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Special Section:
Results from 10 Years of UAVSAR Observations

Key Points:
• Cropland inundation assessment has largely focused on open water
• Quad polarized L-band SAR can help detect under canopy inundation
• The underlying physical mechanisms driving scattering responses and machine learning algorithms had similar outcomes

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Rice Inundation Assessment Using Polarimetric UAVSAR Data

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Abstract
Irrigated rice requires intense water management under typical agronomic practices. Cost effective tools to improve the efficiency and assessment of water use is a key need for industry and resource managers to scale ecosystem services. In this research we advance model-based decomposition and machine learning to map inundated rice using time-series polarimetric, L-band Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR) observations. Simultaneous ground truth observations recorded water depth inundation during the 2019 crop season using instrumented fields across the study site in Arkansas, USA. A three-component model-based decomposition generated metrics representing surface-, double bounce-, and volume-scattering along with a shape factor, randomness factor, and the Radar Vegetation Index (RVI). These physically meaningful metrics characterized crop inundation status independent of growth stage including under dense canopy cover. Machine learning (ML) comparisons employed Random Forest (RF) using the UAVSAR derived parameters to identify cropland inundation status across the region. Outcomes show that RVI, proportion of the double-bounce within total scattering, and the relative comparison between the double-bounce and the volume scattering have moderate to strong mechanistic ability to identify rice inundation status with Overall Accuracy (OA) achieving 75%. The use of relative ratios further helped mitigate the impacts of far range incidence angles. The RF approach, which requires training data, achieved a higher OA and Kappa of 88% and 71%, respectively, when leveraging multiple SAR parameters. Thus, the combination of physical characterization and ML provides a powerful approach to retrieving cropland inundation under the canopy. The growth of polarimetric L-band availability should enhance cropland inundation metrics beyond open water that are required for tracking water quantity at field scale over large areas.

1. Introduction

Rice cultivation practices in the United States typically include managing irrigation water for inundated conditions. In the Arkansas Delta region, for example, rice fields can require 5–20 cm of inundation for seeding, with intermittent or continuous flooding during growth phases until drainage near harvest, and between rotations for wildfowl habitat or land maintenance (Reba et al., 2020). Irrigation practices, access to water, regulatory policies, and infrastructure vary across the Midsouth USA resulting in many unique combinations of landforms, irrigation regimes, and water sources. When using flood irrigation, producers have challenges managing and measuring water quantities at the field or paddy level. One well or well outlet can irrigate multiple fields, water is gravity-driven from field to field, underground pipe and plumbing infrastructure can use a combination of ground and surface water, and surface poly-pipe can move water from field to field. In Arkansas, total water use throughout the growing season can range from 382 mm on zero grade (fields without of slope) to 1,034 mm for contour levees (Smith et al., 2007). Regardless of the approach to irrigation, the ground water supply is depleting faster than recharge (Kresse et al., 2014), and public private partnerships are investigating tradeoffs across irrigation regimes, greenhouse gas emissions, water quantity, and management practices (Nalley et al., 2015; Reba et al., 2013; Reba & Massey, 2020). To scale these field experiments the science community and public and private sectors can benefit from synoptic, large area metrics on rice field inundation conditions.

Traditionally, optical satellite remote sensing tools have focused on identifying surface or open water conditions. These sensors and techniques struggle when postharvest residues are present or once crop emergence
begins to influence the signal (Torbick et al., 2011, 2017a, 2017b). Alternatively, active Synthetic Aperture Radar (SAR) technologies operate at longer wavelengths from 1 mm to 1 m. Microwaves penetrate deeper than optical wavelengths and SAR data are sensitive to the structure of vegetation canopies and targets; hence, inundation status under canopy cover can be assessed more effectively using SAR when compared to that of optical data (Torbick et al., 2017b). Full polarimetric SAR sensors transmit and receive pulses of microwave energy at two orthogonal polarizations, typically horizontal (H) and vertical (V) and retain the relative phase between these polarizations. With this configuration, the complex scattering matrix is captured. Polarimetric SAR modes provide a richer data set than single or dual polarization configurations, and show higher potential to extract underlying scattering mechanisms which relate to soil surface and crop structural information (Hosseini et al., 2019; McNairn et al., 2014).

The roughness characteristics of a target are a significant driver of SAR backscatter. Smooth water acts primarily as a forward specular target, producing little scattering of energy back to the sensor. Because of this unique scattering mechanism, SARs have been used extensively to detect surface water (Agnihotri et al., 2019; Ouled Sghaier et al., 2018; Tay et al., 2020). Vegetation canopies, in contrast, produce significant multiple scattering within the canopy and between the canopy of underlying surface. The combination of specular reflection from flooded targets, with diffuse scattering from crop canopies has proved useful in characterizing cropland hydroperiod or the timing, extent, frequency, and duration of paddy inundation (Torbick et al., 2017b). With open access and operational coverage, C-band Sentinel-1 A/B dual polarization data have been employed for rice field inundation assessment. For example, Stroppiana et al. (2019) applied a region-growing algorithm to detect flooded rice fields using VV Sentinel-1 sigma-naught backscatter, achieving an accuracy greater than 70% using optical data as the comparison. Wakabayashi et al. (2019) assessed Sentinel-1 backscatter expressed in gamma naught to reduce the impact of incidence angle. This research used a thresholding technique to detect flooded rice fields in Indonesia with very high accuracies of 98% reported. Thresholding was also applied by Agnihotri et al. (2019), leading to a high accuracy of 93% using the Modified Normalized Difference Water Index derived from Sentinel-2 optical imagery as the comparison measurement. Shen et al. (2019) developed an automatic flood extent detection algorithm for Sentinel-1 and reported an accuracy of 73% using the scattering matrix consisting of VV and VH polarizations. These studies focus on detecting surface or open water rather than water under the vegetative crop canopy. A developed crop canopy can impede penetration of C-band wavelengths (5.5 cm for Sentinel-1) and thus can be less effective for detecting canopy inundation. In addition, dual-polarization (VV-VH) modes are less rich in their characterization of scattering from inundated crop canopies (Huang et al., 2018a, Shin et al., 2020).

The use of longer L-band (23.5 cm) wavelengths, including data acquired by the Phased Array type L-band SAR (PALSAR), has shown some ability to map surface inundation with results depending on SAR configurations and techniques. For example, Ohki et al. (2019) were able to detect flooded extent using PALSAR-2 backscatter with a Kappa of 0.58. In addition to the backscattering intensity, interferometric SAR coherence has been explored for improved flood area detection. In the aftermath of Typhoon Hagibis in Japan, Natsuaki and Nagai (2020) were able to map flood extent using PALSAR-2 imagery to an OA of 80%. Grimaldi et al. (2020) developed a statistical method using probability binning and fuzzy logic to map the flooded status under vegetation cover using L-HH with an OA of 80%.

Generally, more restrictive data policies combined with less frequent repeat observations of polarimetric coverage has limited operational applications of fully polarimetric L-band (Torbick et al., 2017b). To move cropland inundation analysis beyond open water mapping and toward inundation assessment, the science community needs mechanistic, field scale techniques that can retrieve below crop inundation conditions. While a tremendous contribution to continuous monitoring requirements, the limitation of Sentinel-1 to single or dual polarization acquisitions limits the detection of undercanopy inundation. Longer wavelengths that can robustly retrieve underlying scattering mechanisms, such as double-bounce features derived from the Freeman-Durden decomposition (Brisco et al., 2013), are physically meaningful and have shown promise for detecting inundation. This decomposition splits scattering into three components: surface (or single) bounce, double-bounce, and volume scattering components. In this study, we advance model-based decomposition (Huang et al., 2015, 2018b) that generates additional shape and randomness factors. In addition, a machine learning method is trained to use the decomposed parameters for inundation status
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2. Methodology

2.1. Model-Based Decomposition Development

The three-component model-based decomposition was originally developed by Freeman and Durden (1998) with many enhancements over time (i.e., Yamaguchi et al., 2005; Huang et al., 2015). Scattering mechanisms over inundated rice fields are illustrated (Figure 1) to show how surface, double-bounce, and volume scattering compose a response. In this study, a version developed by Huang et al. (2015) that employs a more advanced volume scattering model integrating shape and randomness factors will be used with its framework written as,

\[ T_{33} = P_s \cdot T_s + P_d \cdot T_d + P_v \cdot T_v \quad (1) \]

in which \( T_{33} \) is the three-by-three coherency matrix, the \( P_s, P_d, \) and \( P_v \) terms represent the scattering intensity of the surface, double, and volume scattering components, while \( T_s, T_d, \) and \( T_v \) are the coherency matrices of the surface, double, and volume scattering, in which details of the \( T_s \) and \( T_d \) can be found in Huang et al. (2015).

A strategic enhancement is added in this research application building upon the volume scattering model used by Huang et al. (2015), in that the shape factor and randomness of the scatterer are considered in the volume scattering model (Huang et al., 2018a). The shape factor is defined as,

\[ \delta = \frac{S_{HH} - S_{VV}}{S_{HH} + S_{VV}} \quad (2) \]

When \( |\delta| = 1 \), it corresponds to dipole scattering, while \( |\delta| < 1 \) represents spherical and elliptical particles. In terms of \( |\delta| > 1 \), particles have the characteristics of randomly distributed double bounce scatterers, and when \( |\delta| \to \infty \), it represents the idealized double-bounce scattering. Following the same steps as presented by Huang et al. (2015), we construct the volume scattering model. The improved volume scattering model is written as,

\[ T_v(n, \delta) = \frac{1}{1 + |\delta|^2} \begin{bmatrix} T_{v11} & \delta T_{v12} & 0 \\ \delta T_{v12} & |\delta|^2 T_{v22} & 0 \\ 0 & 0 & |\delta|^2 T_{v33} \end{bmatrix} \quad (3) \]

where
The term $n$ is a randomness factor characterizing the probability distribution of the scatterer ranging from 0 to infinity. When $n = 0$, it represents the uniform distribution which is the Freeman volume scattering model (Freeman & Durden, 1998) and when $n = 1$, it is equal to the Yamaguchi volume scattering model (Yamaguchi et al., 2005). The shape factor $\delta$ is denoted by Equation 2. Therefore, the improved volume scattering model would be a generalized model to characterize the scattering from the canopy. To determine the contribution of the volume scattering, instead of the NonNegative Eigenvalue Decomposition (NNED) used by Huang et al. (2015), (2016), a complete decomposition is used to determine the volume scattering component by a generalized decomposition by Cui et al. (2013). In addition, the randomness factor $n$ is determined by minimizing the Radar Vegetation Index (RVI) derived from the UAVSAR data and the RVI from the improved volume scattering model (Huang et al., 2016). Next, the de-orientation process is performed to compensate the orientation angle induced by the azimuthal slope (Lee et al., 2002). Under the singular value decomposition (SVD), the surface and double-bounce scattering components are determined separately (Cui et al., 2013). The conceptual flowchart of the improved decomposition is shown in Figure 2.

### 2.2. Rice Inundation Mapping

We apply the updated model-based decomposition to the polarimetric airborne UAVSAR data for field inundation retrieval. This approach seeks to take advantage and strengthen the double bounce mechanism between underlying standing water and rice stems (Brisco et al., 2013). The decomposed parameters denoting the double bounce scattering will be applicable for the inundation status detection, which consists of the shape factor, randomness, RVI, and the double-bounce components. As the double-bounce effect increases, the shape factor will increase, randomness and RVI will decrease due to the decrease of scattering randomness, and thus the double-bounce power will increase. Since the double-bounce scattering power is largely influenced by the incidence angle, the percentage of the double-bounce scattering components and the comparison between the double-bounce power and the volume scattering components are used to help mitigate incidence angle impacts. The simple thresholding method using the double-bounce related parameters of shape factor, randomness factor, RVI, and the percentage of the double-bounce are illustrated first and written as,

\[
\begin{align*}
\text{par} \geq \text{thres} & \quad \text{inundated} \\
\text{par} < \text{thres} & \quad \text{noninundated}
\end{align*}
\]

in which $\text{par}$ denotes the decomposed parameters and $\text{thres}$ is the threshold, which will be determined by the histograms of the inundated and noninundated rice fields. A relative comparison between the double-bounce and the volume scattering is written as,

\[
\begin{align*}
P_d \geq P_v & \quad \text{inundated} \\
P_d < P_v & \quad \text{noninundated}
\end{align*}
\]

in which the relative comparison could reduce the incidence angle effect to some extent.

### 2.3. Machine Learning

We compare the physically meaningful decomposition to a popular machine learning technique. Here, we use the RF machine learning method...
from the improved volume scattering model (Huang et al., 2016). Next, the de-orientation process is determined by minimizing the Radar Vegetation Index (RVI) derived from the UAVSAR data and the RVI used by Huang et al. (2015), (2016), a complete decomposition is used to determine the volume scattering (Yamaguchi et al., 2005). The shape factor model (Freeman & Durden, 1998) and when \( n = 0 \) to infinity. When \( n \) pathres inundated \( P \) P noninundated \( P \) thres noninundated \( P \) thres inundated

The randomness factor characterizing the probability distribution of the scatterer ranging from 0 to infinity. When \( n \) is denoted by Equation (2). Therefore, the improved volume scattering will be applicable for the inundation status detection, which consists in which the relative comparison could reduce the incidence angle effect. The simple thresholding method using the double-bounce related parameters of shape factor, randomness factor, RVI, and the percentage of the double-bounce are illustrated help mitigate incidence angle impacts. The shape factor, randomness and RVI will decrease due to the decrease of scattering and the comparison between the double-bounce power and the volume scattering components are used to determine the volume scattering. The impact of wide incidence angle range (20–70° from near range to far range) is evidence in the azimuth direction at the near range. UAVSAR, Uninhabited Aerial Vehicle Synthetic Aperture Radar; RGB, red blue green.

Figure 3. (a) Study region with AM PM UAVSAR flights with (b)–(d) illustrations of AM on July 25, 2019 and PM on July 17, 2019 as RGB composite of double, volume, and surface scattering components. Visible is forest as green showing a dominant volume scattering while inundated crop regions show varying red tones denoting a strong double bounce due to the underlying standing water (b) and (c). The impact of wide incidence angle range (20–70° from near range to far range) is evidence in the azimuth direction at the near range. UAVSAR, Uninhabited Aerial Vehicle Synthetic Aperture Radar; RGB, red blue green.

(Breiman, 2001), which is an ensemble classifier and regressor that has grown in popularity the past several years due to its success in the crop classification and biophysical parameters prediction (Huang et al., 2019). For classification, a random forest obtains a class vote from each tree and then typically applications select a variable using the majority vote. RF applied here, uses Out-Of-Bag (OOB) error samples to customize the number of trees (Hastie et al., 2009). The Gini Index within RF was used to help characterize the influence of predictor variables. The index is a measure of node impurity used in classification regression trees for splitting nodes and pruning trees. In our study, the RF was set to 500 trees with the maximum features of the square root of the number of input features to avoid over fitting. We use the python sklearn package with version 0.23. Some of the meaningful decomposed parameters are then used as the input variables to generate inundation maps over the entire UAVSAR footprint over time.

3. UAVSAR Data, Study Site, and Ground Measurement

The airborne UAVSAR collects in the L-band (23 cm) microwave region and provides full polarimetry with incidence angle from 20° to 70° from the near to far range. The L-band SAR has a noise equivalent better than ~30 dB and produces single look resolution imagery with a resolution better than 2 m (Fore et al., 2015). Its range swath width is approximately 20 km, and it typically acquires data over hundreds of km in a single data-take. The SAR sensor is mounted on an aircraft capable of flying within a 10 m tube for the duration of a data-take, and has an antenna which is electronically steerable to compensate for aircraft yaw. Maximum flight duration is 6 h, and it flies at 41,000 ft to avoid other civilian air traffic. The study area is centered on England, Arkansas near the larger city of Stuttgart (Figure 3). A total of 13 UAVSAR time series observations (Figure 4a) were collected during the 2019 UAVSAR campaign over the southeastern USA. These flights consist of both AM (around 5:00 a.m. local central time) and PM (around 8:00 p.m. local central time) data to capture diurnal conditions. Processing of the full polarimetric UAVSAR data is performed using our custom software platform. The covariance matrix is converted to a three-by-three coherency matrix, followed by a multilook process with a window size of five to reduce the inherent speckle noise. Finally, the data are terrain geocoded to a nominal 30 m spatial resolution.
Major crops within the footprint include corn, rice and soybean with smaller patches of cotton, peanut, fallow, and winter wheat intermixed. The field measurements of the inundated water table depth above the ground are collected for nine rice fields, every half an hour. These measures are collected using pressure transducer water level sensors (CS451, Campbell Scientific, USA) recorded on a data-logger (CR300, Campbell Scientific, USA) positioned in a representative location in each field. Additionally, two stratified, random noninundation samples from corn and soybean fields near the rice fields were included to capture a diversity of major row crops and noninundated conditions.

Irrigated inundation can vary by field depending on soil type, hydrometeorological drivers, landforms, and infrastructure (i.e., pumps, availability of adjacent surface water, depth of subsurface aquifers). Management practices, which are tied to costs and production, vary in the footprint and influence timing of inundation. For example, a temporary inundation of water that is immediately drained (flushing) is used to help promote germination and/or foster plant emergence while typically, after rice reaches the appropriate size and age around day-32, a flood is established and maintained throughout the growing season until draining is necessary for harvesting. In select fields, intermittent dry downs were executed to gauge impacts on production and optimize environmental outcomes. In this effort, the ground measurements nearest to the UAVSAR acquisition time are adopted for consistency.

4. Results and Discussion

A current limitation in optimizing agricultural outcomes and irrigation management are systematic metrics of under canopy inundation at landscape scales. Quad polarization L-band is one tool that can advance physically meaningful indicators of inundation and the availability of L-band platforms continues to expand. In the near future, the National Aeronautics and Space Administration (NASA) will launch the NISAR (NASA Indian Space Research Organization SAR) Mission with operational and open access L-band
For brevity, we summarize the derived L-band SAR terms' ability to mechanistically distinguish inundation status and evaluate performance of a complementing machine learning approach.

### 4.1. Inundation Retrieval Using Scattering Parameters

Exploratory analysis from histograms in Figure 5 shows that the RVI, randomness factor, and proportion of the double-bounce component within the total scattering response are more useful for separating inundated rice fields compared to the other decomposed SAR parameters. Particularly, inundated rice fields have lower RVI with higher and more variable randomness. Physically these relationships are caused when double-bounce is a dominant scattering mechanism, which coincides with a decrease in scattering randomness as the RVI decreases. Further, since the randomness factor is negatively correlated to the RVI, randomness shows higher values when crop fields are inundated.

Other terms show more complex patterns. For example, the shape factor (i.e., sigma), indicates low ability to separate inundated from noninundated rice fields; however, some inundated fields show higher values between 1.5 and 2.0. The proportion of the double-bounce component within total scattering is strongest when it is less than 25%. Since the decomposed double-bounce scattering power is strongly influenced by the incidence angle, caution in interpretation of outcomes along higher, far range incidence angles should be considered. A misclassification caused by extreme incident angles is illustrated in Figure 5 where inundated and noninundated metrics for rice fields are less reliable. Furthermore, the temporal change of the double-bounce, RVI, and shape factor parameters as shown in Figure 6 demonstrates their ability to detect rice field inundation status at the early, middle, and late growth stages. Specifically, the double-bounce scattering (Pd) increases from the early to the middle growth stage due to the enhancement of the dou-
ble-bounce scattering caused by the wave interaction between the underlying standing water and the rice stems, then it decreases due to the field drainage at late growth stages. The RVI shows a decreasing trend from early to middle growth when the rice canopy is almost fully developed. This is due to the low scattering randomness caused by the dominant double scattering. Lastly, the shape factor tends to increase from the early to the middle growth stages when the field is inundated due to the double bounce, as explained in Section 2.1.

Given the exploratory outcomes of SAR parameter inundation detection, a series of confusion matrices were generated to quantify accuracy and retrieval. Here we highlight quad pol $L$-band parameters showing greater ability to distinguish crop field inundation, namely RVI, Randomness factor, and the proportion of the double-bounce scattering component. Thresholds were applied to RVI, Randomness factor, and proportion of double-bounce at 0.15%, 4.5%, and 25%, respectively, using the distributions illustrated in Figure 5. RVI and Randomness achieve a similar overall accuracy and Kappa with their values around 75% and 43%, respectively (Table 1). Physically, the RVI and Randomness show the opposite trend and both represent the scattering randomness, which is evident in their outcomes using accuracy metrics generated from the confusion matrices. This further substantiates that the RVI and Randomness factor are sensitive to similar scattering properties. Using the RVI, Table 1 depicts that there are still some inundated rice fields misclassified as noninundated rice fields with the PA around 56%, while the UA and PA of the noninundated rice fields are all greater than 65%. The OA and Kappa of the percentage of the double bounce scattering are around 67% and 30% respectively, showing a significant improvement compared with the individual double-bounce scattering power as shown in Table 1. However, some noninundated fields are misclassified as inundated rice with the UA of the inundated fields about 50%. In addition to the proportion of the double-bounce scattering, we compared the relative double-bounce and the volume scattering powers as a potential mitigation strategy to circumvent that impacts of incidence angle. This comparison performed well and showed a higher accuracy than using any individual SAR parameter for inundation retrieval. Both PA and UA of the inundated and noninundated are higher than 60% with OA at 75%.

Figure 6. Double bounce, RVI, and shape factor over rice fields (outlined in red) corresponding to the region in Figure 3d at the early, middle, and late growth stages showing the dynamics caused by the rice growth and inundation status. RVI: Radar Vegetation Index.
4.2. Inundation Mapping Using Machine Learning

As previously demonstrated, the RVI, Randomness, proportion of the double-bounce scattering, and the relative difference between the double-bounce scattering power and the volume scattering components, show high potential for generating accurate metrics of inundated and noninundated fields at landscape scales. Here, the tradeoff in using ML is the requirement of training data which might be landscape dependent. Using the ML approach, the OA and Kappa reached 88% and 71% respectively. It is noteworthy that parameters such as RVI, Randomness factor, and proportion of the double-bounce scattering show high PA (above 85%) for noninundated rice fields, while the relative difference between the double-bounce scattering of the surface and volume scattering show high UA (83%) for noninundated rice fields. Therefore, when combined, the ML approach provides a relatively robust and accurate set of inundation metrics across major crop types at landscape scales.

Since the decomposed surface, double-bounce, and volume scattering components are largely influenced by the incidence angle, instead of their absolute power, their percentages are used. The RVI, Shape factor, and the percentages of surface, double, and volume scattering components are used as the inputs for the training. Applying 500 trees to the random forest, the confusion matrix using the leave-one-out cross validation is listed in Table 2, which denotes that all the PA and UA of the noninundated status are around 80%. However there are still some inundated rice fields misclassified as noninundated rice fields with the PA around 75%. The OA and Kappa metrics are around 88% and 71%, respectively. These overall classification results demonstrate the potential of decomposition parameters, couple with a RF classifier, to map rice field inundation. This classification benefits from multiparameter inputs when compared to the single parameter.

### Table 1

|                      | Catalog         | Noninundated | Inundated | Total | UA (%) |
|----------------------|-----------------|--------------|-----------|-------|--------|
| RVI                  | Noninundated    | 8,552        | 2,225     | 10,777| 79.35  |
|                      | Inundated       | 1,486        | 2,825     | 4,311 | 65.53  |
|                      | Total           | 10,038       | 5,050     | 15,088|        |
| PA (%)               |                 |              |           |       |        |
| OA (%)               |                 |              |           |       |        |
| Kappa (%)            |                 |              |           |       |        |
| Randomness           | Noninundated    | 8,232        | 2092      | 10,324| 79.74  |
|                      | Inundated       | 1806         | 2,958     | 4,764 | 62.09  |
|                      | Total           | 10,038       | 5,050     | 15,088|        |
| PA (%)               |                 |              |           |       |        |
| OA (%)               |                 |              |           |       |        |
| Kappa (%)            |                 |              |           |       |        |
| Pd Percentage        | Noninundated    | 6,957        | 1929      | 8,886 | 78.29  |
|                      | Inundated       | 3,081        | 3,121     | 6,202 | 50.32  |
|                      | Total           | 10,038       | 5,050     | 15,088|        |
| PA (%)               |                 |              |           |       |        |
| OA (%)               |                 |              |           |       |        |
| Kappa (%)            |                 |              |           |       |        |
| Pd > Pv              | Noninundated    | 7,927        | 1,622     | 9,549 | 83.01  |
|                      | Inundated       | 2,111        | 3,428     | 5,539 | 61.89  |
|                      | Total           | 10,038       | 5,050     | 15,088|        |
| PA (%)               |                 |              |           |       |        |
| OA (%)               |                 |              |           |       |        |
| Kappa (%)            |                 |              |           |       |        |

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As previously demonstrated, the RVI, Randomness, proportion of the double-bounce scattering, and the relative difference between the double-bounce scattering power and the volume scattering components, show high potential for generating accurate metrics of inundated and noninundated fields at landscape scales. Here, the tradeoff in using ML is the requirement of training data which might be landscape dependent. Using the ML approach, the OA and Kappa reached 88% and 71% respectively. It is noteworthy that parameters such as RVI, Randomness factor, and proportion of the double-bounce scattering show high PA (above 85%) for noninundated rice fields, while the relative difference between the double-bounce scattering of the surface and volume scattering show high UA (83%) for noninundated rice fields. Therefore, when combined, the ML approach provides a relatively robust and accurate set of inundation metrics across major crop types at landscape scales.

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classification results documented in Section 4.1. When all of the data are used for training, the OOB score is around 0.9, showing a high generalization of the trained RF (Hastie et al., 2009). For further validation, we also compare it with the RF using the decomposed surface, double-bounce, and volume scattering components from the original Freeman decomposition under the same RF configurations with the proposed method. Its confusion matrix is also listed in Table 2, which depicts that the proposed method shows a substantial improvement with its OA and Kappa improved by 4% and 10% respectively. This is because the proposed method contains more information (i.e., polarimetric parameters) than that of the Freeman decomposition.

To gauge the ‘importance’ of each input parameter within the ML approach we use the gini index to provide insight on node purity (Figure 7). Here, the RVI and proportion of the double-bounce scattering have higher ‘importance’ compared to surface and volume scattering. This finding helps demonstrate that these SAR terms possess the strongest mechanistic ability to distinguish crop field inundation status independent of canopy cover or growth stage.

### 4.3. Space-Time Patterns

As the availability of \( L \)-band observations continues to expand, the science community is developing landscape scale space-time metrics of under canopy inundation. The percentages of the inundated rice fields across the UAVSAR space-time domain are plotted for three metrics, the RVI and \( P_d > P_v \) responses, and the RF classification output (Figure 8). While each metric is derived using a different approach, the temporal patterns track inundation similarly over time for our test sites (Figure 4b). At the early growth stages, few rice fields are inundated during the period of planting. As rice canopies develop the number of fields flooded increases, with the number of inundated fields peaking later in the growing season. At this point, the RF classifies around 80% of rice fields as inundated. At the late growth stage, rice managers begin to drain fields resulting in a dramatic decrease in the percentage rice fields inundated.

Map examples of the inundated fields including rice and other crop fields are shown in Figure 9. The 2019 United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) Crop Data Layer
By June, approximately 40% of rice fields have undergone inundation from a range of management practices and landforms. By July and into August, many rice fields underwent inundation, which is consistent with anecdotal knowledge of practices in the region. Approaching harvest, metrics show nearly all fields were drained for management purposes. In the middle of the rice growing season, over the regions corresponding to Figure 3d, the detected inundated rice fields that are shown in Figure 10 are easily discriminated from fields not inundated, and are consistent with the Real time Ground photos are retrieved from https://phenocam.sr.unh.edu/webcam/sites/humnok-ericec/. In addition, the rice fields boundaries are also well preserved. Of note, however, this approach was unable to detect differences between managed floods and rainfall-induced inundation. Developing a time series that is relevant to the duration, magnitude, and frequency of field activity is a longer-term need. For example, at NiSAR 12-days repeat intervals or if an overpass happens to occur shortly after a heavy rain event with pooling on zero grade fields, this approach might miss a dry down event or mischaracterize the driver of inundation status. Potentially, ancillary data, such as hydrometeorology or farm field observations, might help mitigate this limitation.

We highlight many additional factors that potentially introduce noise, influence these spatio-temporal patterns, and impact the accuracy of the inundation retrievals. Irrigation practices such as Alternate Wetting and Drying (AWD), where producers intentionally dry down fields for different reasons (decrease water use, greenhouse gas emissions; Runkle et al., 2019; Lampayan et al., 2015) during strategic mid-season growth periods for specific temporal windows (7–10 days) are also influenced by hydrometeorological drivers. Further, in this crop year (2019) producers had some late planting due to widespread flooding in April (Yin et al., 2020). In the study area some farmers planted early April while others planted in mid-June (2½ month difference). These differences

Figure 8. Spatio-temporal comparison of percentage of rice fields that are inundated using three approaches across the UAVSAR space-time domain. Similar trends are observed with mechanistic use of the double-bounce and volume scattering components (Pd > Pv), RVI: Radar Vegetation Index (RVI) and Random Forest (RF) methods. UVSAR, Uninhabited Aerial Vehicle Synthetic Aperture Radar.

Figure 9. Examples of the inundation maps on June 06, July 25, and September 23 corresponding to the early, middle, and late rice growth stages. The bottom figure is the 2019 CDL map (a) and the percentage of the inundated fields over the overlapped region between the AM and PM data (b) showing the high percentage over the rice fields. For the red box, see text. CDL, crop data layer.
in the crop calendar need to be considered in the aggregate metrics for context. Producers who planted in mid-June may have fields that flood up in early or mid-July whereas the farmers that planted in April likely drained fields in early August. The crop calendar can therefore cause extensive spatio-temporal variability in the dates of flooding and draining. This variability also relates to overpass frequency and dates as a flyover might miss a management dry down event. Thus, the use of physically driven metrics and dependence of training data are factors to consider when scaling up.

5. Conclusion

This research investigated the ability of fully polarimetric time series L-band Synthetic Aperture Radar (SAR) to provide inundation metrics for rice, independent of growth stage. The parameters from an improved three component decomposition model were used with a Random Forest classifier to detect whether rice fields were inundated. The Radar Vegetation Index (RVI) and Randomness factor show a similar trend and ability to describe the inundation status, producing high detection accuracy. The shape factor (Sigma) and the absolute double-bounce scattering power were unable to accurately separate inundated rice fields from noninundated fields, likely because the double-bounce scattering power is impacted by changes in incidence angle across range. The proportion of the double-bounce scattering to total scattering and the double-bounce scattering to volume scattering ratio performed better with an Overall Accuracy (OA) and Kappa as high as 75% and 46%. Using multiple decomposition parameters with an RF machine learning method increased accuracies to OA and Kappa of approximately 88% and 71%, respectively, and the double-bounce scattering and radar vegetation indices such as RVI and Randomness factor play key role in the discrimination. The proposed method also outperforms the traditional Freeman decomposition in terms of the inundation detection. When plotted over time, the percentage of rice fields inundated as fields are

**Figure 10.** Detected temporal inundation regions corresponding to the area in Figure 3d using the RF method from the early to the end of growth stages, showing a high discrimination between the inundated rice fields and the noninundated reference fields (outlined in the red rectangular box) at the middle growth stages (July 25 and August 14) when the rice fields are inundated. Ground photos are received from https://phenocam.sr.unh.edu/webcam/sites/humnokericec/. RF, Random forest.
planted and canopies develop, was consistent with ground observations and local knowledge of rice management practices. Future research will tackle monitoring of irrigation of other crops such as corn, wheat, and soybean and inclusion of ancillary data to separate management driven from rainfed inundation. This research is crucial in the lead up to the launch on the L-Band NISAR mission, and will ready the agriculture community to exploit this important source of SAR data.

Data Availability Statement

The authors thank the JPL UAVSAR team for the UAVSAR data and collaborators to help collect the ground measurement data. Reproducible data are available free and open via https://uavsar.jpl.nasa.gov/. At this site, visitors can ‘search for data’ or ‘view deployments’. Under ‘search for data’ the use of the key word ‘NISAR’ will extract all relevant UAVSAR AMPM campaign data flights. Sites used in this effort include Arkansas-1 (NISARA_00,914, n = 27), Arkansas-2 (NISARA_06,800, n = 29), Tifton, GA (NISARA_22,802, n = 21), and Stoneville, MS (NISARA_27,900, n = 24). All flight dates are available and the dates used in this effort include the 2019 season (calendar months June to October). Available in the metadata are instrument (e.g., L-band), flight line ID, and searchable tags. Products available include all data used in this effort that are selectable by Simulated NISAR mode (a), (b), center frequency (1,243, 1,270, 1,253, 1263 MHz), bandwidth (20, 5, 40 MHz), and NISAR polarizations (HH, HV, VH, VV) with options for no dithering (this study), dithered with gaps, and dithered without gaps. Downloads include text annotation file, processing level (SLC), slant range, orthorectified, ancillary files, and additional format options (HDF5) along with all file sizes. KML are available for viewing geolocation and fetching using wget commands are available for automation.

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