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2 **Use of Visible/Near-Infrared Reflectance Spectroscopy to**
3 **Assess Soil Quality Related to Long-Term Tillage Effects**

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22 RCBD; tillage; aggregate stability; organic matter

1 ABSTRACT

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3 Visible/Near-Infrared (VNIR) diffuse reflectance spectroscopy is emerging as an
4 effective method for rapid evaluation of soil properties and may be promising for the
5 simultaneous determination of soil quality indicators. This study employed VNIR diffuse
6 reflectance spectroscopy to analyze treatment effects associated with long-term tillage
7 experiments (plow-till vs. no-till) at three sites in New York State. Dried, ground soil
8 samples collected from field plots were analyzed for VNIR reflectance as well as ten
9 chemical and two physical parameters. Traditional analysis of variance (ANOVA) for
10 complete block experiments was applied to reflectance data from each sequential 1-nm
11 waveband from 420 to 2500 nm. Results revealed highly significant differences in soil
12 brightness associated with tillage treatments at two of three sites, with no-till soils
13 averaging 4% darker than plowed soils across measured wavelengths. ANOVA analysis
14 of reflectance first derivatives demonstrated significant tillage-related variation in the
15 shape of absorption features. Laboratory analysis of the samples revealed increased
16 organic matter, P, K, Mg and Mn, decreased Al, Ca, Cu, and Fe, lower pH, and increased
17 small aggregate stability in the no-till treatments. Partial least squares regression (PLS)
18 analysis was used to determine predictive relations between VNIR data and measured soil
19 parameters. Results indicated that soil organic matter, Al, Mn, and pH had the strongest
20 association with tillage-related variability in VNIR reflectance. VNIR diffuse reflectance
21 spectroscopy shows promise for the assessment of important soil quality indicators,
22 especially if based on larger calibration data sets.

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2 INTRODUCTION

3

4 Visible/Near-Infrared (VNIR) diffuse reflectance spectroscopy of soils is
5 emerging as a rapid and cost-effective method for determination of soil properties
6 (Shepherd and Walsh, 2002). It is particularly useful when large numbers of
7 observations are required to accurately characterize an area or when the cost of analysis is
8 high. Both VNIR (generally 350-2500 nm) and mid-infrared (generally 2500-25000 nm)
9 reflectance data have been successfully used to predict a variety of soil characteristics,
10 including: organic and inorganic C (Brown et al., 2005), C, N, pH and biological activity
11 (Reeves et al., 2001); Fe, Cd, Cu, Ni, and Zn (Siebielec et al., 2004); C, N, extractable
12 Ca, and cation exchange capacity (Chang et al., 2001), manure nutrient concentrations
13 (Reeves and Van Kessel, 2000), mineralogy (Brown et al., 2006), and biological
14 measures (Mimmo et al., 2002). The reflectance signal is affected by soil moisture
15 content, soil particle size distribution, and parent material (Baumgardner et al., 1985;
16 Ben-Dor, 2002; Chang et al., 2001; Whiting et al., 2003), as well as soil development,
17 carbonate content, and iron oxide features (Leone and Sommer, 2000). Soil reflectance
18 has also been shown to correlate strongly with soil organic matter content (Reeves et al.,
19 2002).

20 Following collection of reflectance data, a variety of post-processing methods
21 such as smoothing and derivative computation can be employed to increase the signal-to-
22 noise ratio (Tsai and Philpot, 1998). Transforming the reflectance by calculating a first
23 derivative (Dawson and Curran, 1998; Tsai and Philpot, 2002) generally improves
24 analytical accuracy. Continuum removal (e.g., Mutanga et al., 2004) can be used to
25 compensate for baseline shift among reflectance spectra. Additionally, various
26 researchers convert reflectance to optical density $\ln(1/R)$ prior to analysis (e.g., Reeves
27 and Van Kessel, 2000). Principal components analysis and partial least squares

1 regression can be used to develop correlations between observed spectral data and
2 measured soil properties (Chang et al., 2001; Shepherd and Walsh, 2002).

3 Soil quality assessment is becoming of increasing interest among scientists and
4 farmers (Andrews et al., 2002; 2004). Soil quality includes an inherent and a dynamic
5 component (Carter, 2002; Larson and Pierce, 1991). The former is an expression of the
6 soil forming factors. Dynamic soil quality, on the other hand, generally refers to the
7 condition of soil that is changeable in a short period of time by human impact, including
8 agricultural management practices (Karlen et al., 1997; Mausbach and Seybold, 1998).

9 Soil quality is best assessed through soil properties that are sensitive to changes in
10 management (Larson and Pierce, 1991). Recent United States soil conservation
11 legislation explicitly addresses concerns related to soil quality and emerging programs
12 include farmer payments for soil quality enhancement (NRCS, 2005). Rapid quantitative
13 assessment is therefore a desirable aspect of soil quality research and government
14 programs.

15 The physical structure of a soil plays an integral role in controlling chemical and
16 biological processes (Dexter, 2004; Dexter and Czyz, 2000). A high proportion of stable
17 aggregates in an agricultural soil is desirable, especially in fine- and medium-textured
18 soils, as they sustain a range of pore sizes and promote aeration, water infiltration, and
19 drainage (Kemper and Rosenau, 1986), as well as better soil workability, seed bed quality
20 (Topp et al., 1997), and easy root penetration (Czyz, 2004). In turn, biological and
21 chemical processes, such as root growth, organic matter turnover, macrofauna activity,
22 bacterial and fungal proliferation, and cation charge density on the exchange complex
23 influence pore size distribution, density and stability of soil structure (Magdoff and van

1 Es, 2000). Conventional tillage systems can cause rapid loss of soil organic matter and
2 degrade soil structure (Moorman et al., 2004). Reduction in tillage intensity generally
3 brings about higher aggregate stability, porosity, abundance of root channels and
4 macrofauna burrows, infiltrability and water holding capacity (Bessam and Mrabet, 2003;
5 Liebig et al., 2004).

6 This study combined VNIR hyperspectral sensing and classical analysis of
7 variance (ANOVA) to evaluate tillage treatment effects on measures of soil quality, in the
8 context of complete block agronomic field experiments such as are as commonly used to
9 evaluate agricultural practices (van Es and van Es, 1993). Soil samples were collected
10 from three locations in New York State, where long-term (13- to 32-year) experiments
11 contrasted plow-till and no-till tillage treatments under continuous maize (*Zea mays* L.)
12 production. Previous analyses of these experiments have documented the effect of tillage
13 on soil hydraulic properties (van Es et al., 1999) and maize yield. The objectives of this
14 study were (1) to evaluate the ability of VNIR diffuse reflectance spectroscopy to detect
15 changes in soil quality, specifically plow-till vs. no-till tillage treatments, and (2) to
16 compare variation in VNIR reflectance with observed soil chemical and physical quality
17 measures.

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19

20 MATERIALS AND METHODS

21

22 Sites and Sample Collection

23 Soil samples were collected in the spring of 2004 (April 22 to May 7) from three
24 long-term tillage experiments in New York State (Fig. 1). The experiments contrast
25 plow-till (moldboard plow) and no-till (zero-tillage) management of continuous maize
26 (*Zea mays* L.) plots. Tillage treatments had been maintained for 13 years at two of the

1 sites, located in Aurora, NY (42°43' N, 76°39' W) and Willsboro, NY (44°23' N, 73°23'
2 W). A spatially-balanced complete block (SBCBD) design (van Es et al., 2003; van Es
3 and van Es, 1993) was employed to establish four (Willsboro) or six (Aurora) replications
4 of plow-till and no-till treatments. Management of these two sites is reported in further
5 detail in van Es et al. (1999), and was based on standard Cornell Cooperative Extension
6 recommendations for fertility and pest management.

7 At a third site, located in Chazy, NY (44°53' N, 73°28' W), tillage treatments had
8 been maintained for 32 years. In addition to tillage, secondary treatment data from the
9 Chazy site allowed the contrast of 32 years of silage harvest (whole plant removal) versus
10 grain harvest (stover remained on the field). A standard randomized complete block
11 (RCBD) design with sixteen 6 x 15.2 m plots was employed to establish four replications
12 of each tillage-harvest combination. Maize residues in plow-till plots were incorporated
13 during springtime tillage (moldboard and disk), and were left on the surface in no-till
14 plots.

15 The soil at the Willsboro site is classified as a glacio-lacustrine Muskellunge clay
16 loam (fine, illitic, frigid, Aeric Ochraqualfs) and at the Aurora site as a glacial till-derived
17 Honeoye-Lima silt loam (fine-loamy, mixed, mesic, Glossoboric Hapludalfs). Soil at the
18 Chazy site is classified as Raynham silt loam (coarse-silty, mixed, active, nonacid, mesic
19 Aeric Epiaquepts). All of the sites are tile drained. Climate in the region is humid
20 continental, with approximately 110 cm of precipitation falling annually.

21 Within each plot one soil sample was collected from a non-trafficked inter-row.
22 Approximately 500 cm³ of topsoil (0-7 cm) was carefully removed, placed in a plastic
23 container, and stored under 2°C refrigeration. Samples were subsequently air-dried (24
24 hours in a 60°C oven) and passed through a sample splitter. One half was analyzed for

1 soil aggregate stability. The other half was ground to pass a 2-mm screen and was
2 analyzed for soil nutrient content and hyperspectral reflectance.

3

4 VNIR Spectroscopy

5 The diffuse reflectance of each sample was recorded using a FieldSpecPro
6 hyperspectral sensor (FieldSpecPro Instrument #6368, calibration 1, manufactured by
7 Analytical Spectral Devices, Inc., Boulder, Colorado; ASD, 1997) that was kept in a
8 climate-controlled room. This instrument uses one silicon diode array for shorter VNIR
9 wavelengths (350-1000 nm) and two scanning indium-gallium-arsenide arrays to span the
10 shortwave infrared (SWIR1: 1000-1700 nm; SWIR2: 1700-2500 nm), coupled with a
11 fiber optic cable and light source, to measure the reflectance of target soil samples.
12 Spectral data for each sample consisted of 2151 sequential reflectance values recorded in
13 1-nm increments.

14 Oven-dried soil samples were ground to pass a 2-mm screen, and allowed to
15 equilibrate with ambient temperature (21.8 to 22.4°C) and humidity (43 to 51%) prior to
16 sensing. Soil was spooned into 4-cm diameter optical-quality petri dishes (Electron
17 Microscopy Services Cat#70674-52, manufactured by Willco Wells B.V., Amsterdam,
18 Netherlands), and reflectance was recorded through the borosilicate glass bottom of each
19 dish. A 'muglamp' sensor attachment ([http://www.asdi.com/products-accessories-](http://www.asdi.com/products-accessories-HISP.asp)
20 [HISP.asp](http://www.asdi.com/products-accessories-HISP.asp)) was used to hold a halogen light source at a constant angle from the fiber-optic
21 sensor cable that connected to the sensor. The fiber-optic sensor viewed the sample at
22 90°. A precision-milled sample platform mounted to the muglamp held the sample dishes
23 at a constant distance of 1.5 cm above the surface of the muglamp's glass viewport,
24 approximately 40 mm from the light source and optical cable.

25 The sensor was programmed to average five sequential spectrum readings into
26 each of ten consecutively saved output files. These files were subsequently averaged in

1 post-processing to yield one average reflectance spectrum (1-nm resolution) for each soil
2 sample ('untransformed data'). This method was shown to provide adequate control of
3 signal noise attributable to fluctuations in instrument line voltage. Additionally, rotation
4 of the sample was shown to have a negligible effect on the reflectance signal.

5 Spectral domain filtering was applied to the averaged reflectance measurements to
6 remove signal noise using the S-Plus 6.1 statistical package (Insightful Corporation,
7 2001). Each 1-nm reflectance datum (weighted at 0.2) was averaged with four
8 neighboring values to each side, resulting in a moving average of nine data points. A first
9 derivative of the smoothed reflectance data was subsequently calculated using the
10 Savitsky-Golay algorithm using Unscrambler 9.2 (Camo, 2005), weighing one point to
11 each side. The untransformed and smoothed-first-derivative datasets were then clipped to
12 remove wavelengths near the edges of sensor ranges (removed: 350-420 nm; 961 to 1019
13 nm; 1771-1829 nm and 2481 to 2500 nm).

14 S-Plus 6.1 was used to perform sequential RCDB analysis of variance (ANOVA)
15 for site and treatment effects, using data from each sequential 1-nm waveband. Results
16 were recorded as wavelength-specific ANOVA p-values and R^2 ($\alpha = 0.05$). The
17 Unscrambler 9.2 software package was used to perform partial least squares (PLS1)
18 regression with cross-validation to obtain predictions of soil analytical results from
19 spectral data. The number of PLS factors was limited to two in order to avoid over-fitting
20 the small dataset.

21

22 Nutrient Analysis

23 Oven-dry soil samples were submitted to the Cornell Nutrient Analysis
24 Laboratory, where they were ground to pass a 2-mm screen. Nutrients were analyzed by
25 colorimetric methods following Morgan's extraction (1N NaOH, pH 4.8; Lathwell and
26 Peech, 1965), providing measured concentrations (mg L^{-1}) of Al, Ca, Cu, Fe, P, K, Mg
27 Mn, and Zn. Organic matter (%) was determined by loss on ignition, and pH was

1 determined using a 1:1 soil-to-water extract. Standard RCBD ANOVA analyses were
2 used to test for differences among site and treatment means, using S-Plus 6.1.

3

4 Aggregate Stability

5 Samples of air-dry soil were first crumbled through an 8-mm sieve. Using stacked
6 sieves of 2 mm and 0.25 mm and a catch pan, the soil samples were then shaken for 10 s on
7 a Tyler (Mentor, OH, USA) Coarse Sieve Shaker. Fractions of small (0.25 – 2 mm) and
8 large (2 – 8 mm) aggregates were retained and oven-dried at 40°C. Single layers of
9 aggregates were spread on a 2 mm sieve (large aggregates) and a 0.25 mm sieve (small
10 aggregates). Four sieves at a time were placed 0.5 m below a 0.59 m diameter rainfall
11 simulator (Ogden et al., 1997; van Es et al., 2003) which delivered 12.5 mm of water as 4
12 mm drops in 300 s. Each sieve received 1.9 J of energy over a 300 s simulated rainfall
13 period, based on 0.164 mJ of energy delivered per single drop from a height of 0.5 m.
14 Stones retained in the sieve and slaked soil material that fell through the sieve into a filter
15 funnel were each collected, dried and weighed, and the fraction of stable aggregates was
16 calculated using:

17

18 $WSA = w_{stable}/w_{total}$, where

19 $w_{stable} = w_{total} - (w_{slaked} + w_{stones})$

20

21 The variables w_{stable} , w_{total} , w_{slaked} and w_{stones} are the dry weights of stable soil aggregates,
22 total aggregates tested, aggregates slaked through the sieve, and stones remaining in the
23 sieve after the test, respectively. Standard RCBD ANOVA analyses were used to test for
24 differences among site and treatment means using S-Plus 6.1.

1

2 RESULTS AND DISCUSSION

3

4 Tillage Effect on Soil Reflectance

5 Reflectance of the soil samples generally increased with tillage from near 10% in
6 the visible wavelengths to a maximum of 30 to 60% in the NIR, depending on site (Figs.
7 2 to 5). Seven absorption features were apparent: 1) 450 to 500 nm, 2) 550 to 650 nm, 3)
8 750 to 850 nm, 4) 1350 to 1500 nm, 5) 1850 to 2000 nm, 6) 2150 to 2300 nm, and 7)
9 2300 to 2400 nm (Fig. 2a). Although direct interpretation of spectrum shape is difficult
10 in the VNIR wavelength range where spectral features reflect combined overtones and
11 harmonics of chemical bond vibrations that are observed directly in the mid infra-red
12 (2500 to 25,000 nm), features 1 and 2 generally relate to soil color, features 4 and 5 to
13 soil moisture, and feature 7 to soil moisture and/or soil organic matter content (RSI,
14 2005). Substantial noise was evident below 500nm and above 2300nm due to low signal
15 intensity.

16 For statistical purposes, a standard ANOVA analysis for RCBD experimental
17 designs was used to compare reflectance data within each sequential 1-nm waveband.
18 The ANOVA output is presented graphically in plots b and c of Figs. 2 and 6, and plots c
19 and d of Figs. 3, 4 and 5. Site, tillage, and site*tillage interaction were all found to be
20 highly significant factors (Fig. 2). The site effect is likely attributable to the sensitivity of
21 VNIR reflectance to soil particle size distribution (Ben Dor, 2002) and to inter-site
22 differences in soil type and soil characteristics (Table 1). Because the site effect was
23 significant, tillage treatment effects were subsequently analyzed on a within-site basis.

24 Within sites, the untransformed reflectance data (plot a of Figs. 3 to 5) exhibited
25 significant tillage-associated variation, with effects seen largely as differences in overall
26 soil brightness (magnitude of reflectance) rather than as changes in specific absorption
27 features (spectrum shape). No-till soils at the Chazy and Willsboro sites were on average

1 3.8% and 4.1% darker than plowed soils (plot b of Figs. 3 to 5), presumably owing to
2 increased organic matter content (see nutrient analysis data, below). At the Aurora site
3 (Fig. 5) no significant differences were detected. Using ANOVA analysis, significant
4 tillage effects ($\alpha = 5\%$) were uniformly observed between 500 to 2500 nm at the Chazy
5 and Willsboro sites (plot c of Figs. 3 and 4). The correlation (R^2) between tillage
6 treatment and soil reflectance at the Chazy and Willsboro sites ranged from 30% to 75%
7 depending on wavelength (plot d of Figs. 3 and 4) with the greatest correlation generally
8 observed at higher wavelengths.

9 First-derivative data (Figs. 7 to 9) indicate that tillage also had a significant effect
10 on the shape of reflectance features, explaining up to 80% of observed tillage-associated
11 variation in some wavelength bands. Expectedly, the greatest tillage-associated variation
12 in reflectance first derivatives occurred in the wavebands associated with apparent
13 absorbance features. The correlation between tillage treatment and first derivative of
14 reflectance may perhaps be attributable to tillage-induced variation in soil fertility and/or
15 organic matter content (see below).

16 At the Chazy site, the harvest treatment (grain vs. silage) was not significantly
17 associated with observed variation in soil reflectance (Fig. 6), although the primary
18 tillage treatment clearly affected soil reflectance. The maize stover that was returned to
19 the grain harvest plots evidently did not alter soil brightness or absorption features, which
20 also reflects the less-pronounced effects of harvest treatment on soil properties compared
21 to the tillage effects (Table 1).

22

23 Tillage Effects on Soil Nutrients

24 Significant ($\alpha = 0.05$) inter-site differences were detected for pH, OM, and all
25 measured elements except Ca and Cu (Table 1). Soil type varied among the sites, and the
26 observed significant effects of site and site*tillage interaction are likely attributable to
27 variation in genetic soil composition. Within site, significant tillage effects were

1 observed for pH, OM, and for all elements except Zn, although the level of significance
2 was variable among sites (Table 1). The organic matter content of no-till plots was
3 increased by 1.1 to 1.8% over plow-till in all cases. No-till plots also tended to exhibit
4 higher P, K, and Mg, as well as lower pH, Al, Ca, Cu, and Fe. Interestingly, only the
5 Aurora site showed a significant effect of tillage on Cu, Fe, and K, and only that site
6 showed no significant effect on pH or VNIR reflectance.

7 At the Chazy site, the harvest treatment (grain vs. silage) was associated with
8 significant differences in OM, P, K, Mg, and Al (Table 1), but only within the no-till
9 treatment. In each of these cases the silage harvest treatment was associated with
10 reduced OM and soil nutrients, as might be expected following whole plant removal. In
11 both the plow-till and no-till plots, soil K contents were lower where whole plants were
12 removed (silage) than where residues were returned (grain), presumably due to the long-
13 term removal K in contained in maize stalks.

14

15 Tillage Effects on Soil Aggregate Stability

16 Stability of both large and small aggregates varied among sites (Table 1), likely
17 due to differences in soil texture. Within sites, at all three locations, the no-till treatment
18 had significantly increased small aggregate stability, presumably due to the accumulation
19 of organic matter and stabilizing glues (Magdoff and van Es, 2000). The large
20 aggregates, which were observed to be generally less stable than small aggregates,
21 showed increased stability after 32 years of no-till conditions (Chazy) but showed no
22 significant tillage-associated variation at the 13-year study sites (Aurora and Willsboro).

23 At the Chazy site, the harvest treatment showed a somewhat significant ($\alpha = 0.1$)
24 effect on small aggregate stability within the plow-till treatment (Table 1). However,
25 there was no significant harvest effect on small aggregate stability within no-till plots or
26 overall, and no significant effect on large aggregate stability in either tillage treatment.

27

1 Correlation of VNIR Reflectance with Soil Fertility and Aggregate Stability

2 Soil nutrient content and aggregate stability were associated with variability in
3 spectral reflectance, as determined by PLS analysis (Table 2). Some nutrients (e.g. Mg,
4 Fig. 11) exhibited very different concentrations at the three research sites, leading to high
5 PLS R^2 values when all samples were included (Fig. 11a), but did not correlate well with
6 spectral features within site (Chazy data, Fig. 11b). These nutrients (Fe, K, Mg), as well
7 as nutrients that demonstrated little overall correlation with reflectance (Ca, Cu, Zn) were
8 therefore thought to have little effect on the significant correlation between reflectance
9 data and tillage treatments. Other soil factors (e.g., organic matter OM, Fig. 12)
10 demonstrated significant within-site correlation with spectral reflectance (Chazy data,
11 Fig. 12b). Organic matter content was clearly correlated with reflectance variability (R^2
12 = 0.76), and Al, Mn, pH, P, and small aggregate stability were also significant factors (R^2
13 = 0.46, 0.45, 0.30, 0.27, and 0.42, respectively). It is noted that P is thought to have little
14 direct effect on VNIR reflectance (RSI, 2005), and the correlation between P and spectral
15 data is therefore likely attributable to covariation between phosphorus concentrations and
16 organic matter content ($R^2= 0.54$).

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18

19 CONCLUSIONS

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21 VNIR diffuse reflectance sensing of ground, air-dried soil samples collected from
22 replicated agronomic field experiments detected highly significant tillage-associated
23 variability in soil reflectance (420 to 2480 nm). No-till soils were on average 4% darker
24 than plowed soils across all measured wavelengths, perhaps due to the accumulation of
25 organic matter in the no-till plots (1.8, 1.7, and 1.1% greater than plowed plots at the
26 Chazy, Willsboro, and Aurora sites, respectively). First derivative results identified a
27 number of wavelengths where tillage affected the shape of the reflectance spectra. In

1 addition to reflectance, tillage treatments also had clear effects on soil fertility indicators,
2 organic matter content, and small aggregate stability. For all indicators, no-till treatments
3 were associated with better soil quality. Furthermore, differences were more pronounced
4 in the 32-year trial (Chazy) than in the 13-year trials (Aurora and Willsboro).
5 Correlations derived from PLS analysis indicated that, out of the variables measured in
6 this study, soil organic matter, aluminum and manganese concentrations, and pH had the
7 greatest association with tillage-related variability in soil reflectance.

8 The harvest treatment (grain vs. silage) had no significant effect on soil
9 reflectance, and only a minor effect on small aggregate stability and soil fertility.
10 Overall, the effect of 32 years of continuous tillage had a much larger effect on the soil
11 characteristics than the effect of 32 years of removal vs. retention of maize stover.

12 Although the number of available samples (n=36) was too limited to support an
13 accurate prediction of soil properties from spectral reflectance data, PLS regression
14 analysis indicated a strong correlation between reflectance and organic matter content (R^2
15 = 0.76), which is a critical soil quality indicator (Magdoff and van Es, 2000). It also
16 showed a moderate correlation with Al, Mn, pH, P, and small aggregate stability. VNIR
17 diffuse reflectance spectroscopy shows an ability to assess management-induced changes
18 in some soil quality indicators, and, especially if based on larger calibration data sets,
19 shows promise as a tool for rapidly identifying variability in soil quality parameters.

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TABLES

3 Table 1. Mean soil test values for organic matter (OM %), pH, and soil nutrients (mg
 4 kg⁻¹), and aggregate stability (%) within tillage (plow-till vs. no-till) and harvest (grain
 5 vs. silage) treatments.

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| | Tillage | | | | | | Harvest [#] | | | | | |
|---------------------------------|---------|---------|-----------|---------|-------|---------|----------------------|--------|------------------|---------|----------------|--------|
| | Aurora | | Willsboro | | Chazy | | All plots | | Within plow-till | | Within no-till | |
| | Plow | No-till | Plow | No-till | Plow | No-till | Grain | Silage | Grain | Silage | Grain | Silage |
| OM [†] | 3.8 | 4.9 * | 6.9 | 8.6 ** | 3.4 | 5.2 * | 4.7 | 3.9 | 3.6 | 3.3 | 5.8 | 4.6 * |
| pH [‡] | 7.8 | 7.7 | 6.3 | 5.8 * | 7.7 | 7.3 * | 7.5 | 7.5 | 7.7 | 7.7 | 7.2 | 7.3 |
| P [§] | 6.9 | 17.6 * | 3.9 | 6.6 | 8.4 | 11.4 ** | 11.8 | 8.0 ** | 8.6 | 8.2 | 14.9 | 7.8 * |
| K [¶] | 51.1 | 95.1 * | 106.1 | 116.8 | 37.3 | 62.3 | 67.3 | 32.4 * | 45.8 | 28.9 ** | 88.7 | 36.0 * |
| Mg [¶] | 293 | 329 ** | 570 | 507 | 133 | 190 * | 190 | 133 * | 139 | 127 | 241 | 138 * |
| Ca [¶] | 3417 | 2762 | 2868 | 3076 | 3820 | 3045 * | 3266 | 3598 | 3551 | 4089 | 2982 | 3107 |
| Fe [¶] | 0.8 | 0.3 * | 12.8 | 13.7 | 1.8 | 1.1 | 1.8 | 1.2 | 2.5 | 1.1 | 1.0 | 1.2 |
| Al [¶] | 11.4 | 7.5 * | 32.7 | 43.9 ** | 11.7 | 7.9 * | 9.3 | 10.3 | 12.1 | 11.4 | 6.6 | 9.2 * |
| Mn [¶] | 23.8 | 29.0 * | 25.6 | 16.4 * | 18.9 | 15.0 * | 17.7 | 16.2 | 19.6 | 18.2 | 15.8 | 14.2 |
| Zn [¶] | 1.4 | 0.7 | 2.3 | 4.0 | 0.9 | 1.9 | 2.0 | 2.4 | 1.3 | 0.5 | 2.6 | 1.2 |
| Cu [¶] | 2.1 | 1.6 * | 1.9 | 1.9 | 2.4 | 2.0 | 2.0 | 2.4 | 2.1 | 2.6 | 1.8 | 2.2 |
| Large Aggregates ^{††} | 22.7 | 35.0 | 44.9 | 59.5 | 9.1 | 18.8 * | 13.7 | 14.2 | 7.2 | 11.1 | 20.2 | 17.3 |
| Small Aggregates ^{†††} | 19.2 | 48.7 * | 30.4 | 68.9 * | 17.6 | 45.6 * | 35.6 | 27.6 | 21.6 | 13.6 ** | 49.6 | 41.6 |

* Treatment means significantly different at $P \leq 5\%$

** Treatment means significantly different at $P \leq 10\%$

† Organic matter by loss on ignition

‡ 1:1 soil:water solution

§ Orthophosphate by autoanalysis following Morgan's extraction (1N NaOH, pH 4.8; Lathwell and Peech, 1965)

¶ ICP analysis following Morgan's extraction

Using split-plot data from the Chazy site

†† 2 to 8 mm aggregate size

††† 0.25 to 2 mm aggregate size

- 1 Table 2. Accuracy (R^2) of partial least squares predictions of soil nutrient concentrations
- 2 and aggregate stability using untransformed and first derivative reflectance data.

| | Untransformed | | First Derivative | |
|---------------------------------|---------------|-------|------------------|-------|
| | All Sites | Chazy | All Sites | Chazy |
| Organic Matter [†] | 0.81 | 0.76 | 0.84 | 0.89 |
| pH [‡] | 0.86 | 0.30 | 0.87 | 0.56 |
| Phosphorus [§] | 0.25 | 0.27 | 0.22 | 0.12 |
| Potassium [¶] | 0.30 | 0.00 | 0.32 | 0.17 |
| Magnesium [¶] | 0.79 | 0.01 | 0.80 | 0.18 |
| Calcium [¶] | 0.01 | 0.05 | 0.03 | 0.07 |
| Iron [¶] | 0.52 | 0.04 | 0.55 | 0.07 |
| Aluminum [¶] | 0.87 | 0.46 | 0.85 | 0.50 |
| Manganese [¶] | 0.53 | 0.45 | 0.54 | 0.45 |
| Zinc [¶] | 0.18 | 0.06 | 0.20 | 0.08 |
| Copper [¶] | 0.01 | 0.12 | 0.00 | 0.00 |
| Large Aggregates ^{††} | 0.57 | 0.18 | 0.56 | 0.32 |
| Small Aggregates ^{†††} | 0.23 | 0.42 | 0.23 | 0.47 |

[†] Organic matter by loss on ignition

[‡] 1:1 soil:water solution

[§] Orthophosphate (mg L^{-1}) by autoanalysis following Morgan's extraction

[¶] ICP analysis following Morgan's extraction

^{††} 2 to 8 mm aggregate size

^{†††} 0.25 to 2 mm aggregate size

1 LIST OF FIGURES

2

3 Fig. 1. Map of the study locations.

4 Fig. 2. Effect of site and tillage on soil reflectance.

5 Fig. 3. Effect of tillage on soil reflectance at the Chazy site.

6 Fig. 4. Effect of tillage on soil reflectance at the Willsboro site.

7 Fig. 5. Effect of tillage on soil reflectance at the Aurora site.

8 Fig. 6. Effect of the harvest treatment on soil reflectance at the Chazy site.

9 Fig. 7. Effect of tillage on first derivative of soil reflectance at the Chazy site.

10 Fig. 8. Effect of tillage on first derivative of soil reflectance at the Willsboro site.

11 Fig. 9. Effect of tillage on first derivative of soil reflectance at the Aurora site.

12 Fig.10. Effect of the harvest treatment on first derivative of soil reflectance at the Chazy
13 site.

14 Fig.11. Partial least squares predictions of soil magnesium content (mg Kg^{-1}) for a) all
15 sites (A = Aurora, W = Willsboro, C = Chazy) and b) Chazy only. Upper case
16 lettering indicates plow-till plots, lower case indicates no-till plots.

17 Fig.12. Partial least squares predictions of soil organic matter content (%) for a) all sites
18 (A = Aurora, W = Willsboro, C = Chazy) and b) Chazy only. Upper case
19 lettering indicates plow-till plots, lower case indicates no-till plots.

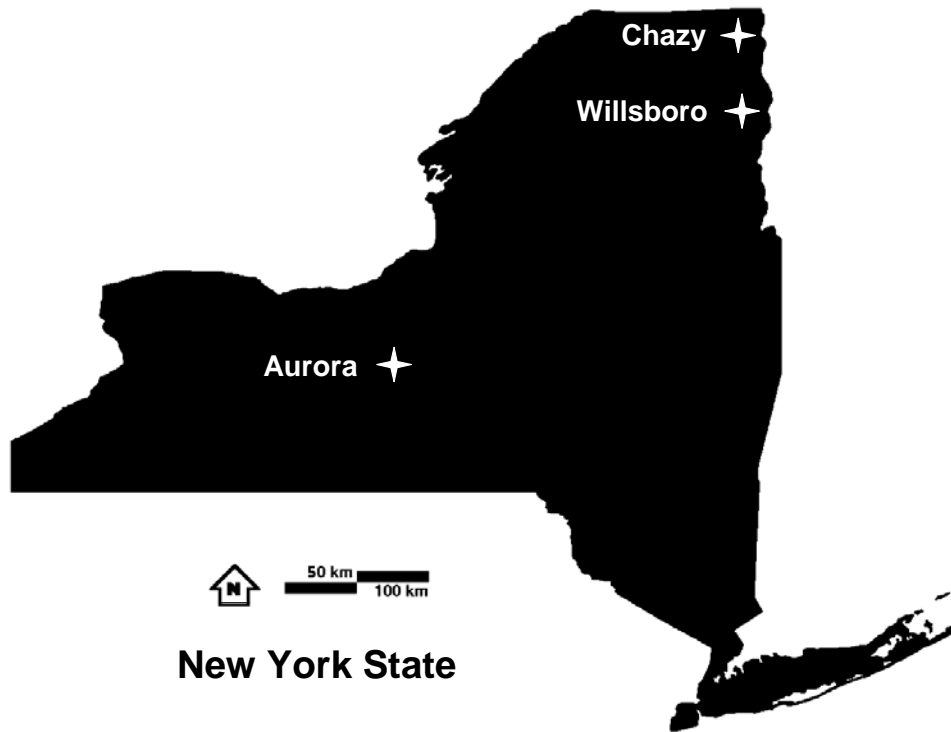
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1 Figure 1.

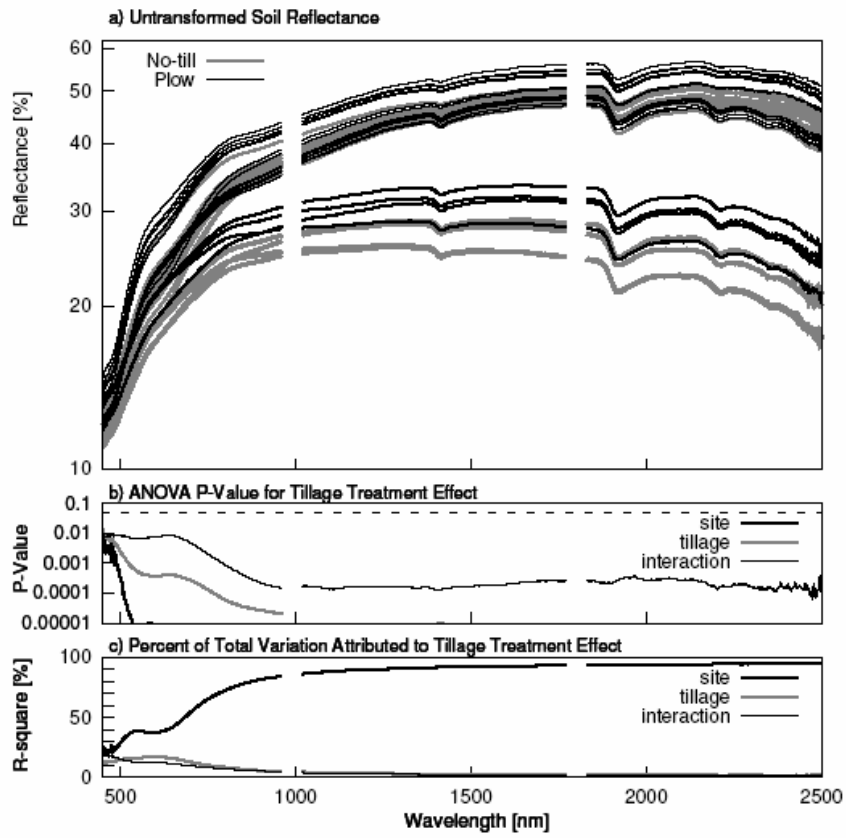


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1 Figure 2.

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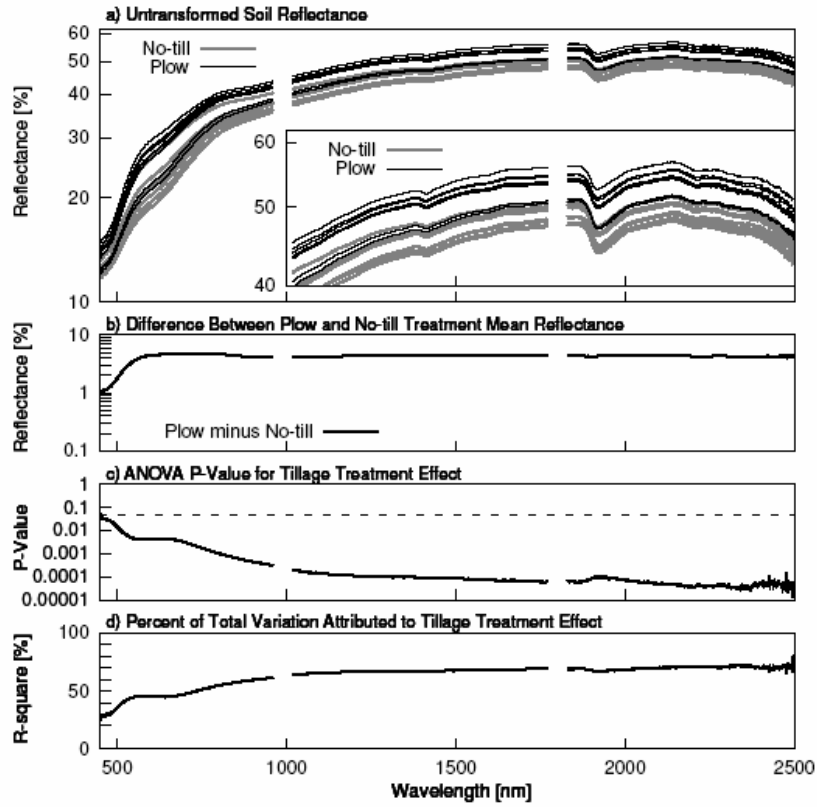


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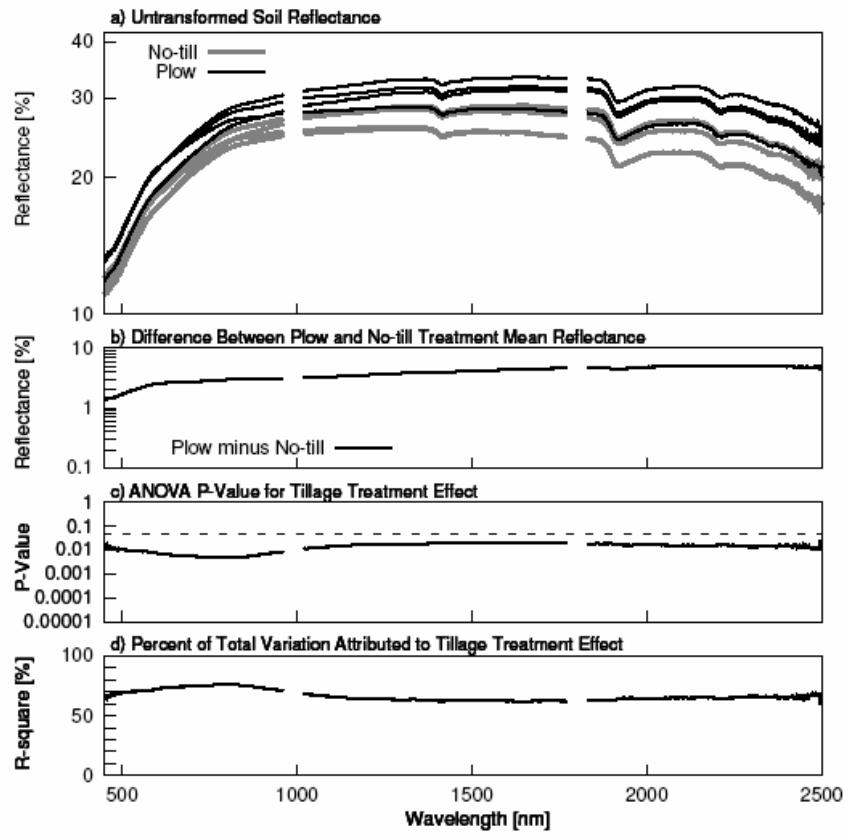
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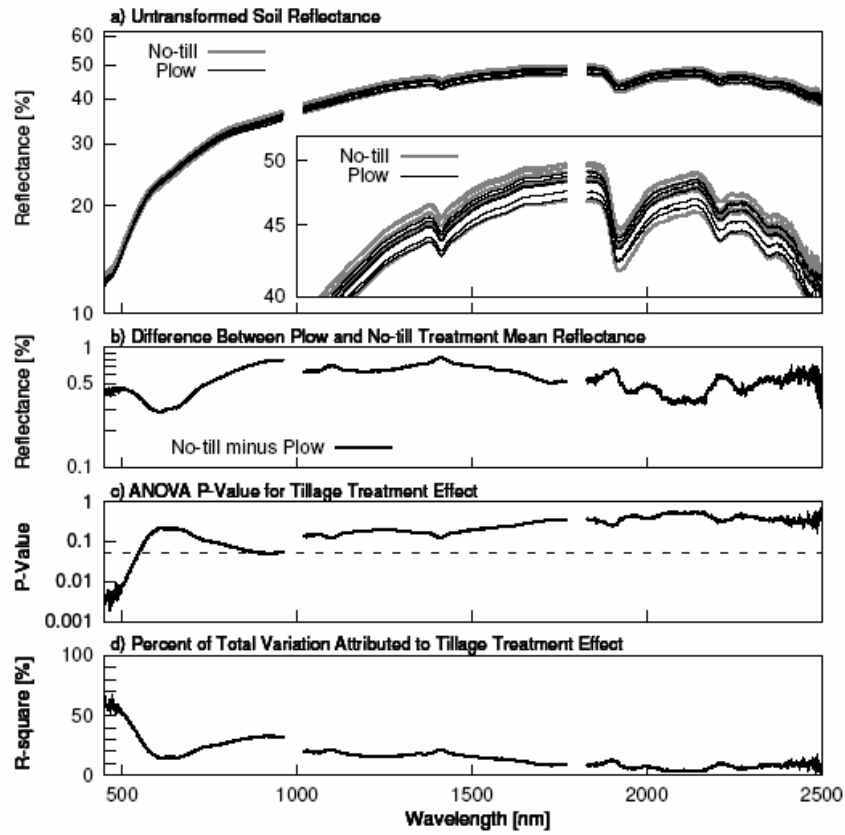
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1 Figure 5.

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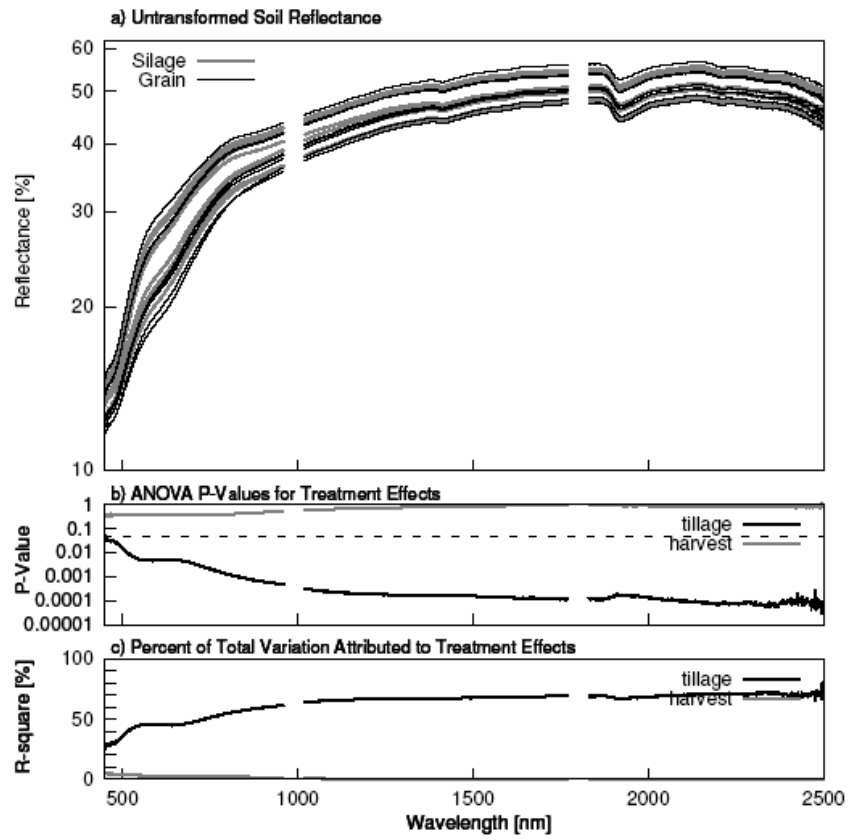
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1 Figure 6.

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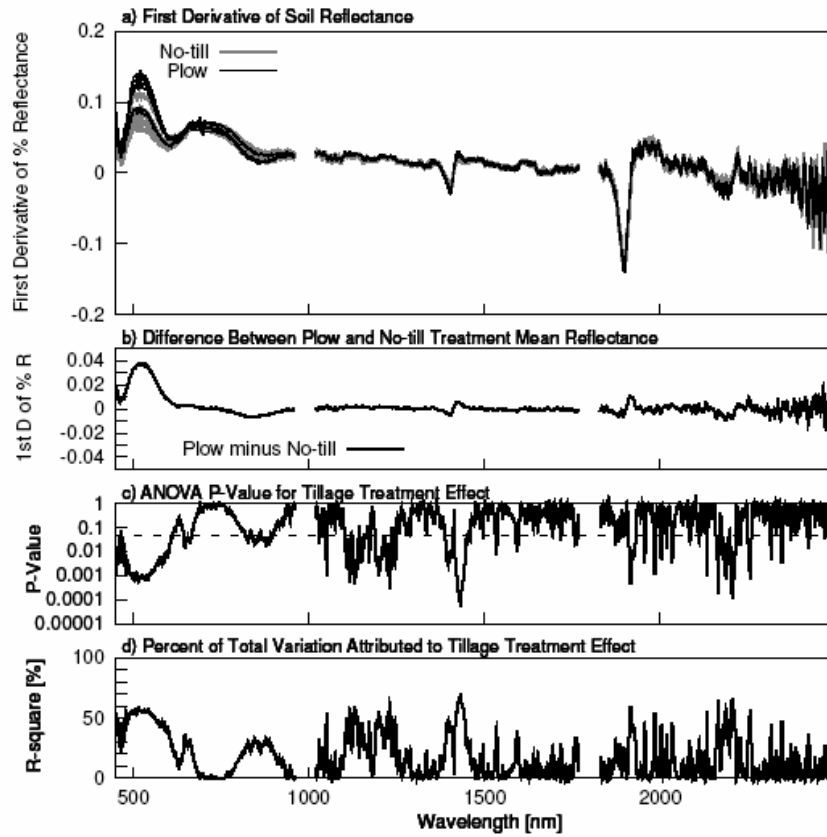
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1 Figure 7.

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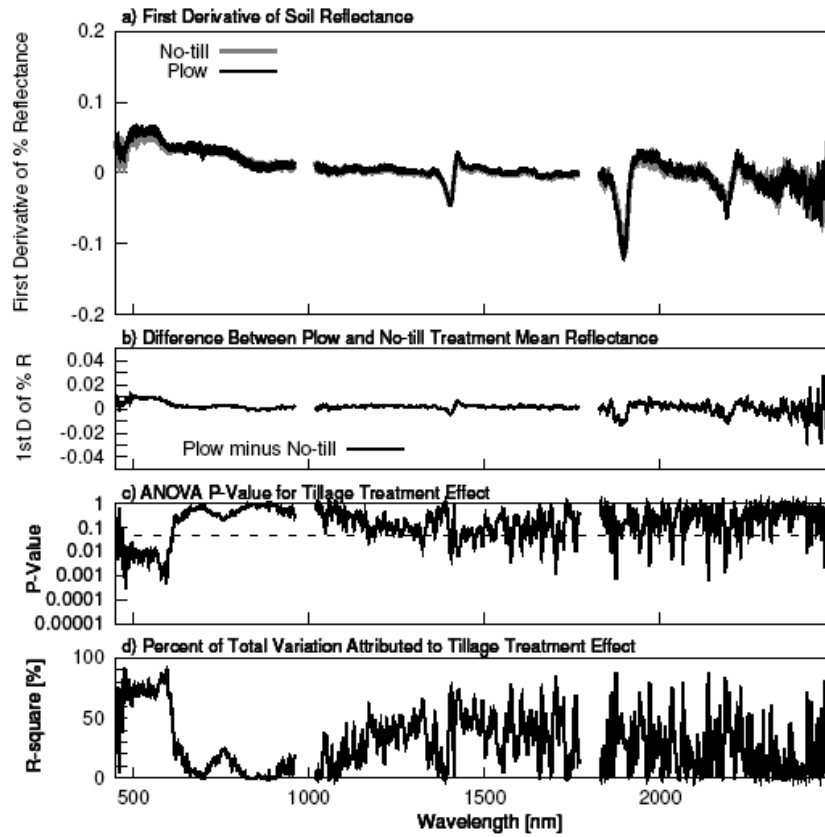
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1 Figure 8.

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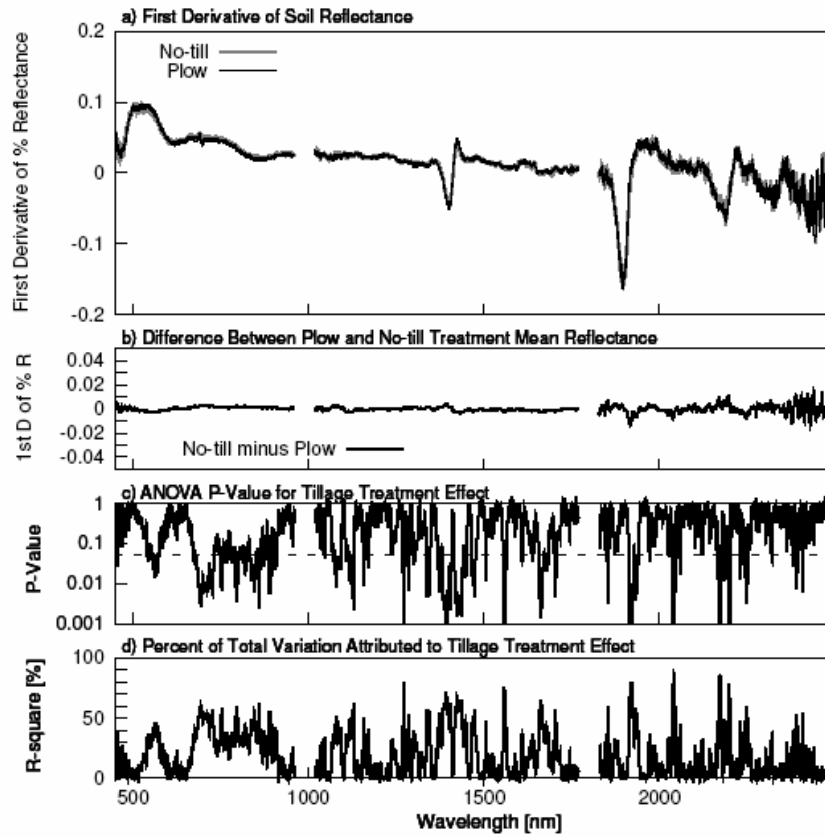
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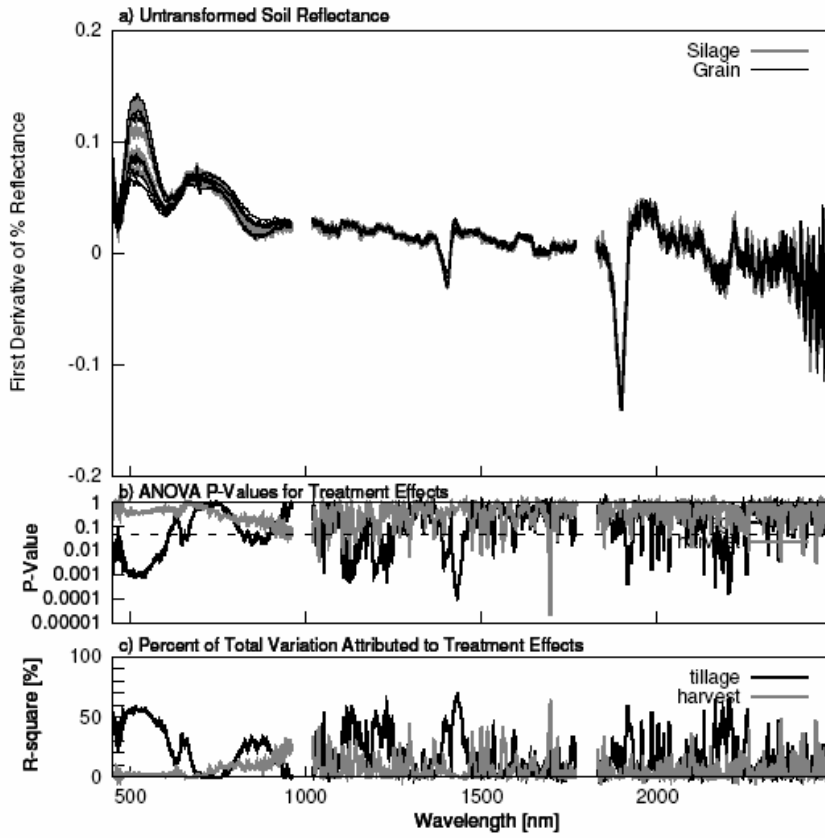
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1 Figure 10.

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1 Figure 11.

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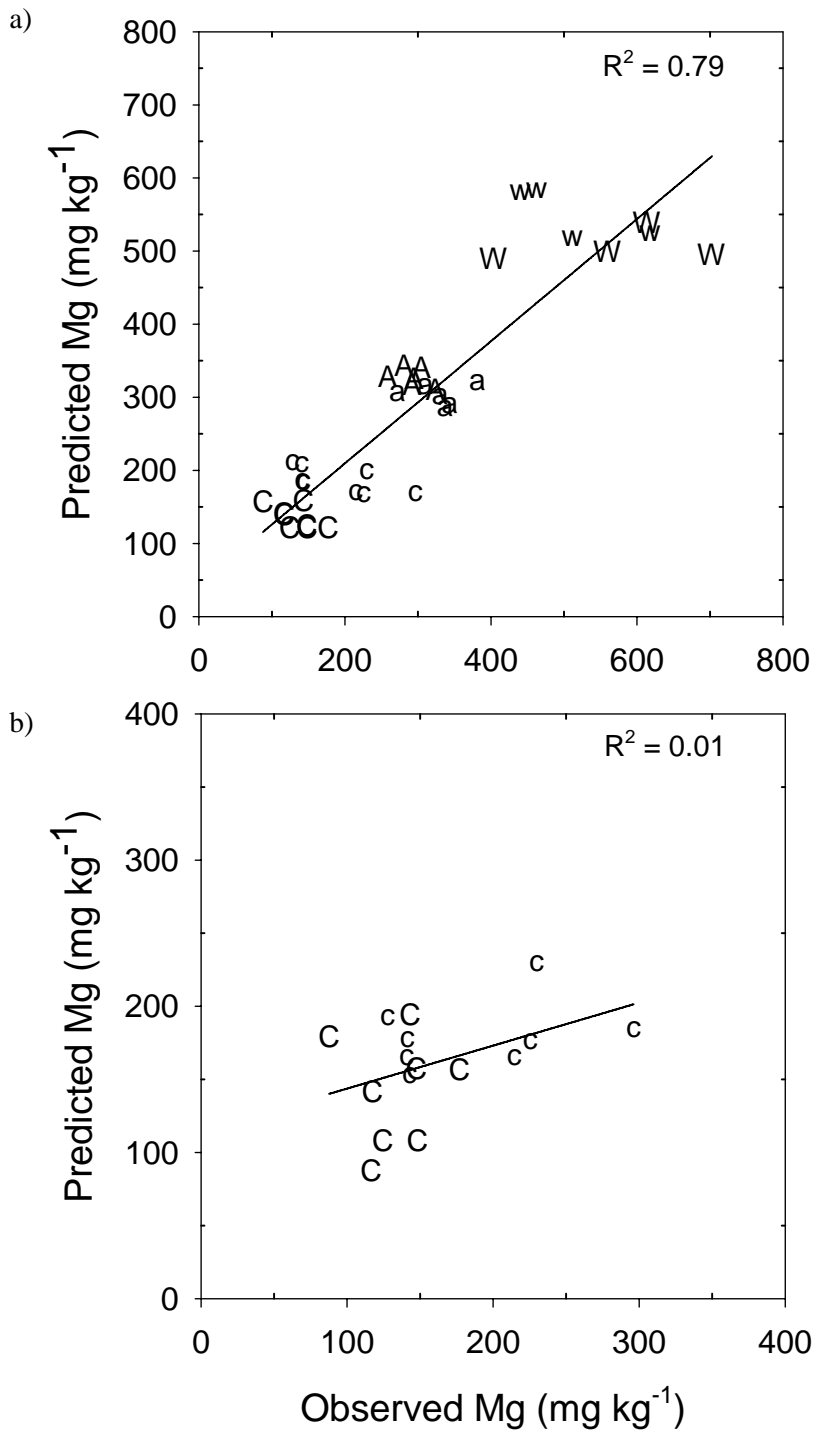
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1 Figure 12.

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