



Assessing Soil Residue Cover, Cover Crops and Erosion using Remote Sensing and Modeling

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by

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Introduction

Soil loss on agricultural fields from wind and water erosion reduces soil productivity. Delivery of eroded sediment to nearby water resources causes turbidity and phosphorus pollution that contribute to increased eutrophication of surface waters. Minnesota rivers, streams and lakes can be better protected from water quality degradation when agricultural practices protect against soil erosion. One practice that is effective at reducing soil loss is conservation tillage, defined as leaving at least 30% of the soil covered by crop residues at the time of planting. Another beneficial practice is the planting of cover crops that protect the soils after harvest in the fall until the next crop is planted in the spring.

Remote sensing methods have been developed to accurately and effectively assess soil residue cover over large areas (Gowda et al., 2001; Daughtry et al., 2006) with imagery from the Landsat satellite and hyperspectral satellite imagery. Gowda et al. (2001) showed that regression models based on Landsat ratios for band 5 (1550-1750 nm) and band 7 (2080-2350 nm) could measure soil residue cover in the lower Minnesota River watershed with an accuracy of between 42-77%.

Assessing soil residue cover at the time of planting has traditionally been accomplished using windshield surveys. This method is time consuming and only assesses a small fraction of agricultural fields within a given county. Traditionally surveys have been conducted by local Soil and Water Conservation District (SWCD) staff. There is a large variability in crop residue measurements across county boundaries due to subjectivity of the methods used. There is a pressing need to develop accurate, more objective methods of assessing soil residue cover at the time of planting over wide areas of the state.

Cover crops are increasingly being planted after harvest of the main crop in fall to reduce soil erosion, take up nitrogen and sequester carbon in soils that are often relatively exposed and unprotected from rainfall and snowmelt runoff. Remote sensing has been investigated as a tool for estimating the adoption of cover crop planting in the Midwestern region (Seifert et al., 2018) and Chesapeake Bay region (Hively et al., 2015). Both studies relied on fall Landsat imagery to estimate the Normalized Difference Vegetative Index (NDVI), which is the ratio of $(NIR-R)/(NIR+R)$, where NIR is near infrared and R is red reflectance. Areas with higher NDVI were associated with cover crops. Neither study attempted to account for interference from perennial crops other than cover crops which are green in the late fall after harvest of grain crops.

Information for crop residue cover in spring and cover crops in fall can be used to improve our ability to estimate soil loss by water and wind erosion on agricultural land. The Daily Erosion Project (DEP) developed at Iowa State University estimates soil erosion and water runoff occurring on hill slopes in Iowa and surrounding states. Estimates are based on hill slope conditions (e.g. topography, crop, precipitation), as well as crop residue cover or cover cropping identified via satellite remote sensing. The DEP team then posts daily estimates of average hill slope soil loss (and water runoff) occurring for each watershed in the DEP coverage area to an online website.

The purpose of this study is to develop a long-term program to systematically collect data concerning crop residue cover in spring and cover crop emergence in fall in order to better estimate trends in adoption of soil conserving practices, and to use these estimates with DEP in order to better estimate soil erosion on agricultural landscapes in Minnesota.

Field Data Collection

Existing tillage transect survey data points were acquired across the 67 agricultural counties within Minnesota from Minnesota State University – Mankato. Survey point locations were stratified by county and agroecoregion, and counties that contained over 100 existing tillage transect locations within a single agroecoregion were identified in order to focus on counties where a robust dataset was available. Seven counties were chosen for further crop residue surveys during this project: Becker, Blue Earth, Clay, Fillmore, Lincoln, Redwood, and Stearns (Table 1). In coordination with local SWCDs, landowners were contacted annually in order to obtain permission to enter their private property for data collection.

An Android tablet with the Collector for ArcGIS (ESRI) application was used in the field to acquire georeferenced field residue cover data. Data attributes regarding current and previous crop were

collected at each point when possible. Photos were taken in triplicate within a 5m radius to create a representative sample that would coordinate to one 30m satellite pixel. Data points were sited within the field at a minimum of 30m away from roads, ditches, and fence lines to improve relevance of on-site photography to satellite remote sensing imagery and avoid mixed pixels in the regression analysis. Photography was also sited out of the headlands where machinery may make extra passes and would not accurately reflect the average residue levels for the entire field. Each photo was taken with the Android tablet's 8 megapixel camera mounted on a monopod held at a standard height of approximately 5 feet above the ground. This resulted in an image of approximately 6.5 by 6.5 feet. Images were then interpreted manually using a regular grid overlay by a user that visually detects either bare soil or residue at each intersection until 100 observations were made for a single image (Figure 1).

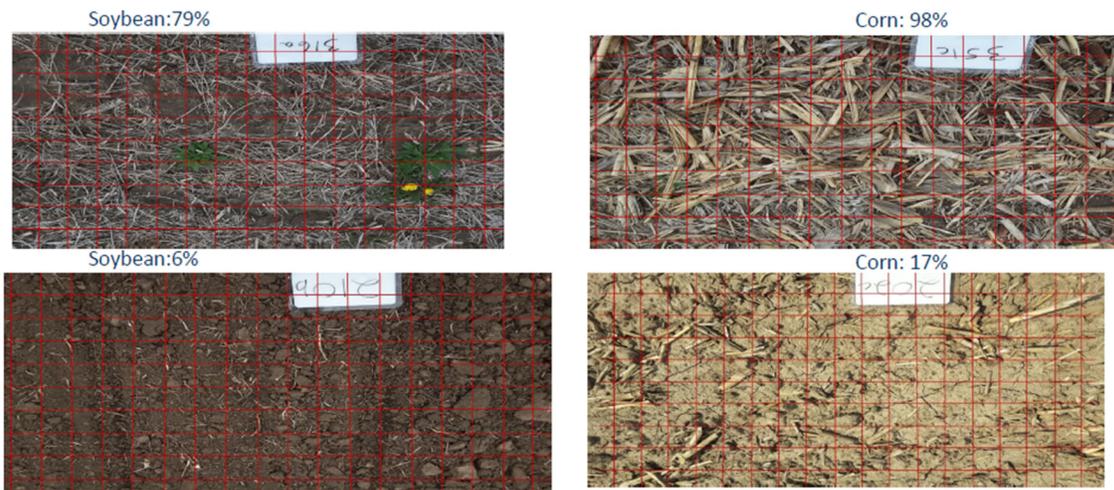


Figure 1. Example of various crop residues for corn and soybeans and reference grid used in photo interpretation.

Field data were only collected in the spring (Table 1) when at least 50% of the specific county had been planted, a clear sky satellite image coordinated to a window within a few days of field work, and field conditions were dry enough to allow entry on foot. Data were generally collected in teams consisting of one U of M representative and a local SWCD staffer to help with landowner permission status, although some SWCDs were trained to collect data on their own. The combination of all the above factors led to annual variability in the amount of data collected.

Table 1. Summary of sampling from 2016 - 2020

| Sampling Year | Counties Sampled | Data Points Collected | Agroecoregions Covered |
|---------------|------------------|-----------------------|------------------------|
| 2016 | 4 | 495 | 10 |
| 2017 | 7 | 1250 | 21 |
| 2018 | 4 | 220 | 7 |
| 2019 | 5 | 444 | 7 |
| 2020 | 3 | 262 | 3 |

Field data collection efforts also took place in the fall in order to evaluate the effectiveness of identifying cover crops with satellite imagery. In the fall of 2016, 119 sites were visited in Fillmore and Redwood counties in attempt to validate potential cover crops. An additional 66 sites in Redwood were visited in 2017, and 60 sites in the Cannon Watershed were visited in 2018, and 22 sites in Becker county were visited in 2019.

Satellite Remote Sensing

Crop Residue Cover

Research has shown Landsat 7 imagery can be used to assess crop residue levels in agricultural fields (Gowda et al., 2001; Daughtry et al., 2006). This study utilizes updated satellite imagery from Landsat 8 and Sentinel 2 satellites. Landsat 8 acquires multi-spectral imagery with a 30m spatial resolution and a 16 day revisit frequency. The Sentinel 2 satellite provides multi-spectral imagery with a 20m spatial resolution and a revisit interval range of 3 to 6 days. These satellites were used in tandem to assess soil residue cover for 67 Minnesota agricultural counties. The approach is based on using multiple linear regression using in situ data as the dependent variable and satellite band and band ratios as independent variables.

Development of crop residue algorithms relies on clear moderate resolution imagery from either Landsat 8 or Sentinel 2 satellites. Imagery is acquired from a short time window in the spring after crop planting has been completed but before plants have emerged. The imagery needs to be atmospherically corrected using a consistent method to ensure reliable results. To develop the crop residue models, imagery values from all spectral bands are extracted using the field data crop residue locations. Combinations between different bands of satellite imagery are then calculated. Once the data are compiled, stepwise regression is used to develop a crop residue algorithm that can be used on similar atmospherically corrected imagery. The algorithm is then applied to the imagery after clouds and cloud shadows have been removed. The Cropland Data layer (CDL) is utilized from the previous year to mask off non-cropland areas where the model would not apply.

With two years of satellite imagery and crop residue field measurements, a universal algorithm has been developed using atmospherically corrected imagery from 2016 and 2017, while a new bottom of atmosphere model was developed in 2019. The algorithm can be used on any similarly corrected imagery from the right time window. A surface reflectance product from EROS data center has been used for the Landsat imagery. A similar method is not currently available for Sentinel 2 imagery; therefore, an in-house Rayleigh scattering correction method was employed that takes into consideration the sun-sensor geometry, ozone, and pressure on a pixel by pixel basis.

The percentage of crop residue on agricultural lands was calculated using the universal algorithms. These calculations were summarized by county, major and minor watershed, and by agroecoregion within Minnesota (Figure 2 -7).

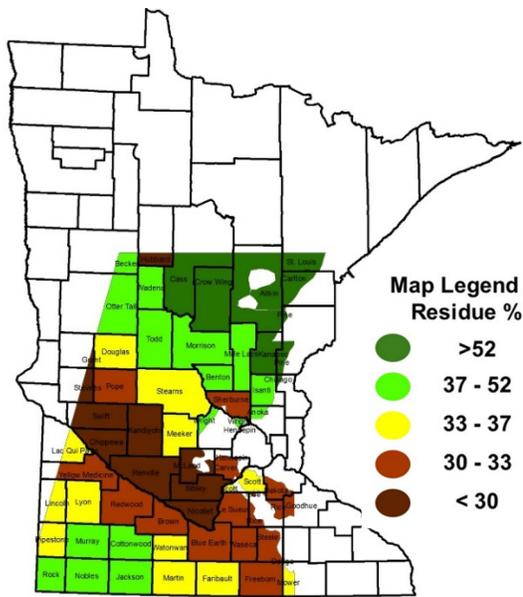


Figure 2. Spring 2016 Sentinel 2 crop residue map created at 30m pixel level and summarized by county.

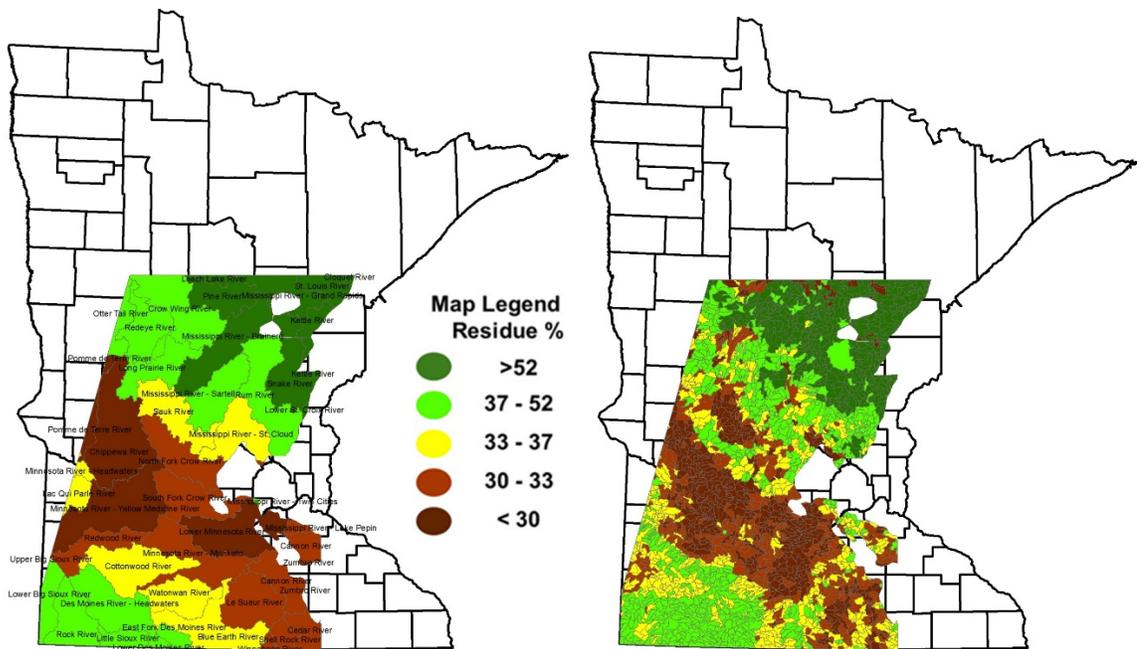


Figure 3. Spring 2016 Sentinel 2 crop residue map summarized at the major (left) and minor (right) watershed levels.

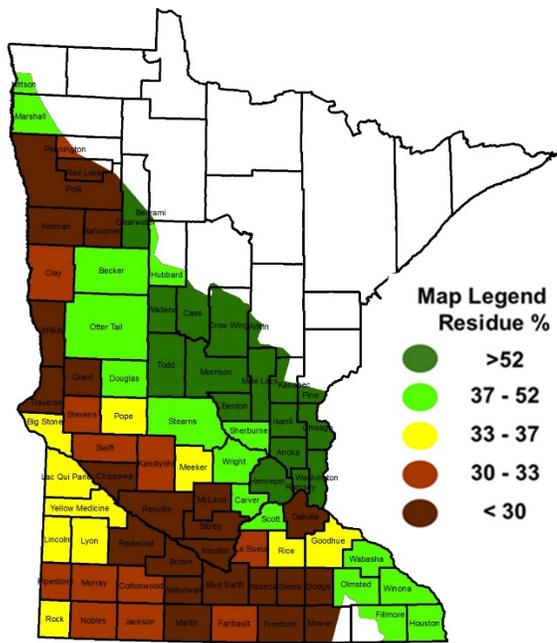


Figure 4. Spring 2017 crop residue map created at 30m pixel level and summarized by county.

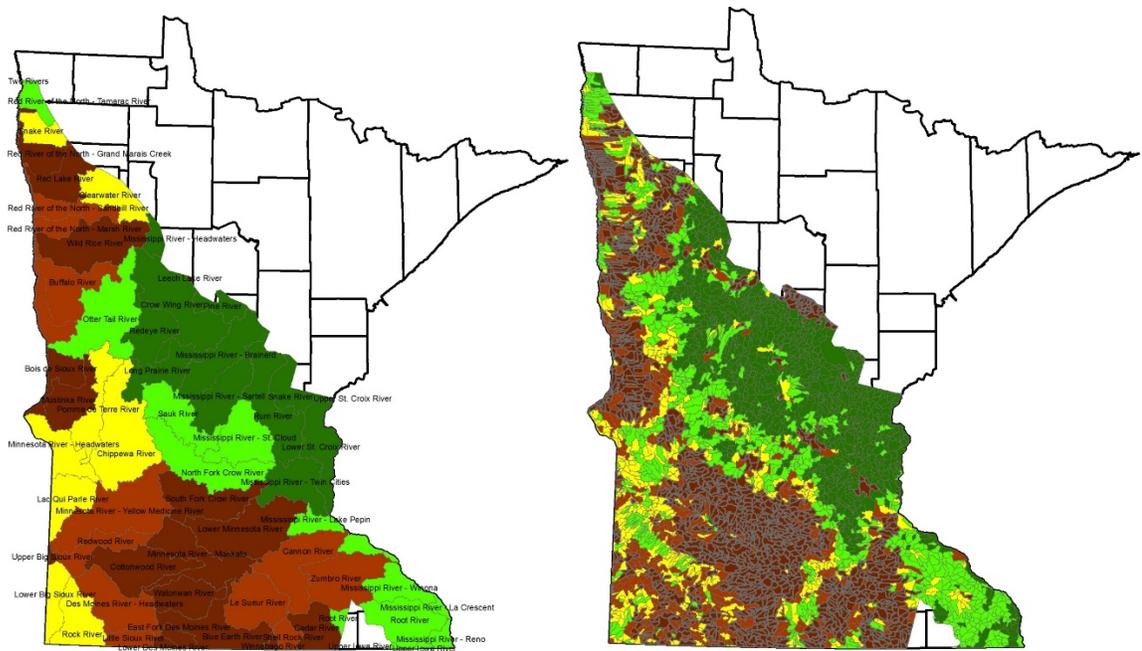


Figure 5. Spring 2017 crop residue map summarized at the major (left) and minor (right) watershed levels.

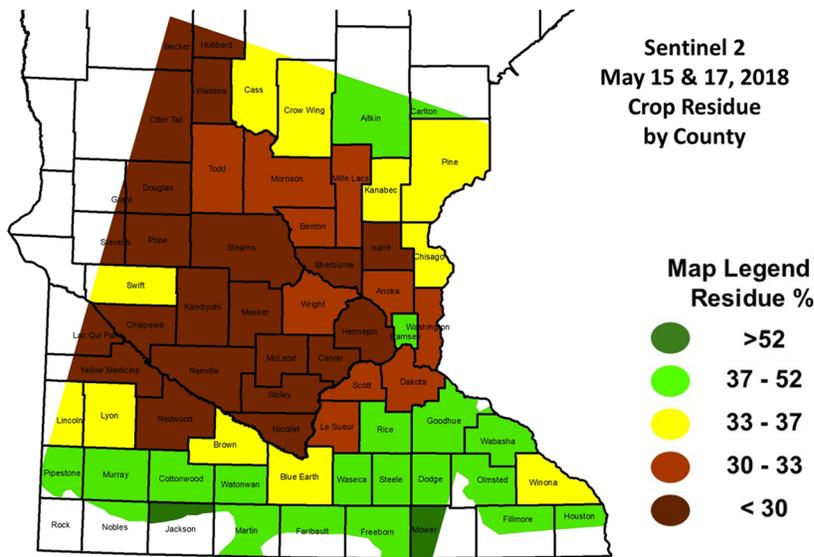


Figure 6. Spring 2018 crop residue map summarized at the county scale.

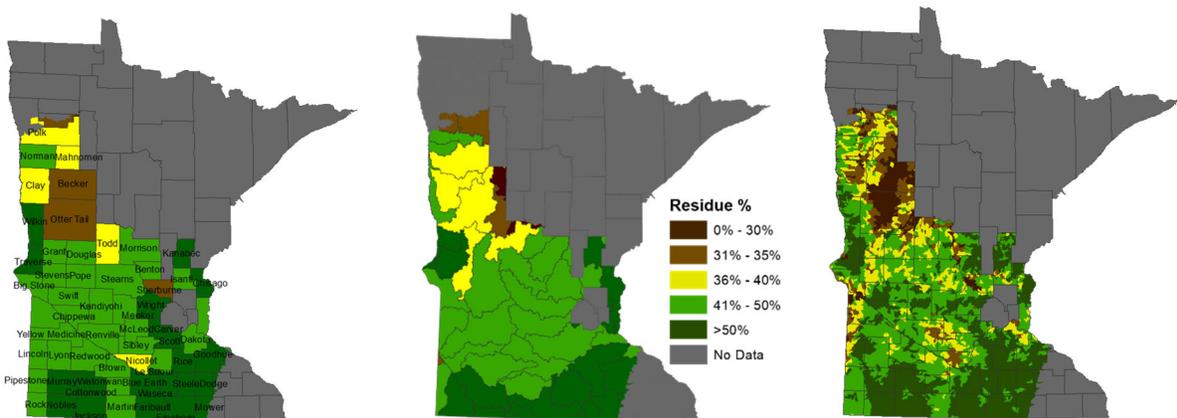


Figure 7. Spring 2019 crop residue map summarized at the county (left) major watershed (middle) and minor watershed (right) levels.

Cover Crops

Ground truth data designed to identify locations where cover crops had emerged were collected in fall of 2016-2019. Data included 45 locations in Fillmore County and 74 locations in Redwood County in fall of 2016, 64 sites in Redwood county for fall of 2017 (very poor emergence of cover crops), 60 sites in Cannon River watershed for fall of 2018, and 22 sites in Becker county for fall of 2019 (poor emergence of cover crops in rest of state).

Clear sky satellite images were collected in a relatively short time window in the fall soon after harvest, but before snowfall, to coincide with collection of ground truth data and assess the effectiveness of identifying cover crops with remote sensing. The Normalized Difference Vegetative Index (NDVI) indicates areas of live green vegetation. NDVI products were estimated from atmospherically corrected satellite imagery for fall of 2016-2019. In accompanying years,

the CDL was used to mask out locations identified as alfalfa, hay, forage, forest, grassland and developed, with the remaining green vegetation assumed to be a cover crop.

In fall of 2016, cover crops were estimated to have germinated on 213,000 ac across southern Minnesota (Fig. 8). About 40% of this was planted after harvest of corn and about 30% after harvest of soybean. Most of the remaining 30% was planted after short season crops such as small grains, canning crops (peas and beans) and sweet corn. As a percentage of crop acreage, less than 2% of the corn and soybean acreage was planted to cover crops, while from 20-50% of the short season crops were planted to cover crops. The highest percentage of cropland planted in cover crops was located along the southeastern region of Minnesota. This region is characterized by steeper topography that is vulnerable to erosion.

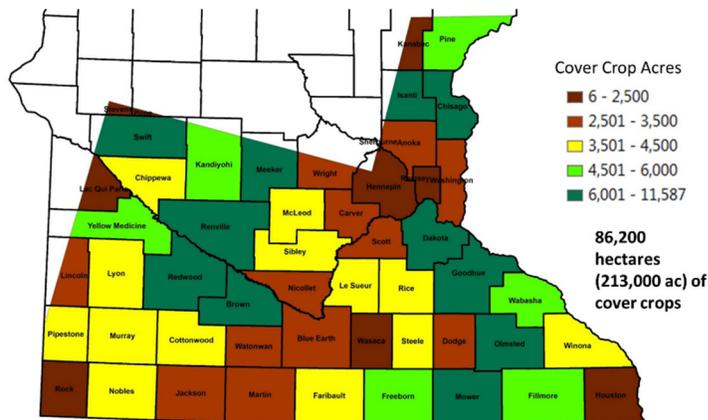


Figure 8. Fall 2016 cover crop map summarized by county.

Satellite estimates of cover crop germination in fall 2016 in the Cannon River Watershed were compared with cover crop planting estimates made by the Cannon River Watershed Partnership. While satellite estimates of cover crop germination in fall of 2016 were 13,786 ac, the Cannon River Watershed Partnership contracted with farmers for cover crop planting on 11,870 ac. The extra acreage estimated by satellite may have been due to farmers who independently planted cover crops.

Extensive cloud cover in fall 2018 prevented statewide assessment of cover crop germination in that year.

Conditions were good for assessment of cover crops in fall of 2019, although special processing was needed to remove high NDVI areas associated with unharvested crops left in the field after an early frost. Sugarbeet crops in the Red River Valley of the North were particularly hard hit by frost, with about 114,000 ac unharvested in fall of 2019. The cover crop assessment in fall of 2019, also does not include land in prevent plant status due to excessive ponding in spring of 2019.

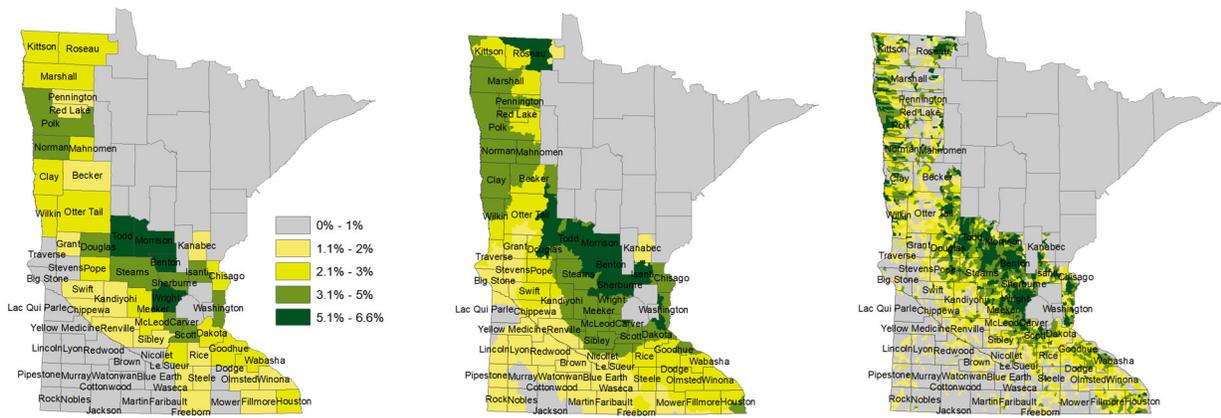


Figure 9. Fall 2019 cover crop map summarized at the county (left) major watershed (middle) and minor watershed (right) levels.

After removing unharvested crop and prevent plant areas from remote sensing imagery, we estimate there were 299,584 acres of emerged cover crops in fall of 2019. This is a significant increase in acreage relative to acreage assessed in 2016, partly because the area surveyed by satellite imagery also increased dramatically from 2016 to 2019.

Erosion Modeling

Daily Erosion Project

Another objective of this study is to assess the magnitude and dynamics of runoff and soil erosion through daily estimation of these processes. Remotely sensed satellite residue estimates from this project are used as an input for the Iowa State University Daily Erosion Project (DEP) Model. The four major DEP components are the soil erosion model (WEPP); the soil, topography, and land management input database; daily weather information; and a sampling and scaling approach for the daily modeling and reporting, respectively, of hillslope soil erosion and water runoff. Substantial revisions from the first version (Cruse et al. 2006) include complex (versus uniform) hillslope modeling, annually updated remotely sensed soil management and land use databases (rather than NRI-supplied information), and hydrological (rather than geopolitical) discretization of the state for analysis and reporting. Outputs reported for each HUC 12 include average daily precipitation, average soil detachment per hillslope and average delivery of detached sediment to the base of the modeled hillslope.

The Water Erosion Prediction Project (WEPP) hillslope model (Flanagan and Nearing 1995) was selected for the DEP. WEPP simulates rill and interrill erosion by rainfall and runoff and spatiotemporal distributions of soil detachment and sediment delivery (Flanagan and Nearing 1995). The basic element on which WEPP is implemented is a hillslope, which consists of one or more overland flow elements (OFEs). In DEP an OFE is implemented as a hillslope segment with a unique combination of soil type and land use for which slope and length is calculated.

Studies have validated the accuracy and unbiasedness of WEPP erosion estimates and confirmed its applicability in a broad range of conditions (Tiwari et al. 2000; Laflen et al. 2004). Motivations to select WEPP for this project include its capability to run continuous daily simulations and for modeling runoff and erosion on complex hillslopes. The DEP executes WEPP as a continuous simulation model to generate minute-level estimates of runoff, soil erosion, and soil moisture across Minnesota that are cumulated daily. The WEPP model simulation requires daily meteorological data, and the field specific crop and soil management parameters needed to run the model are assembled in an annually updated database.

WEPP climate files are generated daily for every 1 km grid cell with 2-minute NEXRAD radar data for precipitation and 25 km grid cells are used to represent wind, minimum and maximum temperature, and solar radiation. In addition to weather, the required WEPP inputs are topography, soils, and agricultural land management. These are described below and in an accompanying Final Report for DEP from Iowa State University.

Digital elevation models (DEMs) were generated from Minnesota's Light Detection and Ranging (LiDAR) dataset collected between 2006 and 2012. This high-resolution topographic data was used to construct discrete hillslopes for modeling erosion by using custom algorithms to generate a hydrologically enforced 3m DEM of 2,276 HUC 12 watersheds (USDA-NRCS, USGS, USEPA, 2012) in Minnesota. Details of the hydrologic enforcement process can be found in Gelder (2015).

The soils and crop rotation data are derived from the Agricultural Conservation Planning Framework (ACPF) database (Tomer, et al., 2017). ACPF boundaries were generated for 2,448 HUC 12 watersheds in Minnesota. Tillage intensity data are estimated from the satellite imagery model for crop residue cover developed for this study. Soil information is obtained from the gridded Soil Survey Geographic Database (gSSURGO) (Soil Survey Staff, 2012). Soil data including texture, organic matter, and cation exchange capacity was extracted from gSSURGO for each soil map unit to generate SOL input files for WEPP.

The final component of the WEPP input database is management, which is separated into crop rotation (or sequences) and tillage practice for each agricultural field in the state greater than 15 acres. Field boundaries are derived from pre-2008 available USDA Common Land Units (CLUs) (USDA-FSA, 2008), and all programmatic data are removed. Crop rotations are determined for each field using the USDA-National Agricultural Statistics Service (NASS) Cropland Data Layer (USDA, 2015). An eight-year rotation is derived from each field's most recent crop history and is used to preprocess the WEPP model to condition crop growth and antecedent soil moisture conditions at model initiation.

Tillage practices are estimated for each field using Landsat 8 and Sentinel 2 satellite-based crop residue data calculated for this study. The amount of residue cover is then correlated to one of six tillage intensity classes used by DEP to simplify management options. These options (Table 2) correspond to moldboard tillage, low, medium, high, and very high intensive mulch tillage, and no-tillage practices.

Table 2. Tillage intensity classes and their corresponding residue levels for Corn and Soybeans.

| Mulch Level | Soybean Residue | Corn Residue |
|-------------|-----------------|--------------|
| No-Till | 25% | 70% |
| Very High | 15% | 45% |
| High | 10% | 30% |
| Medium | 5% | 15% |
| Low | 2% | 5% |
| Moldboard | 0% | 2% |

After determination of crop rotation and tillage practice for each agricultural land parcel, these parcels are rasterized to align with the elevation and soils data. This geo-referenced ensemble of topographic, soil, and land management information is used to extract data to populate WEPP OFE and hillslope input files.

Examples of the Daily Erosion Project output for Minnesota was taken from data for October 21, 2019. Two related products are incident rainfall and runoff (Fig. 10).

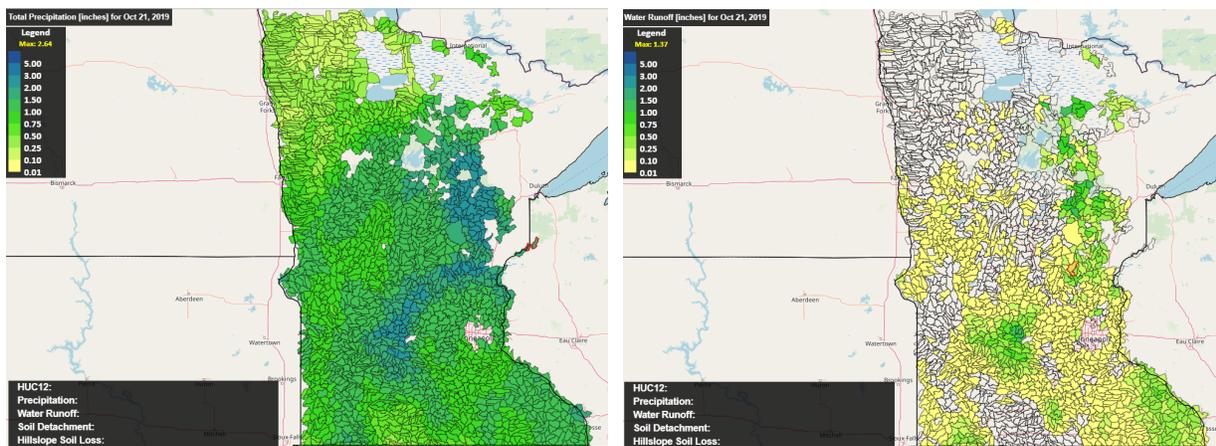


Fig. 10: Daily Erosion Project incident precipitation (left) and runoff (right) for Minnesota on October 21, 2019.

Rainfall and runoff are used to estimate two other related products, namely; soil detachment and hillslope soil loss (Fig. 11). The user can move the mouse over individual HUC12 watersheds to view a display of the actual precipitation, runoff, detachment or soil loss on any particular day.

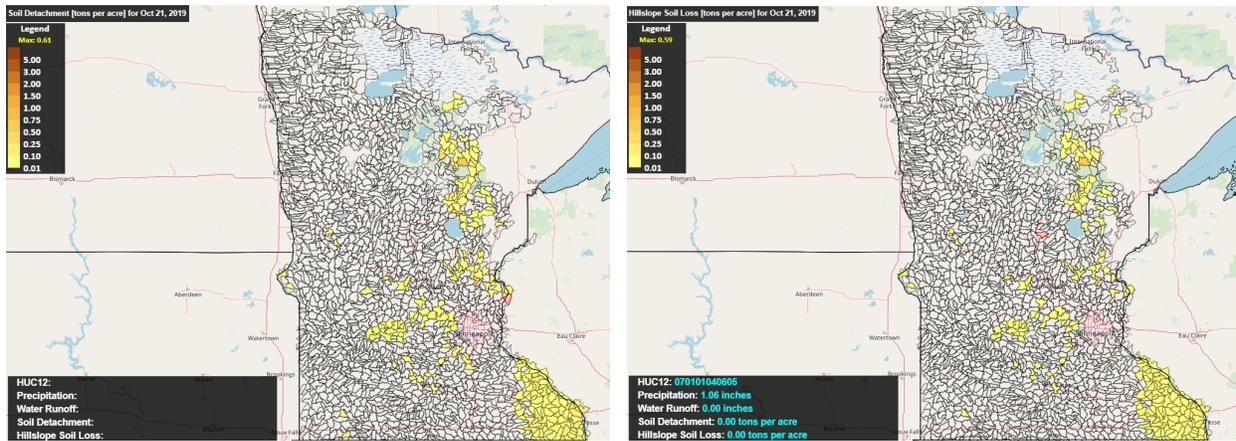


Fig. 11: Daily Erosion Project detachment (left) and soil loss (right) for Minnesota on October 21, 2019.

Ongoing and Future Work

The current focus of work involves the enforcement of hydrologic flow paths within the DEMs. Issues have arisen with bulk scripting, largely influenced by raster processing variations and requirements between ESRI ArcGIS software versions. Hydrologic conditioning is mostly complete within Minnesota with some border HUC12s and some large HUC12s (e.g. Leech Lake, Lower and Upper Red Lake) are still being processed.

Wind Erosion Prediction System

The ISU Daily Erosion Project (DEP) employs the WEPP (Water Erosion Prediction Project) model to determine daily soil erosion (by water) across the western Corn Belt. Daily updates of weather data are used to run the WEPP model in a continuous manner. Crop and soil management parameters are determined via remote sensing analyses, which inform a database (updated annually). While soil erosion by water is an important environmental concern in much of the nation’s breadbasket, wind erosion can also pose a problem for soil and environmental quality. Much of the cropland located west of the Mississippi River is at risk for wind erosion (Fig. 12; from Nordstrom and Hotta, 2004).

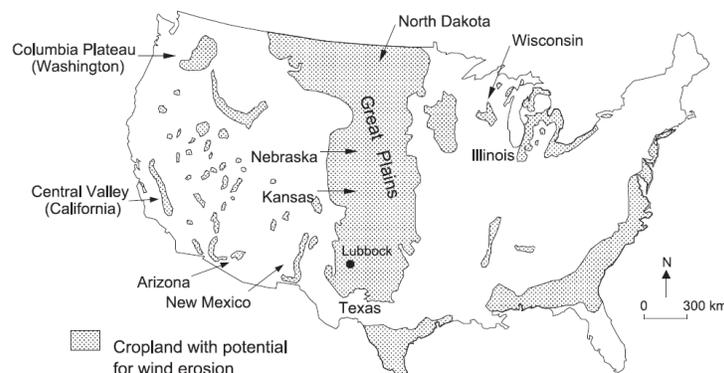


Figure 12. Regions of potential wind erosion in the continental United States. Copied from Nordstrom and Hotta, 2004.

In order to expand the application of the DEP into regions where wind erosion may also be important, we are working to expand the scope of the DEP by incorporating elements from the WEPS model (Wind Erosion Prediction System). Because the WEPP model already utilizes many inputs that are similar to those required by the WEPS model, our approach is to use WEPP inputs where feasible and run the stand-alone erosion submodel (SWEEP) that is part of the WEPS package.

WEPP model inputs are being used to populate SWEEP input files for: soil properties, hydrology, crop rotation and field management, and crop growth (Figure 3). Key additional inputs required for the SWEEP model include data on wind speed and direction as well as field characteristics such as row direction and wind breaks. Ongoing efforts are focused on (1) automating the process by which to pass WEPP parameters to the SWEEP model, and (2) devising approaches to gather remaining required input data (weather and field management) into this integrated framework.

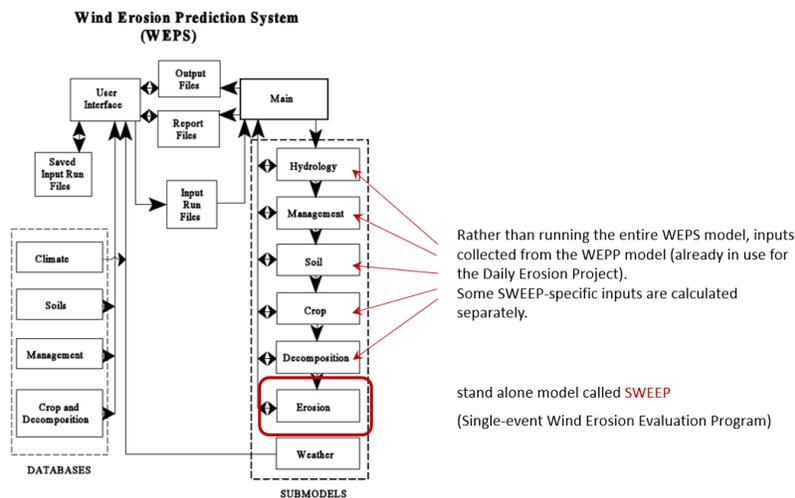


Figure 13. Schematic diagrams showing organization of the WEPS model (from Wagner, 1996) and highlighting the erosion sub-model (called SWEEP). SWEEP inputs relating to hydrology, management, soils, crops, and residue status are imported from the WEPP model or calculated separately.

Where possible, existing parameter values from the WEPP model were imported directly into the SWEEP daily erosion model. This approach was used for two key reasons:

- 1) To keep the model internally consistent by relying on the same environmental conditions for both water and wind erosion, and
- 2) To avoid duplication of modeling efforts and keep the overall project computationally efficient.

Programming Approach

Current efforts for file manipulation, parameter calculations, model parameter updates, and SWEEP model execution are all being handled in the R programming environment and saved as an R script file. A flow diagram of the general order of operations is shown in Figure 14. Necessary WEPP inputs and SWEEP model parameters include Biomass parameters, Soil parameters, and Hydrology parameters.

Current work flow for integrating SWEEP into the DEP framework.
File manipulations and calculations are performed with a script written in the R programming language.

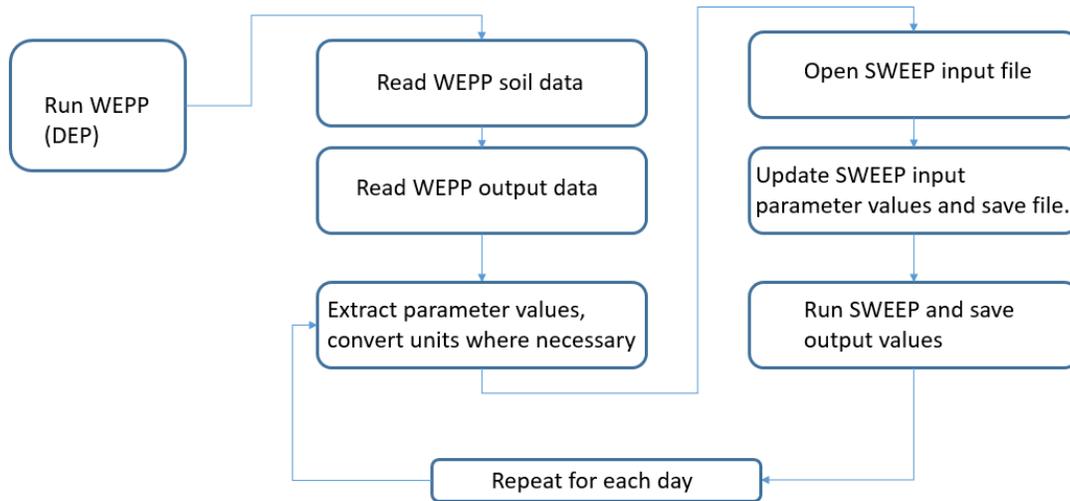


Figure 14. Flow diagram showing the general order of operations for manipulating WEPP outputs from the Daily Erosion Project and using them to update and run the SWEEP wind erosion model.

A sensitivity analysis was performed to determine the impact of soil type, wind speed, crop residue cover and windbreaks on SWEEP erosion estimates. Results of these evaluations show that SWEEP erosion estimates increase as a) soil texture becomes coarser, b) windbreaks are installed, c) crop residue cover decreases, or d) wind speed increases (Fig. 15).

Ongoing and Future Work

Ongoing efforts are focused on incorporating and updating all parameters required to run the SWEEP model based on WEPP outputs where possible. Additional SWEEP parameters will be determined from other available data sources such as pedotransfer functions and/or reasonable estimates compiled from various data sources. Some SWEEP parameters can change depending on crop type. Future work will account for changes in crop type (for both current and previous crops) in order to reflect these input values more accurately. This may involve relying on remote sensing data of land cover and crop residue cover.

Colleagues at IA State University are working to incorporate wind speed data into the DEP-SWEEP model as well as develop a DEP-SWEEP interface and determine a timeline for SWEEP-DEP rollout.

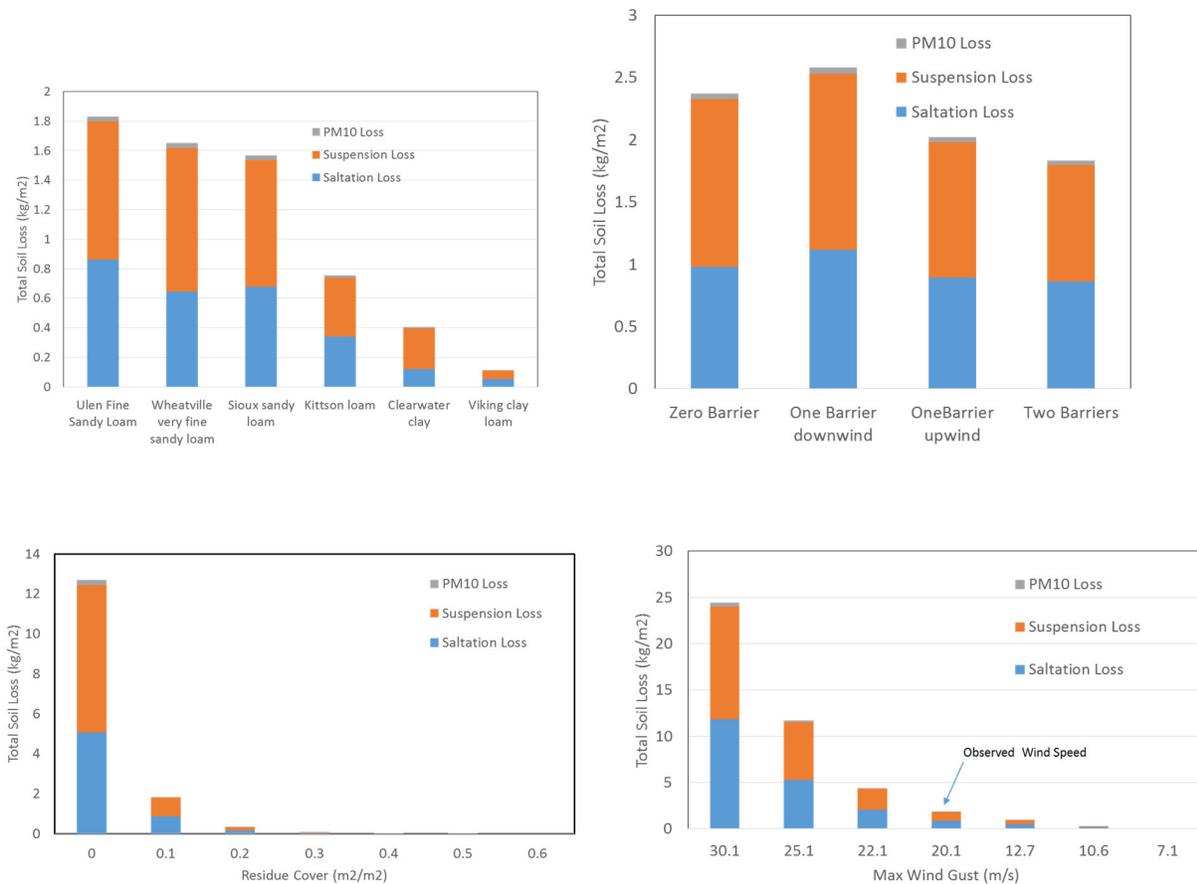


Figure 15. Sensitivity analysis for SWEEP wind erosion model predictions as a function of soil texture (upper left), windbreaks (upper right), crop residue cover (lower left), and wind speed (lower right).

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