Synthetic Aperture Radar (SAR)-based paddy rice monitoring system: Development and application in key rice producing areas in Tropical Asia

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Abstract. Reliable and regular rice information is essential part of many countries’ national accounting process but the existing system may not be sufficient to meet the information demand in the context of food security and policy. Synthetic Aperture Radar (SAR) imagery is highly suitable for detecting lowland paddy rice, especially in tropical region where pervasive cloud cover in the rainy seasons limits the use of optical imagery. This study uses multi-temporal X-band and C-band SAR imagery, automated image processing, rule-based classification and field observations to classify rice in multiple locations across Tropical Asia and assimilate the information into ORYZA Crop Growth Simulation model (CGSM) to generate high resolution yield maps. The resulting cultivated rice area maps had classification accuracies above 85% and yield estimates were within 81-93% agreement against district level reported yields. The study sites capture much of the diversity in water management, crop establishment and rice maturity durations and the study demonstrates the feasibility of rice detection, yield monitoring, and damage assessment in case of climate disaster at national and supra-national scales using multi-temporal SAR imagery combined with CGSM and automated methods.

1. Introduction
Rice is a pivotal political commodity in many Asian countries with its price often serves as a key indicator for government performance [1]. It is therefore crucial for policymakers to control rice trade flow for domestic rice market to be stable. Reliable and regularly available sub-national information on rice area, seasonality, and yield is an essential part of many countries’ national accounting process but existing system may not be sufficient to meet the information demand in the context of food security and policy [4,5]. Nevertheless, this same information is the basis of policy decisions related to imports, exports and prices, which directly impact food security, especially amongst the poor [6–8].

Remote sensing technology offers scalable and unbiased estimates of rice area to support, augment, and complement the existing system based on survey and statistical methods [5]. However, the following are technical challenges for the development of national-scale, operational, remote sensing-based rice crop monitoring systems in tropical monsoon Asia, region where 70% of rice is being produced: (i) Cloud-cover is extensive and pervasive during key rice growing season in this region [10,11], (ii) Wide range of conditions and environment where rice is grown in this region [1,10], (iii) rice cultivation in this region is mainly associated with small holders with relatively small cultivated paddy rice area (< 2
Diverse and complicated cropping calendar practices exist and often a very short distance from field to field in this geography due to all-year suitable growing temperature [1, 13]. The issue of cloud obstruction (i) can be addressed by using Synthetic Aperture Radar (SAR) imagery and the suitability of SAR for rice area mapping have been well documented [14–24]. Optical images, even with multi-temporal compositing, are still unreliable given many consecutive days or weeks data can be unusable due to cloud cover, which is particularly problematic for algorithms that rely on the detection of agronomic flooding at the start of rice growing season [4, 9]. The wide geographic distribution of rice across Asia (i) necessitates wall-to-wall coverage to adequately capture the 144 million hectares [2] of rice area and suggests that automated or low-level supervised processing is required to do this. Automated processing would also be suited to low-cost cloud computing platforms and low-level operator supervision, which could offset the common bottlenecks of infrastructure, bandwidth and human capacity in emerging economies. The wide range of practices and environments (ii) means that rice detection algorithms should be generalizable and robust [9]. Such methods should show high skill for irrigated and rainfed rice, for short (90 day), medium (120 day) and long (150 day+) rice growth duration [1] and for different establishment practices such as direct seeding or transplanting. The spatial complexity (iii) of rice environments requires high-resolution imagery and the temporal complexity (iv) requires high-frequency acquisitions across many months of the year.

Remote-sensing requirements are non-trivial and they go some way towards explaining the dearth of operational rice crop monitoring systems. However, recent launches of Sentinel-1 mission by the European Space Agency (ESA) with SAR carrying sensors together with the state-of-the-art automated processing can provide sustainable solutions to this challenge to map and monitor one of the world’s most important crops.

It is clear from the literature [14–24] that multi-temporal SAR data can be used to detect and map rice fields. However, most of these studies have focused on a limited number of observation locations per study and few studies can test the robustness of rice detection algorithms under different conditions. Varietal choice, crop establishment methods and crop management practices can have a significant effect on the structure of both plant and canopy, the duration and growth rate of the plant and water content. This contextual information on the characteristics of different rice cropping systems must be considered in the development of a robust rice detection algorithm for application over diverse rice environments.

This paper highlights recent initiative from the RIICE project – Remote Sensing-based Information and Insurance for Crops in Emerging economies to involve larger number of study sites (at least 13 sites x 2 seasons within phase 1 and 4 sites x 3 seasons within phase 2) and covers a larger total area (4.78 m ha in phase 1 and 17 m ha in phase 2) than any previous assessment of SAR-based remote sensing for rice mapping. In addition in this project the rice area, seasonality, and SAR back-scatter is coupled to crop model in order to also generate high resolution yield maps. Thus, it is a timely contribution to the literature on the use of SAR for national and sub-national mapping of rice in Asia for food security applications.

2. Methodology

The RIICE project – Remote Sensing-based Information and Insurance for Crops in Emerging economies – tested SAR-based rice monitoring across six countries (India, Thailand, Cambodia, Vietnam, Indonesia and the Philippines) between late 2012 and early 2014 (figure 1). These countries account for 51.5% of the world’s rice area and 45.9% of production, and include both rice net exporters (Thailand, Vietnam, India and Cambodia) and rice net importers (Indonesia and the Philippines) [2]. Beginning from 2015, the project embarked in effort to upscale the SAR-based rice monitoring toward national/sub-national scale in Vietnam, Cambodia, Thailand, and Tamil Nadu, India (figure 1). This international collaborative effort used multi-temporal X-band (phase 1) and C-Band (phase 2) SAR data, semi-automated processing chains, in-season field monitoring, end-of-season validation points to map rice crops across the target areas.
Figure 1. Study sites of the RIICE project during phase 1 and 2 across South and South East Asian Countries.

SAR-based paddy rice monitoring system deploys two core software: MAPscape-RICE and ORYZA Crop Growth Simulation Model (CGSM) [25] and involves SAR image acquisition, integration of SAR data into ORYZA, and generation of yield map (figure 2). MAPscape-RICE processes the SAR data into terrain-geocoded images (backscatter $\sigma^0$ values) to produce the rice area estimates, start of season (SoS), phenological field status, and LAI. LAI values at approximately 33% maturity of the rice variety together with the SoS product are inferred from radar backscatter using cloud vegetation model with parameters calibrated with in situ LAI measurements. ORYZA uses daily weather, management practices, and crop and soil characteristics to estimate rice yield at 14% moisture content. Rice Yield Estimation System (Rice-YES) interfaces the assimilation process of SAR products (SoS and LAI) into the ORYZA crop growth model and facilitate provision of all the necessary inputs for the crop model.

Description of the processing chains to generate rice area using MAPScape-RICE has been previously documented in detailed [26]. Methodology description in this paper is therefore more focused toward complementary modules such as the yield modeling component. Likewise, readers should review previous publication [26] for detailed descriptions the study sites and the SAR data used in the RIICE project phase 1.

In order to consider soil nitrogen dynamic processes, the CGSM uses soil data (https://sites.google.com/a/irri.org/oryza2000/) extracted from the World Inventory of Soil Emission potential (WISE) dataset (http://www.icasa.net/toolkit/wise.htm) and Harmonized World Soil Database (HWSD) (http://webarchive.iasa.ac.at). Some assumptions on puddling effect on physical soil properties have been made. Daily solar radiation data are obtained from NASA Power dataset (http://power.larc.nasa.gov). Daily min and max temperature are obtained by interpolation of weather station data (http://www.ncdc.noaa.gov) using Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) (http://www2.jpl.nasa.gov/srtm/) whereas daily rainfall were obtained from Tropical Rainfall Measurement Mission (http://trmm.gsfc.nasa.gov) until 2014 and from Climate Hazards Group Infra-Red Precipitation with Station data (CHIRPS) starting from 2015. The weather data were set at 15-arc minutes resolution and local data obtained from the National collaborators were also used whenever available.
The yield simulations account for water and nitrogen dynamics based on climatic, soil conditions and management rice practices. Irrigation and nitrogen fertilizer inputs are assumed as recommended for achieving attainable yield. Leaf Area Index (LAI) values at early leaf expansion stage (at 33% of rice maturity progress, roughly 40 days after start of season for 110 days rice) are inferred from radar backscatter using water cloud vegetation model [27] with parameters calibrated with in situ LAI measurements. Inferred LAI are finally used to calibrate the relative leaf growth rates parameters in ORYZA (figure 3).

LAI values at each simulation pixel were grouped in several classes prior to running the CGSM in order to attain processing efficiency while maintaining high resolution of the output (same resolution of the SAR data being used) (figure 4). Post simulation, the yield results were remapped using the look up table containing geo-reference information of the original pixel classified according to the LAI values and in combination with SoS and weather data grid information.

3. Results
Figure 5 shows rice area maps derived from multi-temporal X-band SAR imagery during RIICE phase 1 in the Philippines, Indonesia, India, Cambodia, and Thailand. Summary of the related validation results is shown in table 1. Cosmo-SkyMed (CSK) Stripmap 3m resolution were the source SAR data for all of these maps except for in central Luzon, Philippines (TerraSAR-X, TSX Scansar 10m resolution) and Sivaganga, India (TSX Stripmap 3m resolution), and Central Plain Thailand (CSK Scansar 15m resolution). All of these sites were observed during the wet/monsoon season.

Rice map validation was conducted for each Area of Interest (AOI), led by the national partners given their local knowledge and easy access to the monitored areas. A rapid land-cover appraisal method has been adopted whereby partners travel through the footprint and collect GPS coordinates, photos and land-cover descriptions (and, when necessary, farmer interviews), with a good spatial coverage for approximate 50%-50% distribution across rice and non-rice areas (figure 6).
\[
\sigma^\circ_{N} = \sigma^\circ - \frac{14}{\text{SoS}}
\]

\[
\sigma^\circ_{NF} = S \left( \frac{\sigma^\circ_{N} + 14}{\sigma^\circ_{NVMX} + 14} \right) - 14
\]

\[
\text{LAI}_{EES} = B + A \left( \ln \left( \frac{10^{0.1\sigma^\circ_{NF,EES} - \alpha \cos \theta}}{\sigma^\circ_{BG}} \right) \cos \theta / 2 \beta \right)
\]

\[
\sigma^\circ_{NF,EES} \begin{cases} 
= \sigma^\circ_{NF,1}, & \text{if } i \text{ is within } \pm 2 \text{ days of EES date} \\
= \text{linear interpolated } \sigma^\circ_{NF} \text{ between } i < \text{EES and } i > \text{EES} 
\end{cases}
\]

\[
\sigma^\circ_{UT} = -8.5 \text{ (for vv polarization), } -9.2 \text{ (for vh polarization); } S = 5.5 \text{ (for vv polarization), } 4.8 \text{ (for vh polarization); } \sigma^\circ = \text{SAR backscatter; } \sigma^\circ_{N} = \text{Normalized SAR backscatter; } \sigma^\circ_{\text{SoS}} = \text{Normalized SAR backscatter at the start of season; } \sigma^\circ_{\text{NVMX}} = \text{Maximum value of normalized SAR backscatter during early vegetative phase, approximately SoS + 4 SAR S1A acquisition dates (12 days interval); } \sigma^\circ_{UT} = \text{Upper threshold value for normalized SAR backscatter during early vegetative phase; } \sigma^\circ_{NF} = \text{Normalized and filtered SAR backscatter for LAI calculation using vegetation cloud model; } \sigma^\circ_{NF,EES} = \text{Normalized and filtered SAR backscatter for LAI calculation using vegetation cloud model at the early expansion stage; } S = \text{parameter for filtering SAR backscatter values for LAI calculation using vegetation cloud model; } \text{SoS} = \text{Start of season (day of year); } \text{EES} = \text{Early leaf expansion stage (day of year); } \text{EED} = \text{Duration to early expansion stage (days after start of season); } \text{MTD} = \text{Rice variety maturity duration (days); } A, B, C = \text{vegetation cloud model parameters: plant height & moisture parameters (Shen et al., 2009); } \alpha = \text{vegetation cloud model parameter: backscattering coefficient at full canopy closure (m}^2 \text{m}^{-2}); \beta = \text{vegetation cloud model parameter: coefficient of attenuation per unit canopy water (m}^2 \text{kg}^{-1}); \theta = \text{incident angle of radar beam (°); } \sigma^\circ_{BG} = \text{vegetation cloud model parameter: backscattering from canopy background (m}^2 \text{m}^{-2}).
\]

**Figure 3.** Process diagram for conversion of multi-temporal backscatter into LAI at early expansion state as implemented in the SAR-based paddy rice monitoring system.
Figure 4. Key processing steps to allow efficient & effective yield map generation in the SAR-based rice monitoring system. MAPscape-RICE communicates back and forth with ORYZA and Rice-YES to ultimately generate yield raster. Programmatically LAI & SoS outputs are deconstructed from the raster forms into combination values of LAI x SoS x Weather pixel ID (thick gray arrows) with LAI grouped into several classes. This allows a more efficient processing of yield by running ORYZA only for unique combination of LAI x SoS x WeatherID whereas running yield simulation is avoided for pixels with near identical LAI values and that belongs to the same SoS and Weather ID. The simulation results can then remapped using the Look Up table approach since every pixel were marked (LUTID) prior to deconstruction process. The resulting outputs are simulated yield results (raster) at the same resolution of the backscatter & SoS inputs with relatively efficient processing requirement.

Table 3 shows a summary of the validation data, rice area and rice classification accuracy. Accuracy assessments in the field were generally conducted in-season, in the reproductive or ripening stage before harvesting, but in some cases the field assessment was conducted post-season and rice stubble and farmer surveys were used to confirm that the observed post-harvest situation reflected the presence of a rice crop during the monitored season.

The total classified rice area across these sites is more than 1.6 million hectares but the proportion of the footprint area that was classified as rice varied from 8% to 94% across footprints. The overall classification accuracy was consistently high (86% to 95%). There is no relationship between the classification accuracy and either the rice area or the proportion of the footprint classified as rice. Large, homogeneous and landscape-dominating rice areas and small, fragmented, heterogeneous rice areas are all classified equally well.
Although the classifier can properly detect most rice areas, some land-cover types can cause misclassifications. Wetland or seasonal water bodies that are subjected to drying followed by sudden vegetation growth can contribute significantly to an increase in commission errors. This behaviour is observed for some rivers that drain very quickly and also for water tanks used to store irrigation water (Sivaganga, for example). The temporal signature of this land cover is similar to the typical rice signature, and, if the timing of the event corresponds to the known rice crop calendar, then the discrimination of rice is extremely challenging. One solution is to use multi-temporal SAR or optical images acquired in suitable periods – often outside the rice-growing season – to develop such a mask. In some cases, but this depends on the rice environmental conditions, the use of additional polarizations or the combination of different frequencies (for instance, C- and L-band as shown in [28]) may help in the exclusion of some non-rice areas.

Many of the omission errors were associated with a lack of correspondence between the observed rice crop calendar in isolated areas within the footprint and the acquisition period. This is particularly problematic when rice is sown early with respect to the average crop calendar since the signature does not include the critical land preparation/agronomic flooding, which is the foundation of rice detection. A further problem relates to extremely short-duration varieties, around 90 days, which are transplanted as 15- or 20-day-old seedlings. This means that the remaining vegetative stage in which biomass increases substantially is of very short duration and can be hard to detect, especially if there are cancellations during that time of the season.

Rice classification accuracy was maintained above 85% for the mapping activities using Sentinel S1A data (C-band, 20m resolution) starting from phase 2 of the RIICE project. An example of this is shown by the nation-wide rice area map for the 2015/16 dry season (recession rice) in Cambodia (figure 7) with rice classification accuracy at 87%. Correspondingly, the SAR-based yield estimates were at 93% agreement against reported yield data at district level as evaluated in four southern Cambodian provinces of Kandal, Svay Rieng, Prey Veng, and Takeo.

![Rice area maps generated during the RIICE project phase 1. Rice is green, early/late rice is orange. See previous publication for more detailed version of these maps.](image-url)
Table 3. Summary of accuracy assessments of the rice map outputs of RIICE project phase 1.

| Site                      | Season | Period       | Establishment | Maturity (days) | Water source   | Rice area (ha) | Accuracy |
|---------------------------|--------|--------------|---------------|-----------------|----------------|----------------|----------|
| Cambodia, Takeo           | Dry    | Oct to Apr   | Direct seeding (DS) | 95              | Irrigated (IR) | 150,026        | 85%      |
| Philippines, Leyte East   | Wet    | May to Sep   | Transplanting (TP)  | 114             | IR             | 17,817         | 87%      |
| Philippines, Leyte West   | Wet    | May to Sep   | TP             | 110-112         | IR             | 15,229         | 89%      |
| Philippines, A. del Norte | Dry    | May to Oct   | TP & DS        | 107-123         | IR & some rainfed (RF) | 13,163       | 89%      |
| Philippines, Nueva Ecija  | Wet    | Jun to Sep   | TP & DS        | 95-120          | IR             | 424,801        | 86%      |
| Vietnam, Soc Trang        | Summer | Jul to Sep   | TP & DS        | 125-134         | IR             | 55,216         | 87%      |
| Vietnam, Nam Dinh         | Wet    | Nov to Apr   | TP             | 115-135         | IR             | 64,533         | 95%      |
| Indonesia, Subang         | Samba  | Jul to Jan   | TP             | 130-160         | IR             | 26,015         | 92%      |
| India, Cuddalore          | Samba  | Aug to Dec   | TP & DS        | 135-160         | IR             | 83,871         | 91%      |
| India, Thanjavur          | Samba  | Sep to Jan   | TP & DS        | 100-110         | Semi-dry rice  | 41,825         | 87%      |
| Thailand, Muang Yang      | Wet    | May to Nov   | DS             | 150-175         | RF             | 91,908         | 96%      |
| Thailand, Suphan Buri     | Wet    | Jun to Oct   | DS             | 92-120          | IR             | 555,317        | 87%      |

| Site                      | Season | Period       | Establishment | Maturity (days) | Water source   | Rice area (ha) | Accuracy |
|---------------------------|--------|--------------|---------------|-----------------|----------------|----------------|----------|
| Dry – 2                   | DS – 7 | 92-178       | IR – 12       | 1.65M ha        | 85-95 %        |
| Wet – 11                  | TP – 10| 92-178       | RF – 3        |                 |                |                |

![RIICE rice area (ha) | Rice area accuracy](64533 97%)

Figure 6. Rice area map for 2013/14 Wet Season in Subang Indonesia with validation points for assessing rice area map accuracy. The validation exercise involves ground verification of rice and non-rice of at least 50 points each.
While maintaining rice area classification accuracy above 85%, the SAR-based monitoring system can effectively capture complexity in paddy rice cropping calendar such as the case in Mekong River Delta, Vietnam (figure 8). In this example, paddy rice start of season in An Giang and Dong Thap provinces were characterized with relatively long span of start of season from April to September 2016 with difference between field to fields even within a short distance. The map showed the general trend of relatively earlier rice season start in Dong Thap as compared to An Giang an expression of difference in irrigation water release in the area.

Responding to climate-induced disaster such as typhoon landing in the study area, the RIICE project monitored the extent of resulting floods using the SAR data. An example of this activity is shown in Figure 9. Tropical Storm Mirinae passed through the Red River Delta, Vietnam from 27 July 2016, 18UTC to July 28, 2016, 09UTC. Flood detection involved comparison of SAR images before and after the typhoon event (figure 9 bottom panel). The estimated total flooded areas are 8,256 ha where 1,007 ha represented as flooded rice area. The area affected by flooding from this storm was relatively minor as detected on 1 August 2016 (4 days after the flood event). It is suggested therefore that rice cultivation in Red River Delta was spared from major damage from this tropical storm. Ground monitoring further confirmed that the extent of the flooding was relatively minor and the impact on the rice (at vegetative stage by the time the storm passed the area) was rather insignificant as flooding duration for the affected area was less than 2 days.

Figure 7. Rice area and yield maps for 2015/16 dry season (recession rice) in Cambodia generated during the phase 2 using SAR Sentinel-1 data. Accuracy of rice area classification is 87%. Yield estimates were at 93% agreement against official yield data at district level.
Yield estimate maps derived from C-band SAR data from Sentinel 1A for Mekong River Delta (2014/15 Winter-Spring season) and Red River Delta (2015 Summer season), Vietnam, Suphan Buri, Thailand (2015 Wet/Major season), Cauvery Delta, Tamil Nadu India (2014/15 Samba season), and Southern provinces of Cambodia (2015 Early Wet season) are shown in Figure 10. The map provided assessment of spatial distribution of yield and can be potentially used to target where interventions may be provided. Across these study sites, in these particular seasons paddy rice yield ranged from less than 2.0 t/ha to greater than 6.0 t/ha.

Quality assessment of SAR-based yield estimate results is summarized in table 4 with simulated yields were compared against reported yield at district level from the government source. Aggregated SAR-based yield estimates at district level were within 81 to 93% agreement against official yield statistics. With such reasonable agreement level, this remote sensing-based rice yield monitoring system offers comparative advantage of providing: (i) timely yield information soon after the end of season and even before the season completed as yield forecast, (ii) high level of details (high resolution yield maps), and (ii) process-based yield information to allow further investigation for necessary interventions.

Figure 8. Start of Season (SoS) map for Autumn-Winter season in An Giang and Dong Thap, Mekong River Delta, Vietnam.
**Figure 9.** Assessment of flood damage in Red River Delta, Vietnam, responding to the typhoon Mirinae entering the study area on Jul 27-28, 2016.

### Table 4. SAR-based yield estimate results compared against reported yields for RIICE phase 1 & 2.

| Country or State* | Province or District* | Season | Period covered | Ecosystem | Source of SAR data | Modeled Yield | Reported Yield | Yield Agreement (%) |
|-------------------|-----------------------|--------|----------------|-----------|--------------------|---------------|------------------|---------------------|
| Philippines Leyte (East) | Wet | 2013 May to Oct | Irrigated | CSK | 5028 | 5620 | 84 |
| Philippines Leyte (West) | Dry | 2013 May to Oct | Irrigated | CSK | 3390 | 3485 | 91 |
| Philippines Leyte (West) | Wet | 2013 Dec to 2014 May | Irrigated | CSK | 3870 | 4135 | 91 |
| Philippines Nueva Ecija | Wet | 2014 May to Oct | Irrigated | CSK | 5478 | 5115 | 90 |
| Vietnam Soc Trang (Mekong River Delta) | Summer-Autumn | 2015 Jun to Oct | Irrigated | CSK | 5900 | 5359 | 90 |
| Vietnam Soc Trang (Mekong River Delta) | Summer-Autumn | 2014 Jun to Oct | Irrigated | CSK | 5478 | 5608 | 90 |
| Vietnam An Giang and Dong Thap (Mekong River Delta) | Wet | 2015 Oct to 2016 Apr | Irrigated | S1A | 7172 | 7365 | 86 |
| Vietnam Nam Dinh (Red River Delta) | Summer | 2015 Jul to Nov | Irrigated | CSK | 4818 | 4376 | 84 |
| Vietnam Nam Dinh (Red River Delta) | Summer | 2014 Jul to Nov | Irrigated | CSK | 4986 | 5170 | 88 |
| Vietnam Ninh Binh (Red River Delta) | Summer | 2013 Jul to Nov | Irrigated | S1A | 5273 | 5516 | 88 |
| Thailand Nakhon Ratchasima | Wet | 2013 May to Dec | Rainfed | CSK | 2748 | 2595 | 92 |
| Thailand Nakhon Ratchasima | Wet | 2014 May to Dec | Rainfed | CSK | 2628 | 2825 | 81 |
| Thailand Sepan Buri | Wet | 2015 May to Oct | Irrigated | CSK | 4964 | 4440 | 89 |
| Thailand Sepan Buri | Wet | 2014 May to Oct | Irrigated | CSK | 5086 | 4941 | 93 |
| Cambodia Takeo | Early Wet | 2014 Apr to Aug | Rainfed | CSK | 1750 | 1780 | 95 |
| Cambodia Takeo | Main Wet | 2014 Jun to Oct | Rainfed | CSK | 5304 | 5125 | 90 |
| Cambodia Kandal, Pov Yong, Sreay (Recession Rice) | Early Wet | 2015 Apr to Aug | Rainfed | S1A | 3395 | 3555 | 85 |
| Cambodia Kandal, Pov Yong, Sreay (Recession Rice) | Dry | 2015 Oct to 2016 Apr | Irrigated | S1A | 4490 | 4430 | 92 |

* Upper & lower administrative boundaries of interest for India
Figure 10. Yield estimates maps generated with SAR-based paddy rice monitoring system for (a) Mekong River Delta, Vietnam (2014/15 Winter-Spring), (b) Red River Delta, Vietnam (2016 Summer), (c) Suphan Buri, Thailand (2015 Wet/Major), (e) Tamil Nadu, India (Samba), and (e) Southern Cambodia (Early Wet).
4. Conclusions
The consistently high accuracy of the rice area classification across different rice environments and crop management practices demonstrates that the methodology is appropriate for rice detection across the most common rice agro-ecologies in Asia. The classification is based on a temporal analysis of the $\sigma^0$ signature, including a detection of agronomic flooding at the land preparation and/or seedling stage followed by a rapid increase in biomass relative to the duration of the vegetative stage of the varieties in the SAR footprint. The ground monitoring data are critical for the correct interpretation of the $\sigma^0$ signature, especially for the distinct differences between transplanting and direct-seeding crop establishment methods. It is also demonstrated that this SAR-based monitoring technology can provide reliable, timely, and detailed yield estimates and thus allowing potential necessary intervention and an effective tool to respond to climate related disaster such as typhoon-induce flooding that has potential negative impact on rice production.

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References
[1] GRiSP (Global Rice Science Partnership) 2013 Rice Almanac 4th ed. (Philippine: International Rice Research Institute) pp 283
[2] FAO FAOSTAT http://faostat3.fao.org/faostat-gateway/go/to/home/E (accessed Jun 1, 2014).
[3] Timmer C P 2010 Food Security in Asia and the Changing Role of Rice. The Asia Foundation. Occasional Paper 4
[4] Xiao X, Boles S, Frolking S, Li C, Babu J Y, Salas W, Moore B 2006 Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images Remote Sens. Environ. 100 95–113
[5] Gumma M K, Thenkabail P S, Maunahan A, Islam S, Nelson A 2014 Mapping seasonal rice cropland extent and area in the high cropping intensity environment of Bangladesh using MODIS 500m data for the year 2010. ISPRS J. Photogramm. Remote Sens. 91 98–113.
[6] Balagtas, J V, Bhandari H, Cabrera E R, Mohanty S, Hossain M 2014 Did the commodity price spike increase rural poverty? Evidence from a long-run panel in Bangladesh Agric. Econ. 45 303–312
[7] Mittal A 2009 The 2008 Food Price Crisis: Rethinking Food Security Policies (New York) pp 1–40.
[8] Dawe D, Timmer C P 2012 Why stable food prices are a good thing: Lessons from stabilizing rice prices in Asia. Glob. Food Sec. 1 127–133
[9] Boschetti M, Nutini F, Manfro G, Brivio P A, Nelson A 2014 Comparative analysis of
normalised difference spectral indices derived from MODIS for detecting surface water in flooded rice cropping systems \textit{PLoS One} 9 e88741

[10] Huke R E, Huke E H 1997 Rice area by type of culture: South, Southeast, and East Asia, A revised and updated data base p 32

[11] NASA Cloud Fraction (1 month Terra/MODIS) 1 FAO FAOSTAT http://faostat3.fao.org/faostat-gateway/go/to/home/E (accessed Jun 1, 2014)

[12] Pandey S, Byerlee D, Dawe D, Dobermann A, Mohanty S, Rozelle S, Hardy B editors. 2010 Rice in the Global Economy: Strategic Research and Policy Issues for Food Security p 477

[13] Nguyen T T H, De Bie C A J M, Ali A, Smaling E M A, Chu T H 2012 Mapping the irrigated rice cropping patterns of the Mekong delta, Vietnam, through hyper-temporal SPOT NDVI image analysis \textit{Int. J. Remote Sens.} 33 415–434

[14] Ulaby F T, Allen C T, Eger G, Kanemasu E 1984 Relating the microwave backscattering coefficient to leaf area index \textit{Remote Sens. Environ.} 14 113–133

[15] Le Toan T, Laur H 1988 \textit{Multitemporal and Dual Polarisation Observations of Agricultural Crops by X-band SAR Images} Proc. of the 1988 Int. Geoscience and Remote Sensing Symp. IGARSS ’88. Remote Sensing: Moving Toward the 21st Century International 3 1291–1294

[16] Inoue Y, Kurosu T, Maeno H, Uratsuka S, Kozu T, Dabrowska-Zielinska K, Qi J 2002 Season-long daily measurements of multifrequency (Ka, Ku, X, C, and L) and full-polarization backscatter signatures over paddy rice field and their relationship with biological variables \textit{Remote Sens. Environ.} 81 194–204

[17] Suga Y, Konishi T 2 October 2008 \textit{Rice crop monitoring using X, C and L band SAR data} Proc. SPIE 7104 Remote Sensing for Agriculture, Ecosystems, and Hydrology X,710410 doi:10.1117/12.800051

[18] Bouvet A, Le Toan T, Lam-Dao N 2009 \textit{Monitoring of the rice cropping system in the mekong delta using ENVISAT/ASAR dual polarization data} Geosci. Remote Sensing, IEEE Trans. 47 517–526

[19] Oh Y, Hong S Y, Kim Y, Hong J Y, Kim Y H 2009 \textit{Polarimetric Backscattering Coefficients of Flooded Rice Fields at L- and C-Bands: Measurements, Modeling, and Data Analysis} Geosci. Remote Sensing, IEEE Trans 47 2714–2721

[20] Kim Y H, Hong S Y, Lee Y H 2009 Estimation of paddy rice growth parameters using L, C, X-bands polarimetric scatterometer \textit{Korean J. Remote Sens.} 25 31–44

[21] Lopez-Sanchez J M, Ballester-Berman J D, Hajnsek I 2011 \textit{First results of rice monitoring practices in Spain by means of time series of TerraSAR-X Dual-Pol Images} Sel. Top. Appl. Earth Obs. Remote Sensing, IEEE J. 4 412–422

[22] Lopez-Sanchez J M, Cloude S R, Ballester-Berman J D 2012 \textit{Rice Phenology Monitoring by Means of SAR Polariometry at X-Band.} Geosci. Remote Sensing, IEEE Trans 50 2695–2709

[23] Inoue Y, Sakaiya E. 2013 \textit{Relationship between X-band backscattering coefficients from high-resolution satellite SAR and biophysical variables in paddy rice} Remote Sens. Lett. 4 288–295

[24] Inoue Y, Sakaiya E, Wang C 2014 \textit{Capability of C-band backscattering coefficients from high-resolution satellite SAR sensors to assess biophysical variables in paddy rice} Remote Sens. Environ. 140 257–266

[25] Bouman B A M, Kropff M J, Tuong T P, Wopereis M C S, Ten Berge H F M, van Laar H H 2011 \textit{ORYZA2000: modeling lowland rice} International Rice Research Institute, Los Baños, Laguna

[26] Nelson A, Setiyono T, Rala A B, Quicho E D, Ravis J V, Abonete P J, Maunahan A A, Garcia C A, Bhatti H Z M, Villano L S, Thongbai P, Holecz F, Barbieri M, Collivignarelli F, Gatti L, Quilang E J P, Mabalay M R O, Mabalot P E, Barroga M I, Bacong A P, Detoito N T, Berja G B, Varquez F, Wahyunto, Kuntjoro D, Murdiyati S R, Pazhanivelan S, Kannan P, Mary P C N, Subramanian E, Rakwatin P, Intrman A, Setapayak T, Lertma S, Minh V Q, Tuan V Q, Trinh D H, Nguyen Q H, Kham D V, Hin S, Vresas T, Yadav M, Chin C, Nguyen N H 2014
Toward an operational SAR-based rice monitoring system in Asia: Examples from 13 demonstration sites across Asia in the RIICE project. *Remote Sensing*. 6 10773-10812

[27] Attema E P W, Ulaby F T 1978 Vegetation modeled as a water cloud *Radio Science* 13 357-364.

[28] Holecz F, Barbieri M, Collivignarelli F, Gatti L, Nelson A, Setiyono T D, Boschetti M, Manfron G, Brivio P, Quilang E, Obico M, Minh V Q, Kieu D P, Huu Q N, Vtasna T, Intrman A, Wahyunto, Pazhanivelan S 2013 *An Operational Remote Sensing Based Services for Rice Production Estimation at National Scale* ESA Living Planet Symposium, Edinburgh