Remote Sensing Based Crop Monitoring Techniques: A Case Study for the Navajo Nation

Varatharajaperumal Thangavel[1], Sudhagar Nagarajan[2], Madasamy Arockiasamy[3], Md. Tarique Khan[4], George Sklivanitis[5]

[1]vthangavel2024@fau.edu, [2]snagarajan@fau.edu, [3]arockias@fau.edu
[4]tkhan@navajotech.edu, [5]gsklivanitis@fau.edu
[1,2,3] Department of Civil, Environmental and Geomatics Engineering Florida Atlantic University, Florida, USA
[4] School of Engineering, Math & Technology Faculty, Navajo Technical University, Crownpoint, New Mexico, USA
[5] Department of Electrical Engineering and Computer Science, Florida Atlantic University, Florida, USA

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Abstract

Agriculture plays a major role in eradicating poverty, promoting prosperity, and nourishing a projected 10 billion people by 2050 globally. In a changing climate, achieving optimal agricultural yields requires a deeper understanding of available natural resources and crops. This is especially important for places like the Navajo Nation, which faces significant challenges in food supply chain management due to various factors such as water demand, water quality, and insufficient information about land fertility and crops timings/seasons. Additionally, it is the largest Native American reservation in the U.S. It covers 27,425 square miles across Arizona, Utah, and New Mexico and has a population of 165,158 people, according to the 2020 census. Agriculture has been a key part of life in the Navajo Nation since the late 19th and early 20th centuries, playing a big role in the region's development and stability. However, the lack of knowledge about decisions and actions during the crop growing season has resulted in lower crop productivity, as evidenced by the USDA statistical report for the Navajo Nation in 2012 and 2017. To support farmers by providing better decision-making and actionable insights, high-resolution, open-source Sentinel-2 satellite images are being used to develop advanced crop mapping techniques for identifying the spatial extent of various agricultural crops in the Navajo Nation. To address this, a collection of research papers was reviewed, leading to the development of a new methodology for analysing Sentinel-2 data from the 2017 and 2023 growing seasons within the Navajo Nation. The collected data was pre-processed by creating monthly median composites of surface reflectance to remove noise and enhance the results more accurately. After preprocessing, spectral indices were calculated from the spectral bands, including NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), GCVI (Green Chlorophyll Vegetation Index), and LSWI (Land Surface Water Index), to differentiate the crops more precisely. The training datasets were obtained from the USDA's Crop Data Layer (CDL) and split into 80% for training and 20% for validating the Random Forest supervised classification algorithm. The classification resulted in an accuracy of 80%. Finally, the accuracy of the results was compared with independent ground truth data. This research identifies notable discrepancies between the CDL data and the Navajo Nation agricultural census statistical report, particularly in estimating corn acreage for the *Chinle* and *Fort Defiance* agencies. Ultimately this approach information is used to provide actionable insights to Navajo Nation farmers.

1. Introduction

Agriculture is central to human society, providing essential food and resources while supporting economic stability and development. It serves as a significant foundation for the livelihoods of millions worldwide and has been recognized for its role in addressing global challenges such as poverty, hunger, and environmental sustainability. With a world population projected to reach nearly 10 billion by 2050, agriculture faces immense pressure to increase production sustainably and adapt to changing climatic conditions (FAO, 2021; United Nations, 2019). This demand makes agricultural innovation crucial to ensure food security, economic growth, and environmental health.

In many regions, agricultural challenges are exacerbated by climate change, which affects weather patterns, water availability, and soil fertility. Extreme weather events, such as droughts, floods, and temperature fluctuations, disrupt crop yields and threaten the livelihoods of farmers, especially in developing nations where resources are limited. These challenges have highlighted the importance of sustainable agricultural practices and climate-resilient crop production systems to secure food supplies in the face of uncertainty (IPCC, 2019). At the same time, agriculture itself is a significant contributor to environmental issues, such as greenhouse gas emissions and deforestation, which calls for a balanced approach that maximizes productivity while minimizing negative impacts on ecosystems (World Bank, 2020).

To address these issues, technological advancements in agriculture have become a vital part of modern farming. Technologies such as remote sensing, precision agriculture, and machine learning enable farmers to make data-driven decisions that improve efficiency and sustainability. Remote sensing, for instance, uses satellite data to monitor crop health, soil moisture, and land-use patterns in real time. This information allows farmers to respond promptly to changes in crop conditions, leading to better yields and resource management. In addition, precision agriculture techniques help optimize inputs like water, fertilizers, and pesticides by applying them only where needed, reducing waste and environmental impact (Sustainable Agriculture Research & Education, 2021).

These advancements are especially beneficial for regions facing specific agricultural and environmental challenges, such as the Navajo Nation in the United States. The Navajo Nation covers a vast, arid region, and local agriculture is essential for the community's food security and economic stability. However, the region's challenging climate, limited water resources, and soil conditions make traditional farming difficult. By integrating modern technologies, farmers in such regions can gain actionable insights into crop health, soil quality, and water use, enabling them to make timely decisions to support crop growth under challenging conditions (USDA, 2020).

This research work explores the potential of remote sensing-based crop monitoring as a solution for remote areas like the Navajo Nation, providing an overview of how these technologies contribute to sustainable agriculture. By combining satellite imagery and field sensors data, farmers can optimize the use of

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natural resources, enabling more efficient crop management. These technologies allow for informed decision-making on critical aspects and stages. As a result, they not only help increase crop yields but also ensure the sustainable use of essential resources, such as water and soil. High-resolution satellite imagery, when integrated with data analysis, improves the accuracy of agricultural activity monitoring, providing farmers with timely and reliable information. This enables them to make decisions that enhance productivity while addressing environmental and resource-based challenges.

In recent years, remote sensing technologies, particularly satellite imagery, have played a crucial role in improving agricultural practices, especially in crop mapping and classification. High-resolution satellite imagery i.e., Sentinel-2 has significantly enhanced the accuracy of crop classification by providing 10-meter surface reflectance data, which improves field boundary detection and overall classification precision compared to lower-resolution data like the 30-meter Cropland Data Layer (CDL) (Tran et al., 2022). These advancements are complemented by the use of spectral indices such as NDVI and NDWI, which help monitor crop health, soil conditions, and water usage. Remote sensing methods often integrate machine learning algorithms like Random Forest (RF) and deep learning models, allowing for the automation of crop mapping by processing large-scale data sets and improving classification accuracy, even with limited early-season data (Zhang et al., 2022; Hao et al., 2016). Additionally, the combination of multisource satellite data, including imagery from Landsat 8 & 9 and Sentinel-2, with historical CDL data, has led to the development of tools like the In-Season Crop Data Layer (ICDL), which provides timely and accurate crop classifications across vast regions (Li et al., 2024). These innovations enable farmers to make informed decisions about crop selection, irrigation, and pest management, ultimately supporting sustainable agriculture. The integration of remote sensing data with other resources, such as soil sensors and weather forecasts, further enhances the ability to optimize resource use, leading to improved crop yields while minimizing environmental impacts (Guan et al., 2017; Alami et al., 2023). These technologies not only address the challenges of precision in crop classification but also offer promising solutions for sustainable agricultural practices, especially in regions facing specific environmental and resource-based constraints.

Recent research has led to the development of new methods that combine these technologies, such as categorizing crops from April through November 2017 and comparing the results with databases like CDL and Agricultural Census information. This approach aims to improve the accuracy of existing agricultural data, providing valuable insights for decision-making and supporting sustainable agricultural practices in remote regions. This work underscores the potential of these advancements to transform agriculture, particularly in regions with unique environmental challenges.

2. Study Area

The Navajo Nation, the biggest land tract kept by a Native American tribe in the United States, covers 27,425 square miles (70,000 square kilometres) in northeastern Arizona, southeastern Utah, and northwestern New Mexico, as shown in figure 1 (Navajo Families). It is divided into five agencies: *Chinle (Central) Agency*, *Eastern Navajo (Crownpoint) Agency*, *Fort Defiance Agency*, *Shiprock (Northern) Agency*, and *Western Navajo (Tuba City) Agency*. Each agency manages the welfare of its communities, focusing on areas such as agriculture, land use, natural resources, and economic development, aiming to enhance the quality of life for the Navajo people.

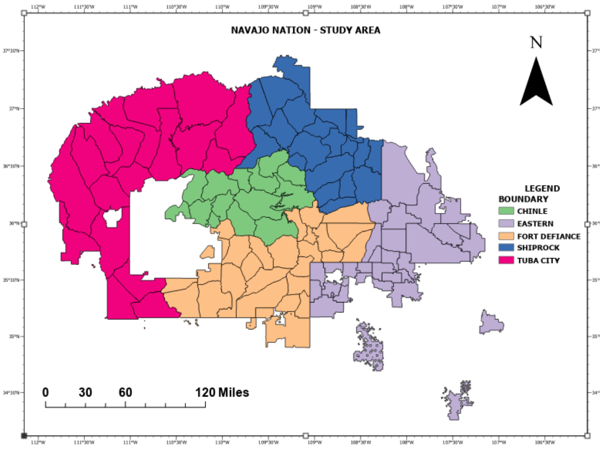

Figure.1. Navajo Nation - Study Area Extent/Boundary

According to the 2010 Census, the reservation has a total population of 173,637 individuals, including 169,321 Native Americans. The total land area is 17,035,180.68 acres, and the overall Navajo population in the United States is 331,813 (Census Reporter, 2020). With a land base larger than the state of West Virginia, the Navajo Nation is one of the largest tribal governments in North America. It operates as a sovereign nation under agreements with the U.S. Congress.

3. Methodology

The entire workflow of this research project is outlined in figure 2, which spans from the initial data collection phase to the final stages of accuracy assessment and result comparison.

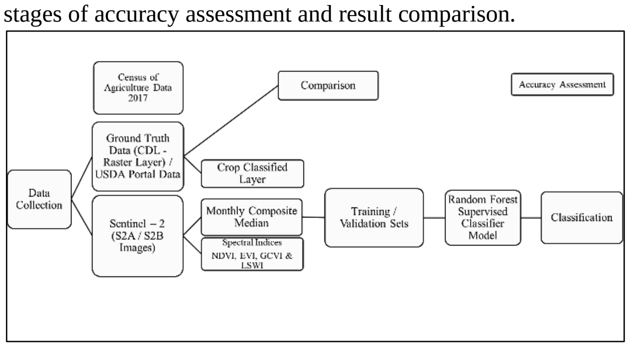

Figure.2. Methodology flowchart for the Research work

The analysis was conducted using satellite imagery, the Google Earth Engine platform, and the Random Forest (RF) supervised classification model, ensuring an efficient approach to the classification and analysis of the agricultural data. Two different types of data were obtained during the data collection phase: Sentinel-2 data, which is publicly available and open source, with a 10m resolution for the selected bands and 30m and 60m resolution for the remaining bands (Sentinel Hub Documentation). The data were retrieved from the Copernicus Data Space Environment website (Copernicus). Additionally, the duration of the crop season (i.e Corn), from April to November, was selected based on the crop calendar available on the U.S. Department of Agriculture (USDA) website. The USDA crop calendar provides important insights into planting and harvesting periods for various crops, which helped define the time frame for this study. This period aligns with typical crop growing seasons in the Navajo Nation, where seasonal variations and agricultural practices are closely tied to climate and soil conditions. By analysing crop data during this time frame, the research aims to capture the most relevant agricultural activity to improve classification and productivity insights (USDA, 2020). On the other hand, the Cropland Data Layer (CDL), with a 30m resolution, was obtained from the USDA website and is freely accessible (Figure 3). The red-colored rectangular box in figure 3 highlights an area within the Navajo Nation that shows a higher level of agricultural activity according to the CDL data.

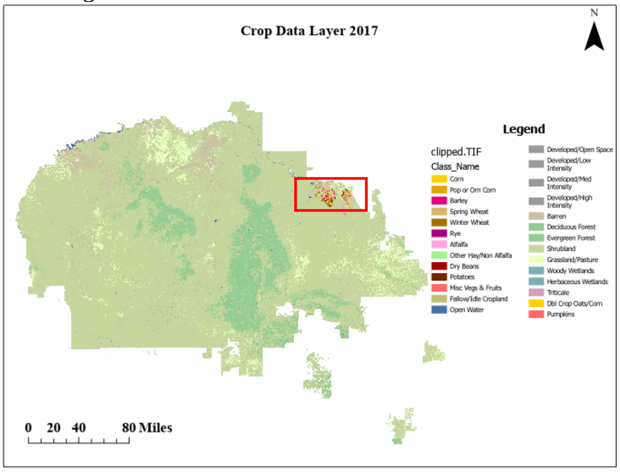

Figure.3. Crop Data Layer from USDA for the year 2017

This dataset is a critical resource for agricultural monitoring, policymaking, and research, enabling accurate and comprehensive analysis of crop distributions and land management practices. Both datasets correspond to the year 2017. For better visualization and differentiation of agricultural land from other vegetation types, the combination of Sentinel-2 bands 2, 8, and 11 is effective. These bands enhance the ability to distinguish agricultural land from surrounding vegetation (Figure 4). Furthermore, the research required the Navajo Nation Agriculture Statistical Report for a more comprehensive understanding of crop statistics (USDA, 2017). Therefore, the report for the year 2017 was obtained from the USDA website (Table.1).

Crops	Farms	Acres
Corn, traditional, acres	1,977	4,977
Hay and haylage, acres	482	30,010
Vegetables, acres	1,243	8,394
Cantaloupes, acres	209	83
Honeydew melons, acres	102	45
Squash, all, acres	1,013	798
Watermelons, acres	826	802

Table.1 Agriculture Statistical Report for Navaja Nation (Source: USDA National Agricultural Statistics Service)

Figure.4. Band Combination for Agriculture Land for the selected Region (Red-Color- Rectangular box

3.1 Monthly Median Calculation

To improve the accuracy of the agricultural crop classification, it was essential to preprocess the Sentinel-2 data by reducing noise and mitigating atmospheric disturbances. This was achieved by calculating the monthly mean and median of the Sentinel-2 data. These monthly calculations help to smooth temporal variations and remove transient anomalies such as cloud cover and atmospheric interference, which could otherwise distort the vegetation signal. The mean and median values for each month provide a clearer and more consistent representation of vegetation and land cover dynamics, improving the reliability of subsequent spectral indices calculations.

3.2 Spectral Indices

Based on the literature review (Cai, Y et al., 2018), selective spectral indices were chosen for the research work. These indices are essential in agricultural crop classification and mapping, as they provide vital information on crop health, growth, and type, which aids in decision-making for agricultural management. Spectral indices have been widely used to enhance crop monitoring, allowing for the detection of plant stress and variations in growth stages (Fensholt et al., 2012). In this research work, four main spectral or vegetation indices were calculated using Sentinel-2 satellite data: the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Green Chlorophyll Vegetation Index (GCVI), and Land Surface Water Index (LSWI). The corresponding equations for these indices are expressed in Equations (1) to (4). These indices help to differentiate crop types effectively.

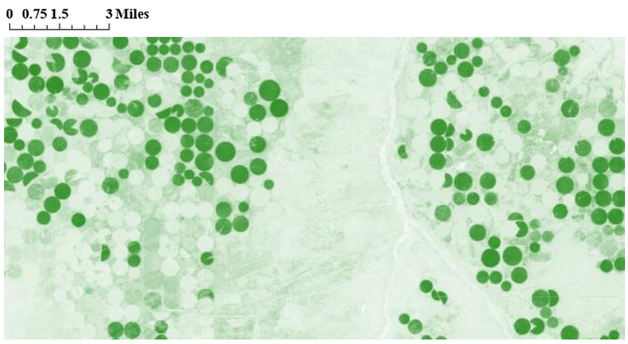

Figure.5. NDVI calculation for the Month of April 2017

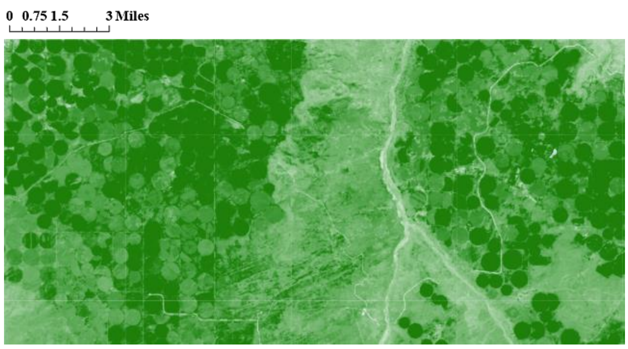

Figure.6. GCVI calculation for the Month of April 2017

The Normalized Difference Vegetation Index (NDVI) is widely used to assess vegetation health by calculating the difference between red and near-infrared (NIR) reflectance. High NDVI values indicate healthy vegetation, which reflects strongly in the NIR and absorbs red light effectively. This index is valuable for monitoring crop growth, detecting stress conditions, and estimating crop yields, as it helps differentiate between vegetated and non-vegetated areas, supporting land cover classification and change detection (Figure 5).

The Green Chlorophyll Vegetation Index (GCVI), sensitive to chlorophyll content, is used to estimate plant chlorophyll levels, which are crucial indicators of crop health and productivity. GCVI helps identify nutrient deficiencies or stress caused by environmental factors (Figure 6). The Enhanced Vegetation Index (EVI) enhances sensitivity to vegetation in areas with high biomass by correcting for atmospheric and soil background effects. It is particularly useful in dense canopies and provides more reliable vegetation monitoring than NDVI in such areas (Figure 7).

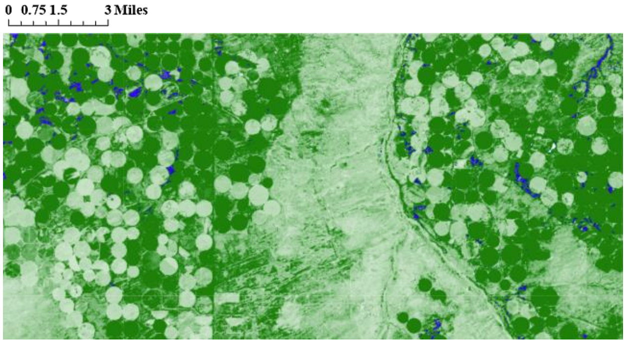

Figure.7. EVI calculation for the Month of April 2017

The Land Surface Water Index (LSWI) monitors surface water content and detects changes in water availability, which is vital for irrigation management and drought assessment. LSWI provides insights into the interaction between vegetation and water resources, helping to assess plant water stress and overall health (Figure 8).

Figure.8. LSWI calculation for the Month of April 2017

The Spectral Indices are calculated for each month of the growing season (April to November 2017). Thus, there are a total of 8 months and 4 indices, resulting in 32 layers overall.

$NDVI = (NIR-RED)/(NIR+RED)$ ------- **(1)**
$GCVI=NIR/GREEN-1$ ------- **(2)**
$EVI=G\times(NIR-RED)/(NIR+C1\times RED-C2\times BLUE+L)$ ---- **(3)**
$LSWI=(NIR-SWIR1)/(NIR+SWIR1)$ ------- **(4)**

3.3 Training Samples

To train the Random Forest supervised classifier model, the CDL layer was used as the ground truth. Training samples were collected for each crop type based on the statistical data from the Navajo Nation Report. These crops included alfalfa, corn, dry beans, popcorn corn, potatoes, pumpkins, shrubland, grassland, open water, winter wheat, and evergreen forest. For each crop type, 120 training points were selected (Figure 9). The training samples for all crop types were merged to ensure comprehensive and accurate classification. The Random Forest (RF) supervised classifier was trained using these merged training samples, which were split into 80% for training and 20% for validation. The classification process was then carried out using the trained model, producing a reliable output for agricultural crop mapping.

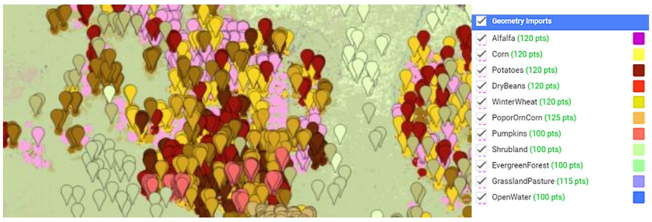

Figure.9. Training Samples data in CDL Data

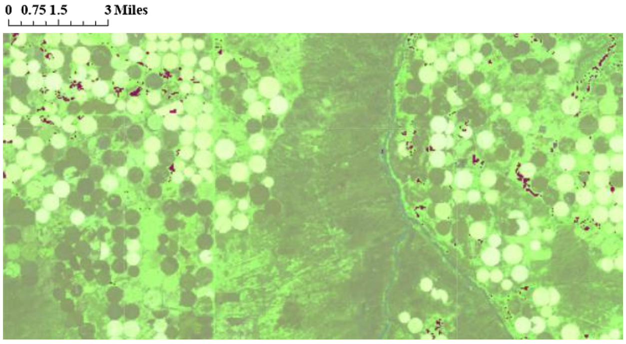

Figure.9. Combined Spectral Indices layer for the Month of April 2017

4. Results and Discussion

4.1 Classification Results

The red-colored rectangular box in Figure 3 highlights a region within the Navajo Nation characterized by higher agricultural activity, as indicated by the Cropland Data Layer (CDL) data. This region was the primary focus of the classification analysis. The combined spectral indices layers (Figure. 10) were classified using the training samples and the Random Forest Supervised Classifier Model, resulting in a total of 8 layers. Each of the 8 layers (from April to November) was individually classified. But some groups of pixels were misclassified into incorrect classes. To address this issue, the monthly combined indices (i.e., 8 layers) were merged into a single layer using the mean reducer function in Google Earth Engine. The classification process was then repeated using the training samples and the RF supervised classifier model. The results clearly demonstrated that the new categorization was superior to the previous results. (Figure 11).

4.2 Accuracy Assessment

The accuracy of the classified layers was assessed to evaluate the performance of the Random Forest (RF) supervised classifier model. Training and validation samples were taken from the 2017 Crop Data Layer (CDL), with 80% used for training and 20% for validation. The classification achieved an overall accuracy of **80.07%** and a Kappa coefficient of **0.78**.
A confusion matrix was also used to calculate User's accuracy, which measures how well pixels of a class are correctly identified, and Producer's accuracy, which reflects the likelihood that a pixel from a class is correctly classified. These metrics, along with overall accuracy and the Kappa coefficient, provided a comprehensive evaluation of the model's performance (Table.2).

4.3 Comparison with Databases

The classified layer’s crop acreage for corn was compared against CDL and Agricultural census records. According to the agricultural census, two agencies: *Chinle* and *Fort Defiance* reported higher corn acreage within the Navajo Nation compared to other regions, as shown in Table 3.

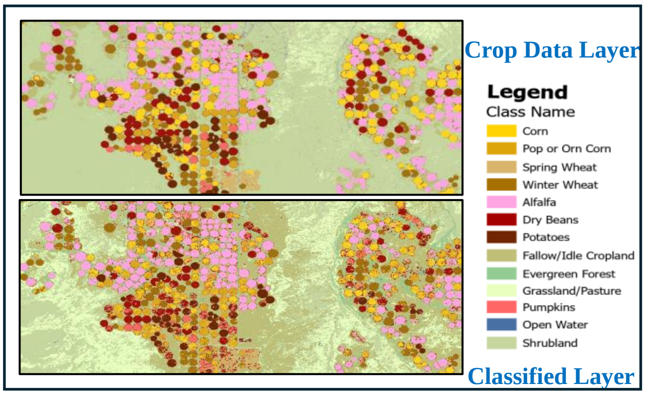

Figure.11. Result Comparison of CDL & Classified layer

	Alfalfa	Corn	Potatoes	Dry Beans	Winter Wheat	Pop Orn Corn	Pumpkins	Shrubland	Ever Green Forest	Grassland Pasture	Open Water	Sum	User's Accuracy
Alfalfa	20	0	0	0	2	0	0	0	0	0	1	23	86.96
Corn	0	11	0	1	0	6	2	0	0	1	0	21	52.38
Potatoes	0	1	15	0	0	1	0	0	0	0	0	17	88.24
Dry Beans	0	0	0	24	0	0	4	0	0	1	0	29	82.76
Winter Wheat	0	0	0	0	19	0	0	0	0	0	0	19	100.00
Pop Orn Corn	0	6	0	0	0	17	2	0	0	0	0	25	68.00
Pumpkins	0	0	4	4	0	1	16	0	0	0	0	25	64.00
Shrubland	0	0	0	0	0	0	0	22	2	2	0	26	84.62
Ever Green Forest	0	0	0	0	0	0	0	0	25	1	0	26	96.15
Grassland Pasture	0	1	0	0	1	0	1	4	0	19	0	26	73.08
Open Water	0	0	0	0	0	1	0	1	0	0	17	19	89.47
Sum	20	19	19	29	22	26	25	27	27	24	18	256	
Producer's Accuracy	100.00	57.89	78.95	82.76	86.36	65.38	64.00	81.48	92.59	79.17	94.44		80.39

Table. 2 Confusion Matrix of Random Forest Classification

The classified layer and *Chinle* agency cron acregae is available in figure 12 and similarly The classified layer and *Fort Defiance* agency cron acregae is available in figure 13.

Agency	No. of Farmland (16129)	Corn(Acres) (4977)
Chinle	3428	1539
Fort Defiance	4047	865

Table.3 Corn Acreage data from Agriculture Statistical Report

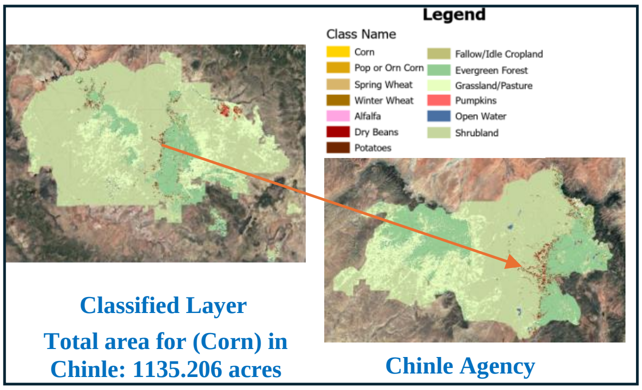

Figure. 12 *Chinle* agency cron acregae from classified layer

Additionally, data from the Soil Survey Geographic Database (SSURGO) provides further insight into agricultural activities within the Chinle Agency of Navajo Nation, highlighting farmland distribution (Figure 13).

According to the CDL data, there is no spatial information indicating agricultural activities within the *Chinle* (Figure.14) and *Fort Defiance* agencies in the Navajo Nation. A summary comparison of corn acreage based on different databases is provided in Table 4.

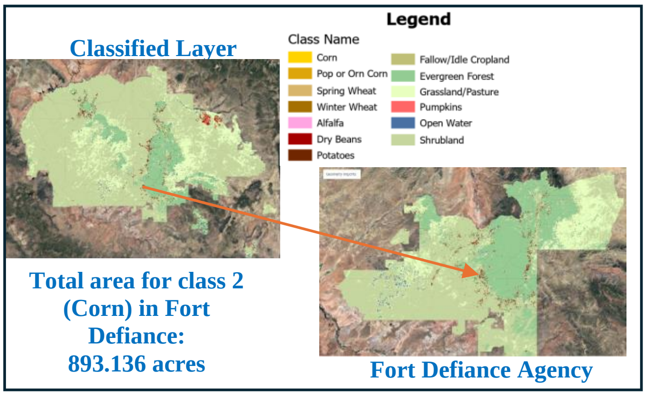

Figure. 12 *Fort Defiance* agency cron acregae from classified layer

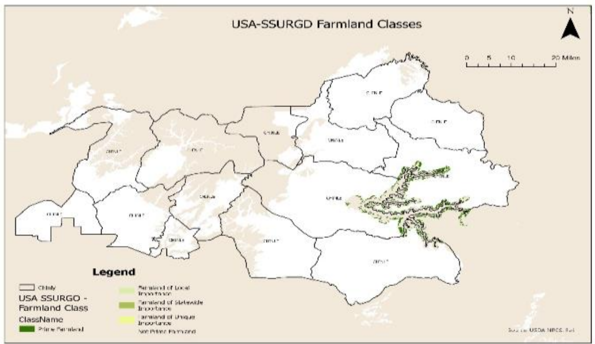

Figure.13. Chinle Agency with SSURGO Farmland Layer

Agency	CDL 2017	Census of Agriculture 2017 (Acre)	Classified layer 2017 (Acre)
Chinle	Nil	1539	1135.206
Fort Defiance	Nil	865	893.136

Table.4 Corn Area Comparison with Different Databases

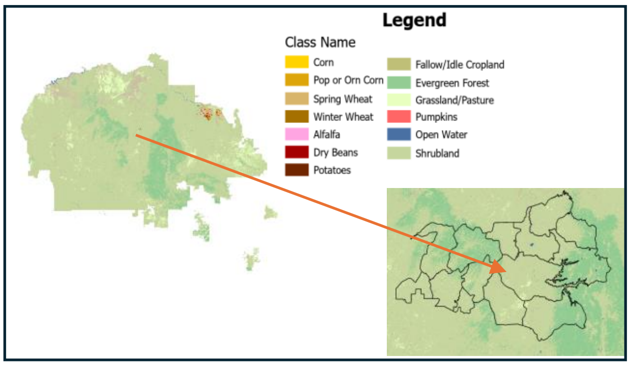

Figure.14. Chinle Agency with Crop Data Layer

5. Conclusion

This research identifies notable discrepancies between the CDL data and the Navajo Nation agricultural census statistical report, particularly in estimating corn acreage for the *Chinle* and *Fort Defiance* agencies. Using Sentinel-2 data and spectral indices, the study achieved nearly 80% classification accuracy, effectively aligning corn crop data from the Census of Agriculture, CDL, and the classified layer for the year of 2017. These results emphasize the challenges of aligning datasets from different sources in agricultural monitoring, while also demonstrating the potential of remote sensing techniques for improving accuracy.

In future work, the focus will be on refining the crop classification process by exploring various machine learning algorithms to enhance accuracy and robustness. Furthermore, extending the study to analyze data from multiple years will allow for the identification of temporal trends and better capture the dynamics of crop changes over time. Additionally, validating the model with ground truth data will be crucial to assess its real-world accuracy, ensuring that the classification results align with observed crop patterns. By incorporating these elements, the accuracy and reliability of agricultural monitoring in the Navajo Nation will be significantly improved.

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