seedling**	**Transplanting**	**Maximum tiller number**	**Panicle formation**	**Flowering**	**Harvest**
Time	**Variables**				**35 days**	**30 days**

Figure 1: The depth of water required during the different rice growing events and stages and the duration of rice growing events and stages. (Source: http://www.fao.org/docrep/t7202e/t7202e0g.jpg)

Remote sensing, the science of acquiring information regarding the earth's surface is becoming increasingly important in the field of agriculture today. Remote sensing is finding its way into rice monitoring applications (Poh et al., 2006). Different remote sensing data sources have been used to map crop areas (Nguyen, Gruber,

& Wagner, 2016), crop phenology (Shihua et al., 2014), and to monitor change in production over space and time (McNairn & Shang, 2016). Furthermore, remote sensing is also used to monitor the irrigation system by providing valuable information which can be vital not just for water management, but also for the diagnosis of the performance of the system including planning and evaluation (Bastiaanssen, Molden, & Makin, 2000).

Historically, photointerpretation with Landsat 1 imagery alone (Draeger, 1976) or combination with field boundary information (Rundquist, Hoffman, Carlson, & Cook, 1989) was used for the first time in the study of the irrigation system. Different methods were developed with time, optical sensors have been used extensively to conduct research at the regional scale, but the presence of clouds led to data gaps in detecting and monitoring crops, especially in the humid and subhumid tropics where most of the world's rice is grown. This issue can be addressed by Synthetic Aperture Radar (SAR) providing a reliable source of data on crops (McNairn & Shang, 2016). As proven, SAR can be used in tropical regions where most of the optical imageries are affected by cloud coverage (Bégué et al., 2017).

SAR measures the intensity of energy scattered from the targets towards the sensor. The properties of the target affect the scattering behaviour as well as the backscattering intensity. When radar waves encounter a dielectric discontinuity, scattering from the target occurs. The reason behind this discontinuity is due to the presence of water which has a higher dielectric constant than air. Nelson et al. (2014) have shown that SAR data can be used to detect the lowland rice ecosystem (both irrigated or rainfed) through the unique temporal signature of backscattering coefficient exhibited by crops. However, the study did not look at any potential difference in SAR signal between irrigated and rainfed systems. The crop establishment method, the depth and duration of standing water in the fields before and during crop growth period and the accumulated biomass may vary with rice water sources. Thus, this will have a direct bearing on the SAR backscattering which would help to distinguish the different rice systems (Chakraborty et al., 1997).

1.2. Literature review

Since the 1980s, satellite remote sensing has been used increasingly in the classification of irrigated land because of its contribution in real-time information for the continuous monitoring of land surface on a regional scale (Jin et al., 2016).

Jin et al. (2016) identified three primary methods to classify irrigated and rainfed wheat areas. (1) The water resources inventory which was developed by the Food and Agriculture Organization (FAO) was used to map the distribution of irrigated fields globally using statistical data (Siebert & Döll, 2000). But in general inventory data cannot reflect the spatial distribution of irrigated and rainfed areas timely and accurately (Jin et al., 2016). (2) Unsupervised classification to distinguish irrigated and rainfed areas (Biggs et al., 2006): This method is useful when the local knowledge is not sufficient to perform classification. However, a significant difficulty with this classification is to identify the number of classes (Jin et al., 2016). Also, after the unsupervised classification, the calibration and combination of each cover type are highly affected by subjective factors such as operator skill. (3) Supervised classification to distinguish irrigated and rainfed fields using different satellite data. Kamthonkiat et al. (2005) used SPOT vegetation and rainfall data of 10-days synthesis to differentiate irrigated and rainfed rice in a temporal agricultural system in Thailand. Similarly, Gumma et al. (2015) used MODIS to analyse the different rice growing environments in Odisha, India. In supervised classification, several classes are identified based on the training samples which helps in increasing the classification accuracy.

Further, there is a long history of rice crop area mapping with SAR imagery. SAR uses longer wavelength (0.1 to 1m) to gather surface information. It can provide information independently of cloud coverage and illumination conditions (Ribbes, 1999) and can penetrate through the cloud (Shao et al., 2001). Kurosu, Fujita, & Chiba (1995) used ERS-1 C-band SAR to monitor rice crop growth. Le Toan, Laur, Mougin, & Lopes (1989) used X-band SAR images for multi-temporal and dual polarisation observations of agricultural vegetation. In summary, these studies have shown that longer wavelengths (L and C band) penetrate deeper into the rice plant than shorter wavelengths while shorter wavelengths (X band) interact with rice grain water content and the weight of the grain sufficiently to show a dual-peak in the temporal signature of backscattering during the rice growing season (Suga & Konishi, 2008). Multi-temporal SAR data can be used to retrieve the rice growing cycle based on the temporal variation in the SAR backscattering signal (Nguyen et al., 2015).

The launch of Sentinel-1A on April 3rd, 2014 by the European Space Agency (ESA) under the European Commission's Copernicus program has tremendously increased SAR data availability (Potin, Bargellini, Laur, Rosich, & Schmuck, 2012). The Sentinel-1 SAR instrument operates at 5.405 GHz (C-band corresponding to a radar wavelength of about 5.6cm) with dual polarisation with a revisit time of 12 days (Chen, Son, Chen, Chang, & Chiang, 2016). It provides the opportunities to map small rice fields at different scales because of its high spatial resolution which is 20m in its main Interferometric Wide Swath operating mode (Chen et al., 2016). Furthermore, the launch of Sentinel-1B on 25th April 2016 is enhanced the revisit time for continuous radar mapping of the earth providing improved spatiotemporal coverage of the earth surface (Kramer, 2017).

The C-band of Sentinel-1 supports operation in dual polarisation (HH+HV, VV+VH) implemented through one transmit chain (switchable to H or V) and two parallel receive chains for H and V polarisation (ESA, 2013). Different polarisations have been used in various studies for mapping rice fields. VV and VH polarised backscatter images give different backscatter coefficient values in different rice phenological conditions. It has been demonstrated that VV polarised backscatter is generally higher than VH polarised backscatter through the rice-growing season, and backscattering coefficients (both) gradually increase during growing period until they reach the end of maturation stage (Nguyen et al., 2016). In comparison, HV polarisation data from ENVISAT Advance Synthetic Radar (ASAR) operating at C-band providing has different backscattering mechanism than VV and HH and may be more sensitive to change of biomass of crops and vegetation (Chen, Lin, & Pei, 2007). There are differences in water management and subsequent crop growth between irrigated and rainfed systems that may be detected by SAR remote sensing. We proceed with a general description of rice crop management and growth and then look at differences in the two main systems, irrigated and rainfed lowland.

The majority of the world's rice grows in a flooded or saturated field, which is unique for cereal crops. The water requirement for growing lowland rice is 1.4 litres/sec/ha during the whole rice growing period (Sembiring, Makarim, Abdulrachman, & Widiarta, 2011). If there is sufficient water, the rice field is saturated or flooded prior to the establishment until the start of the harvest to enable easier harvesting. After the crop is established (CE) in the field, the rice crop grows rapidly through the vegetative phase such as panicle formation (PF) until flowering (F) which occurs around 60 days after germination. Flowering (F) is also the time of peak biomass, after which the crop enters the ripening phase for around 30 days. The ripening phase then lasts another 30 days where the crop's energy is spent on producing grain while overall biomass decreases until harvesting (Ha).

The pre-season flooding of the field results in low radar backscatter response at that time. When the crop grows to flowering stage and gains biomass from tillering, panicle formation and flowering then the backscatter response increases proportionally due to interaction from double-bounce and direct volume scattering mechanism until crop ripening (Torbick, Chowdhury, Salas, & Qi, 2017). After ripening and close to the harvest, rice fields are usually drained if the area is still flooded which may cause a shift toward a levelling off or decline of the backscatter (Torbick et al., 2017).

Irrigated rice offers the advantages of sufficient and more efficient water use and high tolerance to water stress (Facon, 2000). Irrigated rice usually has higher biomass than rainfed rice, which generally results in higher rice yield (Sembiring et al., 2011). Tan et al. (2015) investigated the radar sensitivity to rice biomass at C-band with full polarisation in different rice phenological stages by establishing rice biomass model from multi-temporal ASAR AP images. This difference in biomass could also be used to separate irrigated and rainfed rice fields, but varietal choice, nutrients and pest and diseases can also influence biomass and so water management is not the only source of difference in biomass.

In irrigated systems, water is provided by irrigation canal or water pumped from surface or ground sources into the rice fields to soak the field before crop establishment. The field then remains flooded until it is drained shortly before harvesting Water availability in rainfed systems depend on the time of rain (Bouman, Lampayan, & Tuong, 2007). When the rice field is well irrigated, there is less time lag between soaking and transplanting; whereas in the rainfed rice field, where the water availability depends upon rain, the time delay between soaking and transplanting can be relatively long (GRiSP, 2013a). During the period when the soil is not flooded, even rain during that time is less likely to result in surface runoff which can delay the time required to re-flood the field (Massey, Walker, Anders, Smith, & Avila, 2014). This time gap could be used to detect the different rice ecosystems (irrigated and rainfed) with SAR. SAR technology has been utilised by Bolanos et al. (2016) to identify surface water and to monitor it, suggesting that the duration of flooding and/or the degree of saturation can be used to separate irrigated and rainfed rice systems. Table 1 shows the different characteristics of irrigated and rainfed rice fields. It also shows how SAR technology can be used to distinguish these features in the literature.

Table 1: Different characteristics of irrigated and rainfed rice fields and the use of SAR application, based on the reviewed literature. The blue box and number represent the features that can be detected by SAR and were related with the blue box of Figure 2

S. No	Features	Irrigated rice field	Rainfed rice field	Previous related SAR applications
1	Water availability	Earlier and longer	Linked to rainfall and shorter	Pulvirenti, Chini, Pierdicca, & Boni (2016) used interferometric coherence in SAR data for mapping inundation in agriculture and urban environments
2	Biomass	Higher	Lower	Zhang, Huang, Chen, Wu, & Wang (2008) integrated rice canopy scattering with Genetic Algorithm Optimization Tool to simulate rice biophysical parameters to estimate rice biomass using L-band, HH mode of ALOS/PALSAR radar imagery
3	Cropping season	2-3 crops per year	1 or possible of 2 crops per season	Nguyen, Clauss, et al. (2015) used multi-year ENVISAT ASAR WSM data to map rice seasonality
4	Yield	Higher	Lower	It is challenging to differentiate yield from irrigated and rainfed rice fields directly using SAR

Figure 2 shows how backscatter response relates to different rice phases and field status and links the different SAR aspects mentioned in Table 1 to the phases and field status (blue boxes and numbers), for detecting different features of the crop. These different responses of backscatters with the various characteristics of rice can be used to discriminate between irrigated and rainfed rice fields using one or more classification approaches.

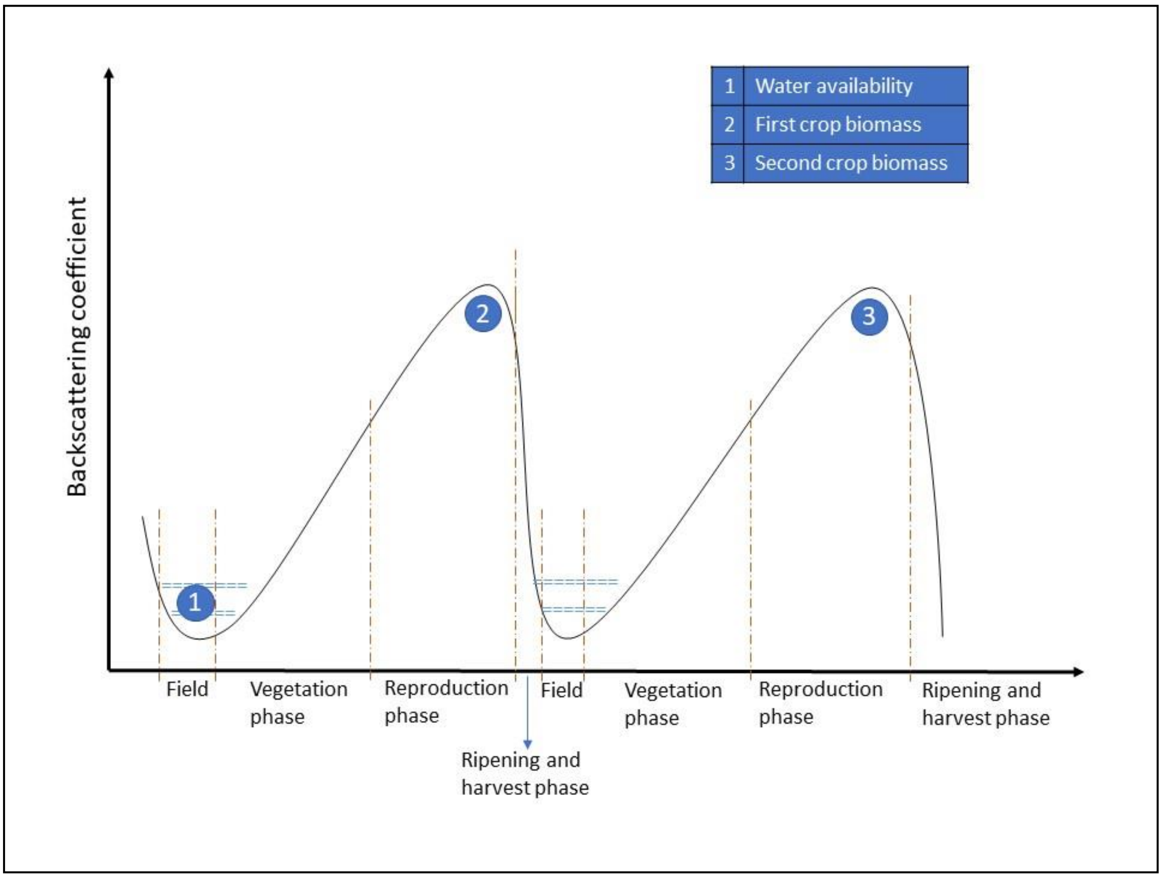


Figure 2: The backscatter response in different rice phases and field status The blue boxes and the numbers represent the features related to the condition of water availability and the rice plants. It is linked with the blue boxes in the table which relates the literature with these features.

There are many classification techniques for differentiating and classifying crops. The traditional Maximum Likelihood Classification (MLC) is one of the first approaches utilised for classifying crop types and is the most common method used for classification of remotely sensed data (Wessels et al., 2004). With the availability of sufficient ground truth data, high accuracy can be obtained, and the crop map of moderate quality can be produced timely to facilitate near-real-time water uses estimates (Zhong, 2012). But the problem with MLC is that it requires a large set of training data which may result in high costs in data collection.

Different algorithms have been used for classification to generate encouraging classification results. Biased maximum margin analysis (BMMA), Support Vector Machines (SVMs) and Artificial Neural Network (ANN) are some of the advanced classification techniques, used for supervised classification (Jain & Tomar, 2013). BMMA is one of the most efficient classification methods which uses local analysis and benefits from the advantages of semi-supervised approach (Jain & Tomar, 2013). Zhang, Wang, & Lin (2012) have presented the effectiveness of semi-supervised BMMA in interactive image classification. However, the disadvantage of BMMA is it suffers with global maximum problem (Jain & Tomar, 2013). ANN is a non-parametric approach without any assumption about the data whereas SVM is a binary non-parametric classifier developed by statistical learning theory (Jain & Tomar, 2013). Priyadarshini & Malik (2017) have demonstrated how a modified ANN could be used for the classification of SAR images. Jin et al. (2016) used the SVM classification method to avoid subjectivity in the description of NDVI thresholds for classifying irrigated and rainfed wheat. However, the disadvantages of both SVM and ANN are it requires training to use which is time consuming and costly (Jain & Tomar, 2013). All the above-mentioned classification techniques have advantages and disadvantages. Therefore, careful selection of a proper algorithm is crucial.

A decision tree is another commonly used approach for crop classification. The decision tree has been found to be one of the best classification technique as compared to others techniques such as MLC and Neural network (Pal & Mather, 2001; German, West, & Gahegan, 1999). It is independent of data probability distribution, is of non-parametric nature (Choudhury & Chakraborty, 2006) and is less sensitive to non-linearities in the input data than most classification methods (Rogan et al., 2003). The advantage of decision tree classification over all other classification techniques is it is very simple, can be trained quickly and can also be used without the knowledge of class distribution (Friedl & Brodley, 1997). Several researchers have used decision tree for crop classification using SAR data. For example, Nguyen, Wagner, Naeimi, & Cao (2015) used the decision tree image classification technique to discriminate the different type of rice crop based on the unique seasonal patterns of the double rice crop in the magnitude of SAR backscatter coefficient throughout the growth cycle. Similarly, Yang et al. (2014) used decision tree algorithm to discriminate the phenological state of rice.

1.3. Problem Statement and Motivation

Irrigated arable land accounts for around 40% of the world's harvest but covers only 20% of the total arable land area (Du, Kang, Sun, Zhang, & Zhang, 2010) out of which 70% is in Asia (Boucher, Myhre, & Myhre, 2004). According to the Philippine Statistics Authority (2016), irrigated agricultural land in the Philippines in 2015, summed up to 1.73 million hectares which demonstrated an average increase of 2.46% per year from 2011 to 2015. In the Philippines, agricultural water management mainly abides by the improving flood control and irrigation performance and for improvement of water management precedes more on the irrigation system performance (Labiano, 2014). Usually, crop yield highly depends upon the water availability; the crop yield will be higher when crops are fully irrigated as compared to non-irrigated (Pervez & Brown, 2010). Increasing the amount of irrigated area is seen as the best way to increase rice production, but useful spatial information on where irrigation currently takes place is often lacking.

Out of all irrigated agricultural land in the Philippines, 75% is irrigated in the wet season and 70% in the dry season, giving a cropping intensity of 146% a year (Patrocinio, 2012). This high crop intensity requires an efficient irrigation system which provides adequate water. In the Philippines, irrigated rice has high productivity and high yield. Few studies had been carried out to identify irrigated rice fields in the Philippines. Asilo et al. (2014) had carried out a study on mapping rice where irrigated, and rainfed rice was distinguished in two provinces (Nueva Ecija and Pangasinan) using hyper temporal MODIS and multi-temporal SAR. However, the SAR information was not used to estimate irrigated and rainfed area, and this information is still lacking. In addition, the situation of water supply shortage, water distribution and irrigation dysfunction could lead to decrease in crop intensity and the yield. It is very vital to estimate the realistic location of the irrigated field for evaluation of water presence for agriculture and ensuring food security. The importance of a well-functioning irrigation system was realised by the government of the Philippines around 2010, so they considered to improve the efficiency of the irrigation system as one of the strategies in their Food Staples Sufficiency Program 2011-2016. Also knowing where the irrigated fields are located, it would help the Department of Agriculture in the Philippines to monitor rice and develop maps of irrigated and rainfed rice.

Many studies have been conducted using remote sensing technology for monitoring agriculture and mapping different crop types (Xu, Yang, Long, & Wang, 2013), estimating crop yields (Peng et al., 2014), and differentiating the stages of crop phenology (Shihua et al., 2014). However, only a few studies are available for the identification and mapping of irrigated crops (Ozdogan, Yang, Allez, & Cervantes, 2010). In addition, accurate classification methods for identification of irrigated area are still lacking or require improvements in classification methods (Zheng, Myint, Thenkabail, & Aggarwal, 2015). Many of these studies were carried out at the regional and global scale using coarse resolution satellite data like MODIS, ENVISAT, and SPOT. These studies bring significant uncertainty when research is to be conducted in regions where irrigation is typically localised to small and scattered area.

To overcome the above-mentioned disadvantages of having coarse resolution remote sensing technology in differentiating irrigated and rainfed areas, Synthetic Aperture Radar (SAR) based techniques have been identified as one of the best alternatives for mapping and monitoring rice crop phenology and rice water sources from local, regional to global scale (D. B. Nguyen et al., 2016). SAR data are sensitive to rice texture variation and flood conditions (Choudhury & Chakraborty, 2006) and capturing flood stage at the right time in SAR image is essential for the identification of rice field (Kurosu, Fujita, & Chiba, 1997).

Based on the literature, although there is a long history of rice cropland mapping with SAR imagery, only limited studies have been carried out to detect the rice water management practice. There is a need to distinguish different rice water sources which are necessary for the water management, crop management, and production. Different water sources mean the different amount of water available for rice and rice requires different amount of water during different rice growing events and stages (Bouman et al., 2007). SAR backscatter can be extracted from the time series images for the monitoring of rice field and to identify different rice water available in different rice growing events and stages. Different polarisation, band ratios and the combination of polarisations can be used to find the most discriminative information for separating rice fields with different water sources.

Considering the importance of identifying different water sources and the abilities of SAR technology, this research looks at the temporal signature of rice in different water conditions. It also aspect the backscatter coefficient of rice with different water sources in different rice growing events and stages and will aim to discriminate them.

1.4. Conceptual framework

The conceptual framework shown in Figure 3 contains two provinces: Nueva Ecija and Tarlac of the Philippines. These provinces are the major system boundary which has many villages inside it. Rice fields (canal irrigated, water pump supplemented and rainfed), villager (farmers) and irrigation system are the elements inside the villages. Rice fields have two major rice ecosystems; irrigated (canal and water pump supplemented) and rainfed. Both rice ecosystems have their characteristics based on the water present in the field, crop yield, crop establishment method. Remote sensing technology is another system which is contributing to the major system by taking Sentinel-1A multi-temporal images. These images are tested using the field data which is collected using GPS points of the rice fields and questionnaire survey with the villagers.

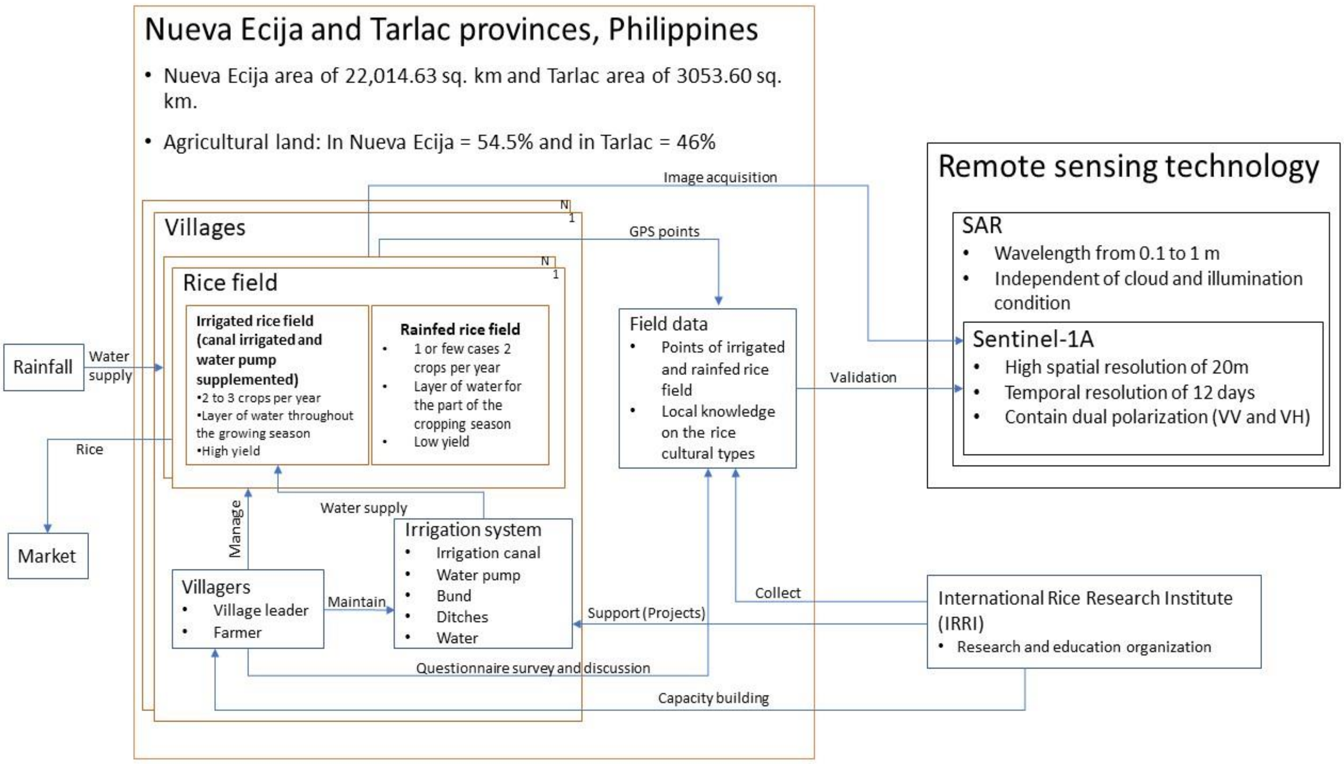


Figure 3: Conceptual framework for detecting rice water management practices using SAR multi-temporal imagery

1.5. Research identification

1.5.1. Research objectives

Overall objective

The overall objective of this study is to understand and detect rice fields with different water sources (canal irrigated, rainfed and water pump supplemented) in two provinces (Nueva Ecija and Tarlac) of the Philippines using multi-temporal Sentinel-1A data.

Specific objectives

I. To identify the suitable polarimetric data to distinguish rice fields with different water sources.
II. To identify the appropriate rice growing events or stages where the rice fields with different water sources can be distinguished.
III. To find the threshold and develop set of rules for differentiating rice fields with different water sources using a decision tree.

1.5.2. Research questions

I. Which polarisation or the combination of polarisations will give the most accurate discrimination between rice fields with different water sources?
II. Which rice growing events or stages will be most suitable to distinguish rice fields with different water sources?
III. What are the threshold and rules for differentiating rice fields with different water sources developed using decision tree?

1.5.3. Research hypothesis and Expected outputs

The hypothesis with expected outputs for each research questions are shown in Table 2.

Table 2: Hypothesis for each research question with their expected outcomes

Questions	Hypothesis	Expected outcomes
Research question I	H_0: There is no significant difference between the polarisations and combination of polarisations in differentiating rice fields with different water sources H_1: VH polarisation shows the better significant difference between rice fields with different water sources	Recommendation of suitable polarisation to distinguish rice fields with different water sources
Research question II	H_0: Rice fields with different water sources cannot be distinguished in any of the rice-growing events or stages. H_1: During crop establishment, the rice fields with different water sources can be distinguished	Recommendation of the rice-growing events or stages when rice fields with different water sources can be distinguished from SAR data
Research question III	H_0: Decision tree cannot be used to identify thresholds and to set rules for distinguishing rice fields with different water sources H_1: Decision tree classification method can be used to differentiate rice fields with different water sources	Thresholds and set of rules to distinguish rice fields with different water sources

2. STUDY AREA AND DATA

2.1. Study area

2.1.1. Geographical location

The study area covers the two provinces of Nueva Ecija and Tarlac located in Central Luzon, the Philippines shown in Figure 4 and covering an area of 5,751.33 km² and 3,053.60 km² respectively. The geographical location of Nueva Ecija and Tarlac are 15°35'N 121°00'E and 15°30'N 120°30'E respectively. The field visits were carried out in Bongabon, Aliaga, Santa Rosa and Talugtug municipalities of Nueva Ecija and Tarlac city and La Paz municipalities of Tarlac.

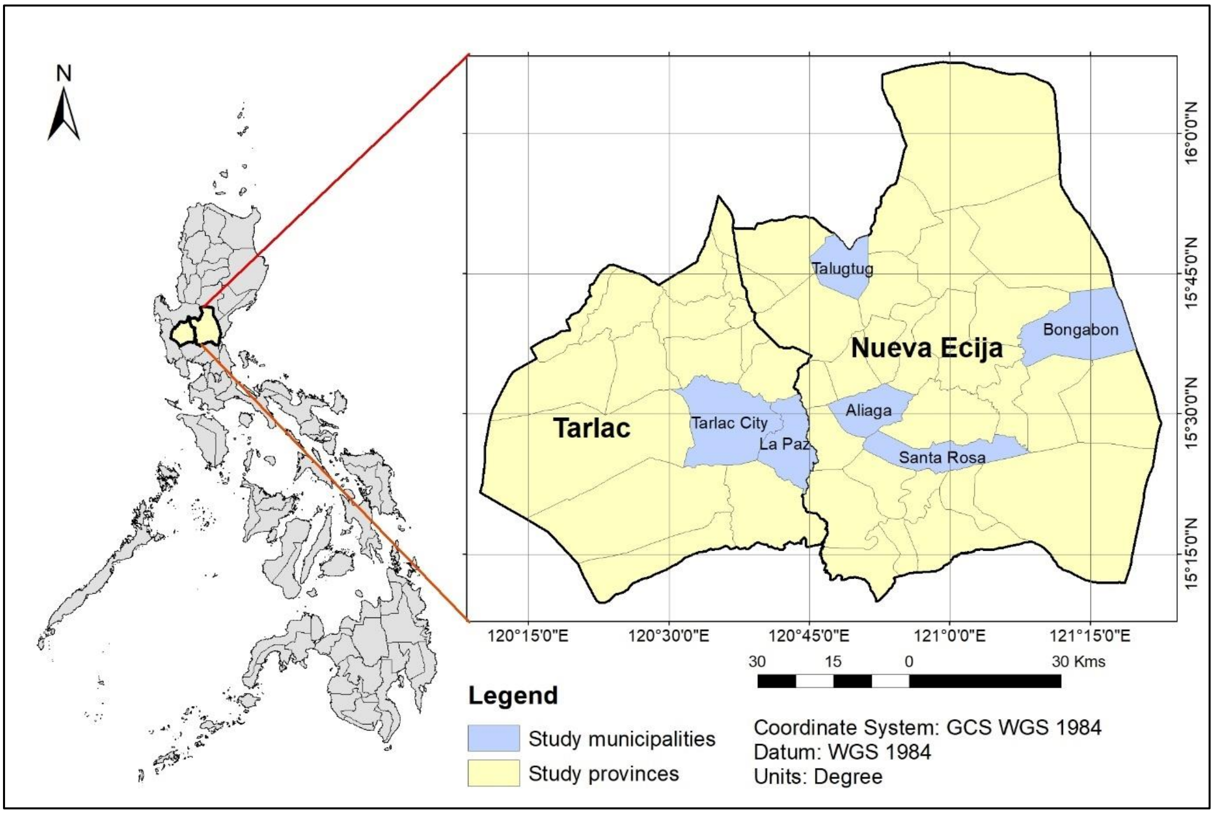


Figure 4: The study area showing the provinces and the municipalities visited during the fieldwork

2.1.2. Topography and climate

The topography of Nueva Ecija is characterised as low-lying alluvial plains and rolling uplands. On the other hand, it is generally level to gently sloping in Tarlac with 75% plains and rest of the areas is hilly or mountainous as shown in Figure 6.

Based on the rainfall distribution, the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) has recognised four types of climate in the Philippines which are described in Table 3.

Table 3: Types of climate found in the Philippines and their characteristics (Source: http://www1.pagasa.dost.gov.ph/index.php/27-climatology-and-agrometeorology)

Climate types	Description
Type I	Two pronounced seasons, dry from November to April and wet during the rest of the year. Maximum rain period is from June to September
Type II	No dry season with a very pronounced maximum rain period from December to February. There is not a single dry month. Minimum monthly rainfall occurs during the period from March to May
Type III	No very pronounced maximum rain period with a dry season lasting only from one to three months, either during the period from December to February or from March to May. This type resembles types I since it has a short dry season
Type IV	Rainfall is more or less evenly distributed throughout the year. This type resembles type 2 since it has no dry season

Tarlac has only one type of climate that is Type I, whereas three types of climate are found in Nueva Ecija: Type I, Type III and Type IV. Average monthly rainfall from 1901 to 2015 of 6 municipalities Bongabon, Aliaga, Santa Rosa, Talugtug, Lapaz and Tarlac city of Nueva Ecija and Tarlac provinces are shown in the Figures 5.

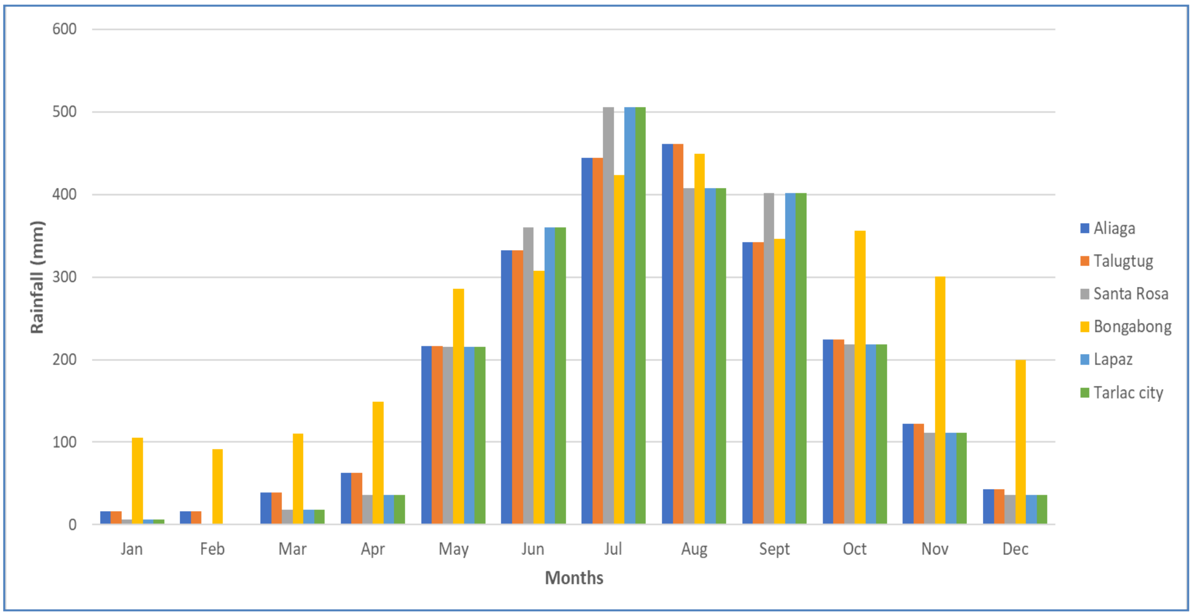


Figure 5: Average monthly rainfall of five provinces (Aliaga, Talugtug, Santa Rosa, Bongabong, Lapaz and Tarlac city) from 1901 to 2015, (Source: http://sdwebx.worldbank.org/climateportal/?page=country_historical_climate&ThisRegion=Asia&ThisCCode=PHL)

2.1.3. Agriculture status

Out of the above-mentioned areas of Nueva Ecija and Tarlac, 54.5% of the land is devoted to agriculture in Nueva Ecija and 46% in Tarlac. Both provinces, Nueva Ecija and Tarlac, have high rice production, ranking 1st and 6th in the Philippines respectively boosted by irrigation facilities. According to Philippines Food Security Information System (PhilFSIS), both provinces have two rice cropping seasons which is presented in Table 4.

Table 4: The cropping calendar of two provinces. (Source: http://philfsis.psa.gov.ph/index.php/id/24/prov/0349)

Provinces	Rice cropping	Cropping calendar	
		Sowing/Planting period	**Harvesting Period**
Nueva Ecija	1st cropping	Beginning of January - End of December	Beginning of January - End of December
	2nd cropping	4th week of December - End of February	2nd week of March - 2nd week of May
Tarlac	1st cropping	Mid of May - End of July	Beginning of September - Mid of November
	2nd cropping	Beginning of November - End of January	Beginning of March - Mid of May

Both provinces are facilitated by irrigation systems. The national and communal irrigation systems are the major water providers whereas some private irrigation system and other governmental agencies also play an important role in water supply for irrigation. Major river basins of Philippines like Pampanga, Talavera and Penaranda rivers lies in Nueva Ecija. Since the 1920s, both Nueva Ecija and Tarlac had been facilitated by irrigation system by the national irrigation system. In 1923, Talavera Irrigation System had been officially opened in San Jose, Munoz, Talavera and Sto. Domingo municipalities of Nueva Ecija and irrigated 9120 ha of area. On the other hand, in 1927, O'Donnel Irrigation System had been officially opened for Tarlac city, Capas and Concepcion municipalities of Tarlac and irrigated 3270 ha of the area (National Irrigation Administration, 1990). Many new irrigation systems were constructed in both provinces, the development of irrigation system was increased with time and demand. In 1930, Pernaranda Irrigation system had been opened in the service of Pernaranda, Gapan, San Isidro and Cabiao municipalities of Nueva Ecija (National Irrigation Administration, 1990). Upper Pampanga River Integrated Irrigation System (UPRIIS) which is mainly for irrigation was fully operated in 1975.

According to the Philippines Statistics Authority, till 2016, in Nueva Ecija, 89% of the rice area is facilitated by irrigation while only 11% are rainfed. In the case of Tarlac, 92% of the rice area is facilitated by irrigation while only 8% are rainfed. The annual area (ha) of the irrigated and rainfed rice fields from 2011 to 2016 in Nueva Ecija and Tarlac provinces are shown in Table 5.

Table 5: The area (ha) of the irrigated and rainfed rice field harvested in two provinces between 2011-2016. (Source: http://countrystat.psa.gov.ph/?cont=10&pageid=1&ma=O80LUAHC)

	Provinces	Annual					
		2011	**2012**	**2013**	**2014**	**2015**	**2016**
Irrigated Rice field area (ha)	Nueva Ecija	249,571	265,802	277,185	280,756	270,509	279,075
	Tarlac	107,494	114,365	123,214	125,830	123,587	122,859
Rainfed Rice field area (ha)	Nueva Ecija	37,250	38,387	38,191	37,528	37,937	34,373
	Tarlac	9,240	8,890	11,650	10,615	10,499	10,921

According to the MISTIG survey carried out by IRRI in 2013/14, in Nueva Ecija province, 79% of the cultivated area in Bongabon municipality was irrigated, 38% of the cultivated area was irrigated in Talugtog municipality, 79% of the cultivated area was irrigated in Bongabon municipality and 97% of the cultivated area was irrigated in Santa Rosa municipality. In Tarlac province, 69% of the cultivated area in Tarlac city municipality was irrigated, and only 28% of the cultivated area was irrigated in La Paz municipality.

2.2. Elevation data

The information on the elevation of the study area was obtained from Shuttle Radar Topographic Mission (SRTM) with 1-ARC (30m) resolution. Four scenes of September, 2014 were downloaded freely from http://earthexplorer.usgs.gov/ in 1-ARC resolution and blended to make mosaic covering the whole study area. This data was used to extract the elevation of rice fields with different water sources and to test whether the rice fields have significantly different elevations or not. Digital Elevation map was produced based on the SRTM data shown in Figure 6.

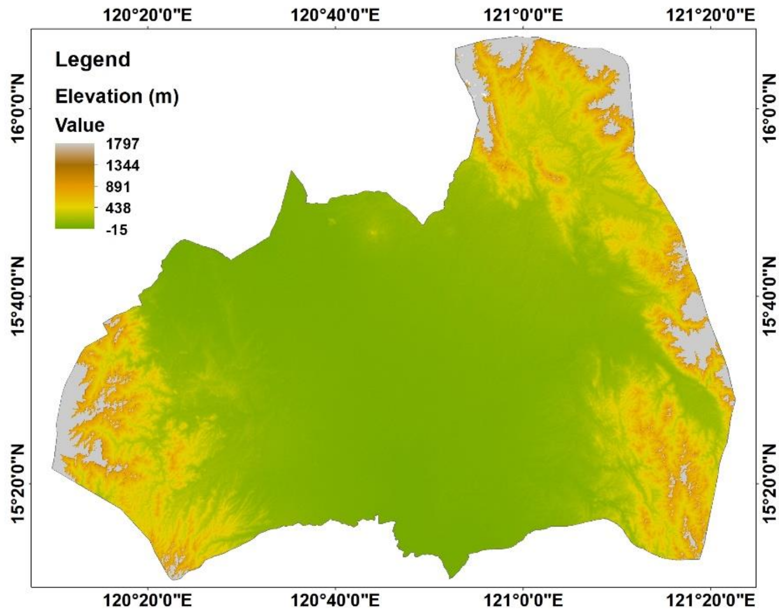


Figure 6: Digital elevation map of the study area based on SRTM data

2.3. Satellite data

Rice fields can be mapped using SAR time series based on the increase in backscatter intensity throughout the phenology for rice which grows above the water surface and interacts with the incident radar signal (Bouvet & Le Toan, 2011). In this research, Sentinel-1 satellites images were used. The Sentinel-1 satellite mission is a polar-orbiting satellite constellation for the continuation of C-band Synthetic Aperture Radar (SAR) observations. C-band measurements were used to classify the landscape and characterise rice field. Sentinel-1A platform was launched on 3rd April 2014 providing the 12 days revisit time, and after the launch of Sentinel-1B platform on 25th April 2016, C-band imagery was available once in every six days for some priority regions of the European Space Agency (ESA) (Kramer, 2017). Sentinel-1 carries a C-band sensor at 5.405 GHz (radar wavelength of about 5.6cm) with an incidence angle between 20° to 45°, and the platform follows a Sun-synchronous, near-polar, circular orbit at the height of 693 km. Sentinel-1 collects data in 4 acquisition modes with different swath and spatial resolution with a single (HH or VV) as well as dual polarisation (VV+VH or HH+HV). Table 6 shows the characteristic of the four modes.

Table 6: Characteristics of 4 acquisition nodes present in Sentinel-1. (Source: https://sentinel.esa.int/documents/247904/685163/Sentinel-1_User_Handbook)

Modes	Properties
Stripmap mode (SM)	80km swath, 5m*5m resolution, single-look
Interferometric Wide Swath mode (IWS)	240km swath, 5m*20m resolution, single-look
Extra Wide Swath mode (EWS)	400km swath,20m*40m resolution, single-look
Wave mode	20km*20km vignettes, 5m*5m resolution, single look

Out of these four modes of Sentinel-1, the IWS mode is regarded as a primary operational mode for the study of land, agriculture, forestry and other natural applications (ESA, 2013) and provides dual polarisation (VV and VH) imagery (Bitar, 2016). Sentinel-1 is the first satellite built with interferometric wide swath mode which is a standard acquisition mode over European water and land masses for interferometric application, for example, digital elevation model (DEM) (Velotto, Bentes, Tings, & Lehner, 2016). Each mode can produce three levels SAR product: Level-0, Level-1 (single look complex (SLC) and ground range detected (GRD)) and Level-2 (Ocean). Among this product, Level-1 GRD product is detected, multi-looked and projected to the ground range and can be in high and medium resolution. It has approximately square resolution and pixels spacing with reduced speckle effect at the cost of reduced geometric resolution (Mansaray, Huang, Zhang, Huang, & Li, 2017). Hence, this study focused on Sentinel-1A GRD images using IWS mode to acquire data from April to October 2017 as shown in Table 7.

Table 7: Characteristics of the images acquired from Sentinel-1A for this research

Satellite	**Sentinel-1A**
Sensor	SAR-C
Product-level	GRD
Order by	Descending
Image Mode	IWS
Polarisation	VV and VH
Date acquisition	6 Apr, 18 Apr, 30 Apr, 12 May, 24 May, 5 Jun, 29 Jun, 11 Jul, 23 Jul, 4 Aug, 16 Aug, 28 Aug, 9 Sep, 21 Sep, 3 Oct, 15 Oct and 27 Oct

Sentinel-1A data from IWS mode was used in this research. They are in the dual polarisation of VV and VH. This study tried to identify the most suitable polarisation and the combination of polarisations for distinguishing rice fields with different water sources. All the data from the Sentinel-1A are freely available from the ESA Open Data Hub and can be easily downloaded from the website of ESA (https://scihub.copernicus.eu/dhus/#/home).

2.4. Field data

2.4.1. Previously collected data

MISTIG survey data

A farmer survey was carried out by IRRI in 2013/14 as part of a management information system (MIS) for rice research evaluation and impact assessment (http://ricestat.irri.org/mistig/) in top four rice producing provinces namely Bulacan, Nueva Ecija, Pampanga, and Tarlac of Central Luzon. 15 municipalities of these four provinces were randomly selected having rice area more than 2000 ha. Four villages in each municipality were again randomly selected. Systematic sampling was carried out to conduct a survey of 20 farmers per village. Detailed information about the location of farmers and their rice farming practices (including rice water sources) were collected in this survey. The survey contains information on farmer household location but not field location. This survey was used to prepare the fieldwork plan and to identify farmers for interview and subsequently to visit their rice fields during field data collection. The survey data was provided by IRRI to support this research.

CLLS survey data

The Central Luzon Loop Survey (CLLS) was conducted in 2015/16 by IRRI for the six provinces (Bulacan, Nueva Ecija, Pampanga, Tarlac, Pangasinan and La Union) of Central Luzon during the wet season (May -October) of 2015 and dry season (November – April) of 2016. The primary objective was to monitor changes in rice farming in Central Luzon. This survey has a history going back to 1966 where 95 farms with 120 parcels were sampled along a loop of the national highway passing through six provinces, and the same panel of households has been interviewed regularly since then. In 2015/16 the number of parcels increased to 209. The information on different rice farming along with sources of water for rice production in the different season which were collected in this survey is accessible in IRRI Dataverse (https://dataverse.harvard.edu/dataverse/RiceResearch?q=central+luzon+loop+survey) which was used in this research as well. This data was used to compare with the field data and to validate whether the collected field data can represent the study area or not. The survey data was provided by IRRI to support this research.

2.4.2. Collected field data

A field survey of rice field was conducted from 24th September to 10th October 2017 for 17 days to identify the rice fields with different water sources during the wet season. This field survey helped to understand the different rice water management practices through the interviews conducted with the farmers from the MISTIG survey and from the information collected in their fields. 99 farmers with 123 plots were visited in the field from 15 villages of 6 municipalities located in 2 provinces as indicated in Table 8 and Figure 7.

Table 8: Number of farmers interviewed, and the plot surveyed per village in the study area

Province	Municipality	Village	No. of farmers	No. of plots
Neuva Ecija	Aliaga	San Felipe	6	6
		Pantoc	6	8
	Bongabon	Calaanan	5	5
		Macabaclay	7	10
		Pesa	6	8
		Vega	10	13
	Santa Rosa	Berang	6	7
		San Isidro	6	9
	Talugtug	Alula	5	6
		Cabiangan	6	7
		Villa Rosario	10	11
Tarlac	Tarlac City	San Manuel	6	7
		Villa Bacolor	8	9
	La Paz	Macalong	6	10
		Rizal	6	7
		Total	99	123

GPS coordinates of each plot's boundaries were collected, and farmers who owned those plots were interviewed with a set of questions. A set of questionnaires were developed to address all the answers regarding rice water sources, rice water management practices, crop establishment method, fellow duration and crop phenology and presented in Appendix 1. Based on these questions, information related to cropping season, phenology of rice in irrigated and rainfed rice fields, cropping system, cropping calendar, and other information from their local knowledge which enabled to distinguish irrigated and rainfed rice were obtained.

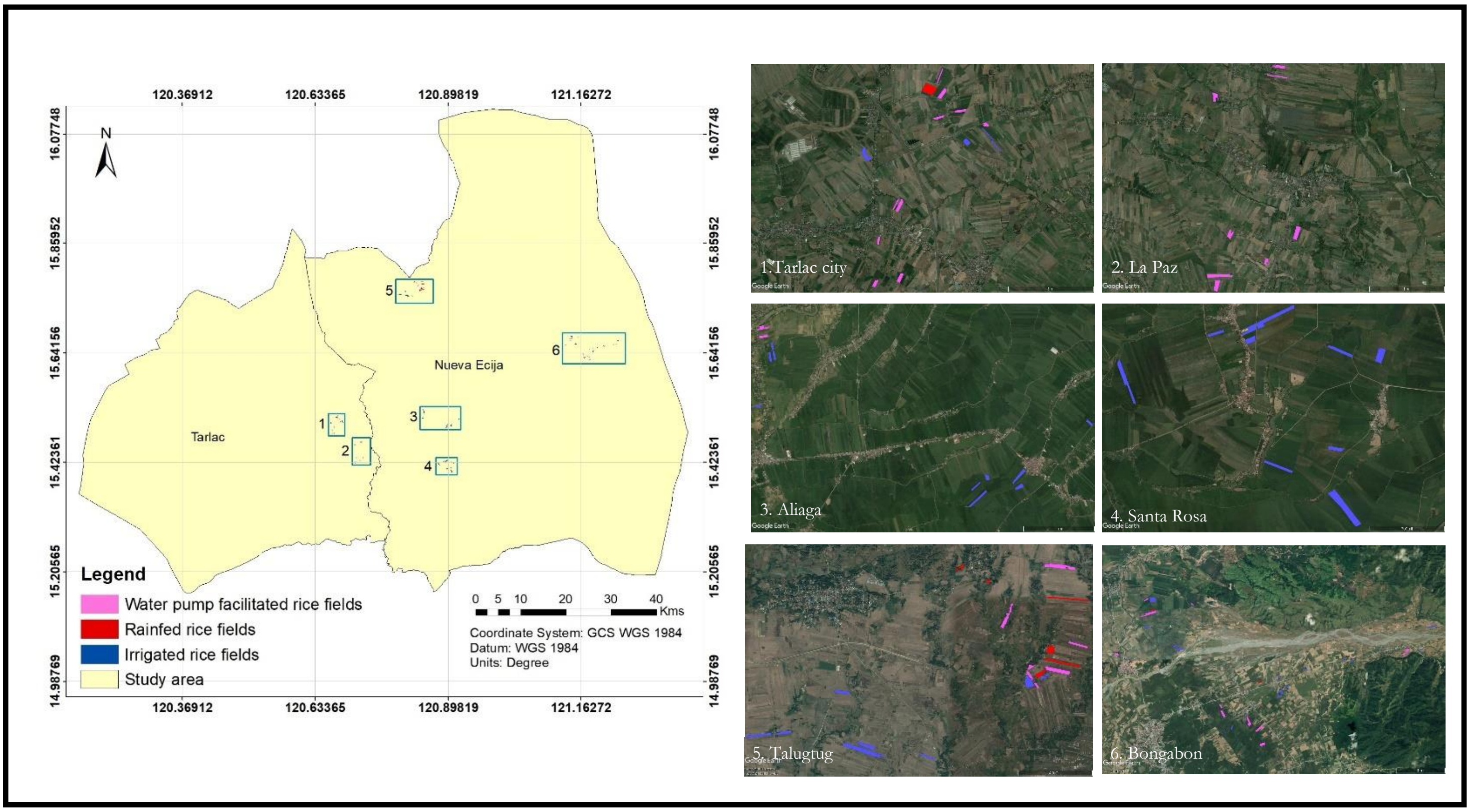


Figure 7: The study area and the location of samples collected in different municipalities of Neuva Ecija and Tarlac provinces

2.4.3. Additional data

Administrative boundary data were downloaded from the GADM database, version 2.8 (http://www.gadm.org/download). The boundaries of the main National Irrigation Administration-Upper Pampanga River Integrated Irrigation System (NIA-UPRIIS) irrigation system in Nueva Ecija was provided by IRRI, however, these boundaries were not well georeferenced. In addition, the water release date from the irrigation canal under NIA-UPRIIS was provided to identify the exact date of water available for the canal irrigated rice fields in Neuva Ecija provinces. Irrigation service by UPRIIS is divided into 5 area divisions and based on that area water released dates were scheduled. But in general, water released in May-July until September-November in wet season. These dates helped in analysing the backscatter profile and compare with the dates from field observations.

2.5. Field equipment and software

Table 9 and Table 10 show the list of equipment's used in the field and the software to process and analyse the data.

Table 9: Equipment's used in the field and their purposes

Field materials	Purpose
Mobile GPS: HP 4700 IPAQ + Arc Pad and Garmin eTrex 30(x)	To locate the farmer's house and to collect coordinates of the canal irrigated, rainfed and water pump supplemented rice fields
Measuring tape	To measure the height of the plant
Field sheets and pencil / Tablet	Data recording
Questionnaire sets*	To conduct questionnaire survey with the farmer to get the knowledge on rice water sources, cropping system, crop calendar and crop phenology
Rubber shoes	For the safety purpose in the rice field
Camera	To capture pictures in the rice fields

*Note: One common set of questionnaires were developed with colleagues who conducted MSc research on rice in the Philippines to address all the answers regarding rice water sources, rice water management practices, crop establishment method, fellow duration and crop phenology as shown in Appendix 1.

Table 10: Software used in the research and their purposes

Software	Purpose
Sentinel Application Platform (SNAP 5.0) Tool box	Image sub-setting Radiometric calibration to convert DN values into backscattering coefficient ($\sigma°$) values Multi-temporal Speckle filtering Terrain correction and 30^{o} incidence angle normalisation
ENVI 5.3	Extracting backscatter coefficient of multi-temporal SAR imageries based on the rice plots
ArcGIS- ArcMap 10.3	Locating and creating the polygon of rice fields
R -studio Version 1.0.153- © 2009-2017	Statistical analysis and Decision tree
Microsoft office excel 2016	Data management and graph presenting
Microsoft office word 2016	Project report writing

3. METHODOLOGY

The research methods included the fieldwork design, data collection, data preprocessing, and statistical data analysis to answer the objectives and research questions and to differentiate rice fields with different water sources.

3.1. Field sampling design

MISTIG survey conducted by IRRI in 2013/14, used a systematic sampling method to select 20 farm households of each village for rice research impact analysis on 15 random municipalities of 4 provinces (Bulacan, Nueva Ecija, Pampanga, and Tarlac). It used the skip factor of 10 farmers, on an average of 200 farmers in each village. IRRI had provided the information regarding the location of farmers' household and information about the farmland for this research.

The purposive sampling design was employed to collect data in the field, and 99 farmers were selected from 15 villages of 6 municipalities as shown in Table 8. This method was chosen since the samples of specific farmers' fields needed to be collected. It was very important to aim to collect a representative number of samples for canal irrigated, rainfed and water pump supplemented rice fields. Based on the information provided by the IRRI (MISTIG) data, particular farmers' fields were selected for sampling and for collecting information about rice fields based on their water sources.

3.2. Field data collection

In the field, we first mainly selected farmers from the MISTIG survey. Those farmers were interviewed as shown in Figure 8 with the set of questionnaires which includes the information about the rice water sources, cropping practices, crop establishment methods and the dates of different rice growing phase. The interviews were facilitated by the enumerators who translated the questions to their local language. The questionnaires are included in Appendix 1.

After the completion of the interviews with the farmers, rice fields of the farmers were visited. In the field, coordinates of rice fields were measured with the help of Garmin GPS (Garmin eTrex 30x). Considering the different shapes and sizes of the rice fields, it was necessary to identify the proper shape of the rice fields for which we consulted the owner (farmer) of the rice fields and sketched the shape of the rice fields as indicated in Figure 9. Based on this sketch, the GPS coordinates on the edges of the rice field were measured. An exmple of the rice field is shown in Figure 9.

Figure 8: Interviewing the farmers with the help of enumerator in the middle

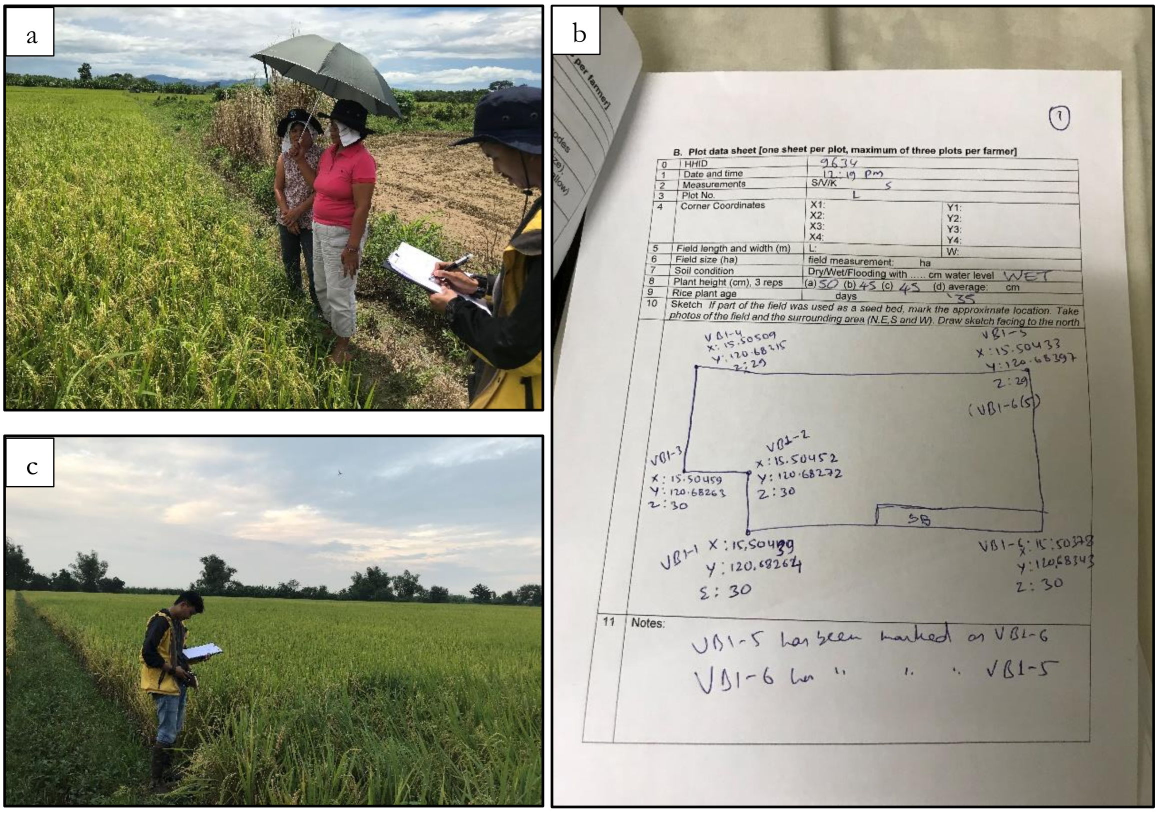


Figure 9: a) Sketching the rice field with the help of the farmer, b) Sketch of the rice field with the GPS coordinates on the edges, c) Recording the GPS coordinates on the edge of the rice field

3.3. Data analysis

Figure 10 shows the main elements of the study and how the data from the Sentinel-1A and the field are analysed to distinguish the canal irrigated, rainfed and water pump supplemented rice fields.

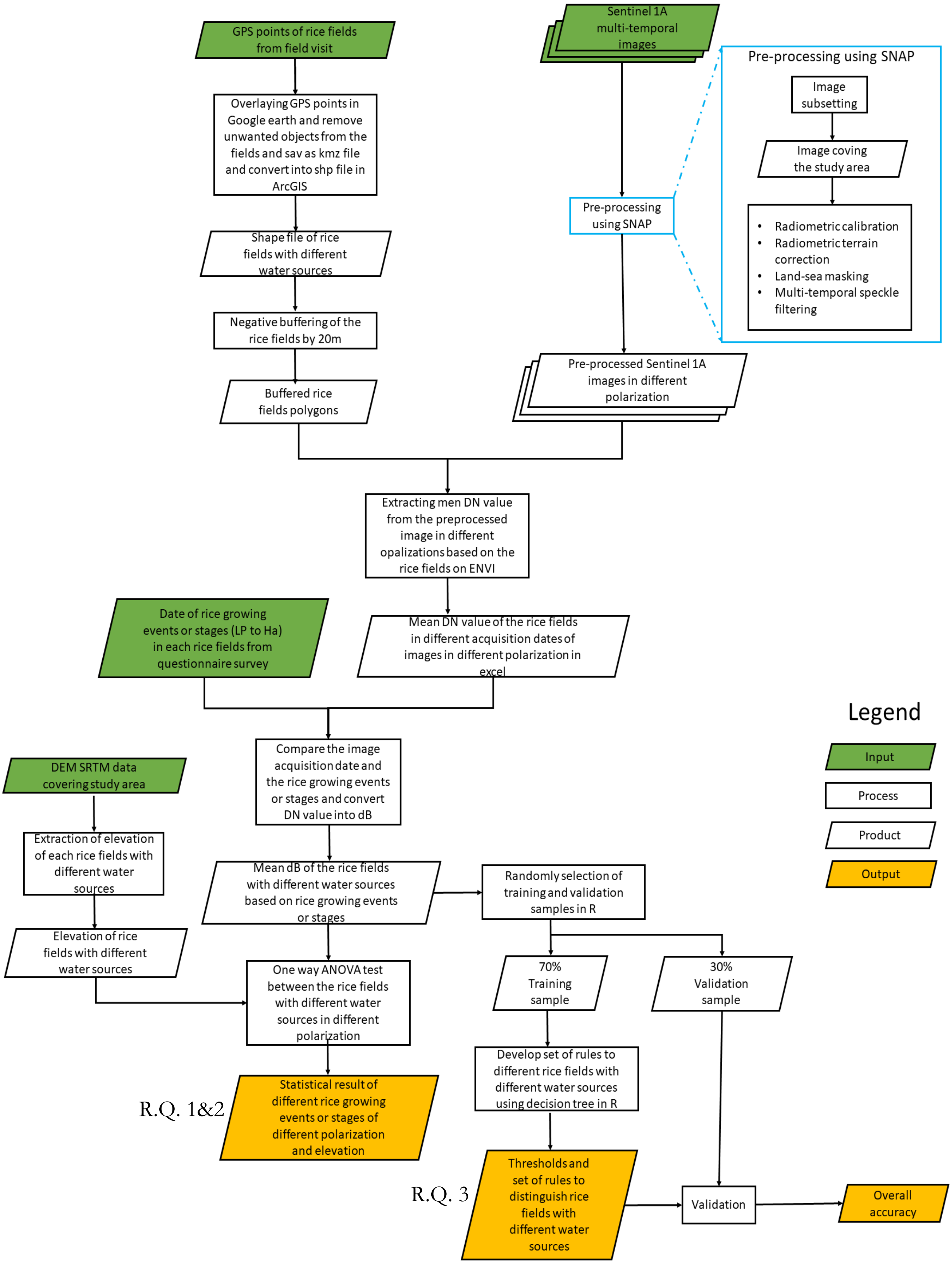


Figure 10: Flowchart showing the research method

3.3.1. Sentinel data pre-processing

17 Sentinel-1A images from 6 April to 27 October 2017 were acquired to cover the wet season over the study area and to identify the rice fields with different water sources based on the analysis of multi-temporal backscatter coefficient (dB). The multi-temporal images of Sentinel-1A acquired for this study were automatically pre-processed using the Sentinel Application Platform (SNAP). It is a common software for all Sentinel images and also is ideal for other remote sensing image processing and analysing (Mansaray et al., 2017). The software automatically converts the digital number (DN) value of each pixel into backscatter coefficient value using the equation given below:

$$\text{Backscattering coefficient } (\sigma°) = 10\log 10\ (b_0) \qquad (1)$$

Where b_0 is the per pixels image intensity or digital number (DN).

These 17 images were downloaded in GRD (Ground Range Detection) format which were already detected, multi-looked and projected to the ground range. Pre-processing of GRD images were carried out using graph builder shown in Figure 11.

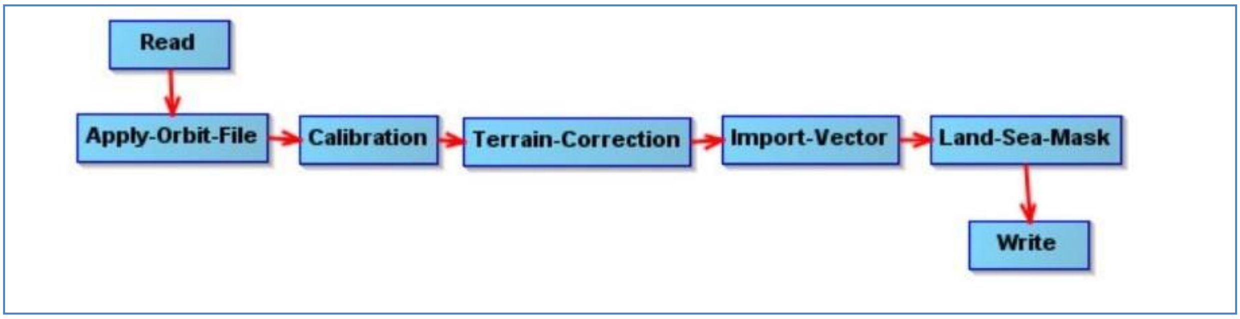
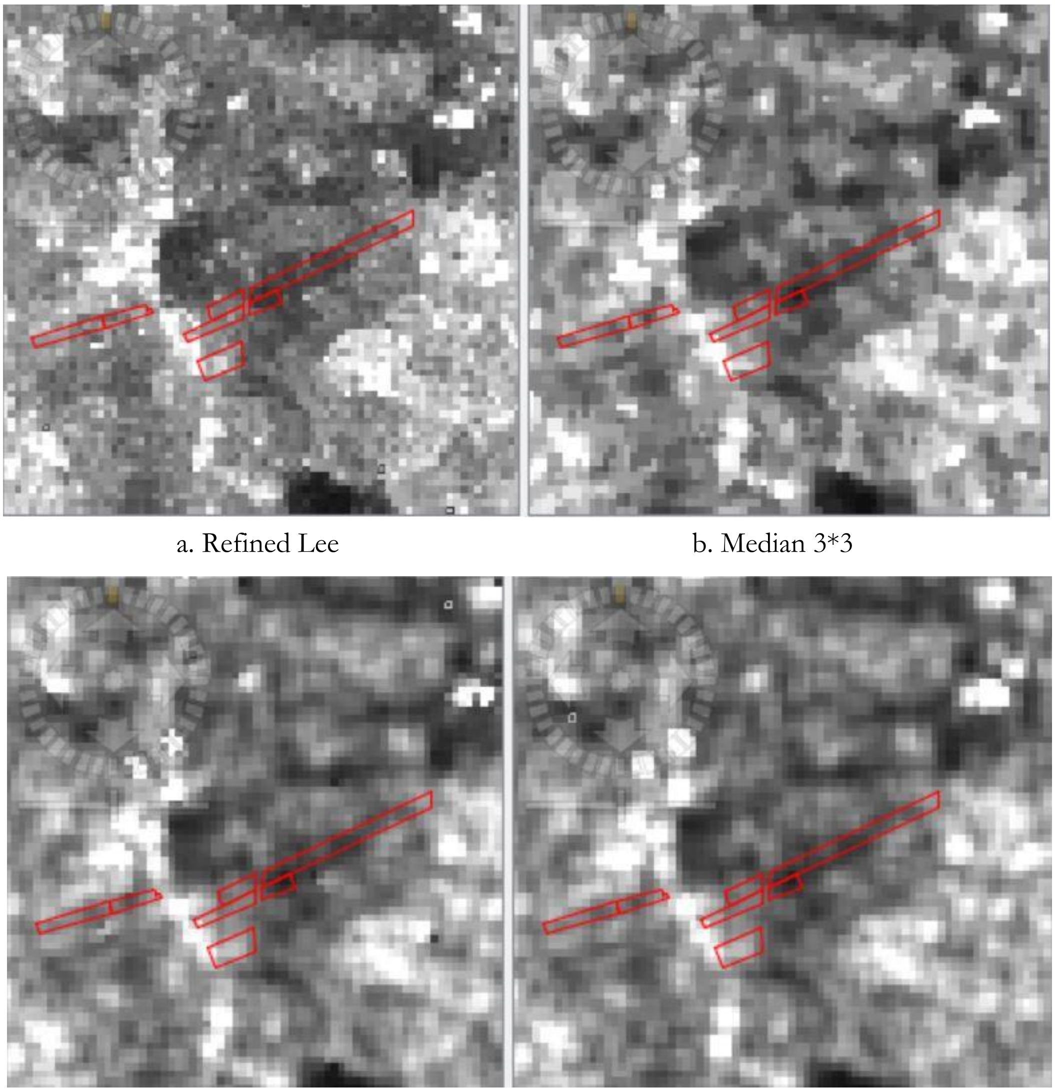


Figure 11: Step carried out to pre-process the Sentinel-1A images using graph builder

In SNAP. The GRD data were transformed to backscatter coefficient by the following process.

1. Apply Orbit file: The orbit file provided accurate satellite position and velocity information. It helped to update the orbit state vectors in the abstract metadata of the product. This gave additional and more precise information about the image acquisition, which was useful later when stacking the two or more products that are not taken on the same day.
2. Calibration: GRD images did not include radiometric correction which means it had significant bias remained. Therefore, it was essential to calibrate these images because it corrected images so that the pixel values truly represented the radar backscatter of the reflecting surface. The radiometric correction was also necessary for the comparison of SAR images acquired with different sensors or acquired from the same sensor but at different times, in different modes, or processed by different processors.
3. Terrain correction: Due to topographical variations of a scene and the tilt of the satellite sensor, distances could be distorted in the SAR images. Some distortion might have occurred if image data does not directly locate at the sensor's Nadir. Terrain corrections were intended to compensate for these distortions so that the geometric representation of the image might be as close as possible to the real world. Terrain Correction geocoded the image by correcting SAR geometric distortions using a digital elevation model (DEM) and producing a map projected product.
4. Land/sea masking: This step was done to mask the pixels of the ocean and to preserve the pixels of land. All pixels of the ocean were set to no data value. Here in this study, the pixel outside of the study area was masked to no data value.

5. Sub-setting: In sub-setting, the images were confined to study area. It created the spatial subsets of images. Spatial subset images were given by pixel positions or geographical polygon. It helped to remove the unwanted pixel those were out of the study area and got the pixel values inside the study area.
6. Stacking: It helped to collocate two or more spatially overlapping images. During stacking the pixel values of one image (the slave) were resampled into the geographical raster of the other image (the master).
7. Multi-temporal speckle filtering: Multi-temporal filtering was based on the assumption that in all images of time series, the radar beam illuminated same resolution element on the ground and corresponded to the same slant range coordinates (Nelson et al., 2014). Within the multi-temporal filtering, four speckle filters (Boxcar 3*3, Median 3*3, Gamma map 3*3 and Refined lee) from the SNAP were applied and compared shown in Figure 12 to remove the speckle from the images. According to the Figure 12, the Refined Lee filter was found to be the best among other filters because it preserved the edges and less information from the main image were lost as compared to other filters. Lavreniuk et al. (2017) in his study also concluded that the most accurate and useful filter to reduce speckle from the images in ESA SNAP toolbox for crop mapping task was the Refined Lee.



a. Refined Lee　　b. Median 3*3

c. Boxcar 3*3　　d. Gamma map 3*3

e. Google earth image f. Original

Figure 12: Comparison of the filters results of VH-polarized SAR image acquired on 24-05-2017

3.3.2. Extraction of backscatter coefficient

Once all the images were pre-processed based on different polarisations, the mean digital number values of 116 plots (rice fields) in different polarisations were obtained using ENVI software. In ENVI, mean digital number (DN) of each plot were extracted in different dates of image acquisition. For this, firstly, the unwanted objects inside the polygon of rice fields like seedbeds, huts, and trees were removed as shown in Figure 13 and then the rice fields were negatively buffered (-20m) to remove the edge pixels and unwanted pixels of the plots. This was done to reduce the influence of bordered pixel and unwanted objects in the plot pixels. Though rice fields bigger than 0.5 ha were selected, due to the shape of the rice fields some of the rice fields were very narrow and could not be negative buffered. In this case, the rice fields were left as it was, without buffering to maintain the number of rice plots. It might have influenced the backscatter value, but we assumed that the influence was negligible. Second, DN values of each rice field in different dates of acquisition during the wet season were extracted from the pre-processed images and their various polarisations using ENVI.

After extracting the mean DN value of 116 plots in different dates of the wet season from the pre-processed Sentinel-1A images using ENVI, the mean DN values were converted into backscatter values (dB) using equation 1.

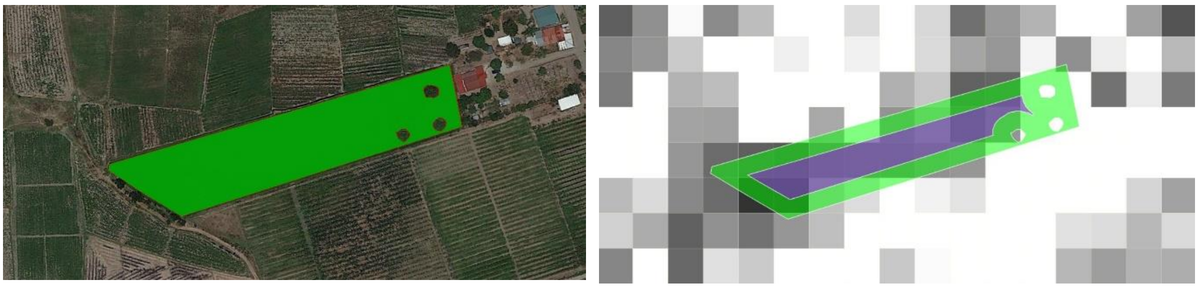


Figure 13: Removing unwanted objects from rice field and negative buffering of 20m (purple colour polygon in the image) to remove the effect of edge pixels and unwanted pixels

3.3.3. Comparison of polarimetric data

Sentinel-1 SAR is a dual polarisation radar which means it can transmit a signal and receive in both horizontal (H) and vertical (V) polarisation. In agriculture ecosystems, this polarimetry can help in crop type identification, crop condition monitoring and soil moisture measurements In this research, multi-temporal backscatter signature of VV, VH, and VV-VH were compared to differentiate canal irrigated, rainfed and water pump supplemented rice fields during different rice growing events and stages.

Basic statistics of the backscatter coefficient from canal irrigated, rainfed and water pump supplemented rice fields during different rice growing events and stages were then computed. These include the minimum, maximum, mean, standard deviation, standard error of the backscatter values in different rice growing events and stages of rice fields with different water sourcers based on different polarisation. An Analysis of Variance (ANOVA) was employed to evaluate the difference in the backscatter coefficient in different rice growing events or stages between the rice fields with different water sources. First, the one-way ANOVA was used to test if significant difference at 95% confidence interval exists between the rice fields of different water sources during different rice growing events or stages in VV, VH and VV-VH. And then, the next step was to identify the event or stages of which polarisation, the difference existed and then compared the difference in p-value.

3.3.4. Comparision of elevation data from SRTM

Digital elevation model information of the study area was obtained from SRTM data. The elevation of each rice field with different water sources were extracted from the data.

One-way ANOVA was performed to test whether the elevation of rice fields with different water sources are significantly different or not. It also used the 95% as the level of confidence which means if the p-value is less than 0.05, the rice fields with different water sources have significantly different elevation.

3.3.5. Threshold identification using Decision Tree

After identifying the appropriate polarisation and the best rice growing events or stages to differentiate rice fields with different water sources using one-way ANOVA, the next step was to divide the sample into training and test data. 70% of the collected field samples was randomly selected as training data and the rest 30% was selected as test data using Rstudio as shown in Table 11.

Table 11: The number of samples in training and test datasets in each rice fields with different water sources

Class	Training data (70%)	Test data (30%)
Canal irrigated rice fields (IR)	42	18
Rainfed rice fields (RF)	7	3
Rice fields supplemented by the water pump (WP)	32	14

Based on the training dataset shown in Table 11. The threshold and set of rules were developed to differentiate IR, WP and RF using Decision Tree in Rstudio. Decision tree is widely used classification method since it is relatively fast as compared to other classification methods and is straightforward and easy to understand (Pal & Mather, 2003).

In DT classification, a decision tree is created in two phases: 1) Tree growth phase where training data are repeatedly partitioned until all examples in each partition, belong to each class or the partition, is sufficiently small and 2) Tree pruning phase the dependency on statistical noise will be removed.

A tree is composed of 3 nodes as shown in Figure 14: Root node which contains all the data, Set of internal nodes which splits data and Set of terminal nodes (leaves of the tree) (Pal & Mather, 2001). Each node in a tree contains one parent node and two or more descendant nodes as shown in Figure 14. Based on the data provided, a tree is sequentially subdivided according to the decision framework defined by the tree itself until the leaf has been reached.

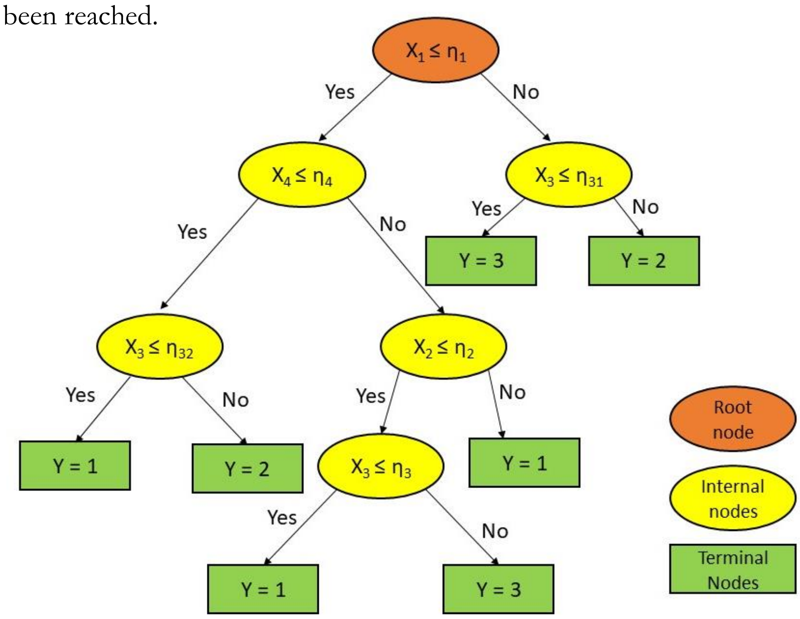


Figure 14: A decision tree for a five-dimensional feature space and three classes. The Xi 's are the feature values, ηi's are the thresholds, and Y is the class label (Pal & Mather, 2001)

A decision tree was developed using rpart.plot package in Rstudio. The rpart program builds the classification and regression tree models (CART) using a two-procedure resulting binary tree. The first is to identify the best split between the classes and once separated then a similar method is applied to each subgroup and so on until no improvement can be made. The second is cross-validation for trimming back the full tree (Therneau & Atkinson, 2018).

3.3.6. Accuracy assessment

The threshold and ruleset to differentiate rice fields with different water sources were identified based on the training data, and validation of the classifications was performed using the test dataset and a confusion matrix. Error matrix or confusion matrix is a table often used to validate the classifier performance where rows represent the class of the predicted sample, and the column represents the class of the reference sample. Once this matrix is generated correctly, it can be used to calculate the individual class accuracies (User and Producer), overall accuracy and kappa coefficient (Story & Congalton, 1986).

Overall Accuracy: The overall accuracy is the number of the correctly classified data divided by the total number of test data. It can be used to check the quality of classification. However, overall accuracy cannot give how well the classifier worked for each of the different classes. If the number of test data of one class is proportionately higher regarding other class, then it will bias the overall accuracy.

User's and Producer's Accuracy: The user's and producer's accuracy often called the error of omission and commission respectively. The error of omission is based on the reference data whereas error of commission is based on the predicted data. A commission error is defined as including an area into a thematic class when it does not belong to that class while an omission error is excluding that area from the thematic map when it belongs to the map (Story & Congalton, 1986).

The Kappa Statistic: Cohen's kappa coefficient is another widely used measure to check the quality of classification which can be derived from the error matrix (Bakx, W., Janssen, L., Schetselaar, E., Tempfli, K., Tolpekin, V., & Westinga, 2013). Kappa coefficient can represent the accuracy of the classification in a better way than overall accuracy since it considers the inter-class arrangement.
Mathematically, Kappa coefficient is computed as,

$$k = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} * x_{+i})}$$

Where r represent the number classes, x_{ij} is the number of observation in row i and column j of the error matrix, N is the total sum of all elements of the error matrix. $x_{i+} = \sum_{j=1}^{r} x_{ij}$ and $x_{+i} = \sum_{j=1}^{r} x_{ji}$ are the marginal totals for row i and column i respectively.

4. RESULTS

4.1. Field data analysis

Out of 123 fields visited during fieldwork, only 116 fields were found to be rice fields. Once the data of 116 rice fields were collected, a dataset was created using Excel. The GPS points measured on the edges of the rice fields were used to create polygons of rice fields in ArcGIS. Based on analysing this dataset, it was summarized that most of the rice fields visited in Nueva Ecija were canal irrigated while in Tarlac most of the rice fields were supplemented irrigation from the water pump and there were very few rice fields that were completely dependent on rain in the study area as shown in Figure 15.

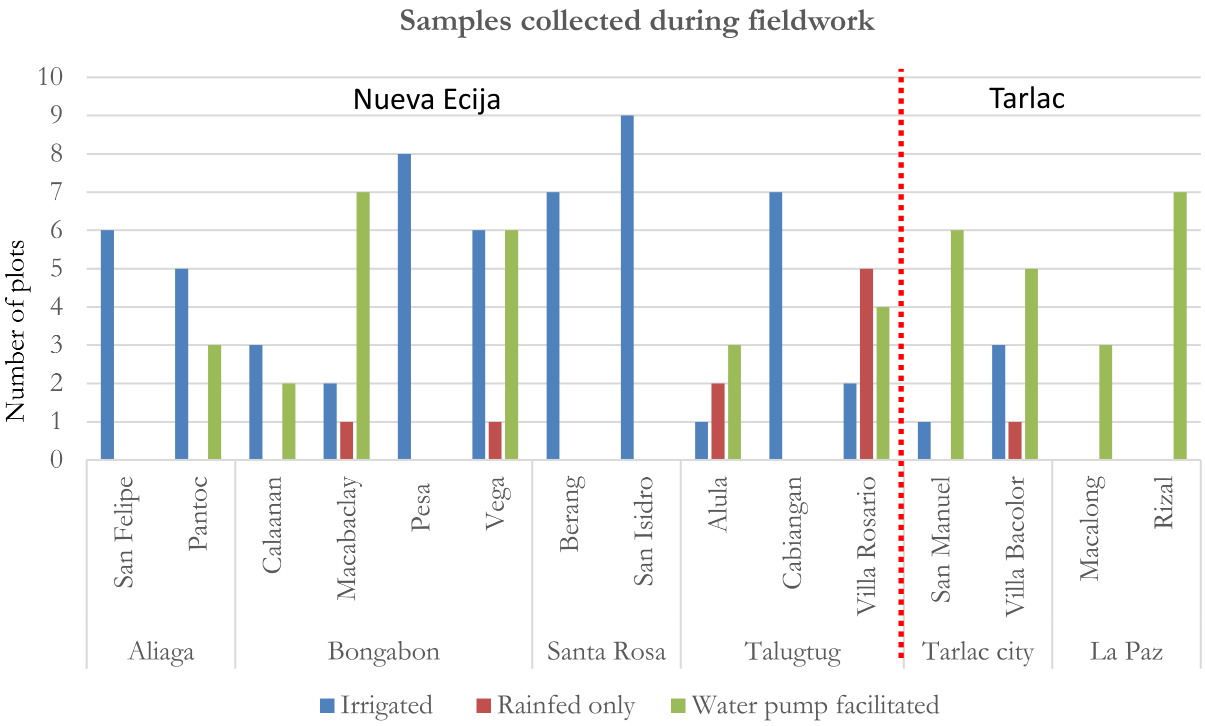


Figure 15: Distribution of rice field by different water sources in the study area where, in Nueva Ecija, there are total of 90 sample rice fields (IR=56, RF=9 and WP=25) and in Tarlac, there are total of 26 sample rice fields (IR=4, RF=1 and WP=21) of rice field which were collected during fieldwork.

From the data collected for this study, it was found that in Nueva Ecija, 62.22% of rice fields were canal irrigated, 27.78% were water pump supplemented, and only 10% were completely rainfed. In Tarlac 15.38% of rice fields were canal irrigated, 80.77% were water pumped, and only 3.84% were completely rainfed. To validate and check whether these samples were representative or not, the data were compared with the data obtained from MISTIG and the CLLS as shown in Table 12.

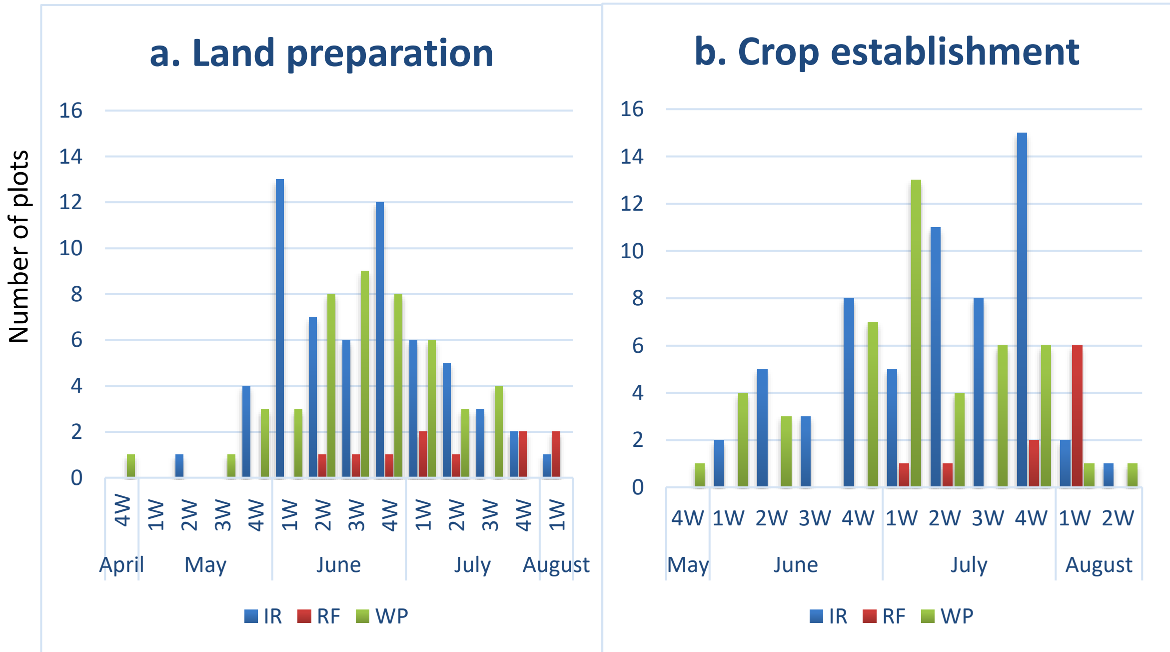
Table 12: Number of rice plots surveyed in this study and compared the data with the data provided by IRRI (MISTIG and CLLS) based on rice fields by water sources

	Province	IR (plots)	WP (plots)	RF (plots)
This study	Nueva Ecija	56 (62.22%)	25 (27.78)	9 (10%)
	Tarlac	4 (15.38%)	21 (80.77%)	1 (3.85%)
MISTIG	Nueva Ecija	733* (82.5%)		155 (17.5%)
	Tarlac	244* (85.6%)		41 (14.4%)
CLLS	Nueva Ecija	31 (70.5%)	9 (20.5)	4 (10%)
	Tarlac	3 (30%)	6 (60%)	1 (10%)

*In MISTIG survey, canal irrigated rice fields and rice fields with water pumps were considered as irrigated rice fields.

As seen in Table 12, the percentage of canal irrigated rice fields was high in Nueva Ecija whereas in Tarlac, the percentage of water pumped rice fields were higher. When comparing the study data with CLLS and MISTIG data, it was found that there are few differences in the percentage of canal irrigated, rainfed and water pump supplemented rice fields in the study area. The reason behind this had been discussed in the discussion section 6.1. Therefore, even with few differences, data collected in the field could represent the study area and the rice water sources that farmers were using in each province.

During fieldwork, it was found that different farmers used different dates for land preparation and crop establishment in their rice field. Further, the results also showed that the rice fields which were canal irrigated and water pump supplemented were found to prepare the land earlier as compared to the rice fields depending upon rain. Most of the canal irrigated and water pumped suplemented rice fields started land preparation during the last week of May and early June while land preparation in rainfed rice fields started in the second week of June till July as illustrated in Figure 16(a). The situation is similar to the crop establishment where the majority of canal irrigated and water pumped suplemented rice fields established rice crop earlier during last week of June until last week of July. Whereas in rainfed rice fields, farmers' established rice crop during the first week of July until the first week of August as shown in Figure 16(b).



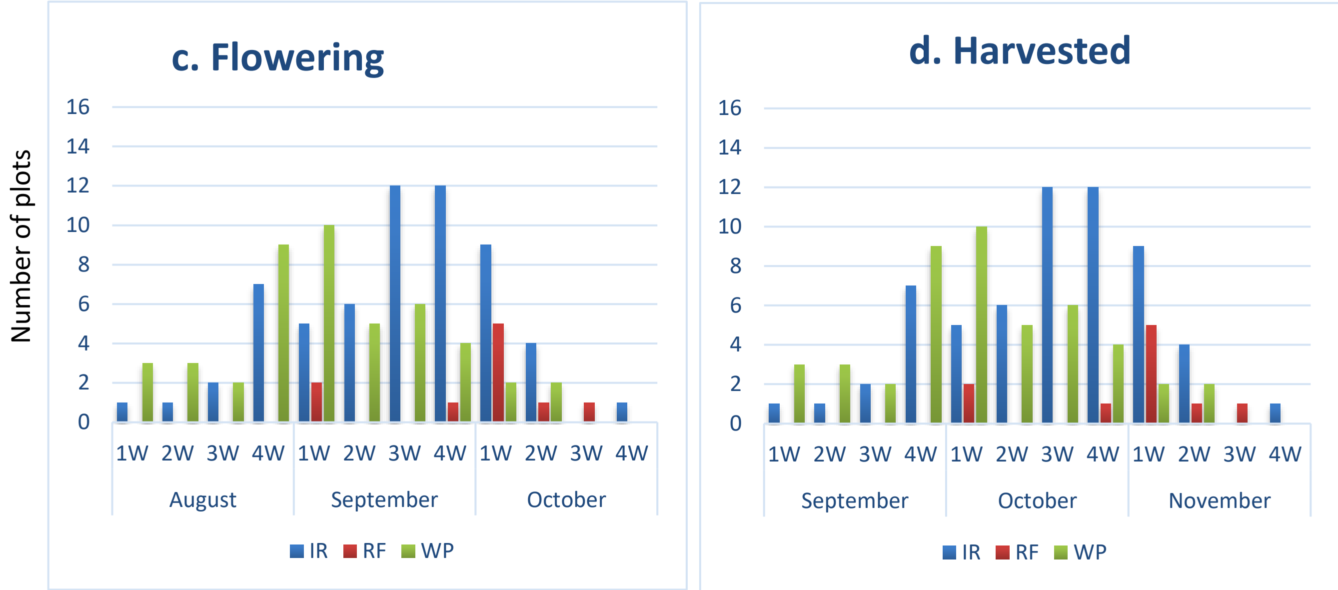


Figure 16: Timing of different rice growing phases based on the sample collected in the field. a) Land preparation, b) Crop establishment, c) Flowering and d) Harvested

During the interview, it was found that the rice varieties, for example, RC222, RC160, NSIC82 etc. with flowering duration from 90 to 120 days were used in the study area during the wet season. Based on the varieties of rice and the water availability, rice plant reached flowering stage in a different date and got harvested after one month of the flowering stage as shown in Figure 16(c and d). All the rice fields were harvested using Harvester (mechanical harvesting machine).

It was identified that in June, farmers used water from irrigation canal to flood their rice field for the first time as shown in Figure 17. The farmers also used water pump as supplement irrigation in June for the first time. In some cases, farmers waited for the rain, but due to delay and insufficient rain, the use of water pump increased and lasted till August in some plots as shown in Figure 17.

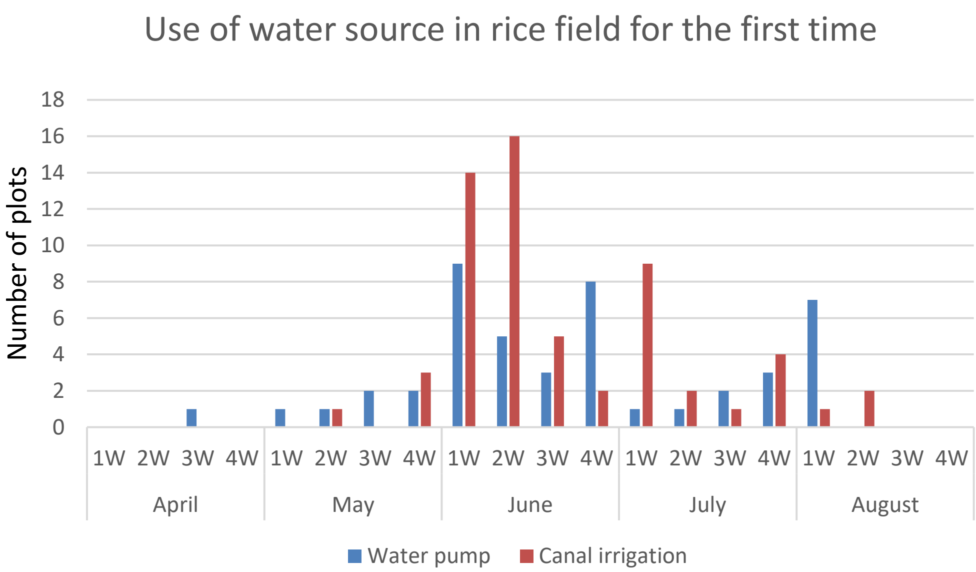


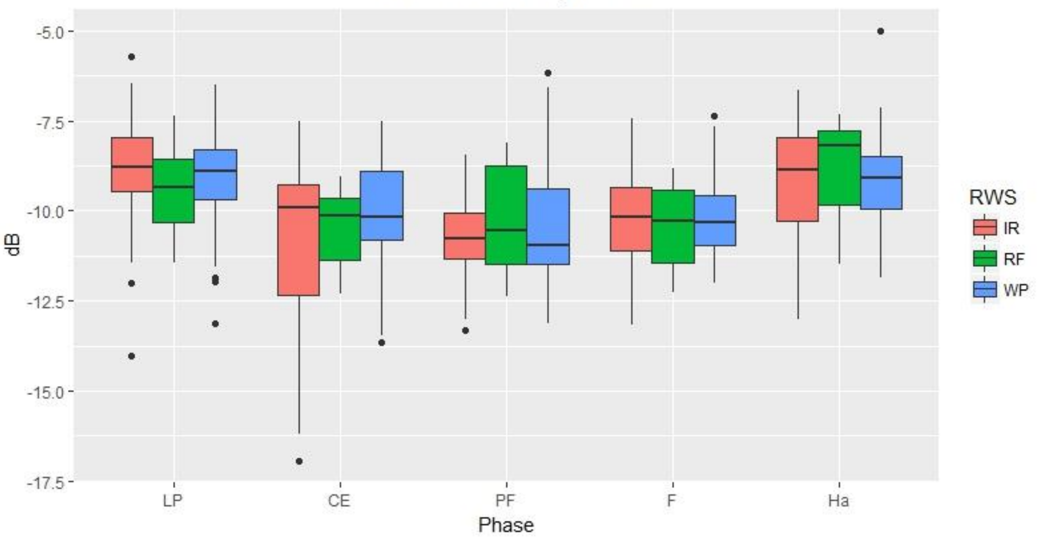
Figure 17: Water availability of rice fields using irrigation canal and water pump for the first time

4.2. Comparison of temporal rice backscattering signature

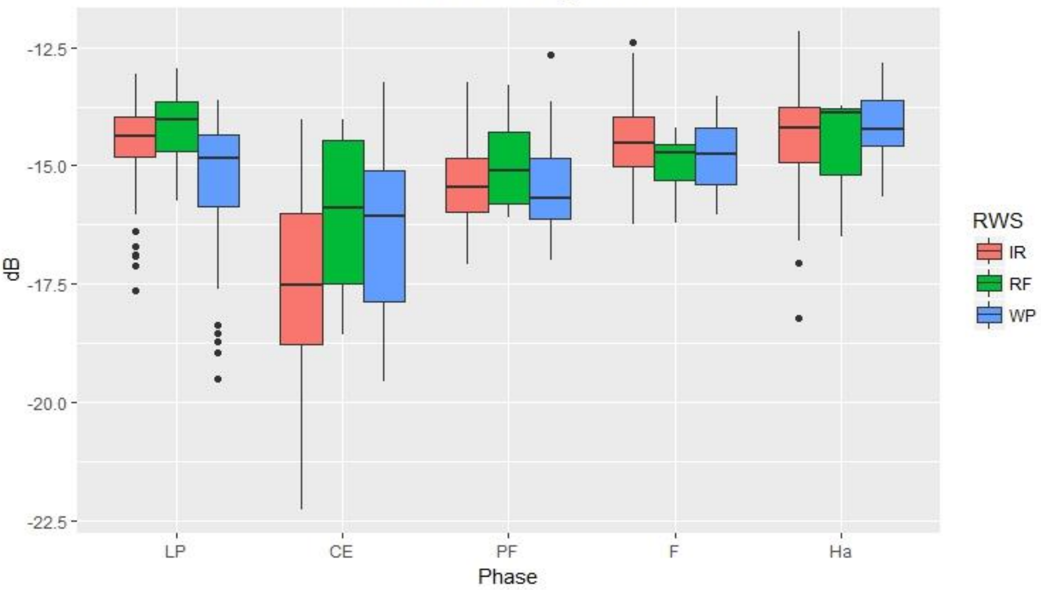
Based on the data collected from the questionnaire survey, dates of land preparation (LP), crop establishment (CE), panicle formation (PF), flowering (F) and harvest (Ha) were identified for each rice fields. The extracted backscatter values from ENVI in different acquisition dates were matched with the dates of rice growing events and stages. The descriptive statistics of extracted backscattering values at different rice growing events or stages (land preparation to harvest) of rice fields with different water sources (IR, RF and WP) and in different polarisations (VV, VH and VV-VH) have been summarised in Appendix 3.

When the backscatter values were extracted from the pre-processed Sentinel-1A images for the visited canal irrigated, rainfed and water pumped rice fields, they were grouped based on the rice growing events and stages (land preparation to harvest) in VV, VH and VV-VH. Based on the grouped backscatter values, the rice temporal backscatter signatures were established for VV and VH and the VV-VH as indicated in Figure 18.

a. VV backscatter signature



b. VH backscatter signature



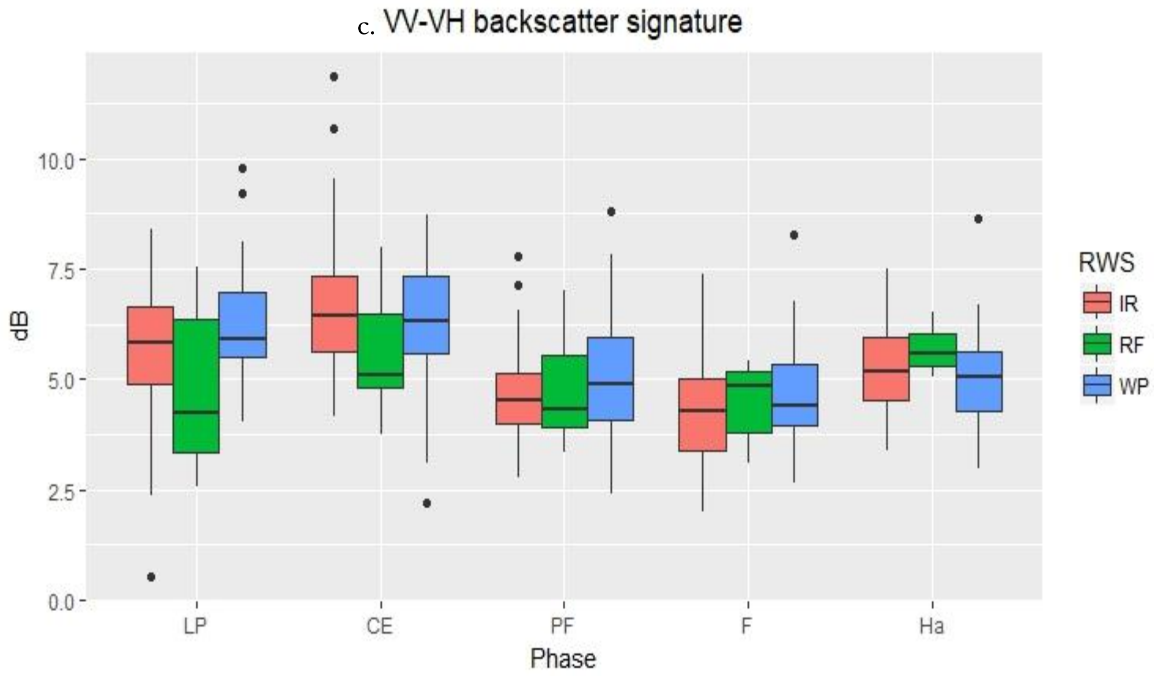


Figure 18: Backscatter coefficient derived from 3 different polarisations (VV, VH and VV-VH) at different rice growing events or stages for observed canal irrigated, rainfed and water pump and rainfed rice fields. The dots represent the outliers in each event or stages, and the lines in the box are the median. The upper half of the box is 25th percentile, and the lower half is 75th percentile, and the extended lines represent the minimum and maximum. a) Rice temporal profile in VV, b) Rice temporal profile in VH and c) Rice temporal profile in VV-VH

It showed that the backscatter coefficient values from VV were higher than that of VH in all rice growing events or stages. In VV, the backscatter value decreased from land preparation to crop establishment and remained saturated until harvest whereas in VH, the backscatter value once decreased from land preparation to crop establishment, however; it increased linearly during rice growing stages. The rice temporal profile of VV-VH did not exhibit any clear pattern.

4.3. Comparison of polarimetric data

Different polarisation to distinguish rice fields with different water sources were compared using one-way ANOVA. The simplified results of the one-way ANOVA during different rice growing events or stages of rice fields with different water sources in VV, VH and VV-VH are shown in Table 13. The complete ANOVA results where the rice fields with different water sources were significantly different during LP and CE of VH and LP of VV-VH are presented in Table 14. The ANOVA results of other stages in all polarisations are shown in Appendix 4.

Table 13: The outputs of one-way ANOVA with the rice growing events or stages where water sources of rice fields were significantly different in different event or stages.

Polarisation	Events or stages (p-value)				
	LP	CE	PF	F	Ha
VH	0.002	0.005	0.245	0.051	0.587
VV	0.410	0.069	0.253	0.747	0.971
VV-VH	0.007	0.092	0.072	0.196	0.422

Table 14: One-way ANOVA results in different rice growing events where the water sources were significantly different

a. One-way ANOVA result during land preparation using VH

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	21.30	2	10.651	6.654	0.002	3.077
Within Groups	180.89	113	1.601			
Total	202.19	115				

b. One-way ANOVA result during crop establishment using VH

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	40.92	2	20.458	5.496	0.005	3.077
Within Groups	420.61	113	3.722			
Total	461.53	115				

c. One-way ANOVA result during land preparation using VV-VH

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	19.55	2	9.774	5.263	0.007	3.077
Within Groups	209.85	113	1.857			
Total	229.40	115				

From the Table 13 and 14, it showed that in VH, during land preparation and crop establishment, and in VV-VH, during land preparation, there was a significant difference between canal irrigated, rainfed and water pump using rice fields at 0.05 level of confidence. The computed p-value for these events in VV and VV-VH was below the critical p-value of 0.05 while VV could not show any significant difference between rice fields by different water sources in any of the rice-growing events or stages. The p-values in rice growing events or stages of VV was higher than the critical p-value of 0.05.

It was found that canal irrigated, rainfed and water pumped rice fields were significantly different at land preparation and crop establishment and based on comparing p-value, the difference showed better in VH than that of VV and VV-VH.

4.4. Comparison of elevation data from SRTM

The descriptive statistics of extracted elevation data of rice fields with different water sources (IR, RF and WP) have been summarised in Appendix 2. One-way ANOVA was carried out to check the significant difference between the elevation of rice fields with different water sources, and the result of one-way ANOVA was shown in Table 15.

Table 15: One-way ANOVA result of elevation data of rice fields with different water sources

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3887.07	2	1943.54	1.39	0.25	3.08
Within Groups	157767.4	113	1396.17			
Total	161654.5	115				

The result of the one-way ANOVA showed that canal irrigated, rainfed and water pumped rice fields did not have significantly different elevation in the study area. The computed p-values from one-way ANOVA were higher than the critical p-value of 0.05.

4.5. Threshold identification using decision tree

For identifying the threshold and to develop set of rules, training data (70%) as shown in Table 11 were used to train the decision tree. Based on the training samples, backscatter coefficient from VV and VH were considered in the decision tree to differentiate rice fields with different water sources.

The thresholds between the different water sources were identified using the rice growing events and stages of VV and VH as variables in the decision tree and was developed in Rstudio using rpart.plot package. Although the rice growing events of VH gave the significant difference between the water sources of rice fields, VV was also used as supporting variables to distinguish different water sources. According to the decision tree shown in Figure 19, ten different rules were developed to differentiate canal irrigated, rainfed and water pump supplemented rice fields. Out of these ten rules, five rules can differentiate canal irrigated rice field, four rules can differentiate rice field supplemented with water pump irrigation, and one rule can differentiate purely rainfed rice field as shown in Appendix 6.

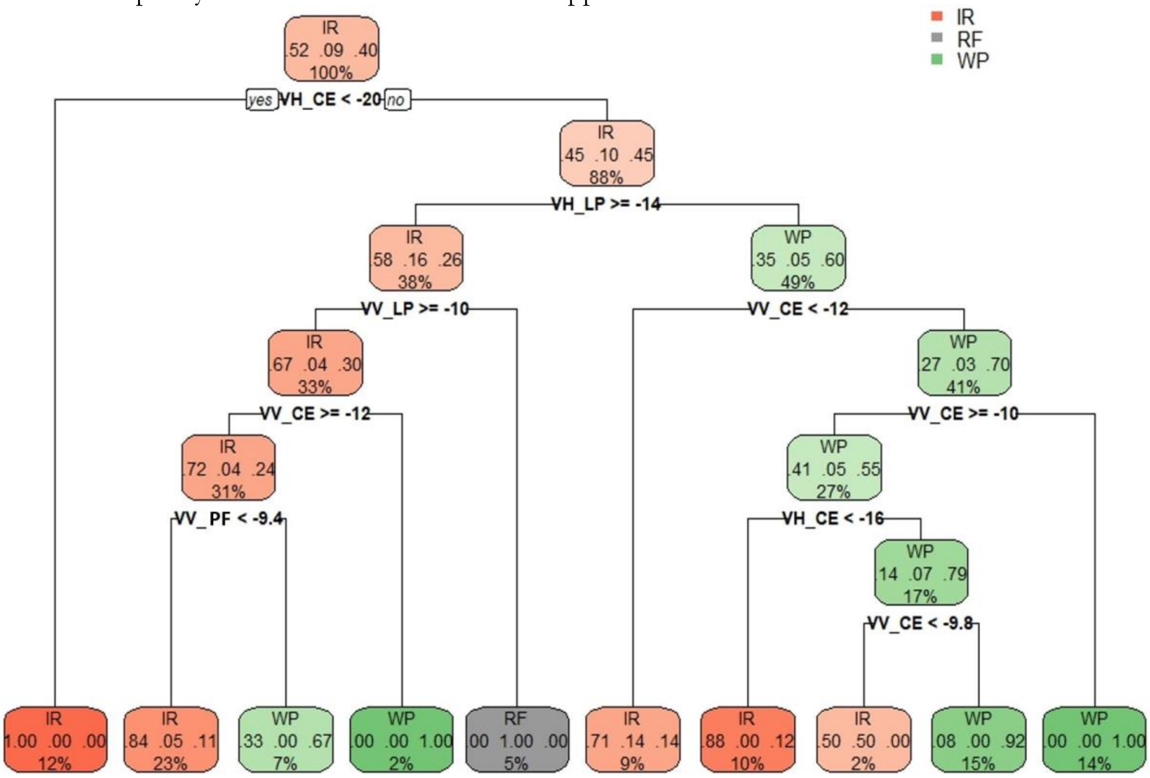


Figure 19: Decision tree developed in Rstudio using rpart.plot package in order to distinguish rice fields with different water sources. Red represents canal irrigated rice fields, grey represents rainfed rice field and green represents water pump supplemented rice fields. The colour intensity in each rice fields represented the probability of getting IR, RF and WP rice fields (Darker the colour, higher was the probability).

4.6. Accuracy Assessment

The classification was based on the number of classes. In this case, there were 3 classes namely IR, RF and WP, and the quality of the classification result was checked based on the test data. It was done by the sampling approach where the output results from the decision tree were selected, and both classification result and the test data were compared.

Table 16: The error matrix with derived errors and accuracy expressed as percentages

Reference / Prediction	IR	RF	WP	Total	Error of Commission (%)	User Accuracy (%)
IR	15	3	3	21	28.57	71.43
RF	0	0	0	0	100	0
WP	3	0	11	14	21.43	78.57
Total	18	3	14	35		
Error of Omission (%)	16.67	100	21.43			
Producer Accuracy (%)	83.33	0	78.57			

The comparison was made by creating error matrix from which different accuracy measures were calculated as shown in Table 16. Overall accuracy was used to check the quality of classification, and it was found to be (15+0+11)/35*100=74.29%.

Except for this overall accuracy, class accuracies were also derived from the confusion matrix. Two accuracies for each class (User and Producer) were identified as shown in Table16, user accuracy for IR, RF and WP were 71.43%, 0% and 78.57% respectively and producer accuracy for IR, RF and WP were 83.33%, 0%, and 78.57% respectively. The Kappa coefficient was also calculated to determine the accuracy of the classification, and it was found to be 0.5161.

5. DISCUSSION

5.1. Field data: observations and interpretations of management options

During the field visit, 123 fields of 99 farmers were visited in 15 villages of six municipalities (four from Nueva Ecija province and two of Tarlac province) as shown in Table 8. Out of 123 rice field visited, it was found that six plots in Macalong village of La Paz municipality were completely flooded, and no rice was grown in the wet season whereas one field of San Isidro village of Santa Rosa municipality grew chilli even in the wet season. Hence, a total of 116 plots of rice fields were surveyed in the study area.

There were different sources of water available for agriculture (rice cultivation) such as water from the small to large scale irrigation canal, water pumped from the ground while some were completely dependent upon rain as shown in Figure 20. In the villages of San Felipe, Pesa, Berang, San Isidro and Cabiangan in Nueva Ecija province, all the rice fields were canal irrigated. In villages such as Rizan and Macabong in Tarlac province, all the rice fields were supplemented by the water pump as shown in Figure 15.

Figure 20: a) Rice field with well managed cemented irrigation canal, b) Rice field with farmers' managed irrigation canal, c) Rice field with supplemented irrigation from the water pump and d) Rainfed rice field entirely dependent on rain.

The rice fields in the study area were selected based on the MISTIG data provided by IRRI, however, in the case of selected rainfed rice fields, many rainfed rice fields which were rainfed during the MISTIG survey now benefitted by irrigation from newly built canals. While comparing the collected data with MISTIG and CLLS, it was found that the percentage of rainfed rice fields were higher in MISTIG and CLLS than the data collected from the field because farmers had changed their water management practice overtime as MISTIG and CLLS were carried out in 2013/14 and 2015/16 respectively. However, issues of water management were observed as the major problem for many of the villages in the study area. For example, in Pesa, there was a well-developed and cemented irrigation canal, but the rice fields along the canals were affected by weeds as indicated in Figure 21 (a). Upon consultation with the farmers in this regard, he explained: - *it was because of the seeds of weed which were transferred from the hills to their rice fields through the irrigation canal.* Similarly, in Macabaclay, although there exists an irrigation canal, no water was available even in the wet season. As for Calanaan village, farmers shifted from rice to vegetable due to the lack of water even in the wet season as displayed in Figure 21 (b). Many irrigation canals had been destroyed due to a typhoon in Calanaan.

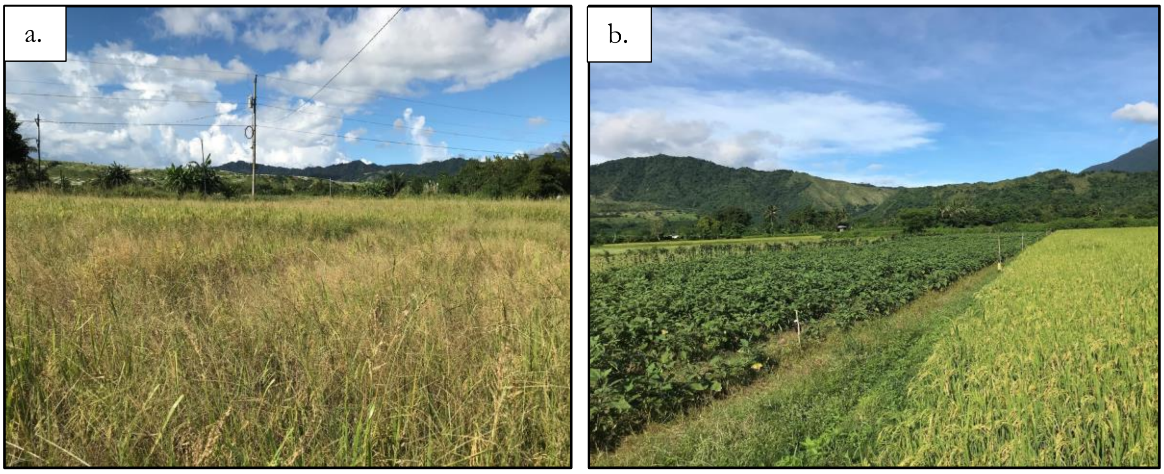


Figure 21: a) Rice field affected by weeds in Pesa and b) Farmers shifted from rice to vegetable even in the wet season (vegetable farming along the rice field) in Calanaan

In the results, it showed that farmers used different dates for land preparation and crop establishment in their rice field depending upon the water sources. It was found that during June both canal irrigated, and water pump supplemented rice fields used water from irrigation canal and groundwater for the first time. Since irrigated rice field received sufficient amount of water from canals and water pump, the farmers of irrigated rice fields started land preparation earlier during last week of May to early June. This was supported by water release data information provided by PhilRice showing that water from the irrigation canal under National Irrigation Administration in Nueva Ecija was released in June.

In the case of rainfed rice fields, the farmers prepared their rice field during the second week of June till July which is supported by the monthly average rainfall in the study area. According to the climate portal of The World Bank Group (2016), the monthly average rainfall in six municipalities of the study area was higher during July and August. It was found that different varieties of rice were used to increase the production and to reduce water stress and based on the varieties of rice and various water sources, rice reached flowering stages on different dates. Further, post one-month of flowering, all the surveyed rice fields were harvested using the mechanical harvester as shown in Figure 22. The lack of access to manpower and given the efficiency of the mechanical harvester in terms of time made the farmers choose this option as explained by the farmers: - *it was due to the lack of labour availability. It was difficult to get the labour, and with the harvester, it was easy and time-saving.*

Figure 22: Use of mechanical harvester to harvest rice field in the study area

It was found that the economic status of a farmer has a great influence in rice cultivation (in terms of buying rice seeds to land preparation and crop establishment to harvest). When the farmers were consulted with respect to the price for rice seeds, they responded: - *the cost of 1 bag (40kg) of inbreed rice seed is 120 Philippines Peso (2 euros), and it requires 2 bags of seed to cultivate 1 hectare of land*. Further, the farmers also informed us that until 2016, in the Philippines, they had to pay a fee of 3,000 Philippines Peso (50 euro) to the National Irrigation Authority for using water from the irrigation canal which is now free of cost. On the other hand, the farmers who could afford to run a water pump would use them to pump groundwater to flood their rice field because of delayed and insufficient rain. The cost of the fuel (diesel) used in pumping water for one hectare of land in a day amounts to 325 Philippines Peso (6 euro). During the wet season, most of the surveyed rice fields were transplanted, and only a few farmers used wet direct seeding (WDS) to establish rice crop as shown in Figure 24. The reason behind the selection of WDS by the farmers was due to the lower cost of WDS as compared to transplanting. The cost of labour to transplant one hectare of land amounts to 4000-7000 Philippines Peso (67-117 euro), and it requires 15 to 10 labours whereas, for wet direct seeding, it costs 800 Philippines Peso (13 euro) for 1-4 labours to broadcast seeds on one hectare of land. However, it has its own advantages and disadvantages. Finally, to harvest, all surveyed rice fields used mechanical harvester for which they pay 10% of their yield as a rental payment.

5.2. Backscatter coefficient analysis and polarimetric data comparison

In the results, it was found that backscatter values at the beginning of rice growing events in VH can be used to distinguish between canal irrigated, rainfed and water pump supplemented rice fields. In VH and VV-VH, we found that the rice fields with different water sources were significantly different. However, in VH, p-value from the statistical analysis was lower than VV-VH.

One-way ANOVA was carried out for statistical analysis and to compare the polarisations. Backscatter values from different rice growing events and stages of IR, WP and RF rice fields were compared to check whether they were significantly different or not for each polarisation (VV, VH and VV-VH). The result of the one-way ANOVA showed that during land preparation, rice fields with different water sources were significantly different in VH and VV-VH. It was also found that during crop establishment in VH, rice fields with different water sources were significantly different. The crop establishment method, the depth and duration of standing water in the fields before and during crop growth period and the accumulated biomass may all vary with the rice water sources. Thus, this will have a direct bearing on the SAR backscattering which would help to distinguish the different rice systems (Chakraborty et al., 1997).

During land preparation, the land was almost bare-with few plants (non-rice). Land preparation involves ploughing, harrowing and levelling the field. Different rice fields have different land preparation requirements. Irrigated rice fields are usually puddled to develop a hard pan and to reduce water loss. In the irrigated rice fields, wet-land preparation methods were generally used. During wet-land preparation, the rice fields are tilled in a saturated or flooded condition which helps to control weed and maintain soil nutrients as shown in Figure 23(a). On the other hand, the rainfed rice fields generally use dry land preparation. The soil does not necessarily have to be puddled and requires less water. Dry preparation is common for rainfed rice fields because it is applicable when water is scarce as shown in Figure 23(b). These different situation in land preparation caused the difference in backscatter coefficient in rice fields with different water sources.

Figure 23: a) Wet land preparation for rice cultivation and b) Dry land preparation for rice cultivation. (Source: http://www.knowledgebank.irri.org/step-by-step-production/pre-planting/land-preparation)

The most common practices of crop establishment methods were transplanting and wet direct seeding in the study area as shown in Figure 24(a & b). In the case of the wet season, most of the rice fields were transplanted. During transplanting, seedlings raised in seedbeds were planted in the flooded fields having standing water as shown in Figure 24(a). It was found that during crop establishment, rice fields showed lowest backscatter value as compared to rice fields during other rice-growing events and stages because of the water present in the rice field. The canal irrigated and water pumped rice fields had shown lower backscatter values during CE than rainfed rice fields due to more surface water in the field. It was also supported by the information provided by the farmers during the interview that due to delay and insufficient rain, rainfed rice fields faced the problem of water scarcity as compared to the canal irrigated rice field where the water was sufficient. In some cases, for example in Tarlac, farmers used water pumps to flood their rice fields due to insufficient water from rain. Calm water surface acts like a mirror for the incident radar pulse and most of the incident radar energy reflected away according to the law of specular reflection (W. Bakx & T. Woldai, 2013). Hence, it appeared darker in SAR images giving lower backscatter coefficient value.

Figure 24: Crop establishment method (a) Transplanting and (b) Wet direct seeding. (Source: http://www.knowledgebank.irri.org/step-by-step-production/growth/planting)

From the box plots in the result section Figure 18, it was found that backscatter coefficient from VV was higher than VH in all rice growing events or stages. The result was in line with the observation of Wu, Wang, Zhang, Zhang, & Tang (2011) and Konishi, Suga, Omatu, Takeuchi, & Asonuma (2008) who identified that the distribution of co-polarisation backscatters such as VV and HH is higher than cross-polarisation such as VH and HV. The backscatter coefficient in VH showed a significant change early in the season, from land preparation to the crop establishment. The change in mean backscatter coefficient from land preparation to crop establishment was higher in VH than VV and VV-VH.

The decrease in backscatter value was more significant in VH than in VV and VV-VH during land preparation to crop establishment. After crop establishment, the backscatter coefficient of VV remained almost saturated until the harvest. The mean backscatter coefficient in VH, however, increased linearly with the growth stage. It was because during the initial stage of rice growing, transplanted rice seedling starts to grow until tilling and then to stem elongation stage which increased the surface roughness causing the diffuse reflection (Inoue et al., 2002). VV was less correlated with the plant variables such as canopy cover, plant biomass than other polarisations whereas VH penetrates more effectively into canopies and shows greater seasonal change than the VV (Kim, Hong, & Lee, 2008). Hence, it showed that backscatter values from VH had a high relation with the rice growth cycle and the temporal profile of VH explained the rice crop age in a better way than VV and VV-VH. This result is supported with research done by Wu et al. (2011) where they observed that the rice growth cycle is highly correlated with the backscatter coefficient from VH whereas with VV the correlation is low.

During flowering, the rice plant reached its peak where the plant gained maximum biomass with high canopy coverage because the backscatter value during this stage increased. In terms of VH, it is primarily associated with the volume scattering from the target which occurs with more canopy closure during the panicle formation (Mc Nairn & Brisco, 2004). In VV-VH, there was no clear pattern identified.

Although the one-way ANOVA result showed that only during land preparation and crop establishment, the rice fields with different water sources were significantly different, p-value (0.051) during flowering in VH was very close to critical p-value 0.05 as shown in Table 13. This could have been due to the number of field observations in the classes. The number of field observations for each class were not equal, and the gap between the number of field observations in the classes were high because farmers changed their water management practices for example, from rainfed to irrigated. During flowering, there was an increase in biomass in rice fields due to increase in canopy coverage. According to Sembiring et al. (2011), biomass in the irrigated rice field where the water was sufficient gives higher biomass as compared to the rainfed rice field. In addition, Kim, Hong, & Lee (2008) identified that VH is sensitive to the biomass and has a high correlation with LAI in incidence angles greater than 45°.

5.3. Elevation data comparison

Based on the data collected in the field and the elevation data obtained from SRTM, it was found that the canal irrigated, rainfed and water pump supplemented rice fields did not have significantly different elevation in the result. The DEM information obtained from SRTM has the resolution of 30m. Since almost, all surveyed rice fields were in the lowland region of the Nueva Ecjia and Tarlac province, and are located close to each other, the resolution of SRTM data was not enough to capture the variability between the canal irrigated and rainfed lowland rice fields in the study area. 116 plots of rice fields were measured in 15 villages which are in the similar elevation range. The complete range of elevation in two provinces was obtained 0 to 1797m whereas the elevation range in 116 plots was 11m to 182m based on the SRTM data. The elevation varied based on the elevation of the village not on the elevation of the plots.

Rice environments are mainly classified based on the altitude and the water sources (GRiSP, 2013b): 1) Irrigated 2) Rainfed (lowland and upland), 3) Flood-prone and 4) Salinity-prone. In this research, almost, all surveyed rice fields were in irrigated (canal or water pump supplemented) or rainfed lowland environment. This might be the reason why there was no significant difference in the elevation of rice fields.

5.4. Threshold identification using decision tree

10 rules were identified using the decision tree algorithm out of which only one rule was generated to distinguish rainfed rice fields. The training data for rainfed rice fields was only 7 which was very low to develop more rules for differentiating rainfed rice fields with other rice fields.

The overall accuracy was used to check the accuracy of the classification and was found to be 74.29% with Kappa 0.5161. Along with overall accuracy, class accuracies were also identified, and it was found that both user and producer accuracies for rainfed rice field were 0%. It was because of the low number of field observations for the rainfed rice field. The classes accuracies for the canal irrigated and the water pumped rice fields samples were relatively higher than the overall accuracy.

The Kappa coefficient was low compared to overall accuracy because the distribution of test sample was not equal between the classes of rice fields with different water sources. Nueva Ecija and Tarlac, are main rice-growing provinces of the Philippines. Most of the rice fields in Nueva Ecija were canal irrigated managed by National Irrigation Authority. In Tarlac, the irrigation canals are not as well developed as in Nueva Ecija, and farmers used water pumps to pump groundwater. Most of the rice fields were either canal irrigated or water pump supplemented in these two provinces which lead to a fewer number of samples for rainfed rice field. Although the number of training and test data for each class of rice fields were limited and unevenly distributed, the obtained overall accuracy was satisfactory.

Given the lack of RF data points, we also created a new decision tree to differentiate the IR and WP only using the training data of IR and WP (removing RF data) to check whether the classification power of the decision tree would improve or not. It was found that the overall accuracy was similar to the previous decision tree as shown in Appendix 7. The classification power of the decision tree did not improve however, it highlighted the different thresholds and set of rules to differentiate IR and WP. Further exploration of these rules and thresholds was not possible due to time constraints, but the suitability of these rules for differentiating between IR and WP should be explored more in the future.

In the decision tree, the selection of variables was made with the Classification and Regression Tree (CART) algorithm which calculates the impurity of each index of every feature and splits them until it gets pure subsets. The decision tree while differentiating IR, RF and WP used the rice growing events (crop establishment) of VH as a root of the tree because this was the event where rice fields with different water sources were significantly different. However other stages of VH and VV were also used in the decision tree.

Different variables were considered to identify the best decision tree in order to get the best classification of the rice fields with different water sources. For example, all the rice-growing events and stages of VV, VH and VV-VH were used as inputs into the decision tree as shown in Appendix 5(b), however, the accuracy was lower than with VV and VH only. Further, the rice growing events and stages in VH and VV-VH were also selected to identify the thresholds in the decision tree as shown in Appendix 5(c) because the rice growing events in these polarisation showed significant differences between rice fields with different water sources, but the accuracy was also lower than with VV and VH only.

The decision tree did not use information from all the events and growth stages. Five rice growing events and stages of VV and VH were considered in this decision tree as shown below:

- Land preparation of VH (VH_LP)
- Crop establishment of VH (VH_CE)
- Land preparation of VV (VV_LP)
- Crop establishment of VV (VV_CE)
- Panicle formation of VV (VV_PF)

Crop establishment stage was the crucial rice growing event in this decision since it had been used many times to develop the threshold and used as a root node of the decision tree. Water plays an important role during crop establishment stage in the wet season. The rainfed rice field may suffer water stress and exhibit significant differences compared to the irrigated field (Facon, 2000).

The decision tree automatically eliminated the variables those are overfitted with the tree. In principle, the rules that do not contribute or help in increasing the accuracy are removed in the decision tree (Quinlan, 1993). For example, the tree only used LP and CE of VH and eliminated others. Similarly, the tree eliminated F and Ha in VV as well since they did not give any additional information to discriminate rice fields with different water sources.

5.5. Limitations and recommendations

Increasing demand for water in rice agriculture has identified the urgent need for improvements in water management practice. From the literature, it was found that SAR technology can be used to identify rice water sources. SAR backscatter can be extracted from the time series images for monitoring rice fields with different water sources. Different polarisation and combination of polarisations can be used to find the most discriminative information for separating rice fields with different water sources (Chitpaiboon, Prakobya, & Kruasilp, 2013). Chakraborty et al. (1997) used ERS-1 SAR data to discriminate rice crop grown under different rice ecosystems and Chitpaiboon, Prakobya, & Kruasilp (2013) used RADARSAT-2 for classification of irrigated rice and yield estimation. However, they did not look at any potential differences in SAR signal between rice fields with different water sources in different rice growing events and stages. It is also very complicated to identify small or fragmented rice areas on the large scale due to the spatial resolution of the available images and the availability of the high repeatable images over large area (Biggs et al., 2006). To understand the backscatter difference between rice fields with different water sources in different rice growing events and stages, Sentinel-1A images were used in this research. These images are freely available with dual polarized and high-resolution mode. The significant advantage of using Sentinel-1 is it works in all-weather condition even in tropical areas where the cloud cover is very frequent (Bégué et al., 2017). The results of this research are expected to be helpful in better understanding the backscattering behaviour of rice fields with different water sources, and therefore in monitoring rice fields using operational SAR systems.

In the Philippines, the National Irrigation Authority (NIA) under the Department of Agriculture looks after construction, operation and maintenance of irrigation system consistent with integrated water resource management principles to improve agricultural productivity and increase farmers' income. This kind of research helps to identify the location of irrigated rice fields which in addition contributes to the construction of new irrigation systems where needed. The need of irrigation canals in different places of the Philippines can be identified with the help of this research. The main objective of NIA is to develop and maintain irrigation systems on a sustainable basis and provide technical assistance in the development of the water sources for irrigation. This research adds value in obtaining the NIA objective by identifying the area of rice fields with different water sources (IR, RF and WP), and the area where new canal irrigation system could be established. Furthermore, this study will also help in monitoring rice and developing map of rice fields with different water sources which can be used by the government of Philippines. The government of Philippines has signed into law a measure pushing free irrigation to farmers who own up to eight hectares of land (Gita, 2018). This will increase the demand for this kind of study to identify the real-time location of irrigated area and area where irrigation canals are necessary in order to benefit all the farmers equally with free irrigation.

However, there are some limitations in this research as explained below:

- Even though, we aimed to achieve the representative number of samples for each IR, WP and RF rice fields through purposive sampling, the samples collected in the field for RF was very limited (number=10). It was because of a change in rice water sources in the study area. Due to the construction of new irrigation canal, rainfed rice fields during the MISTIG survey now benefits from the irrigation. Also, due to the untimely and insufficient rain, farmers had to depend upon water pump. Hence, it was very important to consider the possibility of the farmers in changing their water use practice based on the availability of water while selecting the number of samples. We cannot rely on one-year data, it is better to do this kind of research every year until the system becomes robust.

- Even though we only consider rice fields greater than 0.5 Ha, the shapes of some rice fields are elongated, which means we could not perform negative buffering to remove edge effects. This might influence the backscatter value of the rice fields even though we considered it to be negligible. It is better to select a bigger rice field as possible. However, it will not completely solve this problem, but at least it will minimize the effect on backscatter.

- The backscatter value in different rice growing events or stages and from rice fields with different water sources depends upon the acquisition date of the SAR image. Errors might exist when translating image acquisition date into rice growing events and stages. The revisit time of the Sentinel-1A is 12 days. The shorter revisit time helps to detect the correct backscatter value in different rice growing events and stages. The revisit time can be shorter and more rice growing events and stages could be considered if we incorporate Sentinel-1B images in this kind of study (ESA, 2013). Therefore, data integration is required to take advantage of different satellites and obtain high spatiotemporal resolution datasets for identifying rice fields with different water sources.

- The presence of bunds inside the rice fields influences the backscatter value. Konishi et al. (2008) in his study identified that RADARSAT-S1 backscatter is sensitive to the influence of the bunds, and different polarisation has different sensitivity towards bunds. For example, the influence of bund is higher with HH of ASAR for an off-range angle than VV. Therefore, a similar study by Konishi et al. (2008) on the influence of bunds inside the rice field may be studied further for the Sentinel-1A data in comparing VV and VH.

- Some of the factors such as the presence of plants (weed) other than rice were not considered in this study. The presence of weed in the rice field can influence the backscatter value of the rice fields. For this, it is very necessary to identify the fields that are affected by the weed and carry a test in order to see whether the influence of weed has a significant difference or not. If there results a significant difference, then the field should be eliminated from the study area.

- A decision tree was used to distinguish rice fields with different water sources, and the overall accuracy was satisfactory. However, the comparison and implementation of other advanced classification algorithms are also encouraged to get the differentiation with better accuracy. For example, Son, Chen, Chen, & Minh (2017) used random forests and support vector machines for rice classification using Sentinel-1A data and obtained good accuracy results.

6. CONCLUSION

The main objective of this study was to analyse SAR (Sentinel-1A) data for its potential to detect rice fields with different water sources (canal irrigated, rainfed and water pump supplemented) in the major rice-growing area of the Philippines. This study clearly shows that rice fields with different water sources have distinct temporal backscatter profile in the different polarisation of Sentinel-1A data. The backscatter coefficient variation during the early rice growing events showed a viable proposition for rice fields differentiation mainly in VH.

A series of Sentinel-1A images during the wet season on Central Luzon, Philippines were used to detect different rice fields with different sources of water based on the backscatter temporal variability and backscatter change during the different rice growing events or stages. Fieldwork (24th September to 10th October 2017) was conducted to collect the training and test data of the canal irrigated, rainfed and water pump supplemented rice fields. A total of 116 rice fields were measured and based on these fields the backscatter coefficient between the rice fields with water sources were compared. The conclusions were drawn from the analysis results and explained below based on the research questions:

1. Research question 1, **"Which polarisation or the combination of polarisations will give the most accurate discrimination between rice fields with different water sources?"**
   It is concluded that the backscatter temporal profile of the rice in VH represents rice growth stage in a better way than VV and VV-VH. This is because VH is more correlated with the plant variables such as canopy cover and plant biomass. Comparing the p-values at different rice growing events and stages of different polarisations identified using one-way ANOVA, it is concluded that VH during LP and CE gives the best differentiation between rice fields with different water sources.

2. Research question 2, **"Which rice growing events or stages will be most suitable to distinguish rice fields with different water sources?"**
   It is concluded that during land preparation and crop establishment of the VH and in land preparation of VV-VH, the rice fields with different water sources can be distinguished. It was because of the availability and presence of water in these stages. With the equally distributed sample plots, the rice fields with different water source could be distinguished during the flowering in VH. It is because VH is sensitive towards the biomass and volume scattering which is expected to be high in canal irrigated rice fields as compared to rainfed and water pump supplemented rice fields in flowering stage.

3. Research question 3, **"What are the threshold and rules for differentiating rice fields with different water sources developed using decision tree?"**
   Ten sets of rules and the thresholds were identified using five different rice growing stages and events in VV, and VH as variables in the decision tree to distinguish canal irrigated, rainfed and water pump supplemented rice fields shown in result section Figure 20. Out of these ten rules, five rules differentiate canal irrigated rice fields, four rules differentiate rice fields supplemented with water pump irrigation, and one rule can differentiate purely rainfed rice fields as shown in Appendix 6. This study concluded that the thresholds and the set of rules developed using decision tree algorithm in Rstudio could differentiate the rice fields with different water sources using key events or stages in VV and VH with the overall accuracy of 74.29%.

The above conclusion indicates that the SAR data are feasible for detecting rice fields with different water sources during the wet season when the weather generally remained cloudy. Finally, this research shows that the multi-temporal Sentinel-1A imageries can be used to identify the best rice growing events or stages and polarisation to differentiate rice fields with different water sources. The proposed method can be used in tropical and sub-tropical regions with the availability of sufficient and accurate training samples and multi-temporal data at high spatial and temporal resolution similar to Sentinel-1A or higher.

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APPENDICES

Appendix 1: Set of questionnaires surveyed during field visit

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 seed bed 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				Make a note if this is in cavans and ask how

	payment for harvesting (current crop can be expected yield)				many kg per cavan, this varies by 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 2: Descriptive statistics table showing elevation of rice fields with different water sources

Water sources	Mean	Standard Error	Median	Standard Deviation	Sample Variance	Minimum	Maximum	Count	Confidence Level (95.0%)
IR	57.7	5.157	32.5	39.95	1595.98	11	182	60	10.32
RF	76.8	6.059	80	19.16	367.07	26	98	10	13.71
WP	55.2	5.397	32.5	36.61	1340.03	18	170	46	10.87

Appendix 3: Descriptive statistics tables showing the backscatter values at different rice growing events or stages in different polarisation

a: Descriptive statistics of backscatter values at different rice growing events or stages in VV

VV		Mean	Standard Error	Median	Standard Deviation	Sample Variance	Minimum	Maximum	Count	Confidence Level (95.0%)
LP	*IR*	-8.88	0.19	-8.79	1.47	2.17	-14.02	-5.72	60	0.38
	RF	-9.42	0.41	-9.35	1.31	1.71	-11.43	-7.37	10	0.94
	WP	-9.15	0.20	-8.91	1.38	1.92	-13.14	-6.51	46	0.41
CE	*IR*	-10.94	0.28	-10.23	2.15	4.64	-16.96	-7.51	60	0.56
	RF	-10.46	0.37	-10.14	1.18	1.39	-12.29	-9.03	10	0.84
	WP	-10.51	0.21	-10.15	1.42	2.03	-13.64	-7.51	46	0.42
PF	*IR*	-10.77	0.15	-10.78	1.13	1.27	-13.32	-8.46	60	0.29
	RF	-10.26	0.49	-10.56	1.54	2.37	-12.40	-8.12	10	1.10
	WP	-10.38	0.23	-10.94	1.55	2.39	-13.13	-6.18	46	0.46
F	*IR*	-10.23	0.17	-10.15	1.35	1.82	-13.18	-7.42	60	0.35
	RF	-10.45	0.39	-10.30	1.23	1.51	-12.25	-8.82	10	0.88
	WP	-10.13	0.16	-10.32	1.11	1.24	-12.02	-7.38	46	0.33
Ha	*IR*	-9.10	0.22	-8.85	1.47	2.18	-13.01	-6.64	46	0.44
	RF	-9.00	1.26	-8.18	2.19	4.79	-11.47	-7.33	3	5.44
	WP	-9.16	0.21	-9.09	1.34	1.79	-11.87	-4.99	42	0.42

b: Descriptive statistics of backscatter values at different rice growing events or stages in VH

VH		Mean	Standard Error	Median	Standard Deviation	Sample Variance	Minimum	Maximum	Count	Confidence Level (95.0%)
LP	*IR*	-14.58	0.13	-14.37	1.04	1.08	-17.64	-13.07	60	0.27
	RF	-14.18	0.26	-14.02	0.81	0.65	-15.74	-12.95	10	0.58
	WP	-15.37	0.23	-14.83	1.57	2.47	-19.50	-13.61	46	0.47
CE	*IR*	-17.52	0.27	-17.53	2.10	4.40	-22.27	-14.03	60	0.54
	RF	-16.02	0.54	-15.90	1.72	2.96	-18.57	-14.01	10	1.23
	WP	-16.32	0.27	-15.96	1.83	3.33	-19.55	-13.13	46	0.54
PF	*IR*	-15.36	0.11	-15.46	0.87	0.76	-17.07	-13.25	60	0.23
	RF	-14.96	0.31	-15.11	0.97	0.94	-16.09	-13.29	10	0.69
	WP	-15.50	0.14	-15.70	0.98	0.96	-16.99	-12.66	46	0.29
F	*IR*	-14.50	0.10	-14.54	0.77	0.60	-16.24	-12.39	60	0.20
	RF	-14.97	0.21	-14.72	0.66	0.44	-16.22	-14.19	10	0.47
	WP	-14.81	0.11	-14.77	0.74	0.54	-16.04	-13.53	46	0.22
Ha	*IR*	-14.33	0.17	-14.19	1.17	1.38	-18.21	-12.16	46	0.35
	RF	-14.03	0.23	-13.87	0.39	0.15	-14.48	-13.75	3	0.97
	WP	-14.17	0.11	-14.23	0.73	0.53	-15.65	-12.82	42	0.23

c: Descriptive statistics of backscatter values at different rice growing events or stages in VV-VH

VV-VH		Mean	Standard Error	Median	Standard Deviation	Sample Variance	Minimum	Maximum	Count	Confidence Level (95.0%)
	IR	5.71	0.18	5.85	1.41	1.99	0.50	8.39	60.00	0.36
	RF	4.75	0.59	4.25	1.88	3.53	2.55	7.52	10.00	1.34
LP	*WP*	6.22	0.17	5.93	1.16	1.35	4.04	9.79	46.00	0.35
	IR	6.58	0.18	6.45	1.41	1.99	4.16	11.85	60.00	0.36
	RF	5.57	0.43	5.11	1.37	1.89	3.74	8.01	10.00	0.98
CE	*WP*	6.31	0.19	6.30	1.31	1.72	2.21	8.75	46.00	0.39
	IR	4.58	0.13	4.52	0.97	0.95	2.76	7.79	60.00	0.25
	RF	4.70	0.38	4.33	1.19	1.42	3.33	7.02	10.00	0.85
PF	*WP*	5.12	0.21	4.89	1.40	1.95	2.38	8.83	46.00	0.41
	IR	4.28	0.16	4.26	1.21	1.46	1.99	7.39	60.00	0.31
	RF	4.52	0.27	4.85	0.85	0.72	3.09	5.42	10.00	0.61
F	*WP*	4.68	0.16	4.41	1.12	1.25	2.66	8.29	46.00	0.33
	IR	5.23	0.16	5.18	1.11	1.24	3.36	7.49	46.00	0.33
	RF	5.71	0.44	5.57	0.76	0.58	5.04	6.54	3.00	1.89
Ha	*WP*	5.01	0.16	5.05	1.07	1.14	2.99	8.65	42.00	0.33

Appendix 4: Tables showing the result of one-way ANOVA at different rice growing events or stages in different polarisation

a. One-way ANOVA result during panicle formation using VH

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	2.43	2	1.21	1.42	0.25	3.08
Within Groups	96.35	113	0.85			
Total	98.78	115				

b. One-way ANOVA result during flowering using VH

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3.44	2	1.72	3.05	0.051	3.08
Within Groups	63.72	113	0.56			
Total	67.16	115				

c. One-way ANOVA result during harvest using VH

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.18	2	0.59	0.59	0.56	3.10
Within Groups	88.59	88	1.01			
Total	89.78	90				

d. One-way ANOVA result during crop establishment using VV

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	15.44	2.00	7.72	2.26	0.11	3.08
Within Groups	385.38	113.00	3.41			
Total	400.82	115.00				

e. One-way ANOVA result during panicle formation using VV

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	5.03	2.00	2.52	1.39	0.25	3.08
Within Groups	204.03	113.00	1.81			
Total	209.06	115.00				

f. One-way ANOVA result during flowering using VV

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.92	2.00	0.46	0.29	0.75	3.08
Within Groups	176.81	113.00	1.56			
Total	177.73	115.00				

g. One-way ANOVA result during harvest using VV

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.12	2.00	0.06	0.03	0.97	3.10
Within Groups	180.88	88.00	2.06			
Total	181.00	90.00				

h. One-way ANOVA result during land preparation using VV-VH

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	19.55	2.00	9.77	5.26	0.01	3.08
Within Groups	209.85	113.00	1.86			
Total	229.40	115.00				

i. One-way ANOVA result during crop establishment using VV-VH

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	9.13	2.00	4.56	2.44	0.09	3.08
Within Groups	211.78	113.00	1.87			
Total	220.91	115.00				

j. One-way ANOVA result during panicle formation using VV-VH

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	7.47	2.00	3.73	2.70	0.07	3.08
Within Groups	156.50	113.00	1.38			
Total	163.97	115.00				

k. One-way ANOVA result during flowering using VV-VH

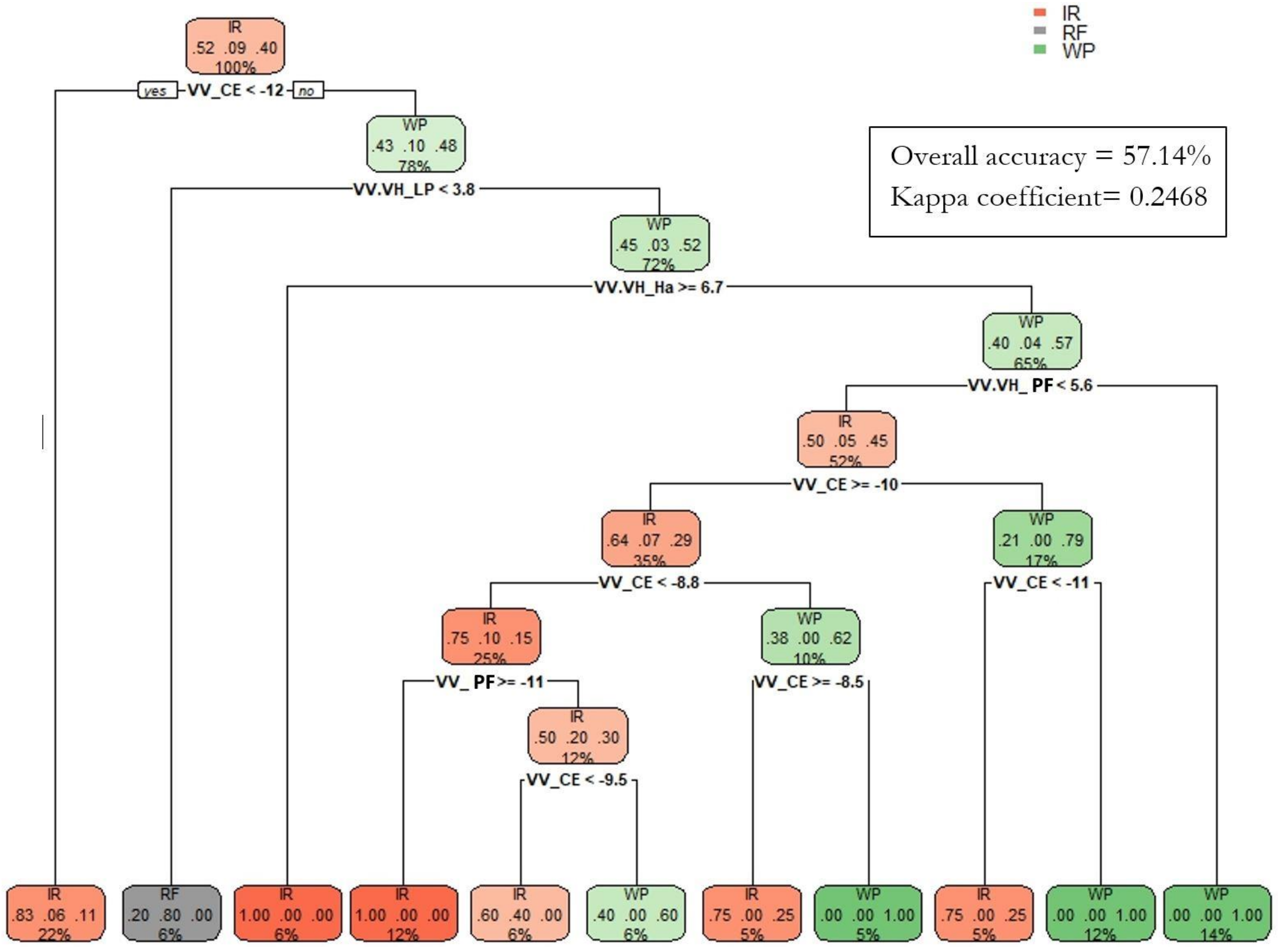
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	4.34	2.00	2.17	1.65	0.20	3.08
Within Groups	148.60	113.00	1.32			
Total	152.94	115.00				

l. One-way ANOVA result during harvest using VV-VH

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	2.05	2.00	1.03	0.87	0.42	3.10
Within Groups	103.76	88.00	1.18			
Total	105.82	90.00				

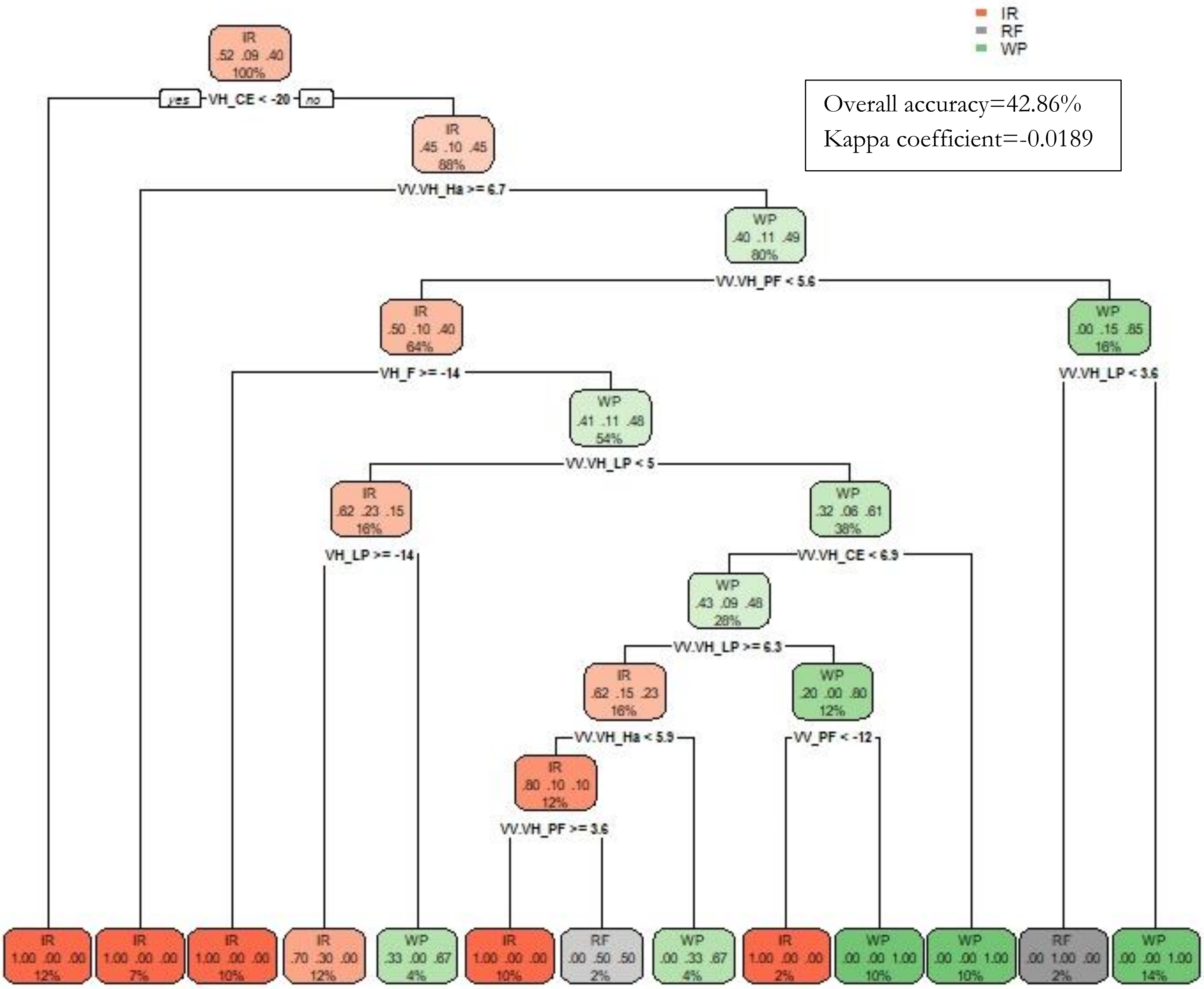
Appendix 5: Decision trees using different polarisation with its overall accuracy and Kappa coefficient

a. Decision tree using rice growing events and stages of VV and VV-VH with its overall accuracy and kappa coefficient

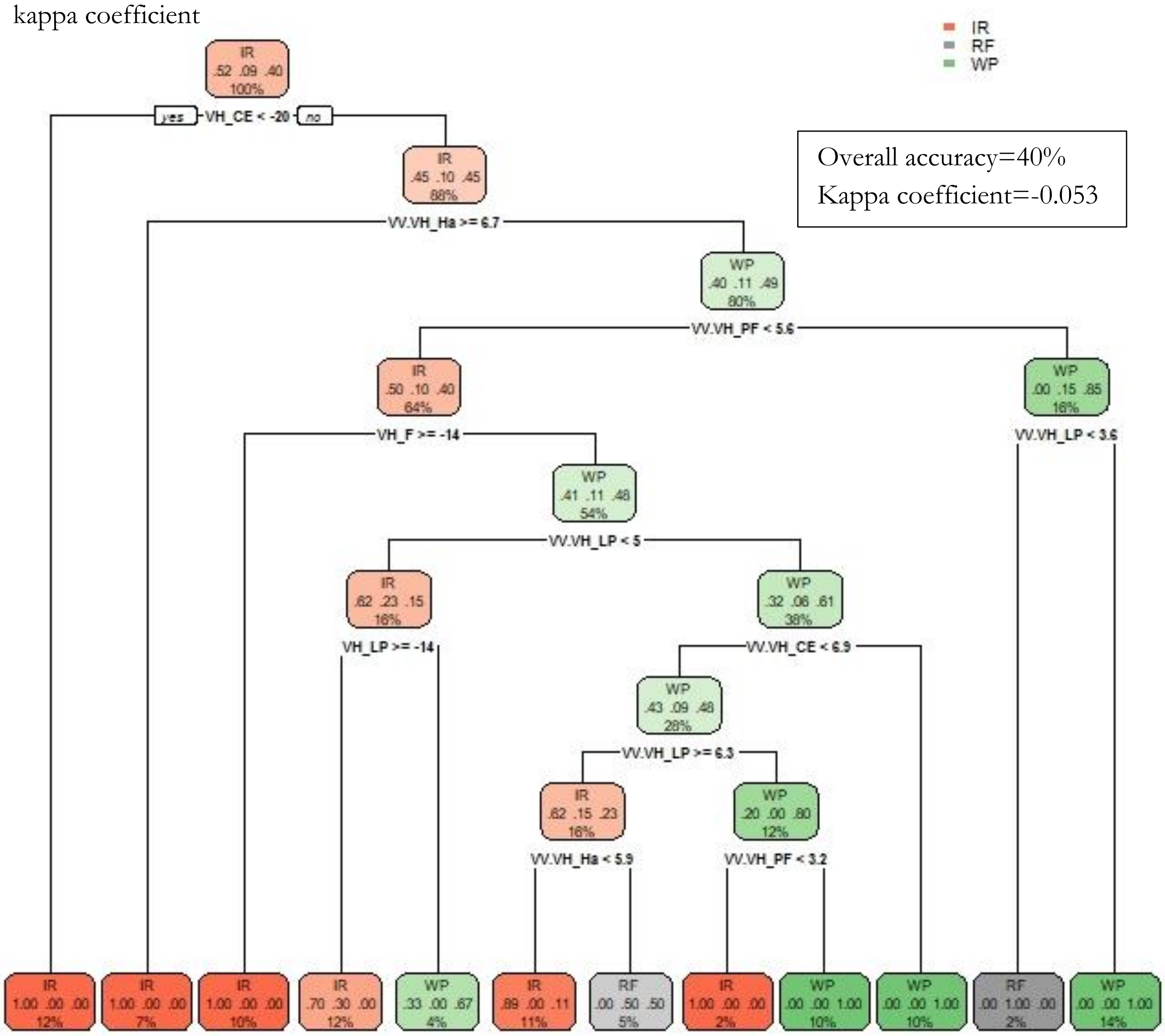


Overall accuracy = 57.14%
Kappa coefficient= 0.2468

b. Decision tree using rice growing events and stages of VV, VH and VV-VH with its overall accuracy and kappa coefficient



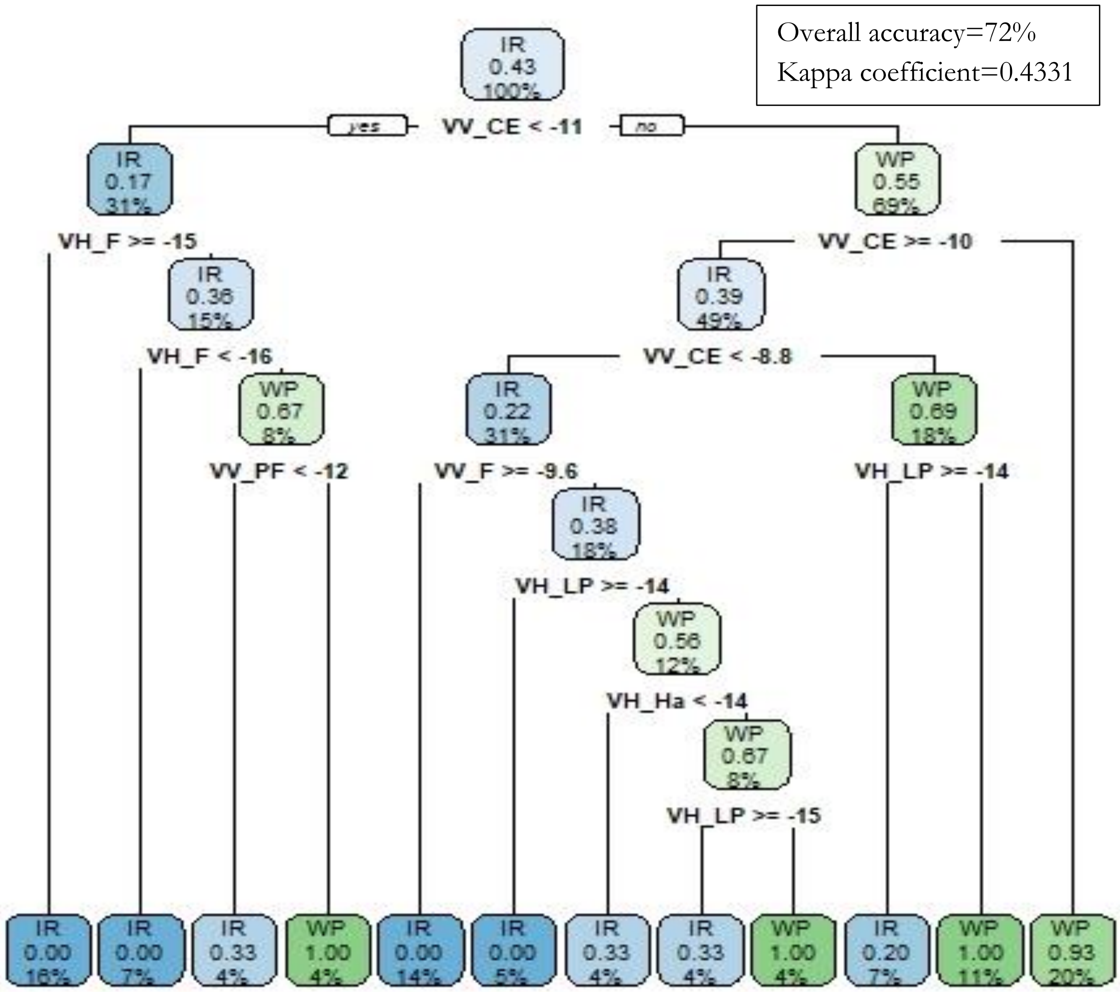
c. Decision tree using rice growing events and stages of VH and VV-VH with its overall accuracy and kappa coefficient



Appendix 6: Set of rules with different thresholds to distinguish rice fields with different water sources developed in the decision tree. The colour matches with the colour in the decision tree shown in Figure 20 and represent their classes

Rice water sources	Rules with thresholds	Probability
IR	VH_CE <-20= IR (100%)	1
	VH_CE>=-20, VH<-14, VV_CE>=-12, VV_CE>=-10, VH_CE<-16	0.88
	VH_CE>=-20, VH>=-14, VV_LP>=-10, VV_CE>=-12, VV_F<-9.4	0.84
	VH_CE>=-20, VH<-14, VV_CE<-12	0.71
	VH_CE>=-20, VH<-14, VV_CE>=-12, VV_CE>=-10, VH_CE>=-16, VV_CE<-9.8	0.5
WP	VH_CE>=-20, VH>=-14, VV_LP>=-10, VV_CE<-12	1
	VH_CE>=-20, VH<-14, VV_CE>=-12, VV_CE<-10	1
	VH_CE>=-20, VH<-14, VV_CE>=-12, VV_CE>=-10, VH_CE>=-16, VV_CE>=-9.8	0.92
	VH_CE>=-20, VH>=-14, VV_LP>=-10, VV_CE>=-12, VV_F>-9.4	0.67
RF	VH_CE>=-20, VH>=-14, VV_LP<-10	1

Appendix 7: Decision tree to classify IR and WP rice fields only with its overall accuracy and kappa coefficient



Overall accuracy=72%
Kappa coefficient=0.4331

Appendix 8: Pictures taken during field visit