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Stephen Austin Cole
Clemson University, sacole@clemson.edu

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COMPARING SSURGO DATA VERSUS GEOSPATIAL FIELD MEASUREMENTS TO ESTIMATE SOIL TEXTURE AND INFILTRATION RATE CLASSES IN GLACIATED SOILS

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Master of Science
Plant and Environmental Sciences

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by
Stephen Austin Cole
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Accepted by:
Elena Mikhailova, Ph.D., Committee Chair
Christopher Post, Ph.D.
Charles Privette, Ph.D.

ABSTRACT

The infiltration rate (IR) of water is a key soil property related to hydrological processes, soil health and ecosystem services. However, detailed measurements of IR in the field and/or laboratory are labor-intensive and expensive to perform. Soil judging in the field provides a rapid and inexpensive method to estimate IR classes based on soil texture, soil organic carbon/matter and soil structure. The objectives of this study were to classify and compare soil texture and IR for the A horizon across the 147-ha Cornell University Willsboro Research Farm using the Soil Survey Geographic (SSURGO) database and field-based measurements. Soil texture was the dominating factor to explain the general trend of Entisols > Inceptisols > Alfisols with regard to IR in the A horizon. In general, the variability in soil texture observed in field measurements was consistent with the variability reported in the SSURGO database, although the SSURGO representative values for soil texture did not completely match measured mean values for all soil map units. With the exception of one soil map unit, estimates of IR classes utilizing soil judging in the field criteria also were consistent when using either SSURGO or field-based data. Estimating infiltration rate classes for ecosystem services frameworks using geospatial analysis of field and/or SSURGO data can be enhanced with emerging technologies (e.g., sensors) and/or easily measured conventional soil properties.

DEDICATION

This thesis is dedicated to my parents Steve and Jennie Cole for their love, and support throughout my life.

ACKNOWLEDGMENTS

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CHAPTER ONE

Comparing SSURGO Data versus Geospatial Field Measurements to Estimate Soil Texture and Infiltration Rate Classes in Glaciated Soils

Introduction

Water, when applied to the surface layer of a soil, infiltrates/permeates into the soil at a speed defined as an infiltration rate (IR) (USDA/NRCS, 1998). The IR of water (e.g., from rainfall or irrigation) is an important component of hydrological processes in soils (e.g., Haan et al., 1993; Ravi and Williams, 1998; Baveye et al., 2016) and has been long-recognized as an important characteristic for soil health (e.g., The Nature Conservancy, 2016; National Science and Technology Council, 2016). More recently, the IR of water has been identified as one of the key soil quality properties linked to ecosystem services: provisional (e.g., food, fuel, fiber, water retention) and regulating (e.g., climate regulation, gas regulation, water regulation, erosion and flood control, water purification) (Adhikari and Hartemink, 2016; Baveye et al., 2016).

Infiltration of water into soils is important for many different reasons (e.g., Haan et al., 1993; Ravi and Williams, 1998). With restricted infiltration, water does not readily enter the soil but ponds on the surface or runs off the land. Runoff can carry sediment, nutrients, pesticides and bacteria from fields into receiving water bodies such as streams, lakes and estuaries. Soils with reduced infiltration have an increase in overall runoff that can contribute to flooding problems and accelerated soil erosion (USDA/NRCS, 1998). A recent study (Prein et al., 2016) suggests that the number of extreme precipitation events will increase across parts of the U.S. in the future as a result of climate change, which will further exacerbate the problems of ponding, runoff, flooding and soil erosion created by reduced infiltration in soils.

In general, the IR for soils is influenced by soil texture, crust, soil organic matter (SOM), compaction, aggregation and structure, water content, frozen surface, porosity and flow paths (USDA/NRCS, 1998; Sajjadi et al., 2016). A low IR typically is associated with heavy clay soils but also can be produced by surface seals resulting from clogged or discontinuous pores, weakened structure and/or soil compaction (USDA/NRCS, 1998). Using a rain simulator, Ben-Hur et al. (1985) studied the effect of soil texture and $CaCO_3$ content on IRs of water in crusted soils and found that soils with ~ 20% clay were most sensitive to crust formation and had the lowest IRs. Bamutase et al. (2010) reported that soil texture, soil organic carbon (SOC) and slope were highly significant in explaining IRs in volcanic soils on Mt. Elgon, Eastern Uganda. Ma et al. (2016) measured water infiltration in soils from reclaimed land and found that both the IRs and the cumulative infiltration were higher in sandy than in loamy soils.

Many different factors, as well as combination of factors, can affect the temporal and spatial variability patterns of water infiltration into soils (Merzougui and Gifford, 1987; Paige and Stone 1996). For example, infiltration varies across temporal and spatial scales due to heterogeneities in soil properties as well as variations in cover and vegetation characteristics (Merzougui and Gifford, 1987; Paige and Stone 1996). In addition, the ability to measure such variations is a function of the measurement technique and scale utilized (Paige and Stone, 1996). Brito et al. (2006) proposed a model of infiltration based on the selection and integration of key hydrogeological parameters (categorized on a scale representing the suitability of the terrain to water infiltration) within a geographic information system (GIS). Using digital elevation models, Khan et al. (2014) compared simulated infiltration spatial patterns with actual field infiltration measurements and observed a positive correlation between the modeled and measured infiltration.

Depending on their intended use, both quantitative values and qualitative classifications are useful to characterize the texture and IRs of soils. Most quantitative estimates of IR are made in the field (e.g., using a ring infiltrometer, disc permeameter, Mariotte-double ring, rainfall simulator method, run off-on-ponding method, run off-on-out method) or in the laboratory (e.g., trickle irrigation method and mini-disk infiltrometers) (Li et al., 2005; Lili et al., 2008). In general, such detailed IR measurements are labor-intensive and expensive to perform (Bamutase et al., 2010; Jiang et al., 2007). Qualitative classes (e.g., Rapid, Medium, Slow) have been used to describe the overall IR of soils for irrigation and other hydrological purposes (Karathanasis et al., 2013) and to characterize soil health and soil ecosystem services (Millennium Ecosystem Assessment, 2005; Adhikari and Hartemink, 2016; Baveye et al., 2016). A hybrid of approaches to characterize IRs in soils using geostatistical tools is becoming more commonly used, but Baveye and Laba (2015) argue that the approach one adopts to characterize spatially-varying soil properties should be dictated by the specific objectives and scale of research. One complication associated with scale is that ecosystem services of soils are typically evaluated on a large spatial scale, whereas management decisions and practices affecting soil health generally are made at the farm or field scale.

The Soil Survey Geographic (SSURGO) database contains soil information displayed by soil map unit (SMU) and is available for most areas in the United States and Territories, Commonwealths, and Island Nations served by USDA-NRCS (Soil Survey Staff, 2016a). Map units describe soils with unique properties, interpretations and productivity, with information collected/reported at scales ranging from 1:12,000 (more detailed) to 1:63,360 (Soil Survey Staff, 2016a). Map units are typically named for the major component present, although each SMU may contain one to three major components and several minor components (Soil Survey Staff, 2016a). The SSURGO database reports a number of soil attributes as three related values referred to as "low," "representative value" and "high." The low and high values denote the typical range of values of that attribute in the corresponding map unit component or soil horizon or layer, while the representative value denotes an average or expected value of that attribute in the corresponding map unit component or soil horizon or layer (Soil Survey Staff, 2016a).

This study was aimed at conducting an assessment of soil texture and estimates of qualitative IR classes for the A horizon of glaciated soils from field-based measurements compared against the information available from the SSURGO database and official NRCS soil series descriptions. Many field-scale management decisions use SSURGO information, but the potential errors associated with this database are largely unknown (Fortin and Moon 1999; Jiang et al., 2007). The specific objectives of this study were to compare soil texture classes and IR classes in the A horizon of glaciated soils across the Willsboro Research Farm using two different data sources: a) values of soil texture and

SOM reported in the SSURGO database for the soil map units (SMUs) present on the farm, and b) values of soil texture and SOC measured in soil cores taken across the farm.

Materials and methods

Study area

The Cornell University Willsboro Research Farm (Figure 1) is located in Willsboro, NY (44° 22' N, 73° 26' W) in the northeastern part of New York State (Sogbedji et al., 2000). The 147-hectare farm is situated on the gently rolling lacustrine plain adjacent to Lake Champlain (Mikhailova et al., 1996). The climate in the area is temperate with a 150 day growing season (Mikhailova et al., 1996). Soils are heterogeneous and highly variable as a result of glacial deposits (e.g., glacial till, deltaic or glacial like sands and clays), and include the soil orders Alfisols, Entisols and Inceptisols (Mikhailova et al., 1996). Boundaries of the soil map units (SMUs) were obtained from the SSURGO database at scale of 1:12,000 (http://www.nrcs.usda.gov./wps/portal/nrcs/detail/soils/survey/) and mapped in ArcGIS 10.4 (ESRI 2016).

Sampling

Fifty-four soil cores were collected in the summer of 1995 on a square grid sampling pattern (Fig. 1) with each grid being 137.16 meters by 137.16 meters. Coordinates (NAD27 State Plane Coordinate System's New York East Zone, using Station ESSEX2 and Poke-A-Moonshine L.O.T. and Bench Mark H 395) and elevation values for the 54 grid locations were obtained from a professional land survey that used an Intelligent Total Station, Set 2C SOKKISHA (standard deviation: $\pm$ 3 mm + 2 ppmD)

(Mikhailova et al., 1996). Undisturbed soil cores were collected with a Giddings hydraulic sampler (Model – GSR-T-S) using plastic tubes with an average diameter of 4.5 cm (Mikhailova et al., 1996).

Laboratory analyses

Capped plastic tubes containing the soil cores were stored vertically in a freezer at approximately 1°C until processing and analysis (Mikhailova et al., 1996). For each soil core, the upper and lower soil horizon boundaries were recorded. Samples from each soil horizon were air-dried, manually ground and passed through a 2-mm-mesh sieve to quantify and remove the coarse fraction. Soil organic carbon (C) of the sieved fractions was determined by dry-combustion spectrometry using a Robo-prep-Tracemass system (Europa Scientific, Cheshire, UK). Particle-size distributions of the less than 2-mm fractions were determined by sieve analysis and pipetting after pre-treating for carbonates and soluble salts with 1M NaOAc (adjusted to pH 5) and removing organic matter with 30% H_2O_2 (Gee and Bauder 1986). Laboratory analysis results for the A horizon of the soil cores are summarized in Table 1 and the distribution of soil textures is shown in Figure 2.

Estimating A horizon infiltration rate classes using soil core or SSURGO data

The A horizon of each soil core was classified for IR based on soil judging guidelines that utilize information on soil texture, soil structure and the percent SOC (Karathanasis et al., 2013). An IR classification of *Rapid* (infiltration rate greater than 7.5 cm per hour) was assigned to A horizons with the soil texture classes of Sand (S) and

Loamy Sand (LS) and with the soil texture class Sandy Loam (SL) if the soils contained more than 1.2% SOC (Karathanasis et al., 2013). An IR classification of *Slow* (infiltration rate less than 0.5 cm per hour) was assigned to A horizons with the soil texture classes of Clay (C), Silty Clay (SiC) and Sandy Clay (SC), but only if they also were massive or exhibited a weak structure (Karathanasis et al., 2013); otherwise these three soil texture classes were assigned a *Medium* IR classification (infiltration rate of 0.5 to 7.5 cm per hour). In addition, all other A horizons that did not match the conditions required for *Rapid* or *Slow* infiltration were assigned to the *Medium* class (Karathanasis et al., 2013).

Soil judging criteria as described above were utilized to assign IR classes to the A horizons for the different SMUs present on the Willsboro Farm using information from the SSURGO database and official soil series descriptions as summarized in Table 2. We used the range of values (i.e., low value to high value) provided in SSURGO for percentage of sand, silt and clay to determine the range of possible soil texture classes for each SMU. In addition, we used the representative values of sand, silt and clay to determine the expected soil texture class of each SMU. When needed for assigning IR classes (e.g., for the sandy loam soil texture class), representative values of percent SOM in SSURGO were converted to percent SOC by dividing by 1.74. The SSURGO database does not report soil structure, so when it was needed for assigning IR classes (e.g., for clay, sandy clay and silty clay soil texture classes) we referred to the official NRCS soil series descriptions.

Results and discussion

It is generally recognized that soil texture and SOM (or its proxy SOC) are the most important basic soil physical properties that influence the IR (USDA, 1998). For the glaciated, heterogeneous soils present on the Willsboro Research Farm, soil texture in the A horizon was highly variable among the different soil orders, with Alfisols generally having more clay and silty clay textures while the Entisols and Inceptisols tended to have more fine sand textures (Fig. 2). For each SMU, Tables 1 and 2 summarize the field-measured and SSURGO-reported values, respectively, for the thickness of the A horizon, the distributions of sand, silt and clay, the percentage of SOC, and the percent coarse fraction of the Willsboro Farm soils.

The soil texture class was determined for the A horizon of each of the 54 soil cores collected and the results aggregated in Table 1. Using the soil judging criteria described previously, IR classes of the A horizon were then assigned to the 54 soil cores and aggregated similarly (Table 1). From the SSURGO-reported ranges of sand, silt and clay for each SMU, the soil texture triangle was consulted to identify all possible soil texture classes for the SMU (Table 2). *Expected* soil texture classes and *expected* IR classes were assigned to each SMU based on the SSURGO representative values reported for sand, silt and clay (Table 2).

Comparing the tabulated results in Tables 1 and 2 reveals many similarities for the SSURGO-based texture and IR classes and the corresponding classes determined from the detailed field measurements. For example, there was generally good (but not perfect) overlap with the A horizon texture classes for each SMU and a consistent trend among the general soil texture of the three soil orders. Similarly, with both the field measurements and SSURGO data a general trend of Entisols > Inceptisols > Alfisols could be observed for the assigned IR classes. The one major exception to the overall qualitative agreement between the SSURGO- and field-based approaches was the Bombay gravelly loam (BoB) SMU, which tended to be sandier on the Willsboro Farm than expected based on the SSURGO data. This, in turn, resulted in a much higher number of BoB soil cores with an assigned class of rapid instead of medium for the IR.

To provide a more rigorous, quantitative comparison between the findings shown in Tables 1 and 2, more advanced data analyses and statistical tests were performed. The approach used was to pose three basic questions about the 54 soil cores which then led to the appropriate corresponding analysis/test: (1) How well did the SSURGO data/results match the soil core data/results for the Willsboro Farm A horizon samples?, (2) Was the overall distribution of qualitative IRs derived from SSURGO significantly different than those resulting from field measurements?, and (3) Were the two different estimates of IR class significantly different at each core location? Each analysis/test was performed collectively on all 54 soil cores and then by soil order.

To address the first question, we first compared the actual soil texture classes measured against the expected class based on SSURGO representative values for sand, silt and clay. For all 54 soil cores, only 9% matched the SSURGO expected soil texture class for the corresponding SMU. However, we found that 69% of the cores matched the expected soil texture class *or an adjacent class on the soil texture triangle* for the corresponding SMU, which we considered good agreement when considering the heterogeneous nature of the soils present on the Willsboro Farm. When broken down by soil order, the results for the first question posed provided additional insight about soil texture. For Alfisols (n = 32), only 3% of the cores correctly matched the expected soil texture class from SSURGO, but that increased to 72% when considering adjacent classes on the soil texture triangle. For Entisols (n = 18), only 6% of the cores correctly matched the expected soil texture class from SSURGO and that increased to 61% when considering adjacent classes on the soil texture triangle. Lastly, for Inceptisols (n = 4), 75% of the cores correctly matched the expected soil texture class from SSURGO but considering adjacent classes on the soil texture triangle did not increase the number of matches. A similar analysis then was conducted on the IR classes to address the first question posed. For all 54 soil cores, 69% matched the SSURGO expected IR class for the corresponding SMU. Broken down by soil order, we found that the estimated IR class for each soil core matched the SSURGO expected IR class for 63% of the Alfisols, 78% of the Entisols, and 75% of the Inceptisols. Taken together, this analysis indicates that use of the SSURGO representative values for sand, silt and clay will result in expected IR classes that will be accurate for 70% to 80% of the soils on the Willsboro Farm.

The second question essentially asked whether the two population distributions of IR classes (i.e., obtained from SSURGO representative values vs. actual field cores) were statistically different which can be addressed with a two-population test for equality of proportions. A significance level of $\alpha = 0.05$ was selected, and because some of the tests utilized small sample sizes we chose Fisher's exact test to calculate p values. When considering all soil cores together (n = 54), Fisher's exact test provided a p value of 0.247

indicating that there was no significant difference between the distributions of SSURGO-derived and field-derived IR classes. Similar findings were obtained with Entisols (n = 18, $p = 0.104$) and Inceptisols (n = 4, $p = 1.000$). In contrast, for Alfisols (n = 32) Fisher's exact test provided a p value of 0.000 which indicated that a significant difference did exist between the distributions of SSURGO-derived and field-derived IR classes for the soil order. Close examination of the A horizon samples from Alfisols revealed that a number of the Bombay (BoB) and Kingsbury (KyA, KyB) soil cores were responsible for the difference because of their sandier textures.

The third question posed was the most powerful because it specifically tests whether the two different methods used to estimate IR class at each soil core location led to statistically different results – the approach itself is analogous to a paired t-test that one would typically use with paired quantitative data. Two different statistical tests were run: (*i*) a one sample sign test of the differences and (*ii*) the more powerful one sample Wilcoxon test, more commonly known as the Wilcoxon signed-rank test, which utilizes the assumption of a symmetric distribution of the differences. Results of these last statistical tests are summarized in Table 3. By either test, the only significant difference was observed with Alfisols for the reasons explained above. For the other two soil orders and for all 54 soil cores examined together, there were no significant differences when using SSURGO representative values of sand, silt and clay vs. actual field measurements to estimate IR classes for water infiltration into the soils.

Conclusions

This study compared soil texture classes and estimated classes of IR as obtained from reported SSURGO values versus actual field measurements of soil properties at the farm scale in glaciated soils of Upstate New York. Soil texture was the dominating factor to explain the general trend of Entisols > Inceptisols > Alfisols with regard to IR class in the A horizon regardless of data source used. Except for one SMU, there was generally acceptable agreement among the SSURGO and field-based approaches. Based on our findings, it appears that the SSURGO database can provide reasonable estimates of soil textures and qualitative classes of IRs that would be useful for incorporation within the frameworks needed to assess soil health and ecosystem services. Although detailed site-specific field measurements must be utilized to ground truth the SSURGO database and better capture any variability that may exist within different SMUs and soil orders, their value must be balanced against the time and expenses associated with actual field and laboratory measurements. To better enhance ecosystem frameworks that properly account for the important role of soils, future efforts should be focused on obtaining higher resolution information in soils using emerging technologies (e.g., sensors) and/or more easily measured soil properties.

APPENDICES

Appendix A

Figures

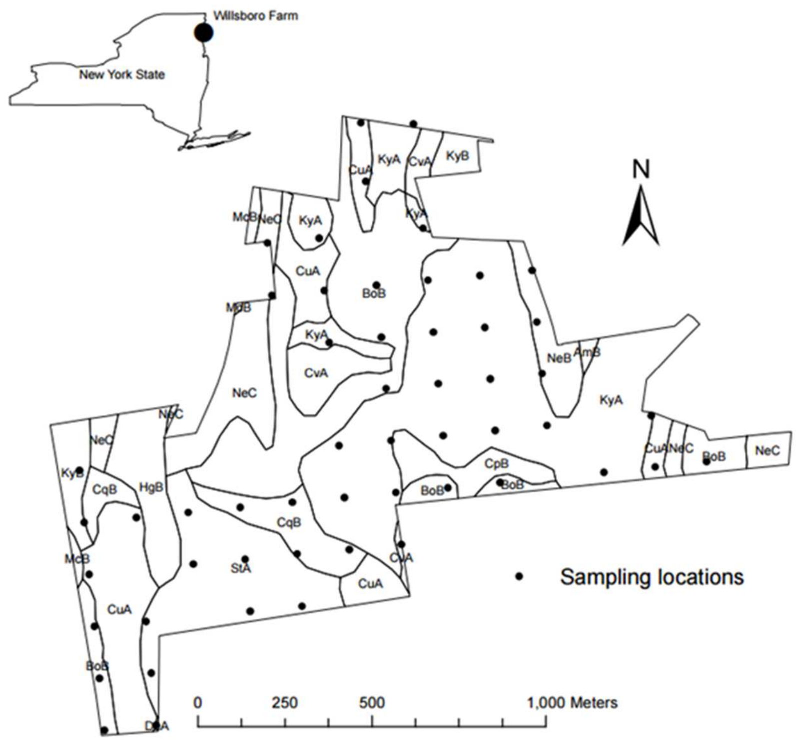

Figure 1. Map of Willsboro Farm, NY with the following soil types: Howard gravelly loam, 2 to 8 percent slopes (HgB); Bombay gravelly loam, 3 to 8 percent slopes (BoB); Kingsbury silty clay loam, 0 to 3 percent slopes (KyA); Kingsbury silty clay loam, 3 to 8 percent slopes (KyB); Covington clay, 0 to 3 percent slopes (CvA); Churchville loam, 2 to 8 percent slopes (CpB); Cosad loamy fine sand, 0 to 3 percent slopes (CuA); Claverack loamy fine sand, 3 to 8 percent slopes (CqB); Deerfield loamy sand, 0 to 3 percent slopes (DeA); Stafford fine sandy loam, 0 to 3 percent slopes (StA); Amenia fine sandy loam, 2 to 8 percent slopes (AmB); Massena gravelly silt loam, 3 to 8 percent slopes (McB); Nellis fine sandy loam, 3 to 8 percent slopes (NeB); Nellis fine sandy loam, 8 to 15 percent slopes (NeC).

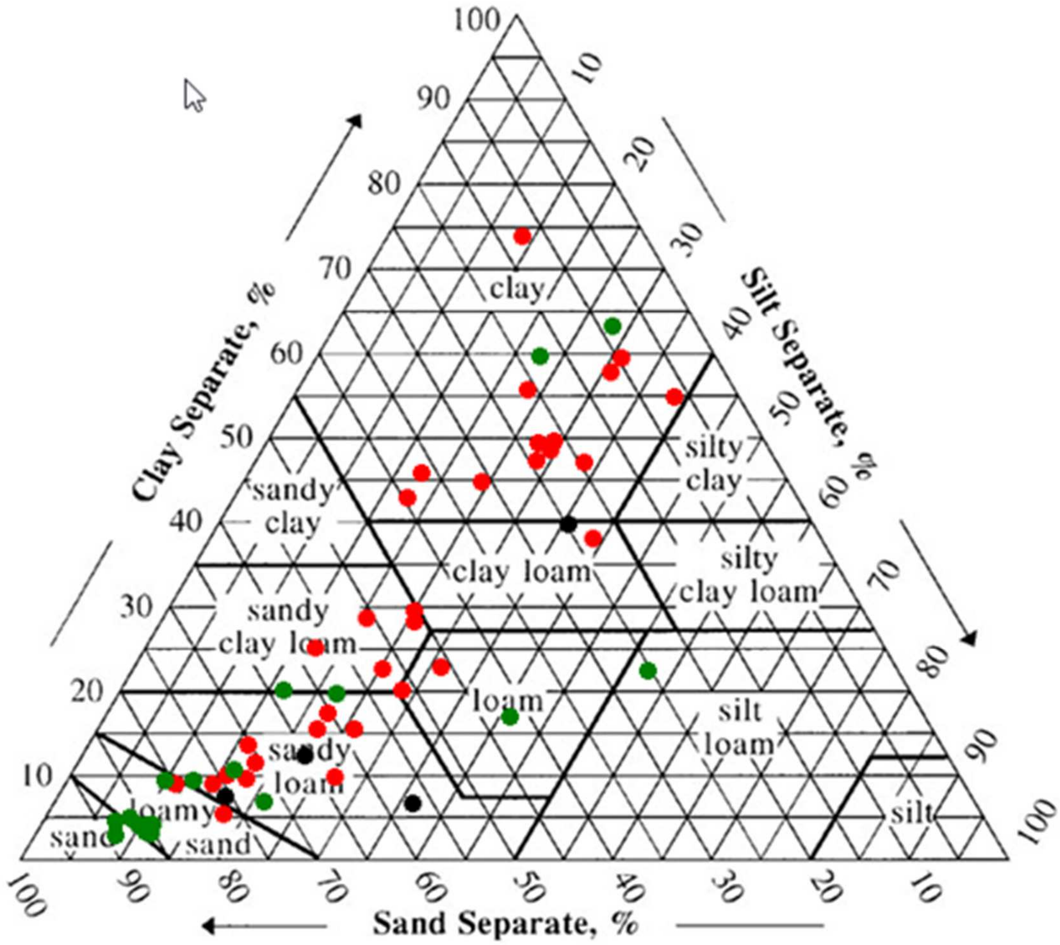

Figure 2. Soil texture of the A horizon from the 54 soil cores: Alfisols (red), Entisols (green), and Inceptisols (black).

Appendix B

Tables

Table 1. Measured and estimated properties of the A horizon for soils present on the Willsboro Farm (original soil core data from Mikhailova et al., 1996).

Soil order / Soil series (Map unit symbol), number of soil cores	Total Area	Measured A Horizon Thickness	Sand	Silt	Clay	Soil Organic Carbon	Coarse Fraction	Texture Class*	Infiltration Rate Class**
	m²	cm	---------------------------		%		---------------------------		
Alfisols (total), n=32	**937940**								
Bombay gravelly loam, 3 to 8 percent slopes (BoB), n=10	270615	21 (± 5)***	65 (± 11)	20 (± 5)	14 (± 8)	1.9 (± 0.4)	23 (± 18)	LS(1) SL(7) SCL(2)	Rapid(8) Medium(2)
Churchville loam, 2 to 8 percent slopes (CpB), n=0	36900	n/a****	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Covington clay, 0 to 3 percent slopes (CvA), n=1	49076	26	13	13	74	4.6	0.13	C(1)	Medium(1)
Howard gravelly loam, 2 to 8 percent slopes (HgB), n=0	58680	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Kingsbury silty clay loam, 0 to 3 percent slopes (KyA), n=19	480679	23 (± 6)	35 (± 20)	26 (± 7)	39 (± 16)	3.1 (± 0.9)	5.9 (± 7.1)	LS(1) SL(2) L(1)	Rapid(3) Medium(16)

								SCL(2) CL(1) C(12)	
Kingsbury silty clay loam, 3 to 8 percent slopes (KyB), n=2	41990	30 (± 14)	59 (± 18)	21 (± 5)	20 (± 13)	1.8 (± 0.6)	2.1 (± 0.3)	SL(1) SCL(1)	Rapid(1) Medium(1)
Entisols (total), n=18	**378691**								
Claverack loamy fine sand, 3 to 8 percent slopes (CqB), n=4	64230	28 (± 10)	61 (± 26)	26 (± 18)	13 (± 9)	2.3 (± 0.5)	6.7 (± 8.6)	S(1) SL(2) SiL(1)	Rapid(3) Medium(1)
Cosad loamy fine sand, 0 to 3 percent slopes (CuA), n=6	168530	19 (± 7)	62 (± 27)	18 (± 12)	20 (± 20)	1.8 (± 0.8)	12 (± 13)	S(1) LS(1) SL(2) L(1) C(1)	Rapid(4) Medium(2)
Deerfield loamy sand, 0 to 3 percent slopes (DeA), n=1	331	22	87	10	3	2.2	1.9	S(1)	Rapid(1)
Stafford fine sandy loam, 0 to 3 percent slopes (StA), n=7	145600	26 (± 4)	75 (± 29)	12 (± 7)	13 (± 22)	1.9 (± 0.8)	2.0 (± 5.1)	S(3) LS(3) C(1)	Rapid(6) Medium(1)
Inceptisols (total), n=4	**157764**								
Amenia fine sandy loam, 2 to 8 percent slopes (AmB), n=0	3185	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Massena gravelly silt loam, 3 to 8 percent slopes (McB), n=0	8479	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Nellis fine sandy loam, 3 to 8 percent slopes (NeB), n=3	39030	19 (± 6)	56 (± 27)	24 (± 10)	19 (± 17)	3.3 (± 0.9)	21 (± 20)	SL(2) CL(1)	Rapid(2) Medium(1)
Nellis fine sandy loam, 8 to 15 percent slopes (NeC), n=1	107070	30	58	36	6	3.3	48	SL(1)	Rapid(1)

* Texture class abbreviations: S – sand; LS – loamy sand; SL – sandy loam; L – loam; SiL – silt loam; SCL – sandy clay loam; CL – clay loam; SiCL – silty clay loam; SC – sandy clay; C – clay; SiC – silty clay. Values in parentheses are the number of soil core A horizons with the designated texture class.

** Infiltration rate classes are defined in the text. Values in parentheses are the number of soil cores with the designated infiltration rate class in the A horizon.

*** XX (± XX): Calculated mean value with standard deviation in parentheses, unless only one soil core was taken from a specified soil map unit.

**** n/a: not applicable. No soil core was taken from the specified soil map unit.

Table 2. Reported and estimated properties of the A horizon for soils present on the Willsboro Farm based on information from SSURGO (2016a) and NRCS official soil series descriptions.

Soil order / Soil series (Map unit symbol)	Reported A Horizon Thickness	Sand*	Silt*	Clay*	Soil Organic Carbon	Coarse Fraction	Texture Class**	Infiltration Rate Class***
	cm	----------------------------		%	---------------------------			
<u>Alfisols</u>								
Bombay gravelly loam, 3 to 8 percent slopes (BoB)	25	33-46-85	0-44-50	0-10-17	2.3	25	LS SL ***L***	Rapid ***Medium***
Churchville loam, 2 to 8 percent slopes (CpB)	23	0-40-52	28-36-65	7-25-40	2.8	0	***L*** SiL SCL CL SiCL SC	***Medium***
Covington clay, 0 to 3 percent slopes (CvA)	23	0-22-45	0-28-65	27-50-90	4.0	0	CL SiCL ***C*** SiC	***Medium***
Howard gravelly loam, 2 to 8 percent slopes (HgB)	25	24-45-85	0-43-50	0-12-27	1.7	30	LS SL ***L*** SCL	Rapid ***Medium***
Kingsbury silty clay loam, 0 to 3 percent slopes (KyA)	23	0-17-45	0-44-65	27-39-90	2.4	0	CL ***SiCL*** C SiC	***Medium***

Kingsbury silty clay loam, 3 to 8 percent slopes (KyB)	23	0-17-45	0-44-65	27-39-90	2.4	0	CL ***SiCL*** C SiC	***Medium***
<u>Entisols</u>								
Claverack loamy fine sand, 3 to 8 percent slopes (CqB)	30	44-79-91	0-16-49	0-5-17	1.7	0	S ***LS*** SL L	***Rapid***
Cosad loamy fine sand, 0 to 3 percent slopes (CuA)	30	44-87-91	0-6-49	0-7-17	2.4	0	S ***LS*** SL L	***Rapid***
Deerfield loamy sand, 0 to 3 percent slopes (DeA)	25	44-79-91	0-17-49	0-5-17	1.7	0	S ***LS*** SL L	***Rapid***
Stafford fine sandy loam, 0 to 3 percent slopes (StA)	25	44-64-91	0-31-49	0-5-17	2.3	0	S LS ***SL*** L	***Rapid***
<u>Inceptisols</u>								
Amenia fine sandy loam, 2 to 8 percent slopes (AmB)	23	33-57-85	0-32-50	0-11-17	2.3	5	LS ***SL*** L	***Rapid***

Massena gravelly silt loam, 3 to 8 percent slopes (McB)	23	15-32-85	0-56-80	0-12-17	4.6	5	LS SL L ***SiL***	Rapid ***Medium***
Nellis fine sandy loam, 3 to 8 percent slopes (NeB)	23	33-64-85	0-22-50	0-14-17	2.3	5	LS ***SL*** L	***Rapid***
Nellis fine sandy loam, 8 to 15 percent slopes (NeC)	23	33-64-85	0-22-50	0-14-17	2.3	5	LS ***SL*** L	***Rapid***

* Values for sand, silt and clay are shown as L-RV-H (L – low value; RV – representative value; H – high value).

** Texture class: see Table 1 footnote for abbreviations. Texture classes listed are possible based on the range of values provided for sand, silt and clay percentages. The expected texture class in bold italics corresponds to the representative values reported for sand, silt and clay for each SMU.

*** Infiltration rate classes are defined in the text. The classes listed are based on the possible soil texture classes of each SMU. The expected infiltration rate class in bold italics corresponds to the expected texture class having the representative values of sand, silt and clay.

Table 3. Results of statistical tests to compare paired estimates of IR class for the A horizon of Willsboro Farm soil cores when derived from SSURGO representative values vs. actual field measurements.

	p value		Conclusion
	Sign Test for Median	Wilcoxon Signed Rank Test	
All soil cores (n = 54)	0.1435	0.142	No significant difference between paired IR estimates
Alfisols (n = 32)	0.0005	0.003	Significant difference between paired IR estimates
Entisols (n = 18)	0.1250	0.100	No significant difference between paired IR estimates
Inceptisols (n = 4)	1.0000	1.000	No significant difference between paired IR estimates

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