EVALUATION OF SENTINEL-1A C-BAND SYNTHETIC APERTURE RADAR FOR CITRUS CROP CLASSIFICATION IN FLORIDA, UNITED STATES

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ABSTRACT

Optical based remote sensing plays an important role in citrus crop change monitoring in Florida, United States (U.S). However, persistent cloud cover during the summer growing season in Florida often limits the application of optical sensors. Synthetic Aperture Radar (SAR) has the advantage over optical data by operating at wavelengths not impeded by cloud cover, rain or a lack of illumination. The objective of this study is to assess the effectiveness of using Sentinel-1A C-band SAR data for classifying citrus in Florida. Twelve individual citrus classifications produced using single date optical or SAR data, as well as multi-date optical and SAR data fusion, are designed and tested. It is found that the classification accuracies of Sentinel-1 C-band SAR data are slightly lower than those of multi-temporal cloud free optical data (approximately 2.5% difference). However, the relatively comparable classification accuracy results indicate that the Sentinel-1 SAR is a useful alternative imagery source particularly in regions with persistent cloud cover.

***Index Terms*—**Sentinel-1, Synthetic Aperture Radar, Agricultural land cover classification, Citrus classification

1. INTRODUCTION

Florida, United States (U.S.) citrus is a $3.34 billion industry, accounting for 49% of total U.S. citrus production. However, the Florida citrus crop declined significantly over the past twenty years, from 329,859 ha in 1996 ~ 1997 to 176,150 ha in 2015 ~ 2016 [1]. This decline in citrus bearing areas is the result of numerous factors including: 1) urban expansion; 2) citrus greening, an incurable bacterial disease; and 3) the increased frequency of extreme weather events, which damage already weakened trees with high winds and flooding. Monitoring changes in the citrus crop over time is important for economic stability, agribusiness and agricultural decision makers. While annual field inspection surveys are conducted to monitor and estimate changes in citrus varieties and hectares going in and out of production, monitoring citrus with remote sensing provides an affordable and efficient method to support field inspection efforts.

Optical data are generally used for most agricultural remote sensing applications including crop area and yield estimation and crop condition assessments. However, optical sensors, such as Landsat 8, cannot penetrate through clouds, which are pervasive in the summer over Florida. Synthetic Aperture Radar (SAR) is not impeded by clouds, rain or darkness and can acquire useful data during most weather conditions. Consequently, the freely available European Space Agency (ESA) Sentinel-1 C-band SAR provides the opportunity to improve citrus land cover mapping in Florida, when combined with available cloud-free optical imagery.

Multi-temporal and multispectral remote sensing using optical data proved to be an effective approach to discriminate crop types [2-4]. However, the availability of optical data are sometimes very limited due to persistent cloud cover in Florida 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 persistent cloud cover, has been investigated in multiple studies [5-8].

This paper presents an assessment of Sentinel-1A C-band SAR for classifying the 2017 citrus crop in Florida. The study objective is to determine if the Sentinel-1A C-band SAR data can improve the identification of the citrus crop in Florida over optical data alone. This paper includes 1) the citrus classification methodology based on a decision tree classifier, 2) the citrus accuracy assessment for twelve classifications with a discussion, and 3) future research plans and conclusion.

2. DATA AND SCOPE

2.1. Study Area

A region within Florida, which is approximately 6357 km^2 (Fig. 1), is selected as the study area for this assessment because the region includes most of the citrus in the state.

The geospatial data used in this assessment include: 1) Sentinel 1-A C-band SAR images acquired on March 26, April 7, May 3 and July 24, 2017; 2) Landsat 8 Operational Land Imager (OLI) Level 1 images acquired on April 7 and May 9, 2017; 3) a citrus mask created using historic Cropland Data Layers (CDLs) [3]; 4) citrus polygon data provided by the USDA National Agricultural Statistics Service (NASS) Florida Field Office for training and validation of the resulting citrus classifications [9] and 5) the United States Geological Survey (USGS) National Land Cover Data Set (NLCD) 2011 for training of non-citrus categories [10].

2.2. Sentinel-1 Synthetic Aperture Radar

The ESA Sentinel-1 constellation includes two polar-orbiting C-band SAR satellites (Sentinel-1A and Sentinel-1B). Sentinel-1A images used in this study have the following specifications: interferometric wide swath (250 km), Level-1 products which have been detected, multi-looked and projected to ground range, 5x20 meter spatial resolution and dual polarization (VV and HH). All Sentinel-1A images were downloaded directly from the ESA Copernicus Open Access Hub < https://scihub.copernicus.eu/>.

2.3. Landsat 8

Landsat 8 30-meter OLI Level 1 images used for this assessment, with the same date and path, were mosaicked. The bands used for this assessment include: bands 3 (visible green), 4 (visible red), 5 (near infrared), 6 (short wave infrared - 1), 9 (Cirrus) and 10 (Thermal Infrared – TIRS-1). All Landsat 8 OLI Level 1 scenes are available at USGS Earth Explorer < https://earthexplorer.usgs.gov/>,

2.4. Citrus Mask

A citrus mask derived from historic NASS Cropland Data Layers (2013 ~ 2016) [3] was used as an ancillary layer in the classifications. The 30m resolution pixels identified as citrus in all four years were included as citrus in the mask**.**

2.5. Ground Reference Training and Validation data

Citrus field polygon data provided by the USDA NASS Florida Field Office were used for training and validation of the citrus classifications in this study. Fig. 2 shows a portion of the citrus field polygon data with blue boundaries, overlaid on aerial photography. All citrus groves are manually delineated and updated yearly based on field inspections which takes place from October through June each year. There are 26,536 citrus groves recorded in the 2017 Citrus Geographic Information System Data Layer. A sample of 30,000 points was used for citrus training and the complete layer, including all polygons, was used for validation of the classifications in this study. The citrus field polygon data are the most accurate, current and comprehensive delineation of the Florida citrus crop available [9].

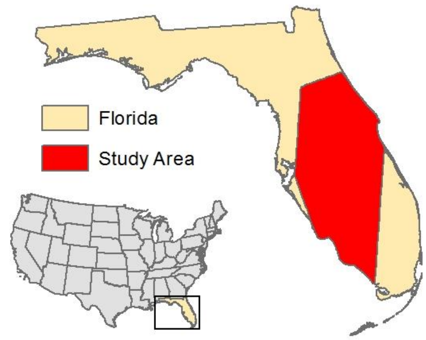

Fig. 1. Florida, U.S. – Study area (highlighted in red) for SAR citrus assessment.

Fig. 2. Zoom of citrus field polygon data used for training and validation. All polygons are manually delineated and attributed, based on annual field inspections, in the USDA NASS Florida Field Office. Blue boundaries outline the citrus groves which are overlaid on aerial imagery.

The USGS NLCD, 2011 was the source for training of all other categories of land cover [10]. The NLCD land cover data set has a 16-class land cover category classification scheme that is applied consistently across the United States at a 30 meter spatial resolution. NLCD 2011 is based primarily on a decision-tree classification of circa 2011 Landsat satellite data.

3. METHODOLOGY

3.1. Sentinel-1A and Landsat 8 preprocessing

All Sentinel 1-A images were first preprocessed with sigma naught calibration, Range Doppler terrain correction and de-speckling (median 5x5 speckle filter) using the ESA open source Sentinel-1 toolbox. The preprocessed same date images were mosaicked, reprojected to Albers Conical Equal Area projection, resampled to 30 meter resolution and set to the map extent of the study area using Hexagon's ERDAS Imagine 2016 software.

All downloaded Landsat 8 OLI Level 1 scenes were reprojected to Albers Conical Equal Area Projection, mosaicked (same date and path) and set to the extent of the study area. The six bands selected in this assessment were the bands identified as most useful in classifying crops by the NASS CDL program.

3.2. See5 Decision Tree Classification

A See5 decision tree classifier [11] (version 2.08), with the boosting option, was used to produce twelve citrus classifications. A sampling ratio of 3% citrus and 97% "other" categories for a total sample size of 1,000,000 points was used for all classifications. This sampling rate was selected because the citrus crop covers approximately 3.2% of the study area (Fig. 1). The identical training sample data set was used for all classifications with the only difference in the classifications being the imagery used as inputs to the decision tree classifier. A citrus mask based on historic CDL data (2013 – 2016) was used as an ancillary layer for all classifications. Twelve individual classification tests were designed (Table 1). They included single dates of optical and SAR images, and multi-date optical and SAR data fusion.

TABLE 1. Citrus Classification Tests with Single or Multi-Temporal Optical, SAR or Optical & SAR Data

Classification Test	Temporal Resolution	Imagery	Date
1	Single Date	Optical	04/07/2017
2	Single Date	Optical	05/09/2017
3	Single Date	SAR	03/26/2017
4	Single Date	SAR	04/07/2017
5	Single Date	SAR	05/13/2017
6	Single Date	SAR	07/24/2017
7	Multi-Temporal	Optical	04/07/2017 05/09/2017
8	Multi-Temporal	SAR	04/07/2017 05/13/2017
9	Multi-Temporal	Optical	05/09/2017
		SAR	05/13/2017
10	Multi-Temporal	SAR	03/26/2017 04/07/2017 05/13/2017
11	Multi-Temporal	Optical	05/09/2017
		SAR	04/07/2017 05/13/2017
12	Multi-Temporal	SAR	03/26/2017 04/07/2017 05/13/2017 07/24/2017

4. RESULTS AND DISCUSSION

The classification experiment results are summarized in Table 2. Results include: citrus producer accuracy, citrus user accuracy, Kappa coefficient and citrus total accuracy. The producer accuracy indicates the omission or False Negative error and the user accuracy indicates the commission error or False Positive error. The Kappa coefficient reflects the difference between actual agreement and the agreement expected by chance. The citrus total classification accuracy incorporates both False Negative and False Positive errors to truthfully reflect the accuracy of the targeted citrus class.

Fig. 3 illustrates the results of one citrus classification test (#9) which was created using a multi-temporal optical (May 9, 2017) and SAR (May 13, 2017) combination. The citrus classification is overlaid over the Florida, U.S. County boundaries. Zooms show classification details with the "citrus" category in orange and the "other" category in tan.

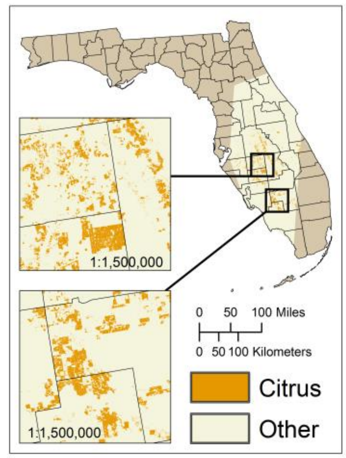

Fig. 3. Citrus classification test #9 created using multi-temporal optical (May 9, 2017) and SAR (May 13, 2017) overlaid over Florida, U.S. County boundaries. This classification achieved an 88.40% citrus producer accuracy, a 77.80% citrus user accuracy, a Kappa of 0.8214 and a 70.55% citrus total accuracy.

As shown in Table 2, classification test #7, which utilized multi-temporal optical data (April 7 and May 9, 2017), achieved the highest citrus accuracy with a citrus producer accuracy of 88.80%, a citrus user accuracy of 78.40%, a Kappa of 0.8270 and a citrus total accuracy of 71.33%. This classification is only marginally improved over multi-sensory classifications #9 and #11. The single optical data classifications #1 and #2 with citrus total accuracies of 70.05% and 70.46% are approximately 2 – 3% improved over those of four single SAR classifications #3, #4, #5 and #6. There is no significant difference in the citrus total classification accuracy among the single date SAR classifications (#3 – #6). This indicates that there are no significant changes detected in SAR signals from March to July. In addition, the multi-temporal SAR classifications (#8, #10 and #12) show no improvement in the citrus total classification accuracy as compared with the single date SAR classifications (#3 – #6). These results are consistent with reality considering there are no significant changes in the citrus canopy from March - July. Therefore, multi-temporal C-band SAR does not improve citrus classification accuracy over single date SAR.

As shown in Table 2, the classification results of multi-temporal SAR and optical data are comparable to that of multi-temporal optical data for citrus classification in Florida. There is no improvement in citrus identification by adding additional SAR scenes as inputs. This indicates that SAR data can be an effective alternative to optical data for citrus classification in regions with persistent cloud cover, like the Florida citrus region. There will be no further improvement, using the SAR data, when multi-temporal optical data are available.

TABLE 2. Citrus Classification Accuracies

Classification Test		Images	Producer Accuracy	User Accuracy	Kappa	Total Citrus Accuracy
1 Date	1	Optical – 04/07/2017	88.40%	77.10%	0.8178	70.05%
	2	Optical – 05/09/2017	88.40%	77.60%	0.8208	70.46%
	3	SAR – 03/26/2017	92.40%	71.50%	0.7995	67.58%
	4	SAR – 04/07/2017	92.80%	71.40%	0.8002	67.67%
	5	SAR – 05/13/2017	92.80%	71.20%	0.7993	67.54%
	6	SAR – 07/24/2017	92.90%	71.20%	0.7992	67.53%
2 Dates	7	Optical – 04/07/2017, 05/09/2017	88.80%	78.40%	0.8270	71.33%
	8	SAR – 04/07/2017, 05/13/2017	90.00%	71.50%	0.7898	66.26%
	9	Optical – 05/09/2017 SAR – 05/13/2017	88.40%	77.80%	0.8214	70.55%
3 Dates	10	SAR –03/26/2017, 04/07/2017, 05/13/2017	90.00%	72.90%	0.7984	67.40%
	11	Optical – 05/09/2017 SAR – 04/07/2017, 05/13/2017	88.10%	77.90%	0.8214	70.54%
4 Dates	12	SAR – 03/26/2017, 04/07/2017, 05/13/2017, 07/24/2017	89.10%	73.30%	0.7970	67.21%

5. CONCLUSIONS

This study evaluates using Sentinel-1A C-band SAR data for the classification of citrus in Florida, U.S. The results show that the highest citrus total classification accuracy (71.33%) was achieved using the multi-temporal optical data. This was followed very closely by the multi-temporal SAR and optical citrus classifications (70.55% and 70.54%). Classification accuracy of single date optical citrus classifications (around 70.0%) is about 2.50% better than that of SAR only single date and multi-temporal citrus classifications (around 67.50%). These results indicate that while the SAR data classification accuracies are slightly lower than those of multi-temporal cloud free optical data, the Sentinel 1-A C-band SAR data can serve as a useful alternative imagery source particularly in regions with persistent cloud cover where the availability of cloud free optical data is limited.

Future research will include 1) the evaluation of SAR texture bands at different window sizes to further improve the classification of citrus in Florida, and 2) assessments comparing optical and SAR data, with and without texture bands, to classify other crop types in U.S. agricultural regions with persistent cloud cover such as the Texas Gulf Coast and Louisiana

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