Integrating Multi-Source Agricultural Data with Machine Learning to Improve Crop Mapping Accuracy: A Case Study of the Navajo Nation

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Abstract

Accurate crop maps are important for agricultural monitoring in water-limited regions because they provide spatial information for crop inventory assessment, land management, and resource planning. In the Navajo Nation, crop classification is challenging because agriculture is influenced by arid environmental conditions, limited water availability, and unevenly distributed cultivated land. This study evaluates a crop-classification workflow for a selected agricultural Region of Interest (ROI) within the Navajo Nation using Sentinel-2 imagery, the USDA/NASS Cropland Data Layer (CDL), and the CDL confidence layer in Google Earth Engine. High-confidence CDL pixels (confidence $\geq$ 95%) were used to construct pseudo-reference samples for the 2017 and 2022 growing seasons, and a 3×3 neighborhood homogeneity filter was applied to reduce local label uncertainty. Spectral predictors derived from Sentinel-2 imagery included the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Green Chlorophyll Vegetation Index (GCVI), and Land Surface Water Index (LSWI). A Random Forest classifier was implemented separately for each year using an 80% training and 20% testing split. The resulting classifications achieved overall accuracies of 87.30% for 2017 and 90.88% for 2022. These results show that confidence-screened CDL samples combined with multi-temporal Sentinel-2 features can support reliable crop classification within the selected ROI under limited reference-data conditions and provide a practical basis for agricultural monitoring in the Navajo Nation.

1. Introduction

Crop mapping provides spatial information on crop distribution, land-use structure, and seasonal agricultural patterns. This information supports agricultural monitoring, land management, and regional planning, particularly in water-limited environments where field observations are limited. Recent crop-mapping studies have increasingly relied on multi-temporal optical imagery, since seasonal crop behavior often provides stronger class separability than single-date spectral response alone. Sentinel-2 has become one of the principal data sources for this purpose because its spatial resolution, revisit frequency, and spectral configuration are well-suited to characterizing vegetation condition and crop development through the growing season (Alami Machichi et al., 2023; Tran et al., 2022; Wang et al., 2022; Zhang et al., 2022).

A persistent challenge in regional crop classification is the availability of reliable reference samples. Field-based training data collection is costly and difficult to maintain consistently across years and across large geographic extents. For this reason, recent research studies have explored the use of map-derived labels and weakly supervised strategies for crop mapping. In the United States, the USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) is widely used in agricultural classification studies, but it remains a classified map product rather than an independent ground reference. Its use in supervised learning therefore requires attention to label quality and uncertainty. Earlier studies have shown that screening CDL-derived samples to retain trusted or high-confidence pixels can improve classification reliability relative to the direct use of unscreened labels (Zhang et al., 2021; Tran et al., 2022).

Another methodological challenge arises from the interaction between predictor resolution and label resolution. When moderate-resolution label products are paired with finer-resolution satellite predictors, mixed pixels near field boundaries and heterogeneous land cover can reduce sample purity. This issue is especially relevant when pseudo-reference labels are used for crop classification. Current research studies therefore emphasize sample refinement, temporal feature design, and careful interpretation of map-derived labels as important components of crop-mapping workflows in data-scarce settings (Alami Machichi et al., 2023; Liu et al., 2023).

Sentinel-2 time-series data support this type of analysis through repeated multispectral observations that can be transformed into vegetation- and moisture-sensitive indices. Indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Green Chlorophyll Vegetation Index (GCVI), and Land Surface Water Index (LSWI) are commonly used to represent crop vigor, canopy condition, chlorophyll-related response, and moisture-related variation. These variables have been used successfully in operational and research-oriented crop classification studies, including workflows that combine seasonal compositing with machine-learning methods such as Random Forest (Cai et al., 2018; Tran et al., 2022; Zhang et al., 2022).

The computational framework is equally important for regional implementation. Google Earth Engine provides direct access to satellite archives and supports image preprocessing, compositing, feature generation, classification, and map production within a cloud-based environment. This enables consistent multi-year processing and reduces local computational constraints. Its use has become common in remote-sensing workflows that require reproducibility and regional scalability (Gorelick et al., 2017; Tamiminia et al., 2020; Xie et al., 2022).

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These methodological considerations are relevant in the Navajo Nation, where agriculture is influenced by arid to semi-arid environmental conditions, limited water availability, and strong spatial variability in cultivated land. Remote-sensing products have already been used in the region for environmental and drought-related monitoring, indicating the broader value of spatially explicit geospatial information for land and resource assessment. At the same time, the Navajo Nation remains less represented in crop-mapping studies than intensively monitored agricultural regions, which makes it an appropriate case for evaluating a crop-classification workflow under limited reference-data conditions (McCullum et al., 2021). Earlier remote-sensing work in the Navajo Nation has also demonstrated the feasibility of Sentinel-2-based crop monitoring and highlighted discrepancies between CDL-derived estimates and reported agricultural statistics, indicating the need for more region-specific classification analysis (Thangavel et al., 2025).

In response to these research gaps, this study develops a crop classification workflow for a selected agricultural Region of Interest (ROI) in the Navajo Nation, with separate classifications conducted for 2017 and 2022. The analysis focuses on crop mapping within the selected ROI, with emphasis on pseudo-reference label refinement, multi-temporal predictor preparation, and class-level evaluation. Unlike workflows that rely on field-collected reference data, the present study evaluates a year-wise classification framework based on confidence-screened CDL pseudo-reference labels and multi-temporal Sentinel-2 predictors under limited reference-data conditions.

2. Study Region and Data Sources

The analysis was conducted within a selected ROI in the Navajo Nation (Figure 1). The ROI was selected from the larger Navajo Nation because USDA/NASS Cropland Data Layer (CDL) data indicate relatively greater agricultural activity in this area, making it an appropriate focus for detailed crop mapping. The study was designed at the ROI scale rather than across the full Navajo Nation in order to evaluate the classification workflow under a consistent local setting while retaining the broader regional context. The Navajo Nation is characterized by arid to semi-arid conditions, limited water availability, and strong spatial variability in land and water resources, all of which influence agricultural activity and land-cover structure (McCullum et al., 2021). The selected ROI covers approximately 1,661.24 km² and includes both cultivated and non-cultivated classes, providing a suitable setting for evaluating class separability and classification stability in a mixed landscape.

The classification workflow relied on two principal geospatial data sources: Sentinel-2 Surface Reflectance Harmonized imagery and the USDA/NASS Cropland Data Layer (CDL). In this study, the integrated data sources consisted of Sentinel-2 observations, annual CDL class labels, and the CDL confidence layer used for pseudo-reference sample refinement. Sentinel-2 imagery was used to derive seasonal spectral predictors, while the 2017 and 2022 CDL products provided the annual crop and land-cover labels for the two study years.

The CDL maps for the selected ROI are shown in Figures 2 and 3 for 2017 and 2022, respectively, to illustrate the spatial distribution of these labels. The associated CDL confidence layer was used during reference-sample preparation to retain

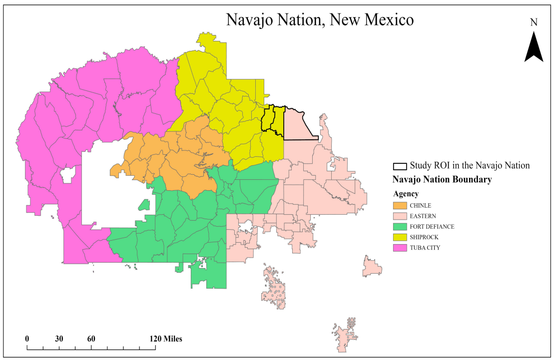

Figure 1. Location of the selected study ROI within the Navajo Nation.

higher-confidence pixels (USDA NASS, 2025; Hao et al., 2020). This strategy is consistent with recent crop-mapping studies that use label-efficient or pseudo-label-based approaches when field-based training data are unavailable or spatially limited (Zhang et al., 2024; Zhang, 2025). Sentinel-2 was selected because its high revisit frequency and multi-temporal coverage make it effective for crop mapping, particularly when seasonal trajectories are used to capture crop-specific phenological differences across the growing season (Savitha and Talari, 2023).

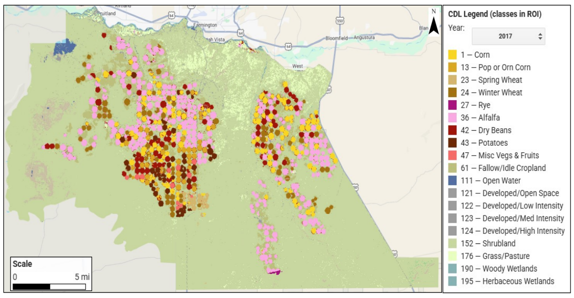

Figure 2. Cropland Data Layer (CDL) map of the selected ROI for 2017.

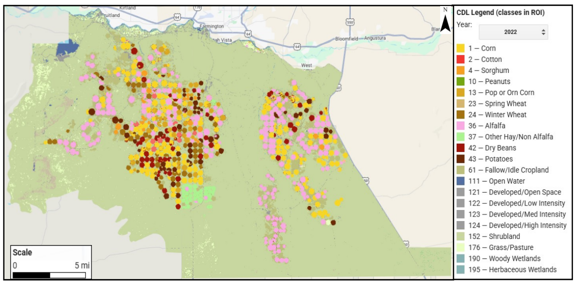

Figure 3. Cropland Data Layer (CDL) map of the selected ROI for 2022.

The analysis was conducted for the 2017 and 2022 growing seasons. These two years were selected so that the same classification workflow could be applied consistently across both annual mapping periods. For each year, Sentinel-2 imagery and the corresponding USDA/NASS CDL products were processed in a cloud-based environment to ensure a uniform procedure for image filtering, compositing, predictor derivation, and classification across the study years (Gorelick et al., 2017).

A 16-class schema was adopted to represent both crop and non-crop categories within the selected ROI. The agricultural classes included alfalfa, corn, potatoes, dry beans, winter wheat, pop or ornamental corn, sorghum, spring wheat, and other hay or non-alfalfa. Additional land-cover classes were included to represent the broader spatial setting of the study area, namely fallow or idle cropland, shrubland, grassland or pasture, barren land, open water, Developed (merged), and a merged other-crops category. Including both cultivated and surrounding non-cultivated classes allowed the classification to reflect the mixed land-cover structure of the ROI rather than limiting the analysis to cropland alone.

Together, Sentinel-2 imagery, CDL-derived class labels, and confidence-based label screening formed the data basis for the classification workflow.

3. Pseudo-Reference Sample Construction

Reference sample preparation was a critical component of the classification workflow because field observations were not available for the study area. In this study, pseudo-reference labels were derived from the USDA/NASS Cropland Data Layer (CDL) rather than from field-collected training samples. Although the CDL is widely used in crop-mapping studies in the United States, it remains a classified map product with its own uncertainty. It was therefore not used directly without screening. Earlier studies have shown that classification reliability can be improved when training samples are restricted to trusted or higher-confidence map pixels rather than using all available labels without refinement (Zhang et al., 2021; Maleki et al., 2024).

The first step in sample construction was to convert the CDL cropland band into the 16-class schema adopted for this study. Several classes were mapped directly from individual CDL codes, including alfalfa, corn, potatoes, dry beans, winter wheat, pop or ornamental corn, sorghum, spring wheat, other hay or non-alfalfa, fallow or idle cropland, shrubland, grassland or pasture, barren land, and open water. Two categories were represented as merged classes. Other crops (merged) was formed from selected CDL categories with limited representation, including pumpkins (229), oats (28), triticale (205), peas (53), and barley (21), while Developed (merged) was formed from developed open space (121), developed low intensity (122), developed medium intensity (123), and developed high intensity (124). Pixels not included in the target class schema were assigned a value of 0 and excluded from subsequent model training and evaluation. This remapping step produced a label image consistent with the classification system applied within the ROI.

After remapping, the CDL confidence layer was used to retain only pixels with confidence values greater than or equal to 95%. This step reduced the influence of uncertain labels in the sample set used for model training and testing.

After confidence screening, a second refinement step was applied to reduce local label inconsistency near field boundaries. Even after low-confidence CDL pixels were removed, boundary pixels could still remain unreliable because they may contain mixed land-cover signals or occur where adjacent pixels belong to different classes. Such pixels are less suitable for pseudo-reference sample construction because their labels may not represent spectrally homogeneous training targets. Previous studies have shown that sample impurity, mixed pixels, and spatial heterogeneity can reduce crop-classification reliability when such pixels are retained in the sample set (Chen et al., 2016; Hao et al., 2020; Zhang, 2025). To address this problem, a 3 × 3 neighborhood mode filter was applied to the reclassified label image, and only pixels matching the local modal class were retained. This step reduced the contribution of locally inconsistent pixels and produced a more spatially homogeneous pseudo-reference layer for subsequent sampling.

Stratified sampling by class was then conducted within the ROI using the refined pseudo-reference labels. This design ensured that each retained class contributed samples to the classification workflow. Previous studies have shown that stratified random sampling can provide more stable crop-type mapping performance than unsystematic or strongly imbalanced alternatives, particularly when class frequencies differ substantially (Aires et al., 2025; Navarro et al., 2021). The sampled dataset was then partitioned into random training and testing subsets for the year-wise classification and evaluation of 2017 and 2022.

4. Methodology

The overall classification workflow is summarized in Figure 4. The workflow included Sentinel-2 preprocessing, feature generation, integration of the refined pseudo-reference labels, year-specific Random Forest classification, and accuracy assessment. All steps were implemented separately for 2017 and 2022 in order to preserve the spectral and label characteristics of each year within the selected ROI.

Sentinel-2 Surface Reflectance Harmonized imagery was used as the predictor source for both study years. For each year, the image collection was filtered to the selected ROI and to the main crop-growing period from April to November. Pixels affected by cloud and cloud shadow were removed using the Scene Classification Layer (SCL). Monthly median composites were generated for April, June, August, and October to represent key stages of crop development across the growing season while limiting temporal redundancy in the predictor set. This compositing approach reduced within-month noise while preserving seasonal variation relevant to crop discrimination (Belgiu and Csillik, 2018; Li et al., 2022; Luo et al., 2021).

From each monthly composite, four spectral indices were derived: NDVI, EVI, GCVI, and LSWI. To supplement the monthly index layers, seasonal summary features were derived from the multi-temporal stack. For NDVI and EVI, maximum, minimum, mean, and amplitude were calculated. For LSWI and GCVI, mean values were retained. This combination of monthly composites and seasonal summary statistics formed the predictor set used for classification.

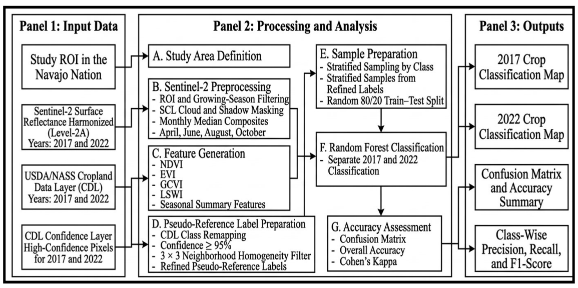

Figure 4. Methodology for ROI-Based Crop Classification in the Navajo Nation.

The resulting predictor set was integrated with the refined pseudo-reference labels described in Section 3. Stratified samples were first generated from the refined label image, and the predictor values at those sample locations were then extracted for classification. For each year, the sampled dataset was randomly divided into 80% training data and 20% testing data. Random Forest classification was then carried out separately for 2017 and 2022 using the corresponding yearly predictor stack and pseudo-reference samples. The classifier was implemented with 150 trees. Random Forest was selected because it is widely used in remote sensing and performs well with complex predictor sets while showing relative robustness to overfitting in classification applications (Belgiu and Drăguţ, 2016; Wei et al., 2023).

For each year, the trained model was applied to the corresponding predictor stack to generate the final classified image, which was then clipped to the ROI. Accuracy assessment was conducted using the withheld testing subset and included the confusion matrix, overall accuracy, Cohen’s kappa, and class-wise precision, recall, and F1-score. This evaluation design provided both summary-level and class-level assessment of classification performance under a consistent year-specific framework.

5. Classification Results

The year-wise classifications produced crop maps for both study years, with stronger overall performance in 2022 than in 2017. The 2017 classification achieved an overall accuracy of 87.30% and a Cohen’s kappa of 0.8622, while the 2022 classification achieved an overall accuracy of 90.88% and a Cohen’s kappa of 0.9017 (Table 1). The corresponding classified maps are shown in Figures 5 and 6.

Year	Training samples	Testing samples	Overall Accuracy (%)	Cohen’s Kappa
2017	2814	693	87.30	0.8622
2022	3121	735	90.88	0.9017

Table 1. Overall classification accuracy statistics for the 2017 and 2022 crop maps within the selected ROI.

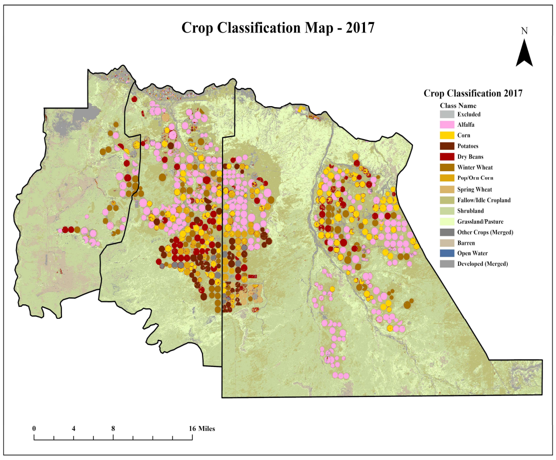

Figure 5. Crop classification map for the selected Navajo Nation ROI for the 2017 growing season.

The confusion matrices and class-wise metrics show that the strongest agreement occurred for several of the major crop classes (Tables 2 to 4). In 2017, potatoes and winter wheat achieved F1-scores of 1.000, while spring wheat, corn, pop or ornamental corn, dry beans, and other crops (merged) also performed strongly (Table 2). In 2022, winter wheat, sorghum, potatoes, open water, other hay or non-alfalfa, dry beans, other crops (merged), and pop or ornamental corn showed high levels of agreement (Table 2). The corresponding class-level agreement patterns are also evident in the 2017 and 2022 confusion matrices (Tables 3 and 4).

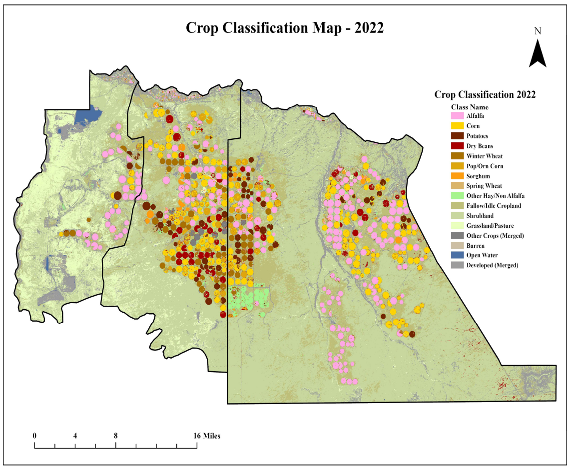

Figure 6. Crop classification map for the selected Navajo Nation ROI for the 2022 growing season.

Class Name	2017			2022		
	Precision	Recall	F1	Precision	Recall	F1
Alfalfa	0.962	0.927	0.944	0.887	0.982	0.932
Corn	0.926	0.893	0.909	0.850	0.829	0.840
Potatoes	1.000	1.000	1.000	0.979	0.959	0.969
Dry Beans	0.926	0.862	0.893	0.942	0.961	0.952
Winter Wheat	1.000	1.000	1.000	1.000	0.981	0.991
Pop/Orn Corn	0.907	0.907	0.907	0.949	0.903	0.926
Sorghum	0.000	0.000	0.000	0.982	0.964	0.973
Spring Wheat	0.946	0.982	0.964	0.000	0.000	0.000
Other Hay/Non Alfalfa	0.000	0.000	0.000	0.952	0.967	0.959
Fallow/Idle Cropland	0.525	0.781	0.628	0.818	0.790	0.804
Shrubland	0.774	0.661	0.713	0.750	0.787	0.768
Grassland/Pasture	0.833	0.732	0.779	0.849	0.849	0.849
Other crops (merged)	1.000	0.980	0.990	0.925	0.980	0.952
Barren	0.767	0.846	0.805	0.000	0.000	0.000
Open Water	0.000	0.000	0.000	0.958	0.979	0.968
Developed (merged)	0.737	0.712	0.724	0.909	0.811	0.857

Table 2. Class-wise F1-scores for the 2017 and 2022 classifications within the selected ROI.

Lower agreement was observed for several mixed agricultural and non-agricultural classes. In 2017, fallow or idle cropland, shrubland, grassland or pasture, barren land, and Developed (merged) showed lower F1-scores than the dominant crop classes (Table 2). In 2022, lower agreement was observed for fallow or idle cropland, shrubland, and grassland or pasture, while spring wheat and barren land had F1-scores of 0 (Table 2). In 2017, sorghum, other hay or non-alfalfa, and open water also had F1-scores of 0 (Table 2). These weaker results were mainly associated with classes that had limited representation or lower separability within the selected ROI.

Confusion Matrix for the 2017 Classification

Reference Class \ Predicted Class	Alfalfa	Corn	Potatoes	Dry Beans	Winter Wheat	Pop/Orn Corn	Sorghum	Spring Wheat	Other Hay/ Non Alfalfa	Fallow/ Idle	Shrubland	Grassland /Pasture	Other Crops (Merged)	Barren	Open Water	Developed (Merged)
Alfalfa	51	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3
Corn	0	50	0	1	0	4	0	1	0	0	0	0	0	0	0	0
Potatoes	0	0	64	0	0	0	0	0	0	0	0	0	0	0	0	0
Dry Beans	0	0	0	50	0	0	0	1	0	5	0	0	0	0	0	2
Winter Wheat	0	0	0	0	70	0	0	0	0	0	0	0	0	0	0	0
Pop/Orn Corn	0	3	0	1	0	39	0	0	0	0	0	0	0	0	0	0
Sorghum	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Spring Wheat	0	0	0	0	0	0	0	53	0	0	0	0	0	0	0	1
Other Hay/Non Alfalfa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Fallow/Idle Cropland	0	0	0	0	0	0	0	0	0	32	6	1	0	0	0	2
Shrubland	0	0	0	0	0	0	0	0	0	10	41	3	0	5	0	3
Grassland/Pasture	1	0	0	1	0	0	0	1	0	1	3	30	0	2	0	2
Other Crops (Merged)	0	0	0	1	0	0	0	0	0	0	0	0	50	0	0	2
Barren	0	0	0	0	0	0	0	0	0	2	2	0	0	33	0	2
Open Water	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Developed (Merged)	0	0	0	0	0	0	0	0	0	11	1	2	0	3	0	42

Table 3. Confusion matrix for the 2017 classification.

6. Discussion

The results indicate that the implemented workflow was able to produce stable year-wise crop classification within the selected ROI, with stronger overall performance in 2022 than in 2017. The higher overall accuracy and kappa in 2022 suggest that the same workflow did not perform identically across the two study years. This type of difference is expected in year-wise crop mapping because classification performance depends not only on model structure but also on annual variation in crop composition, spectral contrast, and the spatial distribution of valid reference samples. Multi-year crop-mapping studies have similarly shown that interannual variation can affect class separability even when the processing framework remains unchanged (Blickensdörfer et al., 2022; Turkoglu et al., 2021).

Confusion Matrix for the 2022 Classification																
Reference Class \ Predicted Class	Alfalfa	Corn	Potatoes	Dry Beans	Winter Wheat	Pop/Orn Corn	Sorghum	Spring Wheat	Other Hay/ Non Alfalfa	Fallow/ Idle	Shrubland	Grassland /Pasture	Other Crops (Merged)	Barren	Open Water	Developed (Merged)
Alfalfa	55	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Corn	0	34	0	0	0	2	0	0	0	0	1	0	4	0	0	0
Potatoes	0	2	47	0	0	0	0	0	0	0	0	0	0	0	0	0
Dry Beans	0	0	0	49	0	0	0	0	0	2	0	0	0	0	0	0
Winter Wheat	1	0	0	0	52	0	0	0	0	0	0	0	0	0	0	0
Pop/Orn Corn	0	3	0	2	0	56	1	0	0	0	0	0	0	0	0	0
Sorghum	2	0	0	0	0	0	53	1	0	0	0	0	0	0	0	0
Spring Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Other Hay/Non Alfalfa	0	0	0	1	0	0	0	0	59	1	0	0	0	0	0	0
Fallow/Idle Cropland	0	0	1	0	0	0	0	0	3	45	8	0	0	0	0	0
Shrubland	0	0	0	0	0	0	0	0	0	7	48	4	0	0	0	2
Grassland/Pasture	4	0	0	0	0	0	0	0	0	0	4	45	0	0	0	0
Other Crops (Merged)	0	0	0	0	0	1	0	0	0	0	0	0	49	0	0	0
Barren	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0
Open Water	0	0	0	0	0	0	0	0	0	0	2	0	0	0	46	1
Developed (Merged)	0	0	0	0	0	0	0	0	0	0	2	4	0	0	1	30

Table 4. Confusion matrix for the 2022 classification.

The strongest class-level results were obtained for several of the dominant crop classes, especially potatoes, winter wheat, dry beans, and corn-related classes. In 2022, sorghum, other hay or non-alfalfa, and open water also showed high agreement, whereas in 2017, spring wheat and other crops (merged) were among the better-performing classes. These patterns are consistent with the role of phenological separability in Sentinel-2 time-series classification, as classes with clearer seasonal trajectories are generally easier to distinguish than classes that are sparse, fragmented, or spectrally mixed. Similar observations have been reported in previous crop-mapping studies, which show that temporal signature strength, class representation, and class imbalance can all influence class-level performance, even when overall accuracy remains high (Blickensdörfer et al., 2022; Gorbunov et al., 2025; Turkoglu et al., 2021; Wei et al., 2023).

The weaker class-wise results also follow a technically reasonable pattern. In 2017, sorghum, other hay or non-alfalfa, and open water had F1-scores of 0, while in 2022, spring wheat and barren land had F1-scores of 0. These outcomes do not indicate failure of the overall workflow. Rather, they are more consistent with limited class support, reduced sample availability after confidence screening and neighborhood filtering, and lower separability for a small number of low-support classes. The USDA/NASS Cropland Data Layer (CDL) legend defines these as valid crop or land-cover classes, but their occurrence within the selected ROI varied by year after confidence screening and neighborhood filtering (USDA NASS, 2025). The confusion patterns further suggest that weaker agreement was concentrated in classes such as fallow or idle cropland, shrubland, grassland or pasture, barren land, and Developed (merged), which are more likely to occur in mixed or transitional settings within the ROI. Previous studies have similarly noted that class imbalance, spatial heterogeneity, and label structure remain important sources of variation in crop-type mapping, even when the overall map accuracy is relatively high (Gorbunov et al., 2025; Turkoglu et al., 2021; Zhang, 2025).

The behavior of the non-crop classes is also important for interpreting the workflow. The inclusion of fallow or idle cropland, shrubland, grassland or pasture, barren land, open water, and Developed (merged) made the classification problem more realistic than a crop-only design, but it also increased the difficulty of separating categories with broader thematic overlap. In this respect, the present results suggest that the confidence-screened CDL pseudo-reference strategy was effective for dominant and reasonably well-supported categories, but less stable for classes that were either weakly represented or more heterogeneous in their spatial expression. This is an important limitation of map-derived training approaches: once pseudo-reference labels are screened for confidence and local homogeneity, the remaining sample set may become cleaner but also smaller and less balanced for some categories. This trade-off is especially important in ROI-scale studies, where some classes already have limited spatial representation.

The present analysis was conducted within a selected ROI rather than across the full Navajo Nation. This design improves local consistency and keeps the classification problem aligned with the actual study extent, but it also means that the reported class-level behavior is ROI-specific and should not be interpreted as a complete representation of all agricultural conditions across the Navajo Nation. In addition, the workflow was deliberately limited to the crop-classification component of the broader research problem. It does not address irrigation demand, crop productivity estimation, or field-based agronomic variables, and the CDL was not treated as an independent ground sample.

Overall, the results show that the year-wise workflow provided a practical basis for crop classification within the selected ROI, with the strongest performance observed for the dominant and better-supported classes. Residual errors were concentrated mainly in classes with limited support or weaker separability. Within the scope of this study, the workflow provides a technically defensible framework for crop mapping in a data-limited agricultural setting, while the interpretation of low-support classes should remain cautious.

7. Conclusion

This study demonstrated a year-wise crop-classification workflow for a selected agricultural ROI in the Navajo Nation using Sentinel-2 imagery and confidence-screened CDL pseudo-reference labels. The resulting classifications achieved overall accuracies of 87.30% for 2017 and 90.88% for 2022, with corresponding Cohen's kappa values of 0.8622 and 0.9017. These results indicate that the workflow was able to separate the dominant crop and surrounding land-cover classes within the selected ROI with strong overall classification performance.

The class-wise results also showed that performance was not uniform across all categories. Stronger agreement was observed for several dominant crop classes, whereas weaker or zero-valued metrics were concentrated in a small number of low-support classes. This pattern suggests that the workflow was most effective for the better-represented classes in the study area, while classes affected by limited support, spatial mixing, or lower separability should be interpreted more cautiously.

Within the scope of this study, the main contribution was the demonstration of a practical ROI-based crop-classification

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framework for a data-limited agricultural setting in the Navajo Nation.

Future work may extend the current crop-mapping framework by integrating field observations and additional agronomic information to strengthen reference data and support broader agricultural monitoring, crop condition assessment, and related resource-management applications.

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