**UAV-BASED SOIL MOISTURE MAPPER AND VISUALIZATION FOR SOYBEAN**

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**Annual report**

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**RATIONALE/JUSTIFICATION FOR RESEARCH:**

The measurement of SM is essential for effective irrigation management for crop production. In-situ SM measurement methods (such as time-domain reflectometry probes) are widely used because of their high accuracy and reliability. However, using invasive SM probes is inefficient for assessing variation of large areas. Over the last several decades, remote sensing approaches have become a popular way of retrieving spatially distributed SM. Several space-born microwave remote-sensing missions were launched to provide surface SM measurements on a global scale. These microwave-based satellite technologies mainly use L-band (1–2 GHz) or C-band (4–8 GHz) observations and produce a surface SM product from active or passive observations. Their spatial resolution varies from several to 25 mi, and temporal resolution varies from 2 days to 12 days, depending on the sensing modalities. Although all existing satellite missions are critical for many large-scale research and scientific studies, they have a coarse spatiotemporal resolution that does not meet the practical requirements for PA applications. Global navigation satellite system reflectometry (GNSS-R) from space is another attractive spaceborne remote sensing technology that has the potential to offer better spatial (4.3 by 0.3 mi) and temporal resolutions compared to missions like SMAP. Recently, our team and other research groups have developed models and algorithms to retrieve SM from land observations of NASA's recent spaceborne GNSS-R mission called Cyclone Global Navigation Satellite System (CYGNSS). Our group generated three publicly available global SM products based on satellite GNSS-R observations. Although CYGNSS-based SM estimations have better spatiotemporal resolution than many satellite-based products, its spatial resolution is not usable for PA. We have transferred and adapted the more mature satellite-based GNSS-R SM retrieval technology to UAV platforms for PA applications. We previously showed that a UAV-based SM mapper platform will be low-cost, easy to operate, and provide low-latency outputs. For this purpose, we have previously performed initial studies to demonstrate the feasibility of the proposed concept. We conducted a preliminary study on a 2.1 acre crop field (corn and cotton) from January 2020 to now (including crop planting through senescence) at Mississippi State University's research farm. A total of more than 500 flight campaigns were performed, which cover different seasons and crop growth stages. In a previous study, we developed a random-forest ML model using surface-reflected GPS signals in combination with vegetation indices via a multispectral camera. Our last model showed satisfactory performance in estimating surface SM with an RMSE of 0.04 ft3ft-3 and a correlation coefficient of 0.78 in corn and cotton fields. This project uniquely will extend our previous study for soybean fields and allow us to develop an SM mapper system specifically for soybean fields.

**Objective:** We will design and implement a UAV-based sensing system to measure high-resolution SM in soybean fields for precision irrigation applications. We will conduct multiple field campaigns to collect datasets for training and validation. This will be the first study that collected GNSS-R data via UAV from a soybean field. We will develop an ML model to estimate SM via learning complex relations between UAV-based measurements and the ground SM. In this objective, we will investigate the effect of soybean canopy and biomass in different growing states on learned model performance. The final goal is to develop a near real-time UAV-based platform so that the end-user, such as a farmer, can directly see a complete SM map of the soybean field on his controlling system, such as a smartphone or a computer, after completing UAV flights.

**REPORT OF PROGRESS /ACTIVITY:**

In the first year of the project, the following tasks/activities are performed:

1. Preparation of conducted study field and UAV system.

2. Flight campaigns

3. Data preprocessing for multispectral images.

4. Flight and GNSS-R data extraction, preprocessing, and data concatenation.

# Preparation of conducted study field and UAV system

A aerial view of a field

Description automatically generatedA map of a study area

Description automatically generatedThe project was conducted in a soybean field (33.482374°, -88.781912°) in R.R. soil research center. Soybeans were planted in the second week of June 2024 and harvested in the first week of November. In the last week of June, 15 soil moisture probes are placed to the different locations of the field. In addition, 7 ground reference points are placed in the corner of the field and the inside of the field. These reference points will be used to generate multispectral georeferenced images. The geographic location of SM probes and reference points were obtained using GPS surveying. Figure 1 shows the study field, SM probes' locations, and ground reference points.

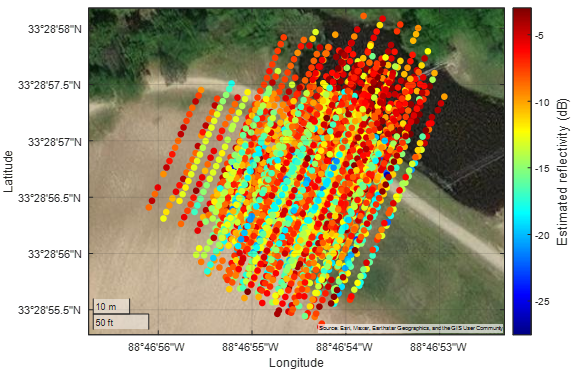
# Flight campaigns

We conducted a total of 20 flight campaigns to collect data from July 26 to November 1. In each flight, we collect GNSS-R data, multispectral images of the field, and UAV telemetry. After each flight, all collected data was saved to a local PC for future data processing.

Figure 2. Flight path.

Figure 1. Soybean study field, soil moisture probe's locations, and ground reference points.

# Data preprocessing for multispectral images.

To obtain georeferences normalized difference vegetation index (NDVI), we perform multiple preprocessing steps. First, we aligned pixels in all spectral bands using the geometric transformation method. Second, radiometric calibration was performed for each multispectral band. Then, we generated calibrated normalized difference vegetation indices (NDVI) of the study field for 18 flight campaigns. Radiometric calibration involves converting the raw pixel values of an image into absolute spectral radiance values, measured in watts per square meter per steradian per nanometer (W/m²/sr/nm). This process accounts for several factors, including the sensor's black level, sensitivity, gain, exposure settings, and lens vignetting effects. All parameters used in the calibration model can be found in the metadata of the TIFF file saved by the RedEdge camera. In this study, we adhere to the instructions and equations provided by micaSense for radio calibration. Finally, georeferencing of multispectral images was manually performed for each experiment using ground control points (GCPs) scattered throughout the field. First, we created an empty raster image that covered the entire study area. In this image, we marked all the GCPs using their latitude and longitude coordinates obtained from previous GPS surveys. This image served as a fixed reference for aligning other unregistered images. Next, using a graphical user interface application, we matched the GCPs in the fixed image with those in the moved images. Our computer code then calculated the transformation matrix and applied it to register the multispectral images. Finally, we calculated the NDVI and saved the data in a GeoTIFF file. Figure 3 shows one of the NDVI maps of the study field on September 9, 2024.

**A screenshot of a heat map

Description automatically generated**

*Figure 4. Calculated specular points on August 20, 2024. The color axis shows the estimated surface reflectivity.*

Figure 3. NDVI of the study field on September 9, 2024. After radiometric correction.

# Flight and GNSS-R data extraction, preprocessing, and data concatenation.

We performed data preprocessing with collected GNSS-R data for 13 available flight campaigns. Then, all different sensor data, including GNSS-R, drone flight log, NDVI, and in-situ measured SM data, were combined. The combined data will be used to analyze the calculated reflectivity and effect of other factors. Also, this dataset will be used in a machine-learning model to estimate the surface soil moisture value of the field. For GNSS-R preprocessing, we have decoded the saved NMEA messages during each flight. In these messages, Recommended Minimum Specific data (RMC) and GPS Satellites in View (GSV) are decoded. From RMC, we obtained the date and time information. From the GSV messages, we extracted unique satellite identifiers, elevation angle, azimuth angle, and signal strength represented by the carrier-to-noise density ratio (C/N0). By using instantaneous drone location and elevation and azimuth angle information, we have calculated GNSS-R surface reflection points for all samples. Figure 4 shows the specular points (SPs) and the estimated surface reflectivity on August 20, 2024. After the SP calculation, we concatenated the GNSS-R, flight log data, NDVI, and in-situ soil moisture measurements based on time and location. We have gridded the study as a 5 by 5-meter grid. The following table shows the statistics for each GNSS mission per flight and the coverage rate of each GNSS mission.

*Table 1. GNSS missions' statistic per flight.*

|  |  |  |  |
| --- | --- | --- | --- |
|  | Statistics per flight | | |
| GNSS missions | Coverage rate (%) | Number of samples | Sample per grid (std) |
| GPS | 99 | 1183 | 9.7(±3.5) |
| Galileo | 43 | 346 | 3.8(±1.5) |
| GLONASS | 98 | 770 | 5.9(±2.2) |
| Beidou | 31 | 199 | 2.4(±1) |
| All | 100 | 2296 | 17(±5.8) |