USING RVI AND NDVI TIME SERIES FOR CROPLAND MAPPING WITH TIME-WEIGHTED DYNAMIC TIME WARPING

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ABSTRACT:

Monitoring and management of agricultural lands are essential due to reasons affecting agriculture, such as increasing population and global climate. With the increase in the temporal resolution of satellite systems, time-series classifications have become popular in cropland mapping. Because annual plants can give similar spectral reflectance values on the same date. In this context, agricultural land (~500 km^2) was selected in the south of South Dakota in the United States. The area includes alfalfa, corn, soybeans, winter wheat plants, developed, grassland/pasture, herbaceous wetlands, and open water areas. The study aims to map croplands with vegetation indices produced by annual Sentinel-1 and Sentinel-2 satellites. In this context, Radar Vegetation Index (RVI) produced from 25 Sentinel-1, and the Normalized Difference Vegetation Index (NDVI) produced from 26 Sentinel-2 satellites were used for 2020. We used the Time-Weighted Dynamic Time Warping (TWDTW) algorithm, which separates and classifies the similarities between two time series with variable speeds with time constraints. For mapping, the indices were classified both individually and combined. The highest overall accuracy (77.2%) was obtained with the combined use of NDVI and RVI. Among the plant classes, the lowest accuracy (83.71%) was found, and it was determined that the plant classes did not mix much. Sentinel-2 satellite is not available before April due to weather conditions in the region. For this reason, since the Sentinel-1 satellite is not affected by weather conditions, it is thought that the use of two satellites together will be beneficial in time series analysis.

1. INTRODUCTION

Cropland monitoring is vital for the estimation of crop yields and spatial distribution of crops for management. In 2015 United Nations declared the 2030 Agenda on Sustainable Development and in total 17 Sustainable Development Goals (SDGs) and 169 targets have been adopted (Url-1). Earth observation and geospatial information through different sensor sources can support SDGs for different sectors.

Remote sensing based crop monitoring can be challenging owing to the growth cycle of crop types. The phenological periods of crops can vary from seeding to harvesting which is relatively short for annual crops. Additionally, crop management and environmental conditions such as soil type, climate, and water demand can also affect the growing periods. In remote sensing classification applications a variety of crop types, and the size of fields can be an indicator to separate classes. For that reason, spatiotemporal variation of spectral information is needed to improve the classification (Blickensdörfer et al., 2022). For the classification of the fields, different remote sensing satellite images with various spectral and spatial resolutions were evaluated individually and together. Especially, the multispectral optical data is well established to monitor vegetation for long-term periods (Singh et al., 2021). As Sentinel-2 satellites of the Copernicus program provide a short revisit time since 2016, its potential has been exploited widely. Meanwhile, it has been also combined with Landsat data for a denser period (Blickensdörfer et al., 2022). The Normalized Difference Vegetation Index (NDVI) is one of the spectral indexes estimated from optical satellites and is sensitive to determining the amount of vegetation have been one of the features to monitor crop types (Belgiu et al., 2021; Singh et al., 2021). Especially, long-term NDVI values can be used to determine phenology analysis and yield estimation purposes. Narin et al., (2019) estimated the yield of sunflower crops using the annual NDVI of Sentinel-2.

Contrary to this, optical systems still have drawbacks due to bad weather conditions. To overcome these situations synthetic aperture radar (SAR) system which has the ability to acquire the same day and night in all weather conditions plays an important role. As SAR systems are sensitive to the biophysical properties of vegetation, they are one of the main sources for different agricultural applications. Nasirzadehdizaji et al (2019) studied the sensitivity of features derived from Sentinel-1 to crop height and canopy coverage for the maize, sunflower, and wheat plants. Kumar et al (2013) showed an alternative index Radar Vegetation Index (RVI) for NDVI using full polarimetric SAR data. As Sentinel-1 has dual-polarization an adopted version is also studied in different applications (Nasirzadehdizaji et al., 2019; Moharana et al., 2021; Tůma et al., 2022).

In image classification, machine learning approaches have been widely used. Cheng and Wang (2019) applied Time-Weighted Dynamic Time Warping (TWDTW) for forest type classification and compared it to the random forest (RF) and support vector machine (SVM). They showed better results with the TWDTW method compared to others. The method is sensitive to periodical variations and uses time series of objects. TWDTW has been successfully applied for crop applications especially using optical images. Chaves et al., (2021) studied large scale changes in farms using MODIS data, Belgiu et al., (2021) studied NDVI of Sentinel-2 with TWDTW, Singh, et al., (2021) used TWDTW Sentinel-2 bands (R,G,B, and NIR) with vegetation indices (NDVI, EVI) and they achieved 86% overall accuracy. Belgiu and Csillik (2018) studied object and pixel-based crop mapping using TWDTW and NDVI of Sentinel- 2 data.

In the literature, its performance of it on SAR images is relatively limited. Olfindo et al. (2020) studied sugarcane classification using Sentinel-1 data. Lie and Bijker et al. (2019) used backscatter and features (polarimetric decompositions, normalized difference polarization index) of Sentinel-1 for the classification of vegetables. Gella et al (2021) compared Sentinel-1 and TerraSAR-X data and applied different features of Sentinel-1 such as indices and decomposition data. Narin et al (2021) investigated the contribution of coherence to backscatter values using Sentinel-1 data. Moharana et al., (2021) used backscatter values, RVI, and cross-ratio values of Sentinel-1 and concluded that RVI has better results than the other features.

The objective of this study is to evaluate features derived from Sentinel-1 and Sentinel-2 for annual crop type mapping using the TWDTW approach. The time series of NDVI and RVI features are used for the analysis. In the results, their performance and the contribution of their combination were tested.

2. MATERIALS & METHODS

2.1 Study Area

In this study, a region with widely planted crops in the world was chosen. However, attention has been paid to the presence of annual herbaceous plants that are frequently mixed with the plant in the study area. In this context, South Dakota, one of the midwestern states of the United States was chosen (Figure 1). The main livelihood of South Dakota is agriculture (Hoover, 2020). In the study area, besides agricultural products, there are water, wetlands, grassland, and developed (man-made structures) classes. The size of the study area is 108345.6 acres. The proportions of the classes in the area are given in Figure 2. The main crops are soybeans and corn which also play an important role globally. It is expected to yield increase in maize, and area expansion of soybean (OECD/FAO,2018). Grass/pasture comes in the third order with a cover of 19 % in the study region.

2.2 Ground Truth and Data Set

The ground truth data of the study area has been downloaded from the Cropland Data Layer (CDL) platform, which is provided free of charge by the USDA's National Agricultural Statistics Service and Agricultural Research Service annually (https://nassgeodata.gmu.edu/CropScape/).

CDL presents land use and crop types with 30 meter spatial accuracy after 2008. Accuracy analyzes of the data are also given. Overall accuracy for 2020 is 84.5% (Url-2). In our study, the dataset consists of 8 different classes with sample numbers are: Alfalfa (2750), Corn (2709), Developed (710), Grassland (2881), Herbaceous Wetlands (2522), Soybeans (2694), Water (589), Winter wheat (2750), and a time series was created from these data samples (Figure 4). Cross-validation (k-fold: 4) was applied to these collected data (75% for training and 25% for testing). The overall accuracy (equation 1) and F-score (equation 2) are used for the accuracy analysis of the classification.

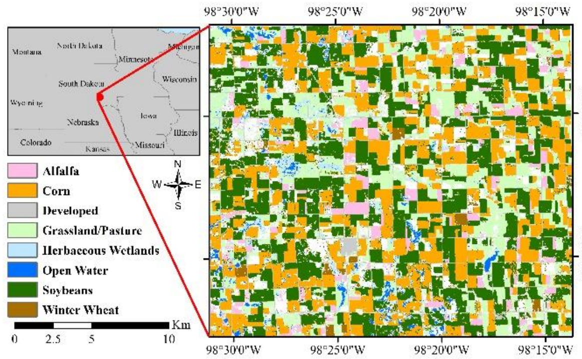

Figure 1. Study Area

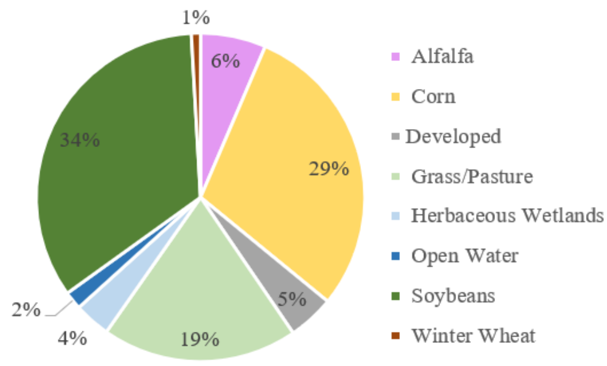

Figure 2. The ratio of land uses in the study area.

$$OA = \frac{TN+TP}{TP+TN+FP+FN} \quad (1)$$

$$F = \frac{2TP}{2TP+FP+FN} \quad (2)$$

Where OA is overall accuracy, TN is true negative, TP is true positive, FP is false positive, FN is false negative, and F is F-1 score.

2.3 Sentinel-2

Sentinel-2A and -2B provide short-term multispectral image acquisitions with 5 days of temporal resolution together. For this study, 26 images from April 2020 to December 2020 were collected (Figure 1). Due to atmospheric conditions first three months there was no available cloud-free data. The 10 m resolution bands of red (band 4) and near-infrared (band 8) bands are used to calculate NDVI as given in equation 3;

$$NDVI = (NIR - RED)/(NIR + RED) \quad (3)$$

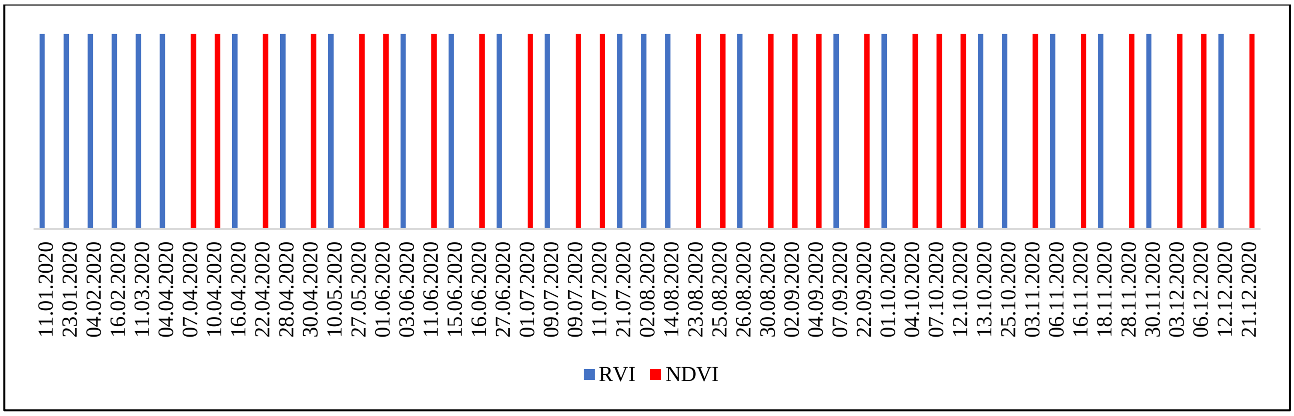

Figure 3. Sentinel 1/2 image acquisitions in 2020.

2.4 Sentinel-1

In total 25 multi-temporal Sentinel-1B images were acquired from January 2020 to December 2020. Each image has dual-polarization, vertical-vertical (VV), and vertical-horizontal (VH). In the preprocessing of Interferometric Wide swath (IW) mode Level-1 Single Look Complex product data firstly radiometric calibration was applied. Then, TOPSAR deburst and merge steps were applied. After that multi looking, topographic correction using SRTM 1Sec DEM data and co-registration was performed. Open source tools of Sentinel Application Platform (SNAP) software (SNAP, 2021) were used for these steps. The sigma naught backscatter values were converted to decibel (dB) values. For each data, RVI is created with equation 4 where σ°_{VV} and σ°_{VH} are the sigma naught values of VV and VH polarized data.

$$RVI = \frac{4\sigma^{\circ}_{VH}}{\sigma^{\circ}_{VV}+\sigma^{\circ}_{VH}} \tag{4}$$

2.5 Time-Weighted Dynamic Time Warping

The samples obtained from the study area were classified with plant indices obtained from Sentinel-1 and Sentinel-2 satellites in 2020. We used the TWDTW classification method, an open-source R package dtwSat for this study. It uses a minimum of two time series of datasets, here we use NDVI and RVI. The method checks the temporal signature of land cover types and maintains dissimilarity measures to assign land cover types. For more information about the code (dtwSat and TWDTW), you can refer to these resources (Maus et al. 2016; Maus et al. 2019; https://github.com/vwmaus/dtwSat).

3. RESULT AND DISCUSSIONS

The time series of NDVI for each class is given in Figure 4. The NDVI series show that among the classes the developed has a stable trend. The alfalfa also shows a stable trend between May and November. Corn and soybean show similar trends but corn provides the highest NDVI value earlier than soybeans. Winter wheat shows high values of NDVI around May and after that month it appears to be similar to developed. The time series of RVI shows variety during the year 2020 compared to NDVI. However, alfalfa, corn, grassland, and herbaceous wetlands show a similar trend until august. After that month alfalfa indicate a stable trend and the others give a declining behavior. The developed class is almost stable which is similar to the results of NDVI. Water shows an increasing value from the beginning of the year to the end of the year.

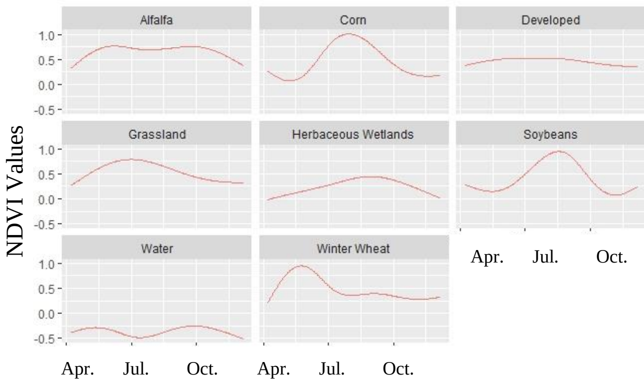

Figure 4. Time series of NDVI

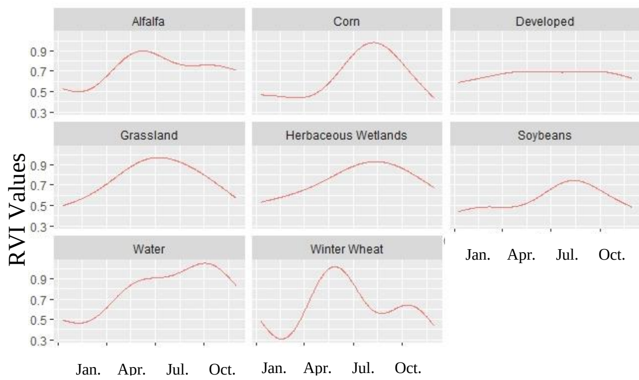

Figure 5. Time series of RVI

In the study, we analyzed the performances of features derived from Sentinel-1 and Sentinel-2 separately. Then, they are combined to show the contribution of their integration (Table 1). The OA showed that NDVI had higher accuracy (75.9%) compared to RVI (56.5%). Their combination slightly improved the OA to 77.2%. considering the classes, even if the RVI image has lower F-1 scores it improved some classes such as alfalfa, developed, herbaceous wetlands, and winter wheat. On the other hand, it also decreased F-1 scores in corn, grassland, soybeans, and water.

F-1 Scores			
Class Name	**NDVI**	**RVI**	**NDVI-RVI**
Alfalfa	0.8581	0.4846	0.8677
Corn	0.9202	0.6375	0.8371
Developed	0.3046	0.2939	0.3746
Grassland	0.7603	0.5238	0.7437
Herbaceous Wetlands	0.3141	0.2276	0.4889
Soybeans	0.9405	0.6918	0.8987
Water	0.6134	0.3375	0.6027
Winter Wheat	0.7926	0.8100	0.8570
Overall Accuracy (%)	75.9	56.5	77.2

Table 1. The accuracy results of the classifications

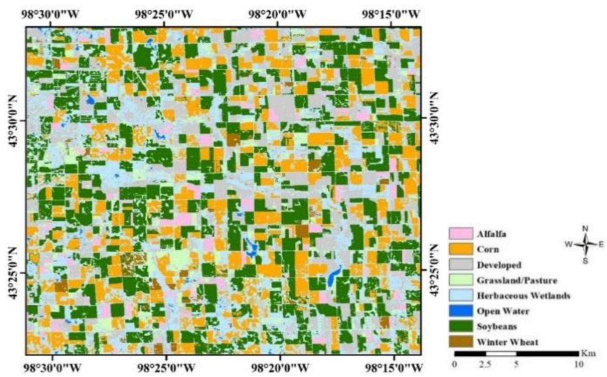

Figure 6. The cropland map

In this case, it is aimed to increase the time-series integration of the two different sensors. However, due to the lack of optical data for the first three months NDVI values started in April. Unfortunately, the full phenology of the crops is not available. According to the growth period, some of the datasets may be reduced. Among the classes two of them, developed and herbaceous wetlands gave lower accuracies than 50%. The developed class covers the man-made structures, however, the region does not cover a high level of impervious structures. Because of that, it is mixed with other short vegetations. Herbaceous wetlands include vegetation depending on the season and are periodically covered with water. Because of that, an increase is noticed in the NDVI images from April to July (Figure 4). The water class is also misclassified and mixed with wetlands. The backscatter values of SAR data might be affected by soil moisture of soil and the roughness of the surface. The weather conditions showed that the region was covered with snow on some days in the winter period which could be the reason for low accuracies in the RVI images. Olfindo et al (2020) achieved high accuracy while using only the backscatter of two polarimetric data of Sentinel-1. However, the region was not very complicated and two classes (sugarcane/nonsugarcane) were considered. Gella et al., (2021) showed that TerraSAR-X with single polarization (HH) provided low accuracy (29%) when used individually. When combined with Sentinel-1 data the accuracy increased from 67% to about 77%. It is noticed that the combination of either different wavelengths as provided by Gella et al., (2021) or different sensors as resulted in this study can improve the accuracy of cropland classification.

4. CONCLUSION

This study analyzes vegetation indices derived from optical and SAR data over cropland. Multi-temporal images of NDVI and RVI are investigated annually for cropland mapping. RVI image did not show high accuracies when it is used individually, however, it added contribution when combined with NDVI. The combination of features of Sentinel- 1 and Sentinel-2 has slightly improved the OA. The results have the potential of integrating merely vegetation indices derived from different sensors.

Further investigation will be focused on the analysis of different locations and additional features that can be derived from Sentinel-1 (coherence, cross-polarized ratio, etc.) and Sentinel-2 (other vegetation indices) will be combined to improve the cropland mapping accuracy.

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