Conservation Technology Information Center

Viridis View Methodology Details for Terion AI

Commercial Contact Curtis Trueb: ctrueb@terion.ai

Technical Contact Douglas Bolton: dbolton@terion.ai

About Terion AI

Terion AI, Inc., founded by Flagship Pioneering, brings together Indigo Ag's Source business and CIBO Technologies to build the leading independent ag-tech platform, applying science, data, and AI to deliver better outcomes for farmers, businesses, governments and the environment. Our MRV engine has enrolled 8M+ acres across 28 US states, sequestering/abating 2.1M metric tons CO2e, and quantifies conservation practice adoption via grower data, remote sensing, and biogeochemical modeling.

The history and evolution of our **Tillage** estimation methodology

Indigo (now part of Terion) began producing field-level tillage estimates using remote sensing in 2020, as an independent check on grower-entered practice data within our sustainability programs. At that point, our programs had not yet accumulated a large base of grower-attested data to train on, so we conducted roadside campaigns across the major corn and soy growing regions of the US to visually assess residue cover and tillage method on fields. These observations were used to train the first version of the model. After several years of running our carbon program, we accumulated substantially more grower-attested tillage data through normal program operations, allowing us to shift model training onto this larger, program-derived dataset and expand both geographic and crop coverage. The model continues to be refined as additional program data accumulate.

The history and evolution of our **Cover Crop** estimation methodology

Our cover crop algorithm was developed alongside the tillage algorithm described above, following the same fundamental approach and motivated by the same need for an independent, remote-sensing-based check on grower-reported practice data. It drew on the same early reference data collection effort and has benefited from the same subsequent expansion in grower-attested training data, so the two algorithms have evolved together over time.

Row crop lands included in our estimates

Corn (maize), Soybeans, Cotton, Wheat, Sorghum

Our imagery source(s), bands, filters, indices, and date ranges

We use a dense time series of Harmonized Landsat Sentinel-2 (HLS) data (2-3 day revisit, 30m resolution) from 2016 to present, summarized to field boundaries we derive from satellite imagery. We also use USDA CDL, gSSURGO, and gridded daily weather data. Core indices from HLS data include NDVI, NDTI, EVI2, and NDWI. We use every available HLS image, since fields can change within days and data gaps can lead to missed events.

How we classify the presence or absence of **Cover Crops**

To detect cover crops, we identify discrete periods of vegetation growth per field using a phenology algorithm applied to the HLS time series, then combine these periods with annual CDL crop type predictions to reconstruct each field's cropping history. Periods of growth between cash crops are considered candidate cover crops. We derive features for each candidate cover crop period and train a model to predict true cover crop presence using our reference data. Because conditions vary regionally, we train separate models for each USDA Crop Management Zone (CMZ), and train summer and winter crop groups separately, since timing of growth differs substantially between groups. Predictions are further informed by a prior derived from the combination of cover crop adoption rates from Ag Census and how a field's vegetation signal compares to other fields in the county. This approach can generalize across the U.S. without relying on fixed calendar-based rules.

How we categorize **Tillage**

Tillage detection uses the same phenology-based logic: we reconstruct each field's cropping history to identify the dormant period between harvest and planting. Within that window, we isolate sub-periods that are defined relative to phenology dates of the cash crop to isolate when the crop residue signal is strongest on each field. We calculate NDTI features over these sub-periods, along with additional predictors, and train a model using grower-reported no-till and till labels. We split fields into crop groups based on the previously grown crop, since the type of residue impacts the spectral signal observed, and train a separate model for each group. Separate models are also trained for each CMZ. Similar to cover crop, we include a model prior that combines tillage adoption rates from Ag Census with the regional context of each field (how the field compares to other fields in the county).

Our efforts to quantify estimate accuracy

For both the cover crop and tillage algorithms, we quantify accuracy using 10-fold cross-validation performed independently within each CMZ. For each fold, we calculate a range of validation statistics, but we pay the closest attention to the F1-score, a standard measure that balances model precision and recall.

Because a given training field can be represented in our reference data for more than one year, we ensure that all observations for a given field are assigned to the same cross-validation fold. Without this precaution, having the same field appear in both the training and testing data in different years could artificially inflate validation scores. This region-by-region validation

approach allows us to report accuracy that reflects out-of-sample performance across the country, rather than a single, national score.

Published references describing our estimation methodology

N/A

Other conservation-related datasets that we could potentially make available to interested parties

Beyond cover crop and tillage, our platform also produces:

- Field boundaries: automatically delineated from satellite imagery.
- Crop yield inferences: field-level estimates (bushels per acre) from vegetation growth characteristics.
- Planting and harvest dates: estimated event timing for major row crops.
- Irrigation presence/absence: field-level classification of irrigation status.
- Crop residue burning: detection of residue burning events on fields.

Conservation Technology Information Center

ctic@ctic.org | CTIC.org

P.O. Box 85 Lafayette, IN 47902 | (319)768-8348