GEO 790
MACHINE LEARNING FOR GIS AND REMOTE SENSING

FINAL PROJECT REPORT

MAPPING TILLAGE PRACTICES IN THE MIDWEST
USING REMOTE SENSING DATA, MACHINE LEARNING, AND DEEP LEARNING

Student: Khuong H. Tran - 10107551
Geospatial Science Center of Excellence, Department of Geography and Geospatial Sciences, South Dakota State University, Brookings, SD 57007, USA.

Instructor: Maitiniyazi Maimaitijiang, Ph.D.
Assistant Professor, Geospatial Sciences Center of Excellence, Department of Geography & Geospatial Sciences, South Dakota State University, Brookings, SD 57007, USA.

1. Introduction

Tillage is an extremely important agricultural practice that usually occurs after harvesting season or before another crop season. It involves soil disturbance to create a uniform planting bed, control weeds, and manage residue (Frouz, 1999; Lobb, 2008). Though, agronomists realized that there are significant destructive influences in long-term progress because tillage induced soil erosion, nutrient leaching, and microbiological properties loss. In the 1960s, they introduced conservation tillage (CST) practices for healthy, productive, and sustainable agricultural development (Busari et al., 2015; Fawcett, 2008). By 2004, about 41% of US cropland was farmed using conservation tillage systems, and such achievement is made in large part by the government subsidy and other programs to encourage no-till (NT) or CST practice (statistics from a national survey by the Conservation Technology Information Center (CTIC)). Mapping and monitoring tillage practices are essential to understand their impacts, guarantee the taxes are spent fairly, and quantify the extent of different tillage practices. The US national survey program was established to collect tillage data at the county level, but it was suspended after ending the funded program in 2004 (reported by CTIC) as the survey program at county level is usually costly and time consuming.

Remote sensing has become one of the most important tools for observing the Earth and monitoring changes in land use land cover, classifying crop types, and many other applications (Asrar and Asra, 1989; Klosterman et al., 2014; Lin et al., 2016; Weng, 2012). However, very limited research have found in mapping and monitoring tillage practices. Beeson et al. (2016) for the first time investigated the use of Landsat Thematic Mapper (TM), Système Pour l'Observation de la Terre (SPOT) High Resolution Geometrical (HRG), Indian ResourceSat Advanced Wide Field Sensor (AWiFS), and Deimos satellite for mapping crop residue and tillage practices in several agricultural fields in Iowa using thenormalized difference tillage index (NDTI) . SPOT and Landsat images offered similar overall accuracy ranges from 64% to 92%, while AWiFS and Deimos had accuracies ranges from 61% to 73%. The study also found that clouds and the revisit interval for each satellite influenced classification accuracy and severely limited the minNDTI approach when there were no any high-quality observations. Another investigation in mapping crop residue and tillage intensity was the use of high spatial and spectural resolution WorldView-3 satellite Shortwave Infrared Normalized Difference Residue Index (SINDRI) (Hively et al., 2019, 2018). The study revealed that SINDRI and the Lignin Cellulose Absorption Index (LCA) derived from shortwave infrared bands are more accurate than spectrally onbroad Landsat indices such as the NDTI. Azzari et al. (2019) alternatively used composites of satellite imagery from Landsat 5, 7, and 8, and Sentinel-1 and 5900 georeferenced fields collected from farmer's reports to map tillage practices in the North Central US region from 2005 to 2016 with accuracies ranging from 75% and 79%. Although, Sentinel-1 currently adds relatively little to classification accuracy compared to Landsat.

NASA currently provides free-of-charge Harmonized Landsat Sentinel-2 (HLS) imagery at 30 m spatial resolution and every 2-3-day temporal resolution that can resolve most of the US crop fields and reduce the effects of cloud and snow cover (Claverie et al., 2018). Recently, machine learning (ML), the study of computer algorithms, are widely used in numerous applications in terms of making accurate decisions or predictions, epscially in remote sensing research (Bangira et al., 2019; Barnes et al., 2021; Wang et al., 2019; Baumhoer et al., 2019; Ma et al., 2019; Zhang et al., 2016; Zhu et al., 2017). For that reason, the combination of remote sensing and computer science is truly potential to identify tillage practices on the US crop fields at high spatial resolution and reduces the interferences of the traditional field surveys which are costly and time-consuming.

Therefore, this study has been conducted to investigate the capabilities of a combination from remote sensing (HLS data) and ML and DL algorithms to classify the tillage practices in the Midwest.

2. Materials

2.1. Study area

Minnehaha county in South Dakota state, U.S. has been selected for our model development. Minnehaha is known as one of the most high production of agricultural county in the southeaster border of South Dakota, covers a part of Sioux Falls city (South Dakota's largest city). Corn and soybeans are two most popular crops in this county (https://www.nass.usda.gov/Publications/AgCensus).

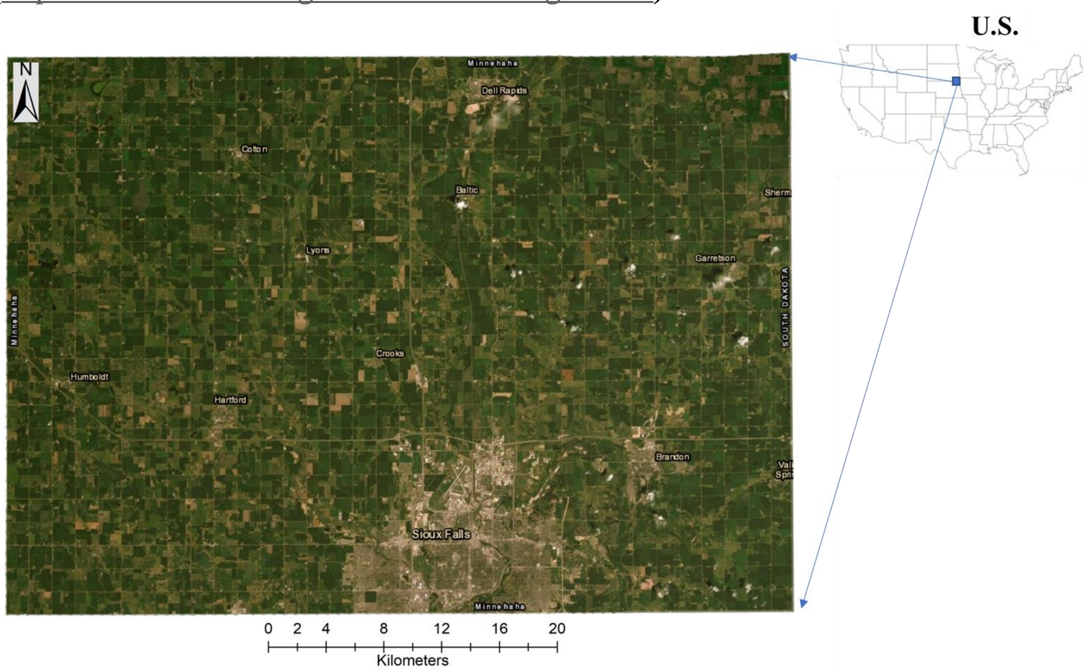

Figure 1. Minnehaha county study area used Google Earth map as background.

2.2. Survey data

The field data collection (ground truth data), was gathered by a windshield survey. A cropland roadside transect survey method is designed to collect tillage practices and crop residue management (CRM) systems. A county road transect route (Figure 2) was established that crosses most high crop production areas and avoids urbanization, forests, rangeland, and heavily traveled federal and state highways. The route direction should be horizontal or vertical (east to west or north to south). The length of the driving route was 157 miles. The survey team consists of four members: NRCS district, soil conservationist, and two graduate assistants from SDSU. A total of 465 fields were visited with geolocation and tillage information no-till/strip-till, mulch-till, reduced-till, and conventional-till/intensive-till. CTIC already provided the standard and recognization for tillage systems, which were applied by many agencies and private industry in the US. First, No-Till/Strip-Till is defined as soil without disturbance after harvesting to planting, except less than one-third of row disturbed, and greater than 30% crop residue remaining. Second, Mulch-Till is identified by greater than 30% residue, but the entire field is tilled. Third, Reduce-Till is also defined as the entire field is tilled, but only 15-30% residue remaining. Fourth, Conventional-Till has less than 15% residue existing, the entire field is tilled by many tools such as moldboard plow, chisel plow, disk, field cultivator.

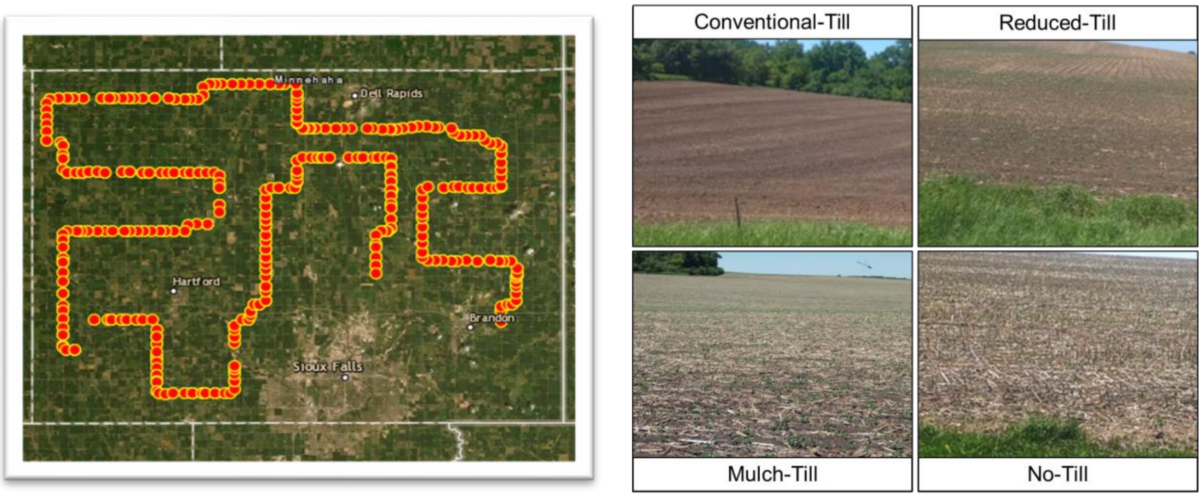

Figure 2. The field locations (left) and 4 tillage practices types (right) in the Crop System Survey for Minnehaha County

2.3. Harmonized Landsat Sentinel-2 (HLS) data

The HLS product is operationally produced in NASA by integrating Operational Land Imager (OLI) onboard Landsat 8 with Multi-Spectral Instrument (MSI) onboard Sentinel-2A/B. It provides a unique surface reflectance seamed from both sensors (OLI and MSI) by a sequence of algorithms, including atmospheric correction, cloud and cloud-shadow masking, spatial co-registration and common gridding, bidirectional reflectance distribution function normalization and spectral bandpass adjustment (Claverie et al., 2018). The HLS product also includes quality assurance (QA) flags indicating low-quality (snow/ice, cloud, cloud shadow, adjacent cloud, and cirrus clouds) and high-quality (others). It is gridded into the UTM-based Military Grid Reference System (MGRS) with a tile coverage of 109.8 × 109.8 km. The temporal resolution is 2-3 days with a spatial resolution of 30 m. Only one HLS tile (14TPP) is fully cover Minnehaha county. A temporal period from the October 2020 to April 2021 was selected for processing the HLS data because the main period for tillage is after harvesting (October) and before planting (April and May).

3. Methodologies

We developed a framework for the tillage practices classification using remote sensing HLS data and classical machine learning and deep learning algorithms (Figure 3). Basically, the 30 m HLS with 2-3-day temporal resolution was used to derive monthly composite time series by median composition method to reduce the impact of cloud and snow cover during the winter period. The survey data with geolocation of visited fields was converted and matched up with HLS pixels. By an integration of two main datasets, the training and testing samples were generated with labels from survey data and features from the HLS median composite time series. Next, tillage practice classification was applied using the classical machine learning (random forest algorithm) and deep learning (deep neural network – DNN and convolutional neural network – 2D CNN and 3D CNN) to evaluate the ability of an integration of remote sensing and machine learning and deep learning for identifying tillage practices in the Midwest.

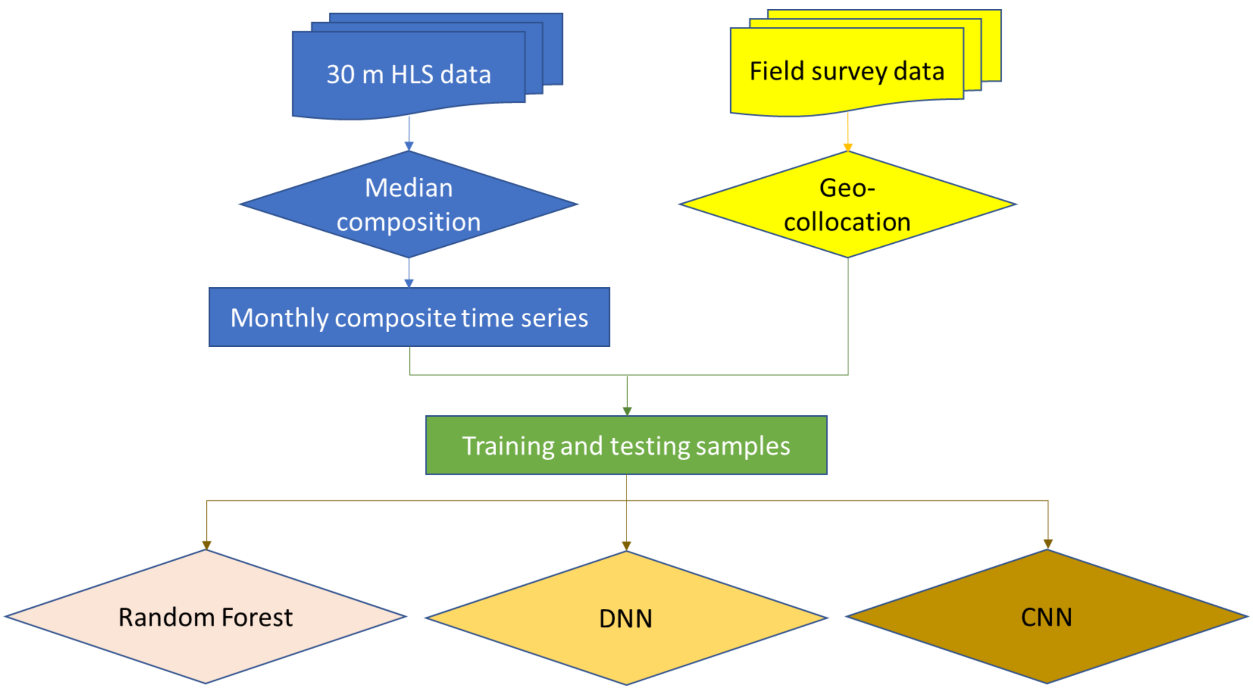

Figure 3. The workflow for tillage practices classification by remote sensing HLS data and classical machine learning and deep learning.

3.1. Median composition of HLS time series

This study used six 30 m bands including blue, green, red, near infrared (NIR), shortwave infrared (SWIR1 and SWIR2) from L30 and S30 products and derive addition twelve other indices (Table 1). The QA was applied to keep only high-quality pixels and remove cloud/snow pixels. To reduce the impact of cloud and snow cover in each image, we decided to use a median composition method to derive monthly composite time series. However, the gaps could be remained in the time series for those months in winter with high percentage of snow, and thus we used linear interpolation to fill those gaps. The generation monthly median composition time series was described in (Tran et al., 2022).

Table 1. The HLS bands and indices used in the classification of tillage practices

	L30	S30	References
Blue	B2		
Green	B3		
Red	B4		
NIR	B5	B8A	
SWIR1	B6	B11	
SWIR2	B7	B12	
EVI	2.5 ∗ (nir − red) / (nir + 6 ∗ red − 7.5 ∗ blue + 1)		(Azzari et al., 2019)
GCVI	(nir / green) − 1		(Azzari et al., 2019)
NDVI	(nir − red) / (red + nir)		(Azzari et al., 2019)
VARI	(green - red)/(green + red - blue)		(Daughtry et al., 2005)
SNDVI	(nir − red) / (red + nir + 0.16)		(Azzari et al., 2019), (Hively et al., 2018)
OSAVI	(1 + 0.16) (nir - red)/(nir +red + 0.16)		(Daughtry et al., 2005)
NDTI	(swir1 − swir2) / (swir1 + swir2)		(Azzari et al., 2019)
NDI5	(nir − swir1) / (nir + swir1)		(Azzari et al., 2019)
NDI7	(nir − swir2) / (nir + swir2)		(Azzari et al., 2019)
CRC	(swir1 − green) / (swir1 + green)		(Azzari et al., 2019)
STI	swir1/swir2		(Azzari et al., 2019)
NDSVI	(swir1 − red)/(swir1 + red)		(Qi et al., 2002) (Hively et al., 2018)

3.2. Generation of training and testing samples

The geolocation of each visited fields was simply converted from geographical coordinates system to the UTM 14N, which is the projected coordinates system of 14TPP HLS tile. After matching the field's geolocation with HLS pixels, a collection of training and testing samples was derived with the tillage label collected from the field survey data and features collected from the HLS monthly median composite time series. The collection was split into training data with 70% of samples and testing data with 30% of samples.

3.3. Classification of tillage practices using Machine learning

Random forest (Breiman, 2001) is known as one of the most popular classical machine learning methods which has been applied to various remote sensing applications, such as mapping land use land cover (Gislason et al., 2006; Rodríguez-Galiano et al., 2011; Wessels et al., 2016), crop classification (Dang et al., 2021; Tran et al., 2022), fire detection (Collins et al., 2020; Ramo and Chuvieco, 2017), and wetland mapping (Liu et al., 2018). Thus, we decided to apply random forest as the first algorithm for tillage practices classification. The RandomForestClassifier from Sklearn python package was trained with hyperparameters tunning. The number of trees ranges from 100 to 500 with an increment of 100, the criterion is gini and entropy, and the max features are auto, sqrt, and log2.

3.4. Classification of tillage practices using Deep Learning

Beside the success of classical machine learning in remote sensing applications, many research have been applied deep learning and obtained higher performance (Dang et al., 2021; Ma et al., 2019; Xie et al., 2019). Therefore, we decided to apply two most popular deep learning algorithms for tillage practices classification, including deep neural network (DNN) and convolutional neural network (CNN). For DNN model, we test an architecture which was applied to predict the crop yield (Maimaitijiang et al., 2020) and modified it for the classification instead of its regression purpose (Figure 4). For CNN, we tested our dataset for both 2D and 3D models. However, we generated a window 21×21 HLS pixels for each sample with a purpose is to create a subset on each field because we assumed that uneven distribution of crop residue on the field could affect the classification accuracy. The involvement of neighboring pixels on the same field may boost the performance of tillage practices compared to the pixel-based classification, which usually ignores the spatial and texture of objects. The CNN architecture is described in Figure 5.

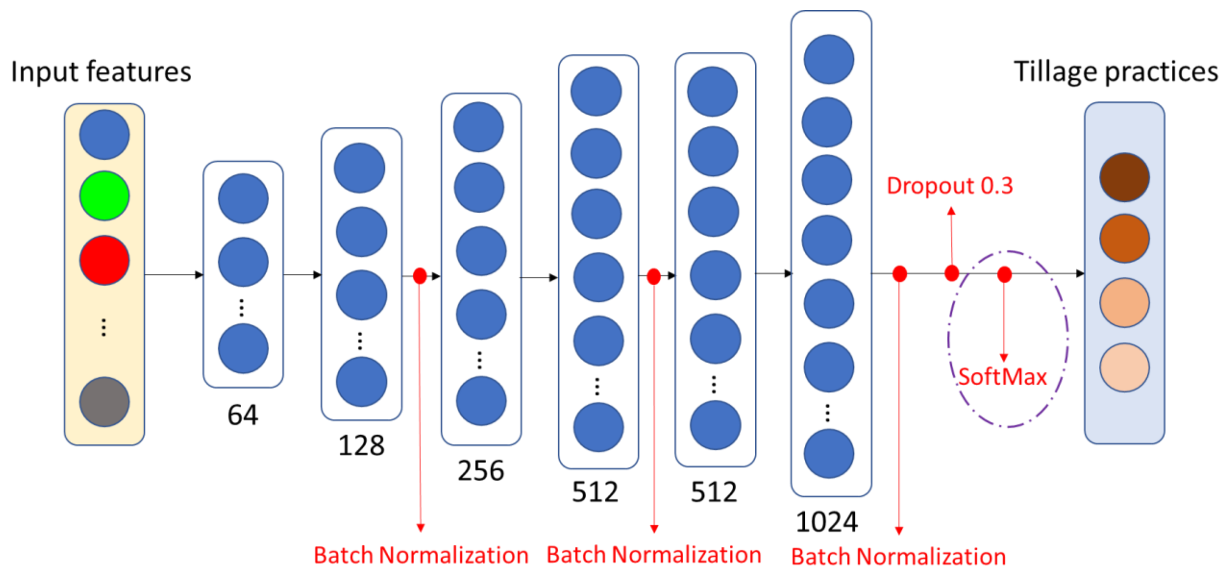

Figure 4. The DNN architecture for tillage classification, which was modified from (Maimaitijiang et al., 2020).

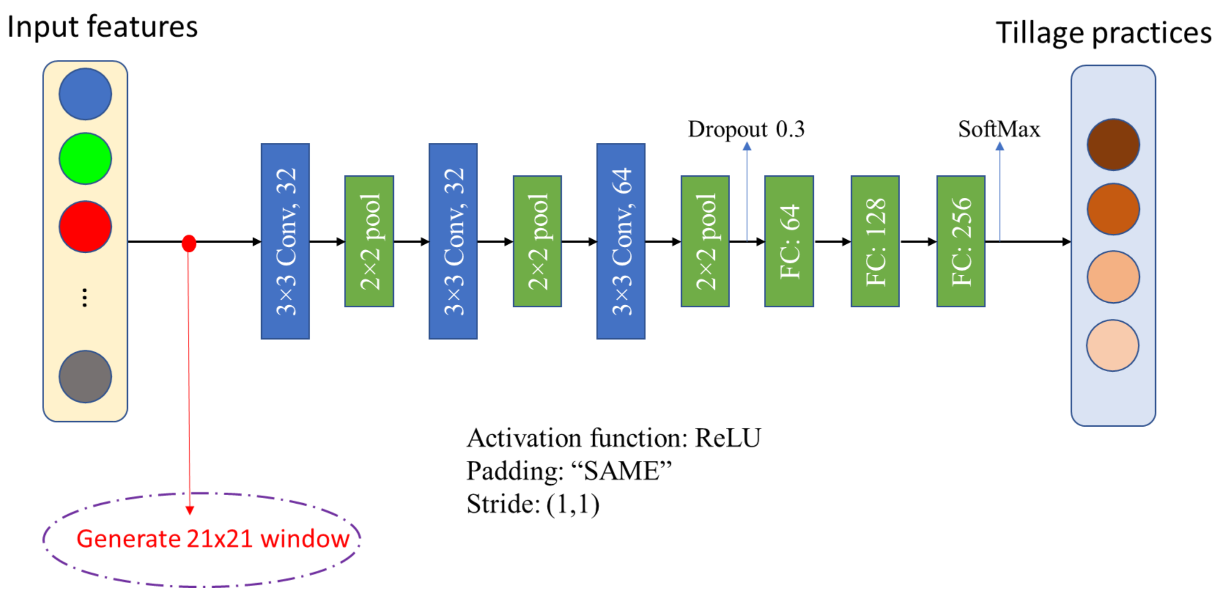

Figure 5. The CNN architecture for tillage classification which was modified from (Maimaitijiang., 2022).

4. Results

4.1. Surface reflectance and highlight features of tillage practices

Tillage practices usually includes soil disturbance, weed control, and crop residue management. However, the tillage practices in the Midwest highly depends on the crop residue on the field. As a result, Figure 6 shows the surface reflectance of six bands on the average of 465 fields for 4 types of tillage practices, which also follows the intensity of crop residue. The conventional tillage has the highest intensity of tillage and very least crop residue, so it has lowest reflectance. Reduced tillage has higher surface reflectance than conventional tillage and lower higher surface reflectance than mulch tillage. While the highest surface reflectance detected from the no-tillage practices.

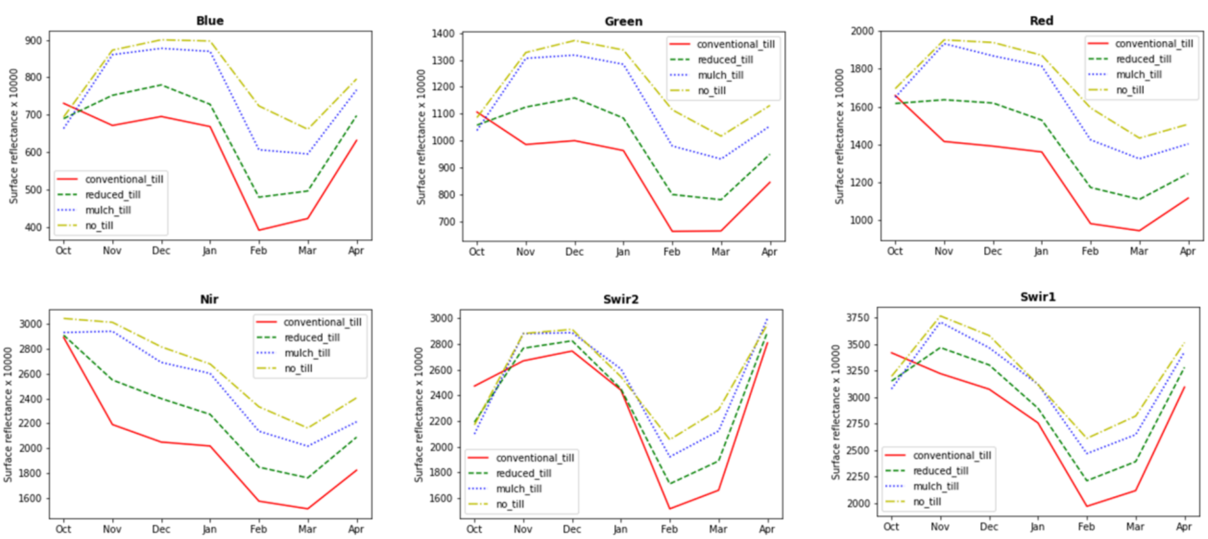

Figure 6. Average of monthly median composition time series on HLS bands for each tillage practices.

Previous studies have investigated the tillage indices for mapping crop residue and tillage intensity (Barnes et al., 2021; Beeson et al., 2016; Daughtry et al., 2005; Hively et al., 2019, 2018) Figure 7 displays the median composite of surface reflectance time series for 4 common tillage indices, including NDTI, STI, NDI5, and NDI7. All four indices indicate a similar pattern as the time series of different HLS bands in Figure 6. No-till has the highest reflectance and followings are mulch tillage, reduced tillage, and then conventional tillage. However, the time series shows that NDTI and STI better observed tillage from November to January and not so clear for other months. While NDI5 and NDI7 show distance patterns for four types of tillage. Overall, the difference in the time series of tillage practices could help to identify crop residue and tillage intensity or tillage classification.

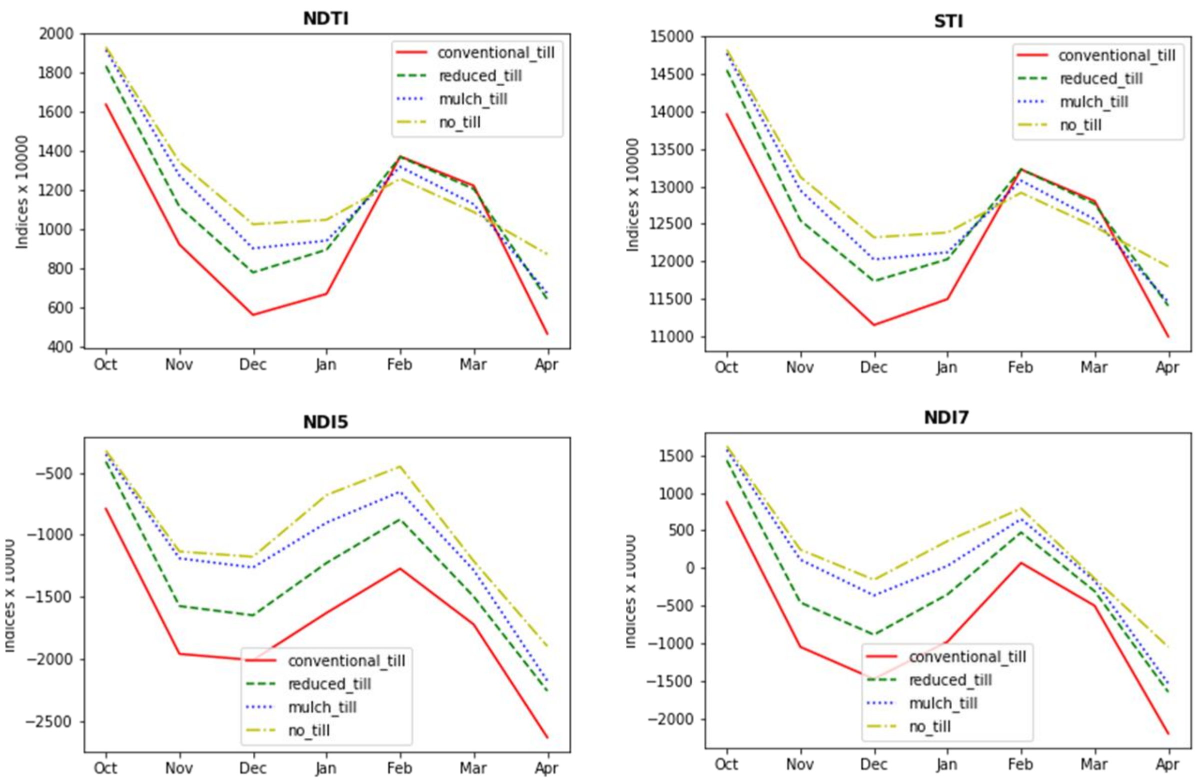

Figure 7. The median surface reflectance time series of tillage indices, including NDTI, STI, NDI5, NDI7

4.2. Classification of tillage practices using Machine learning

The random forest algorithm obtained 100% training cross validation, but the overall accuracy for testing only explains around 50-60% samples. It should be noted that the identification of tillage on the fields is easily confused by the intensity of crop residue, especially mulch tillage and reduced tillage. We also obtained higher confusion in these two classes. Some studies usually combine these two classes into one class called conservational tillage (Deines et al., 2019; Sullivan et al., 2008; Watts et al., 2011).

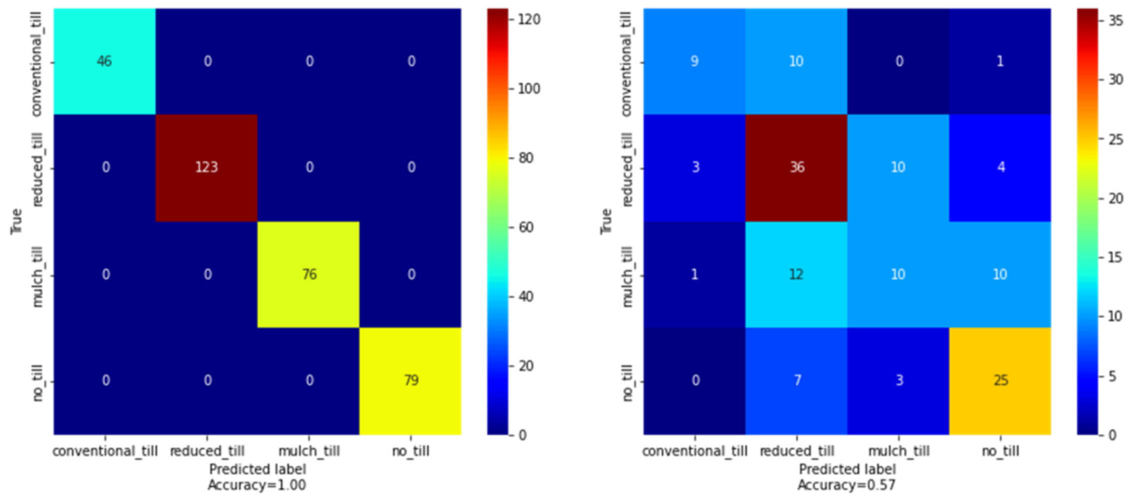

Figure 8. The confusion matrix of training and testing using the random forest algorithm.

4.3. Classification of tillage practices using Deep Learning

4.3.1. Deep Neural Network

Figure 9 shows the loss of DNN model in Figure 4. The training loss reduces when number of epochs increases. However, the validation loss is very jumping, which could indicate a low performance of the current model. Similar to model accuracy, the training accuracy also increases when increasing number of epochs, but the testing accuracy is very noisy. Overall, this DNN is not a good model for tillage classification.

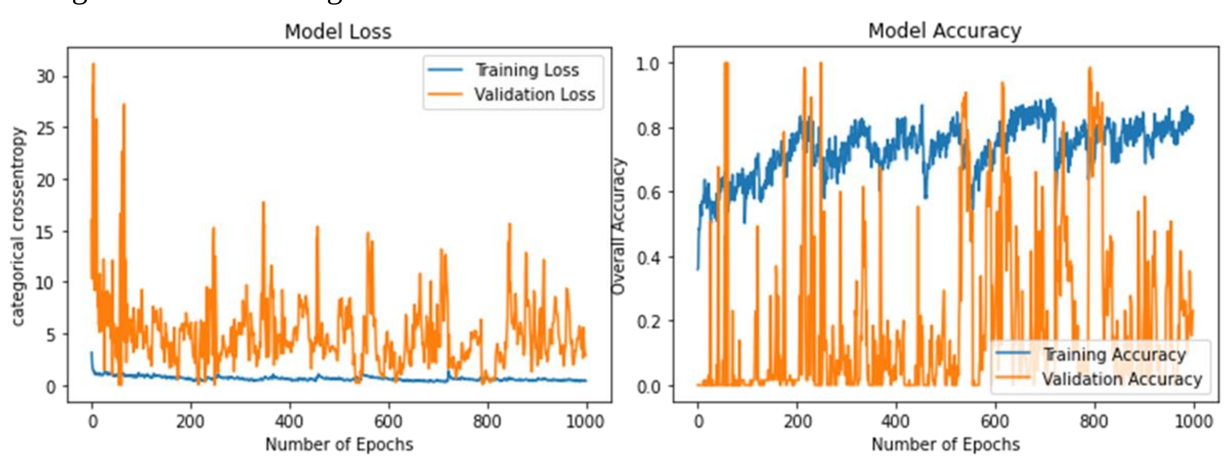

Figure 9. Model loss and accuracy of DNN model.

As a result, the current DNN model shows a low accuracy in the prediction of tillage practices (Figure 10). Most of samples were classified as the no-till.

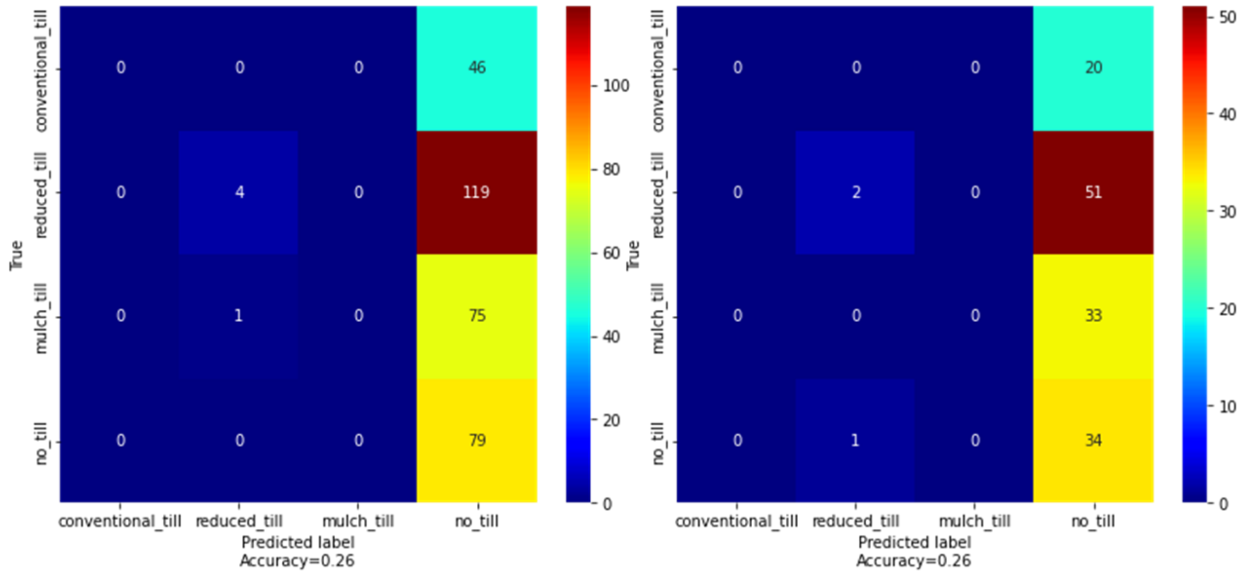

Figure 10. Confusion matrix of using DNN model for predicting tillage practices

4.3.2. Convolutional Neural Network

2D-CNN model (Figure 11) has much less noises compared to the DNN model, the loss reduces along the increase of epochs, but the magnitude of validation loss is high around 250. The model accuracy shows that training accuracy obtained around only 40-50%, while noises occur in the validation. Figure 12 shows 3D-CNN model has better in terms of model loss, the training and validation loss reduce towards 0 when epochs more than 80. In the model accuracy, the training accuracy improved slightly, but testing accuracy did not improve compared to the 2D-CNN. The low accuracy in the validation or testing accuracy indicated a low performance in classification of tillage practices using the current CNN models.

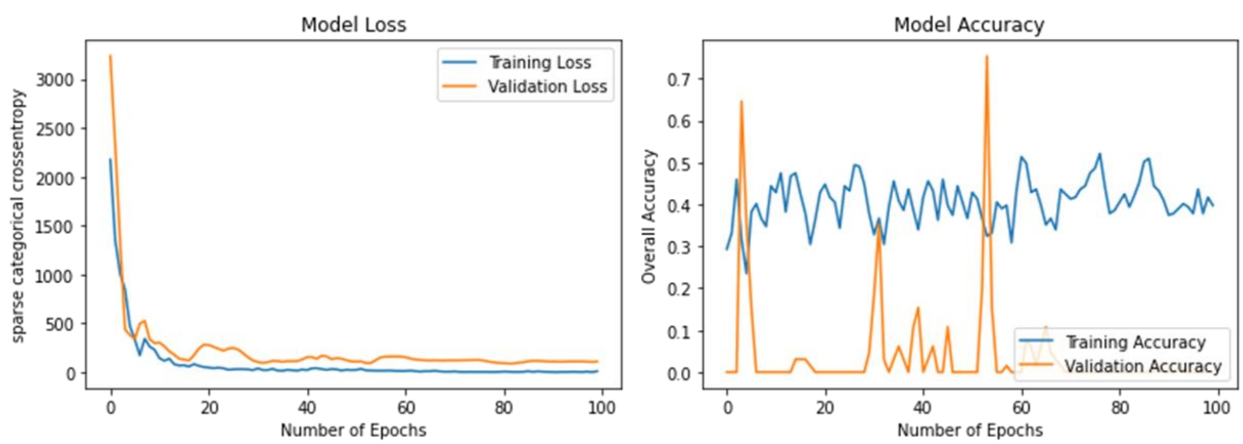

Figure 11. Model loss and model accuracy from the current 2D-CNN model from Figure 5.

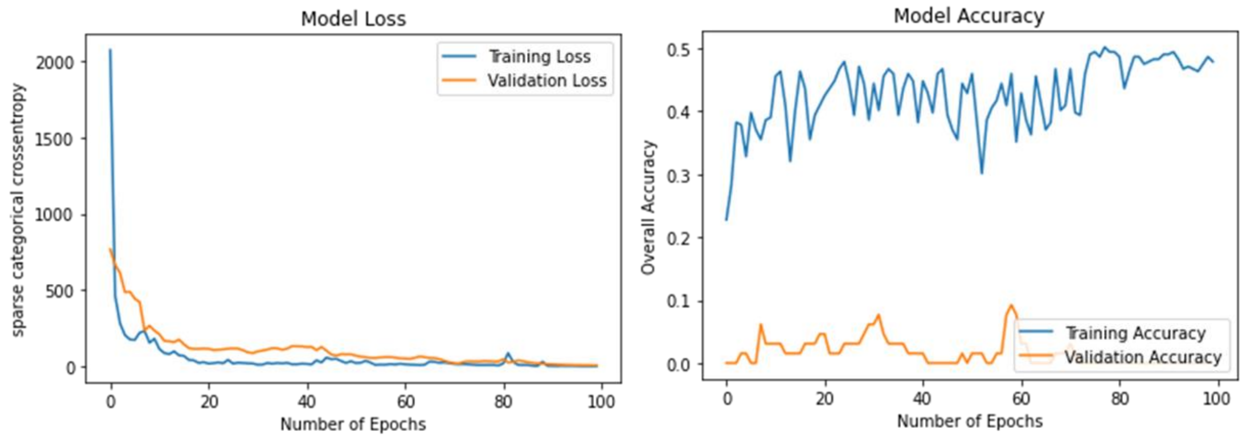

Figure 12. Model loss and model accuracy from the current 3D-CNN model from Figure 5.

5. Conclusions and recommendations

Tillage is one of the most important aspects in agricultural practices, especially in the conservational practice management. However, the uncertainty and lack of research about the long-term impacts of using different tillage methods are becoming one of the matters for encouraging and changing administration and policy in order to apply tillage practices on a large scale. This initial investigation was proposed to validate the ability to use satellite HLS imagery with high spatial and temporal resolution for mapping and monitoring tillage practices instead of organizing traditional surveys, which are usually costly and time-consuming. The classical machine learning obtained only 50-60% overall accuracy with more noises in mulch-tillage and reduced tillage, which could be due to the ignorance of spatial and textural information on the field. We also tested DNN and CNN algorithms based on available architecture for classifying tillage practices. The CNN with less noises compared to the DNN model and 3D-CNN is better than 2D-CNN in terms of building model with smaller validation loss and higher training accuracy. However, the current models obtained very low accuracy in the prediction of tillage practices. The hyperparameters tuning should be investigated for future development. Besides, the architectures of 2D and 3D-CNN models should be considered for the use of deep learning for predicting and mapping tillage practices in the Midwest.

Acknowledgments

We gratefully acknowledge and thank South Dakota View for funding a mini-grant to this project. Also, we would like to give thanks to USDA - Natural Resources Conservation District for organizing the Cropping System Survey. The contributions of all team members played a key role in managing and conducting the project.

References

Asrar, G., Asra, G., 1989. Theory and applications of optical remote sensing.

Azzari, G., Grassini, P., Edreira, J.I.R., Conley, S., Mourtzinis, S., Lobell, D.B., 2019. Satellite mapping of tillage practices in the North Central US region from 2005 to 2016. Remote Sensing of Environment 221, 417–429. https://doi.org/https://doi.org/10.1016/j.rse.2018.11.010

Bangira, T., Alfieri, S.M., Menenti, M., van Niekerk, A., 2019. Comparing thresholding with machine learning classifiers for mapping complex water. Remote Sensing 11. https://doi.org/10.3390/rs11111351

Barnes, M.L., Yoder, L., Khodaee, M., 2021. Detecting Winter Cover Crops and Crop Residues in the Midwest US Using Machine Learning Classification of Thermal and Optical Imagery. Remote Sensing . https://doi.org/10.3390/rs13101998

Baumhoer, C.A., Dietz, A.J., Kneisel, C., Kuenzer, C., 2019. Automated Extraction of Antarctic Glacier and Ice Shelf Fronts from Sentinel-1 Imagery Using Deep Learning. Remote Sensing 11. https://doi.org/10.3390/rs11212529

Beeson, P.C., Daughtry, C.S.T., Hunt, E.R., Akhmedov, B., Sadeghi, A.M., Karlen, D.L., Tomer, M.D., 2016. Multispectral satellite mapping of crop residue cover and tillage intensity in Iowa. Journal of Soil and Water Conservation 71, 385–395. https://doi.org/10.2489/jswc.71.5.385

Breiman, L., 2001. Random Forests. Machine Learning 45, 5–32. https://doi.org/10.1023/A:1010933404324

Busari, M.A., Kukal, S.S., Kaur, A., Bhatt, R., Dulazi, A.A., 2015. Conservation tillage impacts on soil, crop and the environment. International Soil and Water Conservation Research 3, 119–129. https://doi.org/10.1016/j.iswcr.2015.05.002

Claverie, M., Ju, J., Masek, J.G., Dungan, J.L., Vermote, E.F., Roger, J.-C., Skakun, S. v, Justice, C., 2018. The Harmonized Landsat and Sentinel-2 surface reflectance data set. Remote Sensing of Environment 219, 145–161. https://doi.org/https://doi.org/10.1016/j.rse.2018.09.002

Collins, L., McCarthy, G.J., Mellor, A., Newell, G., Smith, L., 2020. Training data requirements for fire severity mapping using Landsat imagery and random forest. Remote Sensing of Environment 245, 111839.

Dang, C., Liu, Y., Yue, H., Qian, J., Zhu, R., 2021. Autumn Crop Yield Prediction using Data-Driven Approaches:- Support Vector Machines, Random Forest, and Deep Neural Network Methods. Canadian Journal of Remote Sensing 47, 162–181. https://doi.org/10.1080/07038992.2020.1833186

Daughtry, C.S.T., Hunt, E.R., Doraiswamy, P.C., McMurtrey, J.E., 2005. Remote sensing the spatial distribution of crop residues. Agronomy Journal 97, 864–871. https://doi.org/10.2134/agronj2003.0291

Deines, J.M., Wang, S., Lobell, D.B., 2019. Satellites reveal a small positive yield effect from conservation tillage across the US Corn Belt. Environmental Research Letters 14, 124038. https://doi.org/10.1088/1748-9326/ab503b

Fawcett, R.S., 2008. Chapter 33 - Environmental Benefits of Triazine Use in Conservation Tillage, in: LeBaron, H.M., McFarland, J.E., Burnside, O.C.B.T.-T.T.H. (Eds.), . Elsevier, San Diego, pp. 519–526. https://doi.org/https://doi.org/10.1016/B978-044451167-6.50036-2

Frouz, J., 1999. Use of soil dwelling Diptera (Insecta, Diptera) as bioindicators: a review of ecological requirements and response to disturbance, in: Paoletti, M.G.B.T.-I.B. as B. of S.L. (Ed.), . Elsevier, Amsterdam, pp. 167–186. https://doi.org/https://doi.org/10.1016/B978-0-444-50019-9.50013-3

Gislason, P.O., Benediktsson, J.A., Sveinsson, J.R., 2006. Random forests for land cover classification. Pattern Recognition Letters 27, 294–300. https://doi.org/10.1016/j.patrec.2005.08.011

Hively, W.D., Lamb, B.T., Daughtry, C.S.T., Shermeyer, J., McCarty, G.W., Quemada, M., 2018. Mapping Crop Residue and Tillage Intensity Using WorldView-3 Satellite Shortwave Infrared Residue Indices. Remote Sensing . https://doi.org/10.3390/rs10101657

Hively, W.D., Shermeyer, J., Lamb, B.T., Daughtry, C.T., Quemada, M., Keppler, J., 2019. Mapping Crop Residue by Combining Landsat and WorldView-3 Satellite Imagery. Remote Sensing . https://doi.org/10.3390/rs11161857

Klosterman, S.T., Hufkens, K., Gray, J.M., Melaas, E., Sonnentag, O., Lavine, I., Mitchell, L., Norman, R., Friedl, M.A., Richardson, A.D., 2014. Evaluating remote sensing of deciduous forest phenology at multiple spatial scales using PhenoCam imagery. Biogeosciences 11, 4305–4320. https://doi.org/10.5194/bg-11-4305-2014

Lin, L., Di, L., Yu, E.G., Kang, L., Shrestha, R., Rahman, Md.S., Tang, J., Deng, M., Sun, Z., Zhang, C., Hu, L., 2016. A review of remote sensing in flood assessment, in: 2016 Fifth International Conference on Agro-Geoinformatics (Agro-Geoinformatics). pp. 1–4. https://doi.org/10.1109/Agro-Geoinformatics.2016.7577655

Liu, T., Abd-Elrahman, A., Morton, J., Wilhelm, V.L., 2018. Comparing fully convolutional networks, random forest, support vector machine, and patch-based deep convolutional neural networks for object-based wetland mapping using images from small unmanned aircraft system. GIScience & Remote Sensing 55, 243–264. https://doi.org/10.1080/15481603.2018.1426091

Lobb, D.A., 2008. Soil Movement by Tillage and Other Agricultural Activities, in: Jørgensen, S.E., Fath, B.D.B.T.-E. of E. (Eds.), . Academic Press, Oxford, pp. 3295–3303. https://doi.org/https://doi.org/10.1016/B978-008045405-4.00832-6

Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., Johnson, B.A., 2019. Deep learning in remote sensing applications: A meta-analysis and review. ISPRS Journal of Photogrammetry and Remote Sensing 152, 166–177. https://doi.org/https://doi.org/10.1016/j.isprsjprs.2019.04.015

Maimaitijiang, M., Sagan, V., Sidike, P., Hartling, S., Esposito, F., Fritschi, F.B., 2020. Soybean yield prediction from UAV using multimodal data fusion and deep learning. Remote Sensing of Environment 237. https://doi.org/10.1016/j.rse.2019.111599

Ramo, R., Chuvieco, E., 2017. Developing a Random Forest Algorithm for MODIS Global Burned Area Classification. Remote Sensing 9. https://doi.org/10.3390/rs9111193

Rodríguez-Galiano, V.F., Abarca-Hernández, F., Ghimire, B., Chica-Olmo, M., Atkinson, P.M., Jeganathan, C., 2011. Incorporating Spatial Variability Measures in Land-cover Classification using Random Forest. Procedia Environmental Sciences 3, 44–49. https://doi.org/https://doi.org/10.1016/j.proenv.2011.02.009

Sullivan, D.G., Strickland, T.C., Masters, M.H., 2008. Satellite mapping of conservation tillage adoption in the Little River experimental watershed, Georgia. Journal of Soil and Water Conservation 63, 112–119. https://doi.org/10.2489/jswc.63.3.112

Tran, K.H., Zhang, H.K., McMaine, J.T., Zhang, X., Luo, D., 2022. 10 m crop type mapping using Sentinel-2 reflectance and 30 m cropland data layer product. International Journal of Applied Earth Observation and Geoinformation 107, 102692. https://doi.org/https://doi.org/10.1016/j.jag.2022.102692

Wang, J., Huang, B., Zhang, H.K., Ma, P., 2019. Sentinel-2A Image Fusion Using a Machine Learning Approach. IEEE Transactions on Geoscience and Remote Sensing 57, 9589–9601. https://doi.org/10.1109/TGRS.2019.2927766

Watts, J.D., Powell, S.L., Lawrence, R.L., Hilker, T., 2011. Improved classification of conservation tillage adoption using high temporal and synthetic satellite imagery. Remote Sensing of Environment 115, 66–75. https://doi.org/https://doi.org/10.1016/j.rse.2010.08.005

Weng, Q., 2012. Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. Remote Sensing of Environment 117, 34–49. https://doi.org/https://doi.org/10.1016/j.rse.2011.02.030

Wessels, K.J., Bergh, F. van den, Roy, D.P., Salmon, B.P., Steenkamp, K.C., MacAlister, B., Swanepoel, D., Jewitt, D., 2016. Rapid land cover map updates using change detection and robust random forest classifiers. Remote Sensing 8, 1–24. https://doi.org/10.3390/rs8110888

Xie, B., Zhang, H.K., Xue, J., 2019. Deep Convolutional Neural Network for Mapping Smallholder Agriculture Using High Spatial Resolution Satellite Image. Sensors . https://doi.org/10.3390/s19102398

Zhang, L., Zhang, L., Du, B., 2016. Deep Learning for Remote Sensing Data: A Technical Tutorial on the State of the Art. IEEE Geoscience and Remote Sensing Magazine 4, 22–40. https://doi.org/10.1109/MGRS.2016.2540798

Zhu, X.X., Tuia, D., Mou, L., Xia, G., Zhang, L., Xu, F., Fraundorfer, F., 2017. Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources. IEEE Geoscience and Remote Sensing Magazine 5, 8–36. https://doi.org/10.1109/MGRS.2017.2762307