# EARLY SEASON WINTER WHEAT IDENTIFICATION USING SENTINEL -1 SYNTHETIC APERTURE RADAR (SAR) AND OPTICAL DATA

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**ABSTRACT**

Early season crop identification is important for food security and economic stability. The USDA NASS uses optical data to provide acreage estimates, each June, to the NASS Agricultural Statistics Board. However, early season crop identification is difficult using optical data alone, because imagery is frequently cloudy during the spring. The purpose of this study is to determine whether using SAR and SAR texture can improve early season winter wheat identification compared to optical data alone. Study areas in the Missouri "Bootheel" (2017 growing season) and Northwest Texas (2018 growing season), United States (U.S.) are selected. The SAR data used in this study are Sentinel-1. Optical data include: Landsat 8, Disaster Monitoring Constellation, and Sentinel-2. Study results show that optical data with SAR achieved the highest winter wheat accuracies, 7.7% higher than optical data alone, in Missouri. Optical with SAR and SAR texture resulted in improved accuracies over optical alone, but only marginally, in Texas. These results indicate that optical and SAR, used together, can potentially improve early season crop identification.

***Index Terms***— Sentinel-1, Synthetic Aperture Radar, Agricultural land cover classification, SAR texture analysis

## 1. INTRODUCTION

Accurate early season crop identification is important to NASS to provide reliable supplemental acreage estimates to the NASS Agricultural Statistics Board. Currently, only multi-temporal optical data are used to produce winter wheat classifications and obtain subsequent crop area estimates.

Multi-temporal and multispectral remote sensing using optical data proved to be an effective approach to discriminate crop types [1-3]. However, the availability of optical data are sometimes limited due to clouds and insufficient to conduct a multi-temporal crop analysis with optical data alone. The analysis of optical and SAR data for crop mapping, particularly in areas with cloud cover, has been investigated in multiple studies [3-8].

Early season crop identification presents challenges when compared with full season assessments conducted in the U.S. To identify the winter wheat crop, it is useful to include both late fall (previous season) and spring imagery in the classification process. Fall images capture winter wheat "emergence" and spring acquisitions capture "heading". In many U.S. agricultural areas spring is the rainy season, which poses challenges for crop identification using optical data. SAR, however, can acquire useful data through clouds, rain and darkness. Moreover, the availability of the ground reference training data are limited early in the growing season.

The purpose of this study is to determine whether using optical data with Sentinel-1 SAR and SAR texture improves early winter wheat identification in the Missouri "Bootheel" and Northwest Texas. This paper includes: 1) a description of the study areas and data 2) the classification method based on a decision tree classifier, 3) an accuracy assessment for 17 test scenarios per study area, 4) test results with a discussion and 5) a conclusion.

## 2. STUDY AREAS AND DATA

### 2.1. Study Areas

The Missouri "Bootheel" (21,175 km$^2$) and a region in Northwest Texas, U.S. (19,309 km$^2$) (Fig. 1), are selected as study areas because they include large quantities of winter wheat, as well as, soybeans, corn, hay, cotton and rice.

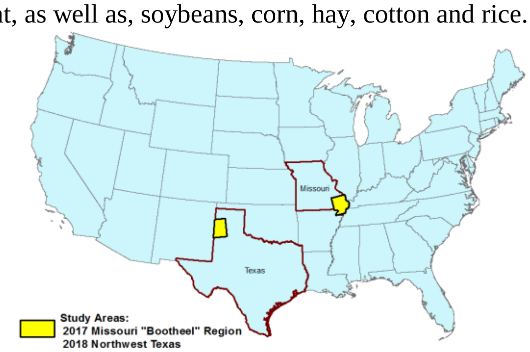


Fig. 1. Two study areas (highlighted in yellow) located in the Missouri "Bootheel" region and Northwestern Texas, U.S.

### 2.2. Sentinel-1 Synthetic Aperture Radar

The data used in this study include both SAR and optical. The SAR data are acquired from the European Space Agency (ESA) Sentinel-1 constellation which includes two polar-orbiting C-band SAR sensors (Sentinel-1A and Sentinel-1B). Sentinel-1 images have the following specifications: interferometric wide swath (250 km) Level-1 products that are detected, multi-looked and projected to ground range, 5x20 meter spatial resolution and dual polarization (VV and VH). SAR images used in the Missouri (2017) assessment were acquired on October 24 and November 17, 2016 and April 22, May 4, May 16 and May 28, 2017. SAR images used in the Texas (2018) assessment were acquired on November 6, November 18 and December 12, 2017 and March 30, April 11, April 23, May 5, May 17, May 29 and June 10, 2018.

Texture features are derived from SAR data and include Mean Euclidean Distance, Homogeneity, Entropy and Grey Level Co-Occurrence (GLCM) Variance all at 5x5, 7x7 and 9x9 window sizes.

### 2.3. Optical Data

Landsat 8 - 30 meter Operational Land Imager (OLI) Level-1 images used for the Missouri assessment were acquired on October 5, October 21, October 30, November 6 and November 15, 2016 and April 15, April 24, May 10, May 26 and June 2, 2017. Landsat 8 - 30 meter OLI images used for the Texas study were acquired on April 28 and May 30, 2018. Bands used for this assessment include green, red, near infrared, short wave infrared – 1, cirrus and thermal infrared – TIRS-1. All Landsat 8 OLI Level 1 scenes are available at USGS Earth Explorer (https://earthexplorer.usgs.gov/).

The Disaster Monitoring Constellation (DMC) DEIMOS-1 and UK2 satellites operate in three spectral bands at a spatial resolution of 22 meters. All three spectral bands were used for all tests. The DEIMOS-1 images used in the Missouri assessment were acquired on April 19, May 6, May 9, and May 16, 2017 and the UK2 images were acquired on April 19, May 6 and May 29, 2017. The DEIMOS images used in the Texas assessment were acquired on May 19 and May 29, 2018 and the UK2 images were acquired on May 3 and June 12, 2018.

ESA Sentinel-2 satellites have twelve spectral bands at 10 to 60 meter resolution. Bands used for this study include green (10 meter), red (10 meter), near infrared (10 meter), cirrus (60 meter), short wave infrared - 1 (20 meter), and short wave infrared - 2 (20 meter). Sentinel-2 images used in the Missouri assessment were acquired on April 24, May 14, and May 21, 2017. Sentinel 2 images used in the Texas assessment were acquired on November 2, 2017 and April 16, April 26, May 6, May 11, May 16 and May 13, 2018.

### 2.4. Ground Reference Data

USDA Farm Service Agency (FSA) Common Land Unit (CLU) data are used as ground reference training and validation data for crop categories in this study. This standardized GIS layer of U.S. crop fields supports commodity and conservation programs. FSA CLU data are updated every growing season when farmers report crop type and acreage for their fields to FSA county offices. The vast majority of wheat planting intentions are reported to FSA due to subsidy programs. However, while wheat planting are reported early in the growing season, other crop planting intentions are reported later in the season (July and August), which adds to the complexity of separating wheat from other crops. The FSA CLU data are administratively confidential and not available for public dissemination [9]. The 2011 United States Geological Survey (USGS) National Land Cover Database (NLCD) is sampled to provide the ground reference training data for non-crop categories [10].

## 3. METHODOLOGY

### 3.1. Image Processing

All Sentinel-1 images are first preprocessed with calibration to sigma naught, Range Doppler terrain correction and de-speckling (median 5x5 speckle filter) using the open source Sentinel Application Platform (SNAP) toolbox, which can be downloaded from the Copernicus Services Access Hub (https://scihub.copernicus.eu/). The Sentinel-1 data are then resampled to 30 meters using a nearest neighbor interpolation and rigorous transformation. The optical data are resampled to 30 meters using cubic convolution, rigorous transformation (Fig. 2).

### 3.2. Decision Tree Classification and Accuracy Assessment

A See5 decision tree classifier [11] (version 2.08), with the boosting option, was used to produce 17 early season winter wheat classifications for each study area. The identical training sample data set was used for all test scenarios in each study area. The only difference in the tests was the input imagery, SAR texture feature and window size. Crop masks based on historic CDL data (2013 – 2016), USGS elevation, NLCD imperviousness, and NLCD canopy datasets were used as ancillary layers for all classifications. Seventeen individual classification tests were designed (Table 1) and replicated for each study area.

The classification test scenarios include optical data only (1), SAR data only (2), SAR with same-date texture features with different window sizes (5x5, 7x7 and 9x9) (3 - 14), optical and SAR and texture (GLCM Variance) (15), optical and SAR only (16), and optical and GLCM Variance texture with a 9x9 window size (17).

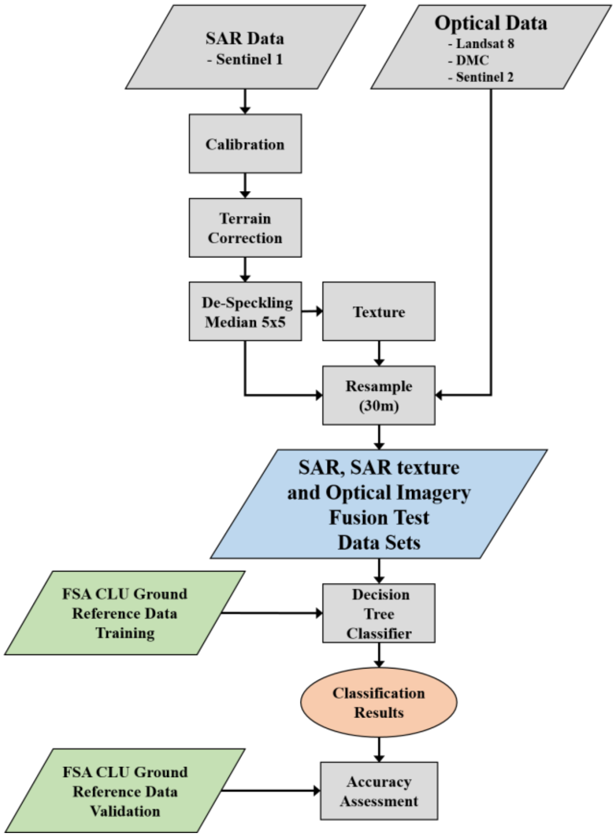


Fig. 2. Method Flow Chart

For this study 70% of the available FSA CLU data are used for training the classifier and 30% are used for validation. Winter Wheat accuracy measures include: producer accuracy, user accuracy, and a balanced accuracy. Producer accuracy indicates omission or false negative error and the user accuracy indicates commission error or false positive error [12]. The new balanced accuracy measure incorporates both false negative and false positive errors to truthfully reflect the accuracy of the targeted winter wheat class [13].

**TABLE 1. Classification Tests**

| TEST | IMAGERY | SAR TEXTURE | WINDOW SIZE |
|---|---|---|---|
| 1 | Optical Only | None | None |
| 2 | SAR Only | None | None |
| 3 - 5 | SAR and Texture | Median | 5x5, 7x7 and 9x9 |
| 6 - 8 | SAR and Texture | Homogeneity | 5x5, 7x7, and 9x9 |
| 9- 11 | SAR and Texture | Entropy | 5x5, 7x7 and 9x9 |
| 12 - 14 | SAR and Texture | GLCM* Variance | 5x5, 7x7 and 9x9 |
| 15 | Optical and SAR and Texture | GLCM* Variance | 9x9 |
| 16 | Optical and SAR Only | None | None |
| 17 | Optical and Texture (no SAR) | GLCM* Variance | 9x9 |

*Gray-Level Co-Occurrence Matrix (GLCM)

## 4. RESULTS AND DISCUSSION

The classification experiment results are summarized in Table 2. Fig. 3 illustrates the results of the Missouri winter wheat classification test (#16) which was produced using optical and SAR imagery. As shown in Table 2, classification test #16 in Missouri, which included optical and SAR without texture, achieved the highest winter wheat accuracies with a producer accuracy of 84.30%, a user accuracy of 72.80%, and a balanced winter wheat accuracy of 64.10%. This classification is only marginally improved over multi-sensory classification test #17 (optical and texture without the original SAR). While the 64.10% balanced accuracy is not as high as desired, it is 7.7% higher than optical alone (test #1). There is only a marginal accuracy difference between all of the Texas classification tests. In Texas, more cloud free images were available for this study than were available in the Missouri “Bootheel” study area. These results indicate that if abundant cloud free optical data are available, SAR does not improve the results significantly. However, if the optical data are limited, due to a reduced number of acquisitions or cloudy conditions, SAR can improve the early season winter wheat classifications. If the original SAR data are available for use with optical data, texture features provide little additional information.

**TABLE 2. Winter Wheat Accuracy Results**

| MISSOURI 2017 | | | | | | |
|---|---|---|---|---|---|---|
| Test | Imagery | SAR Texture | Window Size | Producer Accuracy | User Accuracy | Balanced Accuracy |
| 1 | Optical Only | None | None | 84.10% | 63.20% | 56.40% |
| 2 | SAR Only | **None** | **None** | 67.00% | 76.60% | 55.60% |
| 3 | SAR and Texture | Median | 5x5 | 66.20% | 78.60% | 56.10% |
| 4 | SAR and Texture | **Median** | **7x7** | 66.90% | 74.90% | 54.60% |
| 5 | SAR and Texture | Median | 9x9 | 66.50% | 76.10% | 55.00% |
| 6 | SAR and Texture | **Homogeneity** | **5x5** | 68.90% | 76.10% | 56.60% |
| 7 | SAR and Texture | Homogeneity | 7x7 | 69.50% | 74.90% | 56.40% |
| 8 | SAR and Texture | **Homogeneity** | **9x9** | 70.70% | 75.40% | 57.50% |
| 9 | SAR and Texture | Entropy | 5x5 | 68.50% | 78.30% | 57.60% |
| 10 | SAR and Texture | **Entropy** | **7x7** | 69.60% | 76.20% | 57.20% |
| 11 | SAR and Texture | Entropy | 9x9 | 70.00% | 78.40% | 58.70% |
| 12 | SAR and Texture | **GLCM Variance** | **5x5** | 71.80% | 76.60% | 58.90% |
| 13 | SAR and Texture | GLCM Variance | 7x7 | 72.90% | 75.60% | 59.00% |
| 14 | SAR and Texture | **GLCM Variance** | **9x9** | 73.80% | 78.10% | 61.20% |
| 15 | Optical and SAR and Texture | GLCM Variance | 9x9 | 84.10% | 69.60% | 61.50% |
| 16 | Optical and SAR | **None** | **None** | 84.30% | 72.80% | 64.10% |
| 17 | Optical and Texture – No Original SAR | GLCM Variance | 9x9 | 84.40% | 71.30% | 63.00% |
| TEXAS 2018 | | | | | | |
| Test | Imagery | SAR Texture | Window Size | Producer Accuracy | User Accuracy | Balanced Accuracy |
| 1 | Optical Only | None | None | 92.90% | 63.60% | 60.70% |
| 2 | SAR Only | **None** | **None** | 90.80% | 64.90% | 60.90% |
| 3 | SAR and Texture | Median | 5x5 | 90.90% | 64.80% | 60.90% |
| 4 | SAR and Texture | **Median** | **7x7** | 90.60% | 65.40% | 61.20% |
| 5 | SAR and Texture | Median | 9x9 | 90.30% | 64.20% | 60.10% |
| 6 | SAR and Texture | **Homogeneity** | **5x5** | 90.70% | 64.80% | 60.80% |
| 7 | SAR and Texture | Homogeneity | 7x7 | 90.90% | 64.90% | 61.00% |
| 8 | SAR and Texture | **Homogeneity** | **9x9** | 90.80% | 65.50% | 61.40% |
| 9 | SAR and Texture | Entropy | 5x5 | 90.80% | 64.70% | 60.70% |
| 10 | SAR and Texture | **Entropy** | **7x7** | 90.90% | 65.30% | 61.30% |
| 11 | SAR and Texture | Entropy | 9x9 | 91.10% | 65.00% | 61.10% |
| 12 | SAR and Texture | **GLCM Variance** | **5x5** | 91.10% | 64.50% | 60.70% |
| 13 | SAR and Texture | GLCM Variance | 7x7 | 91.30% | 64.80% | 61.00% |
| 14 | SAR and Texture | **GLCM Variance** | **9x9** | 91.70% | 64.80% | 61.20% |
| 15 | Optical and SAR and Texture | GLCM Variance | 9x9 | 93.40% | 63.70% | 61.00% |
| 16 | Optical and SAR | **None** | **None** | 93.10% | 63.40% | 60.50% |
| 17 | Optical and Texture – No Original SAR | GLCM Variance | 9x9 | 93.20% | 63.60% | 60.80% |

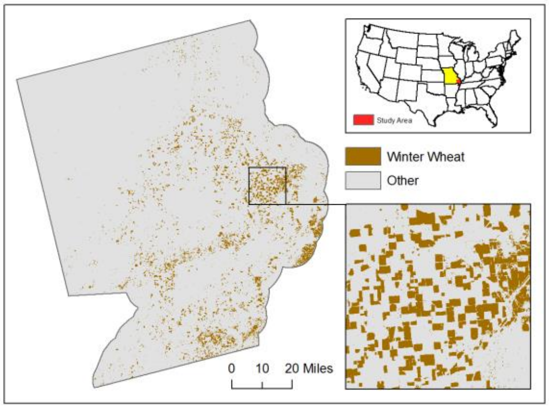


Fig. 3. Winter wheat classification in Missouri where winter wheat is highlighted in brown and other land cover in grey.

## 5. CONCLUSION

Early season crop identification is challenging due to limited cloud free optical data and limited ground reference training data. In the Missouri "Bootheel", a 7.7% increase in accuracy is observed between optical alone (test #1) and the optical and SAR combination (test #16) because the optical data are low quality due to heavy cloud cover. These results indicate that if sufficient cloud free optical data are not available, SAR data can improve classification results. Further, SAR with texture provides improved results over SAR alone. Optical and SAR data without texture provides the highest accuracy results in Missouri. Therefore, the computationally intensive texture features are not necessary, when optical data are available.

In Texas, optical with SAR resulted in improved accuracies over optical alone, but only marginally. Balanced winter wheat accuracies, for all 17 tests, were not significantly different. In this study, abundant optical data were available during the early season. However, SAR data produces comparable classification results. In fact, in Texas, the SAR only classification (test #2) was more accurate than the optical only classification (test #1). These results indicate that SAR can reasonably replace optical data, for early season crop identification.

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