

# Preliminary Classification of Soil, Plant, and Residue Cover Using Convolutional Neural Networks

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## Summary

In agricultural fields, knowledge about the proportion of the soil surface covered with crop residue and vegetation canopy is key for improving soil and water conservation practices. In this study we trained a deep convolutional neural network to automate the classification of bare soil, crop stubble, and live vegetation from downward-facing images of agricultural fields. A comprehensive generic dataset, consisting of 3300 training and 645 test images, was collected from agricultural fields across Kansas State University Agricultural Experiment Stations and the Natural Resources Conservation Service Plant Material Center located near Manhattan, KS. Despite the intricate patterns and color textures resulting from different combinations of soil, canopy, and stubble the trained network showed good performance for automating the classification of land cover from images. The network achieved 87% accuracy over the training dataset and 84% accuracy over the test set.

## Introduction

Soil cover by crop residue and actively growing vegetation is an important factor controlling soil erosion by wind and water. The combination of canopy and residue cover acts as an effective barrier intercepting and deflecting kinetic energy from raindrops that can lead to loss of soil aggregation, soil crusting, runoff, and soil erosion. Soil residue cover can also lead to improved soil moisture conditions by reducing soil evaporation (Flerchinger et al., 2003).

Agronomists and soil conservationists often need to estimate soil cover to determine the risk of soil erosion and the effectiveness of conservation practices. Over the years, several practical methods have been developed to quantify the soil cover in field conditions based on simple principles. The line transect method consists of an operator using a measuring stick or tape to count the number of one-foot marks intersecting stubble pieces and vegetation across the sample area (Sloneker et al., 1977). Line transects are selected at random and are often repeated several times to obtain an accurate average of soil cover values per field. Another common method often used to quantify soil residue and canopy cover is the use of reference photographs. In this method a trained operator uses a predefined set of images representing pre-calculated images of crop residue or green canopy cover for a specific crop to visually compare a selected area in the field to

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the set of reference images. With the advent of more powerful processors, new methods based on digital image analysis have enabled effective image color thresholding (Patrignani and Ochsner, 2015) and more sophisticated approaches using machine learning such as a random forest approach (Riegler-Nurscher et al., 2018). However, the classification of all three components—green canopy cover, crop stubble, and bare soil—still remains challenging because of the wide range of scenarios caused by the combination of soil types, crops, and soil moisture conditions in agricultural fields. The goal of this study was to quantify the fraction of green canopy cover, crop residue, and bare soil by using a deep neural network and a dataset of pixel-wise labeled images.

## Procedures

The image dataset for training and testing the deep convolutional neural network consisted of 3300 downward-facing images collected across multiple cropland fields located in Research Experiment Stations of Kansas State University. Images were collected at about 5 ft from the ground and contained different combinations of bare soil, crop stubble, and green canopy cover. For this study, we trained a deep convolutional, neural network using semantic segmentation classification (SegNet model). The resulting trained model was evaluated by analyzing the confusion matrix and overall accuracy over the test dataset of labelled images. The confusion matrix describes how often the classifier is correct in predicting each class. To evaluate classification performance for each class, we used the F-1 score as a harmonic average on precision and recall for the model accuracy.

## Results

The deep convolutional neural network effectively captured the fraction of the soil covered with crop residue, canopy cover, and bare soil (Figure 1). The trained network achieved 80% accuracy in the first 200 epochs, and after 1000 epochs achieved 87% validation accuracy over the training dataset and 84% accuracy over the test set. Among the three land covers, the trained model was able to identify canopy cover much more accurately. This is likely due to the excellent contrast between green canopy and the background represented by bare soil and residue cover. In most cases, the model was able to classify the strong features such as stems in stubble, but failed at classifying pieces of residue that had color and texture similar to that of bare soil. In this study, we demonstrated that deep neural networks have great potential as a tool for quantifying land cover components from images, which can be used to guide soil and water conservation practices. The group is now working on a web-based application to help field agronomists, farmers, and scientists to easily upload and quantify land cover from digital images.

## References

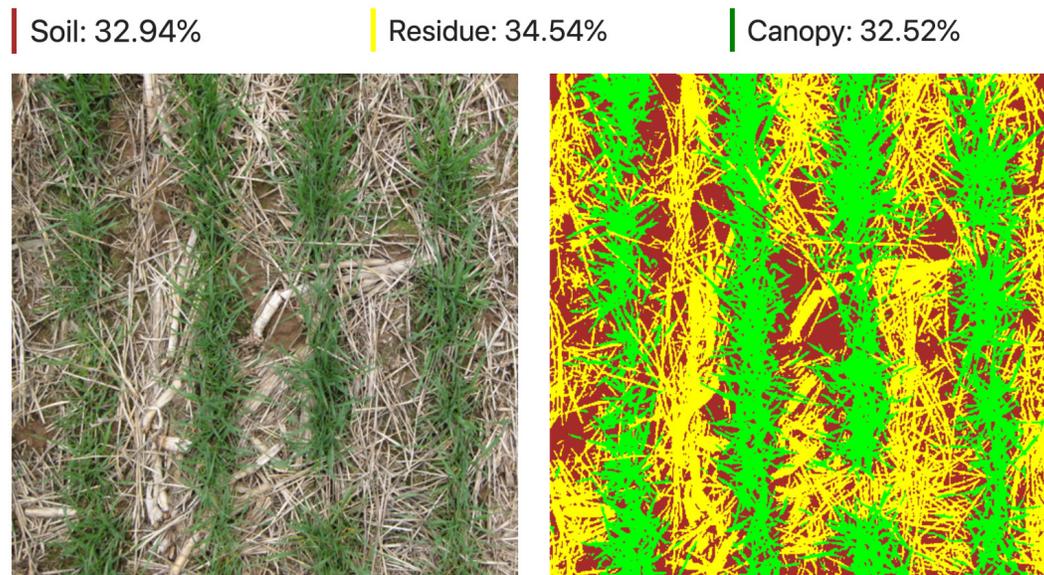
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**Table 1. Soil cover is identified as three key attributes of soil, stubble, and plants. This table indicates the distribution of the images.**

| Category                 | Number of images |
|--------------------------|------------------|
| Soil                     | 212              |
| Stubble                  | 262              |
| Soil and stubble         | 461              |
| Soil and plant           | 410              |
| Stubble and plant        | 112              |
| Soil, stubble, and plant | 1846             |
| Total                    | 3300             |



**Figure 1. Original (left) and predicted (right) crop residue cover, green canopy cover, and bare soil using the trained model for residue cover in no-till winter wheat. Colors in classified images represent bare soil (brown), stubble (yellow), and green canopy (green).**