Preliminary Data Analytics with Satellite Data from Passive and Active Sensors for UMES Agricultural Fields

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Abstract

This exploratory study was conducted for the Stewart Neck research field at the University of Maryland Eastern Shore (UMES), an 1890 land-grant campus. The study investigates the potential use of satellite imagery to support ongoing 'Smart Farming and Precision Agriculture' initiatives on the campus. The work reported here was largely performed by a graduate student in the engineering program in the summer of 2025. An undergraduate student in the computer science program is following up on the effort in the fall semester. A postdoctoral researcher is overseeing the efforts in coordination with the lead faculty. The student extracted Sentinel-1 and Sentinel-2 satellite data for the field from January to December of 2023 and analyzed the soybean vegetation dynamics using Sentinel-2 optical indices (NDVI (normalized difference vegetation index), NDMI (normalized difference moisture index) combined with the Sentinel-1 Radar Vegetation Index (RVI). The study utilizes data from passive optical sensors to construct the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Moisture Index (NDMI). NDVI serves as a proxy for crop health and density, while NDMI provides crucial information regarding vegetation water content and plant stress. To overcome the challenge of high cloud coverage, which frequently obscures passive optical data, the study integrates data from active radar sensors to derive the RVI using Sentinel-1 C-band Synthetic Aperture Radar (SAR) data.

Monthly data from January to December revealed clear seasonal trends: NDVI peaked in July (~0.8) before declining; NDMI showed a sharper post-peak drop, indicating early moisture stress; RVI increased from ~0.7 to ~1.8 with later variability linked to canopy and soil changes. Moderate correlation between NDVI and RVI underscored their complementary insights. Spatial analyses showed consistent crop vigor but varied moisture and structure during peak growth.

The follow up work ongoing in the fall of 2025 is utilizing 2022 corn data for the same field. The production agriculture practices on campus uses corn and soybean rotations during the growing season with wheat as the cover crop during the winter.

This study presents a methodology for cost-effective and comprehensive crop monitoring using publicly available satellite remote sensing data. This preliminary work lays a foundation for incorporating satellite remote sensing data into UMES 'smart farming' programs, providing avenues for learning, discovery, and engagement for students, faculty, and staff in a land grant setting. A key objective is to develop an inexpensive strategy for farmers to gain valuable insights into their fields, crop growth stages, and overall health, thereby reducing reliance on costly ground-based surveys.

1. Introduction

Precision agriculture and smart farming efforts are increasingly relying on satellite remote sensing to provide scalable, repeatable, and cost-effective observations of crop condition at the field scale (Mulla, 2013; Wardlow et al., 2007). The work reported in this paper outlines preliminary efforts undertaken by the smart farming project team at UMES to explore utilization of satellite data to production agricultural practices on campus. UMES is an 1890 land grant minority serving institution in the eastern shore region of Maryland and has more than 350 acres of farmland. Significant portion of the farmland on campus is devoted production agriculture of row crops. Publicly available Earth-observation missions operated under the European Union's Copernicus Programme have transformed access to agricultural data by providing systematic, high-resolution optical and radar imagery at no direct cost (Drusch et al., 2012). Among these missions, Sentinel-2 and Sentinel-1 are particularly relevant for crop monitoring in humid, cloud-prone regions such as the Mid-Atlantic United States.

Sentinel-2 is a passive optical satellite constellation carrying a multispectral instrument (MSI) that measures reflected solar radiation across visible, near-infrared (NIR), and shortwave infrared (SWIR) wavelengths at spatial resolutions of 10–20 m (Copernicus Data Space Ecosystem, 2024). These spectral bands enable the derivation of vegetation indices widely used to quantify crop vigor, canopy density, and moisture status. The Normalized Difference Vegetation Index (NDVI), originally proposed for large-scale vegetation monitoring (Rouse et al., 1974; Tucker, 1979), serves as a robust proxy for green biomass and photosynthetic activity. Complementing NDVI, the Normalized Difference Moisture Index (NDMI) is sensitive to vegetation water content and canopy moisture stress and has been shown to be effective for monitoring corn and soybean water dynamics (Jackson et al., 2010; Ghimire et al., 2020).

In contrast, Sentinel-1 is an active Synthetic Aperture Radar (SAR) mission operating in the C-band microwave region. Unlike optical sensors, SAR systems transmit their own energy and measure the backscattered signal, enabling data acquisition independent of solar illumination and largely unaffected by cloud cover or atmospheric conditions (European Space Agency, 2024). Dual-polarization backscatter measurements (VV and VH) are sensitive to canopy structure, surface roughness, and dielectric properties related to vegetation and soil moisture. Radar-based vegetation metrics such as the Radar Vegetation Index (RVI) provide complementary information to optical indices, particularly during cloudy periods or late-season senescence when NDVI sensitivity to chlorophyll declines (McNairn et al., 2009; Singh et al., 2024).

This paper focuses on the Stewart Neck agricultural research field at the University of Maryland Eastern Shore (UMES), an approximately 80-acre field representative of Mid-Atlantic row-crop production systems. The field follows a corn–soybean rotation with winter wheat commonly used as a cover or rotational crop, consistent with regional agronomic practices (USDA NASS, 2023). In 2022, corn was sown on May 2 and harvested on September 21, while in 2023 soybeans were planted on June 14 and harvested on November 2. Typical Maryland winter wheat planting and harvest windows provide additional context for early-spring and late-fall vegetation signals observed in satellite time series.

The objective of this study is to synthesize multi-year satellite analyses emphasizing Sentinel-2 optical data, while incorporating Sentinel-1 radar observations to address data gaps due to cloud cover. NDVI and NDMI derived from Sentinel-2 are used to characterize crop greenness and canopy moisture during the 2022 corn and 2023 soybean growing seasons, while RVI derived from Sentinel-1 provides complementary information on canopy structure and seasonal transitions. By contextualizing these indices within known planting and harvest dates, this work demonstrates how integrated satellite products can support crop monitoring, engineering and STEM education, as well as precision-agriculture research at an 1890 land-grant institution.

2. Study Area and Cropping Calendar

The Stewart Neck field integral to University of Maryland Eastern Shore (UMES) campus, represents a region characterized by flat topography, humid summers, and frequent cloud cover during the growing season. The approximately 80-acre field is managed for research and teaching purposes and follows standard regional agronomic practices. Corn is typically planted in late April to early May and harvested in early fall, while soybean planting often occurs in early to mid-June with harvest extending into late October or early November. Winter wheat is commonly planted in the fall following harvest and harvested the following summer, contributing to off-season vegetation signals observed in satellite imagery.

In 2022, the field was planted with corn on May 2 and harvested on September 21. In 2023, soybeans were planted on June 14 and harvested on November 2. These documented dates provide a clear temporal framework for interpreting seasonal variations in NDVI, NDMI, and RVI.

3. Data Sources and Processing Overview

Sentinel-2 Level-2A surface reflectance products were used to derive NDVI and NDMI for both years of analysis. Optical imagery was screened for cloud contamination using standard scene classification masks, with cloud-free observations selected to construct monthly composites and time series. Sentinel-1 Interferometric Wide (IW) Ground Range Detected (GRD) products were processed to calibrated, terrain-corrected backscatter using established preprocessing workflows. From dual-polarization VV and VH backscatter, RVI was computed to provide a radar-based indicator of vegetation structure.

Geospatial processing and visualization were conducted using ArcGIS Pro, ESA SNAP, and Python-based analysis tools. Random sampling within the field boundary was used to extract index values for statistical analysis, enabling comparisons across months, seasons, and crop types.

4. Results and Discussion

This section presents representative student-generated figures derived from Sentinel-1 and Sentinel-2 data. All figures were produced by the graduate (engineering) and undergraduate (computer science) student team using ArcGIS Pro, ESA SNAP, and Python.

Figure 1 captures the monthly spatial distribution of Sentinel-2–derived NDVI and NDMI for the Stewart Neck field during the 2023 soybean growing season. NDVI highlights canopy greenness and biomass accumulation, while NDMI captures canopy moisture status. The progression from low early-season values to peak midsummer values and subsequent decline aligns with planting (June 14, 23) and harvest (November 2, 23). Due to cloud cover it was not possible to obtain optical data from Sentinel 2 satellite in May. As shown in Table 1 Sentinel 2 captures 13 optical bands.

Table 1: Sentinel 2 Bands and Resolution

Band	Resolution	Central Wavelength	Description
B1	60 m	443 nm	Ultra Blue (Coastal and Aerosol)
B2	10 m	490 nm	Blue
B3	10 m	560 nm	Green
B4	10 m	665 nm	Red
B5	20 m	705 nm	Visible and Near Infrared (VNIR)
B6	20 m	740 nm	Visible and Near Infrared (VNIR)
B7	20 m	783 nm	Visible and Near Infrared (VNIR)
B8	10 m	842 nm	Visible and Near Infrared (VNIR)
B8a	20 m	865 nm	Visible and Near Infrared (VNIR)
B9	60 m	940 nm	Short Wave Infrared (SWIR)
B10	60 m	1375 nm	Short Wave Infrared (SWIR)
B11	20 m	1610 nm	Short Wave Infrared (SWIR)
B12	20 m	2190 nm	Short Wave Infrared (SWIR)

Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI) values were extracted from 500 randomly distributed points within the field boundary using ArcGIS Pro's Extract Multi Values to Points tool.

NDVI was calculated as:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

NDMI was computed as:

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR} \quad (2)$$

NDVI values characterize vegetation greenness and canopy density, while NDMI reflects vegetation and soil moisture content.

Synthetic Aperture Radar (SAR) analysis was conducted using Sentinel-1 RTC (Radiometrically Terrain Corrected) dual-polarization (VV, VH) products. The Radar Vegetation Index (RVI) was computed using calibrated sigma-naught values (σ0\sigma^0σ0) from the VV and VH polarizations:

$$RVI = \frac{4\ \sigma_{VH}}{\sigma_{VV} + \ \sigma_{VH}} \quad (3)$$

All RVI values were normalized using the 95th percentile method to minimize the influence of outliers while retaining the relative scale across months. To enhance comparability across different dates and field conditions. The normalized RVI was computed as:

$$RVI_{Normalized} = \frac{RVI}{RVI_{95}} \quad (4)$$

Where RVI is the raw radar vegetation index for each pixel and RVI_{95} represents the 95th percentile value of RVI computed across all pixels for the given study area and time period. This normalization ensures that most vegetation responses are scaled within the range 0–1, while values exceeding the 95th percentile are allowed to surpass 1. The indicators acquired from radar provide supplementary insights into the mechanics of crop development. The Radar Vegetation Index (RVI) exhibited a distinct seasonal pattern (Figure 2). RVI values were rather high (0.8–0.95) from January to March, even higher than NDVI. This suggests that the radar was still sensitive to structural scattering, even if there wasn't much vegetation cover. In June (around 0.57), there was a noteworthy dip that happened at the same time as a drop in vegetation density and moisture. RVI steadily rose after July, reaching its highest point in October (≈1.05), when the contributions from canopy structure and dispersion were largest. After this high, RVI values declined quickly in November (about 0.37), which is what one would expect from senescence and post-harvest residue. They then rose somewhat in December (about 0.45).

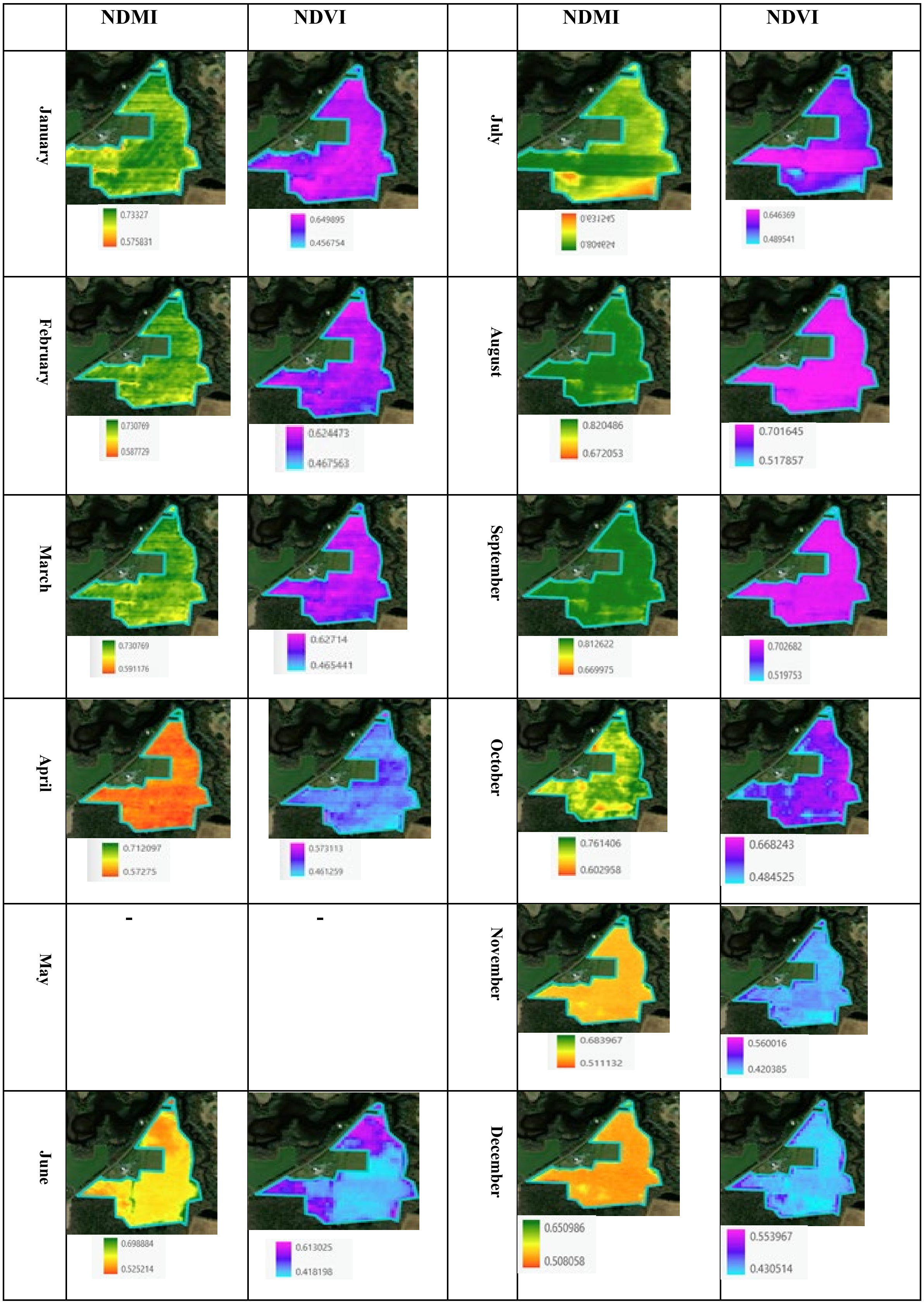

Figure 1: Monthly NDVI and NDMI Maps for Stewart Neck Field (2023 – Soybean)

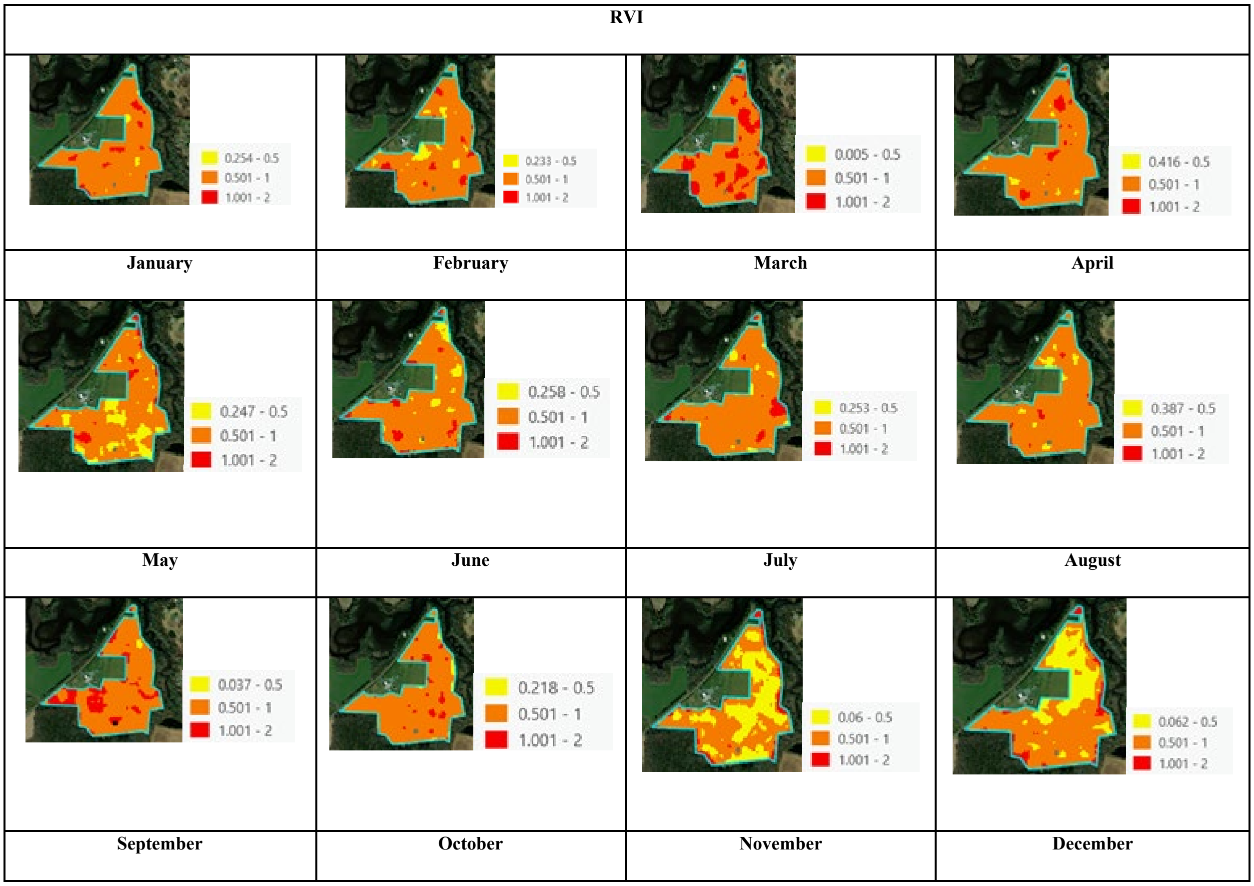

Figure 2. Monthly RVI Maps for Stewart Neck Field (2023- Soybean)

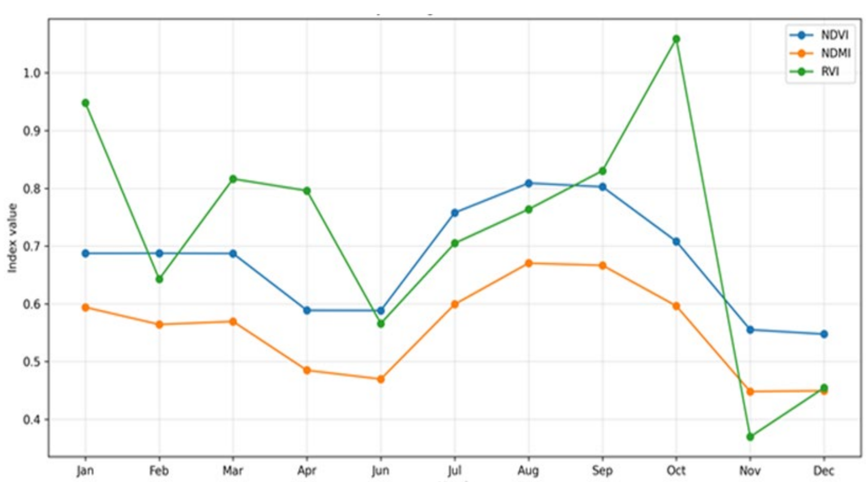

Figure 3. Monthly Average Values of NDVI, NDMI, And RVI (2023)

In general, SAR-based metrics showed changes in structure and scattering the optical indices alone did not show. NDVI and NDMI measured the health of plants and the amount of water in the canopy, whereas RVI showed the structure of the canopy, how it changed over time, and how it changed around harvest time, especially the sharp drop in November that showed the end of growth for the season. Figure 3 captures the variations of NDVI, NDMI, and RVI for 2023 for the Stewart Neck Field.

The results shown in Figures 1-3 were obtained in the summer of 2025 by efforts undertaken by the engineering graduate student who is the first author of the paper and laid foundation for the efforts undertaken by the undergraduate computer science student in the fall of 2025. She worked on the 2022 Sentinel 1 and 2 data for the same field (Stewart Neck). In 2022 the field grew corn. The results captured similar pattern as was observed with the 2023 data. The results have been included in the Appendix. Figure 4 shows the NDVI and NDMI monthly maps. It may be noted that data was available without significant cloud cover for every month including the month of May in 2022. Monthly RVI data was also processed and is shown in Figure 5 in the Appendix. The Figure 6 provides a monthly average value of NDVI, NDMI, and RVI for the year 2022 for the Stewart Neck field. It may be observed that in 2022, Sentinel-2 indices tracked the corn season from May planting to September harvest. NDVI and NDMI rose during summer growth, peaked at maximum biomass and canopy moisture, and fell sharply after harvest, though winter wheat rotations maintained moderate off-season values. Sentinel-1-derived RVI provided complementary insights into canopy structure and surface conditions during both growing seasons. Unlike optical indices, RVI remained responsive during cloudy periods and late-season transitions when NDVI sensitivity diminished. Seasonal RVI patterns showed increases during canopy development and pronounced changes around harvest, reflecting alterations in vegetation structure, residue, and soil exposure.

5. Educational and Institutional Context

This work was conducted as part of ongoing Smart Farming and Precision Agriculture initiatives at the University of Maryland Eastern Shore. The technical development and analysis of satellite-derived data products were led by a graduate student in engineering in 2025 summer, with direct contributions from an undergraduate student in computer science who complemented the efforts in the fall. A faculty mentor (engineering) and postdoctoral researcher (Agriculture and Resource Sciences) provided technical oversight and ensured methodological consistency with established remote-sensing practice.

The graduate and undergraduate students were primarily responsible for Sentinel-1 and Sentinel-2 data acquisition, preprocessing, and index derivation using ArcGIS Pro, ESA SNAP, and Python-based tools, as well as exploratory data analytics, statistical visualization, and figure generation. Several of the results presented in this paper—including monthly NDVI/NDMI trends, RVI seasonal profiles, and selected correlation plots—were produced directly by the student team and are representative of authentic student-generated data products. These figures were selected for inclusion because they clearly illustrate crop phenology, sensor complementarity, and the educational value of working with real satellite datasets.

From an engineering and computer science education perspective, this project provided students with hands-on experience in instrumentation concepts (passive vs. active sensing), data fusion, geospatial analysis, and interpretation of multi-sensor measurements. The low-cost and open-access nature of Sentinel data further supports reproducibility and scalability, making the approach well suited for integration into undergraduate and graduate curricula across engineering, computer science, and agricultural disciplines.

Preliminary efforts reported here have provided the foundation for extension efforts to some of the local farmers. The project team is already working with two local farmers involved with growing row crops who have provided the boundaries of their fields to the project team. The team will study the historical satellite data of their fields and provide suggestions for nutrient and irrigation management over active growing seasons in the future. These efforts are likely to be integrated with thesis and dissertation efforts of interested graduate students working in conjunction with STEM undergraduates in a vertically integrated multidisciplinary teams.

6. Conclusions

This study demonstrates the value of integrating Sentinel-2 optical data with Sentinel-1 radar observations for field-scale crop monitoring at the UMES research field. NDVI and NDMI derived from Sentinel-2 effectively characterized crop vigor and canopy moisture during the 2022 corn and 2023 soybean seasons, while Sentinel-1-derived RVI provided structural information and continuity under cloudy conditions. By anchoring satellite observations to known planting and harvest dates, the analysis illustrates how multi-sensor satellite products can support precision agriculture, research, and education in the eastern shore region.

Although satellite-derived indices alone are not sufficient predictors of yield at fine spatial scales, their integrated use across seasons and sensors offers valuable insights into crop development, stress, and management impacts. This approach aligns well with ASEE priorities by highlighting experiential learning, interdisciplinary integration, and the use of modern sensing technologies in agricultural and engineering education and research.

7. Acknowledgement

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Bibliography

Balaghi, R., & Lebourgeois, V. (2024). An inclusive approach to crop soil moisture estimation: Leveraging satellite thermal infrared bands and vegetation indices on Google Earth Engine. *Agricultural Water Management, 287*, 108468. https://doi.org/10.1016/j.agwat.2024.108468

Baret, F., Jacquemoud, S., & Hanocq, J. F. (1993). The soil line concept in remote sensing. *Remote Sensing Reviews, 7*(1), 65–82.

Copernicus Data Space Ecosystem. (2024). *Sentinel-1 mission overview and data products*. European Union. https://documentation.dataspace.copernicus.eu

Copernicus Data Space Ecosystem. (2024). *Sentinel-2 mission overview and Level-2A products*. European Union. https://documentation.dataspace.copernicus.eu

Drusch, M., Del Bello, U., Carlier, S., et al. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment, 120*, 25–36. https://doi.org/10.1016/j.rse.2011.11.026

European Space Agency. (2024). *Sentinel-1: Radar vision for Copernicus*. https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1

Ghimire, B., Rogan, J., & Miller, J. (2020). Remote sensing of vegetation moisture dynamics using multi-temporal Sentinel-2 data. *Remote Sensing, 12*(19), 3136. https://doi.org/10.3390/rs12193136

Huete, A. R., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment, 83*(1–2), 195–213.

Iqbal, F., Amin, M., & Munir, S. (2024). Integration of Sentinel-1 and Sentinel-2 data for agricultural monitoring. *Agriculture, 14*(10), 2032. https://doi.org/10.3390/agriculture14102032

Jackson, T. J., Chen, D., Cosh, M., et al. (2010). Vegetation water content mapping using Landsat data derived normalized difference water index for corn and soybeans. *Remote Sensing of Environment, 114*(10), 2364–2377.

Kogan, F. (1995). Application of vegetation index and brightness temperature for drought detection. *Advances in Space Research, 15*(11), 91–100.

McNairn, H., Shang, J., Jiao, X., & Deschamps, B. (2009). The contribution of ALOS PALSAR multipolarization data to crop classification. *IEEE Transactions on Geoscience and Remote Sensing, 47*(12), 3981–3992.

Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering, 114*(4), 358–371.

Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA Special Publication*, 351, 309–317.

Singh, S., Jain, V., & Sharma, M. (2024). Assessment of crop phenology using SAR and optical data fusion. *Remote Sensing of Environment, 300*, 113958. https://doi.org/10.1016/j.rse.2024.113958

Thenkabail, P. S., Lyon, J. G., & Huete, A. (2018). *Hyperspectral remote sensing of vegetation*. CRC Press.

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment, 8*(2), 127–150.

USDA National Agricultural Statistics Service. (2023). *Crop planting and harvesting dates for the United States*. https://www.nass.usda.gov

Wardlow, B. D., Egbert, S. L., & Kastens, J. H. (2007). Analysis of time-series MODIS 250 m vegetation index data for crop classification in the U.S. Central Great Plains. *Remote Sensing of Environment, 108*(3), 290–310.

Zhang, Y., McNairn, H., & Shang, J. (2023). Sensitivity of radar vegetation indices to crop structure and phenology. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 16*, 4567–4581.

APPENDIX

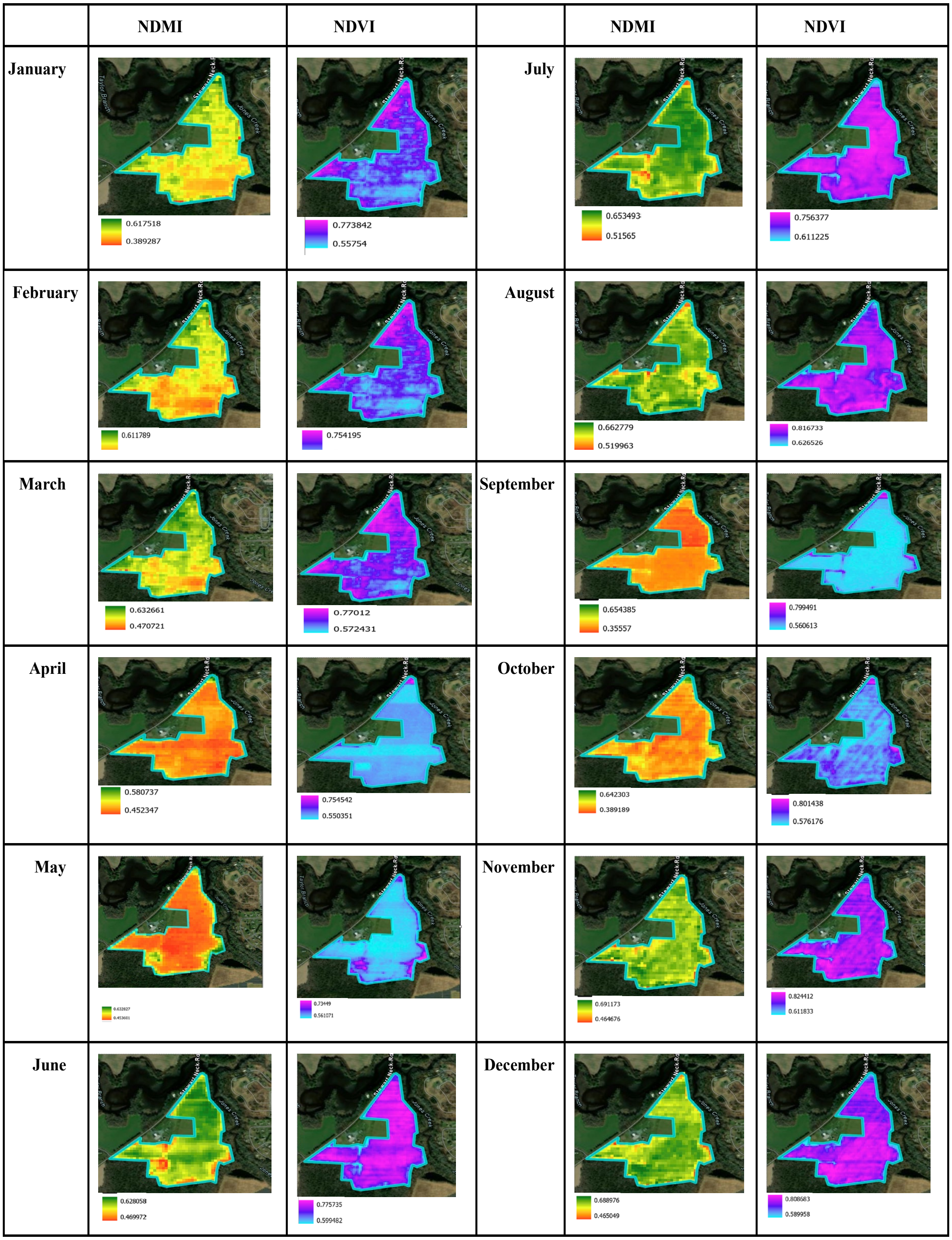


Figure 4: Monthly NDVI and NDMI Maps for Stewart Neck Field (2022 – Corn)

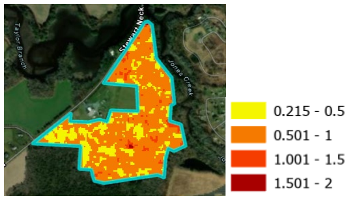
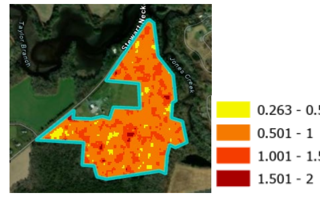
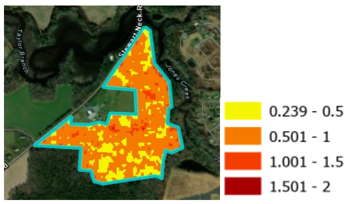
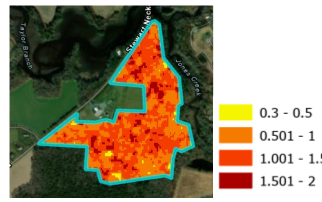
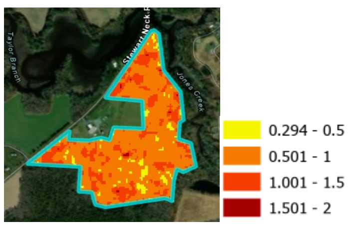
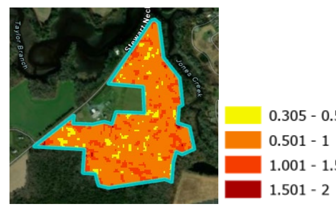
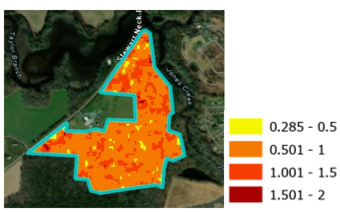
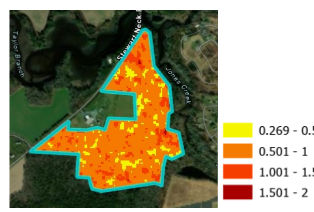
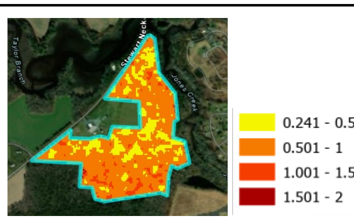
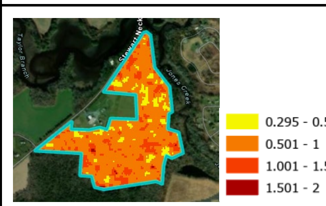
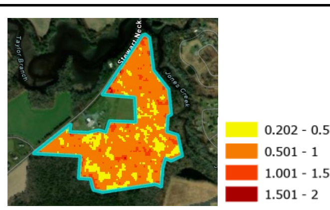
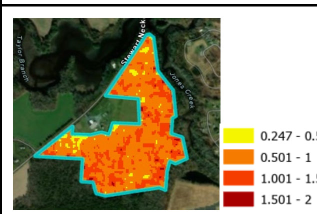
	RVI		RVI
January		**July**	
February		**August**	
March		**September**	
April		**October**	
May		**November**	
June		**December**	

Figure 5: Monthly RVI Maps for Stewart Neck Field (2022 – Corn)

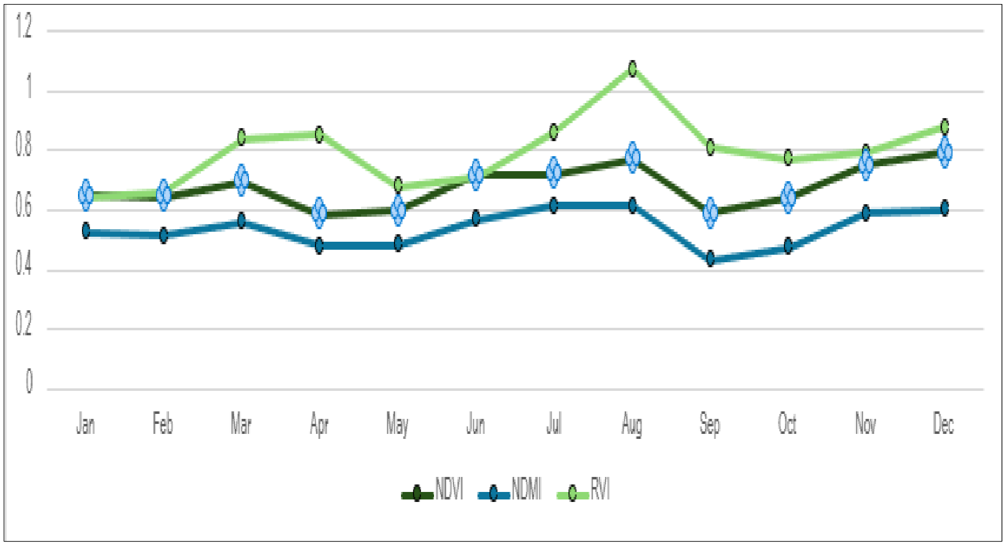


Figure 6. Monthly average values of NDVI, NDMI, and RVI (2022)