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UNDERSTANDING SOYBEAN YIELD LIMITING FACTORS AND THE POTENTIAL FOR AGRICULTURAL INTENSIFICATION IN THE U.S. AND BRAZIL

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ABSTRACT

On-farm and modeling research were used to better understand the impact of soil, plant and climate factors on soybean [*Glycine max* (L.) Merr.] yield. We analyzed yield gaps and solar radiation and water capture efficiencies in full season and double-cropping systems. First, to perform accurate model simulations, we needed a quick and yet accurate method to estimate soil texture of hundreds of samples. We accomplished that by refining a laser diffraction protocol that matched the results of standard sedimentation techniques. Second, to identify variables related to soybean yield variation, we studied 22 site-years over the 2016 and 2017 growing seasons in two regions of Pennsylvania. Solar radiation and water capture, both controlled by planting date, were the main predictors of soybean yield in these regions. The physical and biological soil metrics measured in the comprehensive Cornell Assessment of Soil Health did not correlate to soybean yields. However, the ratio of soil respiration to soil organic matter positively did so. Saturated hydraulic conductivity (K_{sat}) and root depth correlated with both soybean yield and each other. Third, to assess yield gaps and to estimate how efficiently solar radiation and water were used in local environments, we calculated realized and potential indicators of resource capture in two locations in Pennsylvania and two in Southern Brazil using the simulation model Cycles. The measured yield gap varied from 5 to 48% suggesting great potential to increase soybean yields with the available solar radiation and water resources through improved management tactics in 3 of the 4 regions studied. In Pennsylvania, agricultural intensification is limited to double-cropping due to low temperatures that limit available solar radiation, while in some regions in Brazil it is possible to produce a third crop in a year. Finally, we organized an international tour in 2018 with 14 participants including

producers and extension personnel from Pennsylvania to study sustainable soybean production systems in Brazil, and to encourage others we described the main organizational steps and the lessons we learned while planning and executing this tour.

Table of Contents

List of Figures

List of Tables

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Chapter 1. Introduction and Objectives

1.1. Introduction

Brazil and USA currently produce about 65% of the world's soybean supply, with roughly similar annual production in each country. Every year, producers from both nations report a wide range of soybean yields, from 2 to 6 Mg ha^{-1}, even when using similar management tactics. Within fields, there can also be substantial variation in soil and topographic attributes that generate a range of conditions in typical production fields. Understanding the factors that drive these yield variations in soybeans can help producers to determine cost-effective strategies to improve crop productivity and profitability.

Soybean crop producers have done a good job of increasing yield by managing weeds, insects, diseases and growing improved soybean varieties, but understanding and managing the soil variation is still challenging. Top yields appear to be associated with a combination of good crop management tactics and creating ideal soil physical properties or soil health. The effects of soil physics on plant growth have been studied for years (Russel, 1912; Masle & Passioura, 1987; Sadras et al., 2005), but causal relationships with yield are hard to establish and even more difficult to relate to management. The ability of the plants to explore subsoil resources appears to be a central point when looking at yield variations though, and there is evidence that the plant mechanisms that drive root-soil interactions could be related to soil hydraulic properties (White & Kirkkegaard, 2010).

Laboratories are now offering soil testing packages to evaluate chemical, physical and biological indicators of soil health. However, these tests are often too costly for the producer and translating soil health test results into management recommendations remains challenging.

Even though there is a clear need for critical soil health thresholds to guide management recommendations that influence crop yields as pointed out by Cassman (1999), at the present time many soil health studies continue to be mainly descriptive rather than focusing on crop yield responses to specific indicators. Therefore, farmer-focused research is still necessary to identify the most suitable soil health indicators, and ultimately to explain how they relate to crop yields. In Pennsylvania, producers have been unwittingly running long term experiments in their farms with varied combinations of manure, cover crops and no-tillage they have generated a range of soil conditions that is experimentally difficult to accomplish in the short term, but offers a wonderful opportunity to test the relationship among soil variables and productivity in commercially managed fields.

The required sustainable crop production requires not only increases of single crop yields but also a more efficient management of land and water resources, which directly translates to land productivity increases (Sakschewski et al., 2014). A path towards improving natural resource use is to intensify cropping systems by increasing the number of crops produced in the same area per year. In combined systems, crop management decisions must be taken more broadly and certainly not considering only individual crops. For instance, although the soybean yield potential following a winter crop might be reduced by late planting (Beuerlein, 1988), the combined production and profit can be larger than that of soybean alone, making this practice economically competitive, and environmentally friendly. The first logical step towards increasing crop and land productivity may be to assess how close the current yields are to the yield potential and the efficiency of available solar radiation and water use in local environments.

Predictions of soybean performance under different management systems and environmental conditions using crop growth models have been done in other regions (Keating et al., 2003; Jones et al., 2003; Pedersen et al., 2004; Setiyono et al., 2010), but no work was found addressing this subject in the Mid-Atlantic region of the United States. An accurate model supported by reliable soil and long-term weather data can be a great tool to explore the effects of different cropping systems and management in agricultural production (Meinke et al., 2001, Meki et al., 2013). Additionally, modeling can help to understand discrepancies in yield results or year-specific results associated with weather in a cohesive context.

Understanding the soybean yield limiting factors and the production potential of local environments can be done more effectively by involving the producers and agronomists in the process. One opportunity we found valuable was to organize a field tour to discuss management tactics and understand different production scenarios with Penn State clientele in commercial farms of distinct regions of Brazil (South-cold and Cerrado-tropics). Most producers from Pennsylvania rarely grasp opportunities to visit and talk to peers facing distinct production scenarios, especially abroad. Using the group of producers and agronomists already involved in our on-farm research as targeted participants, we planned an international tour in February of 2018. We chose Brazil because Brazilian producers have not only been overcoming the lack of agricultural government subsidies and local infrastructure by increasing production efficiency but have also increased land use efficiency and plant diversification by progressively adopting integrated crop and livestock systems over the past decade. We believe that the interaction with producers, farm cooperatives and research institutes from Brazil is beneficial to both Pennsylvania’s agriculture and livestock production.

1.2. Objectives

The central goal of this research was to study soybean yield limiting factors and yield gaps using field research and crop modelling. The core idea was to expand the current knowledge in sustainable soybean production and to discuss land productivity in the U.S. and Brazil. Since particle size is a critical input for accurate crop model simulations, we also needed a rapid method to analyze hundreds of soil samples from several fields of Pennsylvania as an alternative to the laborious and time-consuming traditional sedimentation techniques. After we validated the cropping systems model Cycles, we aimed to assess soybeans' water and solar radiation capture and yield gaps in single and double-cropping systems. To accomplish these objectives, we collected field data in four locations, two in Pennsylvania and two southern Brazil, and calculated realized and potential indicators of resource capture. The research projects had a close connection with the production and extension sectors from the beginning, and we took advantage of the on-farm research component and used educational tools to accomplish our objectives. Finally, an international tour was organized to discuss successful production systems among researchers, agronomists, and producers visiting Brazilian farms, cooperatives, and research centers. Specifically, the objectives of this dissertation were:

- Refine a laser diffraction protocol for particle size analysis that is compatible with standard soil texture determination methods (Chapter 2);
- Identify the main soil, plant and climate factors related to soybean yield in Pennsylvania (Chapter 3);

- Quantify soybean yield gaps in the Mid-Atlantic U.S. and Southern Brazil, and estimate solar radiation and water capture efficiencies in full season and double-cropping soybean systems (Chapter 4);
- Organize an international tour to study sustainable high-yielding soybean production systems in Brazil, and encourage others by describing the main organizational steps and the lessons learned with this initiative (Chapter 5);

1.3. Chapter Outlines

Chapter 2 describes a laser diffraction methodology for particle size analysis of soils that matches the results of traditional hydrometer and pipette methods. This new technique can allow us to reliably analyze hundreds of soil samples in a couple of weeks, when the traditional alternative could take months.

Chapter 3 identifies the main soybean yield limiting factors in Centre and Lebanon counties of Pennsylvania. Using 22 site-years, the effect of soil, plant and climate factors on soybean yield were studied. Knowing soybean yield indicators can help producers to target cost-effective managing strategies in the region.

Chapter 4 estimates the soybean yield gaps in two regions of the U.S. and Brazil and assesses the potential for agricultural intensification by analyzing full season and double-cropping systems' resource capture efficiencies using the cropping systems simulation model Cycles. These biophysical yield estimations can demonstrate if yield gaps are related to water stresses or other manageable factors that need to be investigated in the field. Analyzing the potential use of water and solar radiation can allow us to demonstrate the potential for double- or even triple-cropping in these regions.

Chapter 5 reports the main organizational steps and the lessons we learned with the international tour we organized to Brazil. This publication can encourage other professionals to organize more international tours like ours and therefore collect similar positive impacts with their clientele.

Chapter 2. Making Soil Particle Size Analysis by Laser Diffraction Compatible with Standard Soil Texture Determination Methods

Core Ideas

- Laser diffraction particle size analysis can produce results compatible with standard pipette and hydrometer methods.
- A key step is to wet-sieve the sand fraction after suspending the soil sample in the dispersant solution.
- The proposed protocol is faster, uses smaller samples, and provides more detail than standard sedimentation methods.

Abstract

The standard sieving, pipette and hydrometer methods for soil particle size analysis (PSA) have three main drawbacks: procedures are tedious, time-consuming, and the results are protocol-dependent. Laser diffraction PSA delivers rapid results using standardized procedures, but so far it has been difficult to reconcile results with those from standard sedimentation methods. The objective of this study was to develop a protocol that would permit direct usage of laser diffraction PSA and render results compatible with current methods. The protocol was developed using 54 standard soil samples from different textural classes. Regression of the laser diffraction PSA against the hydrometer/pipette method yielded coefficients of determination of 0.92/0.9, 0.92/0.94 and 0.99/0.99, and root mean square errors of 0.04/0.05, 0.07/0.06 and 0.05/0.03 for clay, silt and sand, respectively. These statistics are comparable to those obtained by regressing results of the hydrometer against the sieve and pipette methods.

A key factor in securing accurate and precise results was limiting the particle size range of the samples by wet sieving the sand fraction. This created representative samples and stable soil dispersed suspensions, allowing accurate estimations of particle size distribution for clay and silt fractions without empirical transformations. Results obtained with the proposed protocol matched those of standard sedimentation analyses for a wide range of soils, encouraging further adoption of laser diffraction for soil PSA.

2.1. Introduction

The particle size distribution of the soil mineral fraction modulates physical, chemical, and biological properties, including soils' hydraulic properties, pore size distribution, shrink and swell capacity, and erodibility and sedimentation properties, with implications for agroecological, mechanical, hydrological, geological, and engineering applications (Gee and Or, 2002; Hillel and Hatfield, 2005; Blake and Steinhardt, 2008; Merkus, 2009; Bieganowski et al., 2018). Hence, multiple bodies have developed particle size classification systems to catalog the effects of particle size distribution on such properties, and on the properties and the functions of particulate media, including the International Organization for Standardization (ISO), the ASTM International standards, as well as the soil texture classification by the U. S. Department of Agriculture Natural Resources Conservation Service (USDA-NRCS) and the International Soil Science Society ISSS, now International Union of Soil Science – IUSS (Gee and Or, 2002; Blake and Steinhardt, 2008; FAO, 2014; USDA, 2017; Moeys et al., 2018).

The most common methods for soil particles size analysis (PSA) are the sieving, pipette and hydrometer methods (Gee and Or, 2002). The pipette and hydrometer methods are based on gravitational sedimentation principles and, in combination with sieving, constitute the foundation of soil texture classification standards around the world (Loveland and Whalley, 2000; Blake and Steinhardt, 2008). These methods have three main drawbacks: results are protocol-dependent, and procedures are both tedious and time-consuming. Significant errors arise from variations in chemical dispersant concentration, sample size, type of cylinder used, temperature fluctuations, sieving time, variation of time intervals used to record hydrometer or pipette measurements, and fundamental differences in the methods' assumptions of particle shape (Allen, 1997; Gee and Or, 2002; Eshel et al., 2004; Syvitski et al., 2007; Merkus, 2009). These errors are particularly pronounced at the extremes of the particle size spectrum; sedimentation methods do not reliably measure particles larger than 50 µm because these particles settle rapidly; and these methods also tend to overestimate clay content due to particle-fluid interactions that interfere with the sedimentation process (Chung and Hogg, 1985; Allen, 1997; Matthews, 2007; Merkus, 2009).

Over the past 30 years, improvements in technology, particularly in computational capacity and sensor accuracy, have opened the possibility of laser diffraction for particle size analysis (Agrawal and Pottsmith, 2000; Di Stefano et al., 2010; Bieganowski et al., 2018). This has translated into an increased number of articles related to laser diffraction PSA in the soil science literature, summarized in the recent review by Bieganowski et al. (2018). Laser diffraction PSA has many advantages, including the use of standardized procedures to deliver rapid results, with more precise differentiation into a high number of size intervals. More detailed soil particle size information will enable advances in the understanding of fundamental hydraulic, hydrologic, structural and biological soil processes, including development of more accurate pedotransfer functions for soil hydraulic properties (Schaap et al., 1998), and new insights into biological processes regulating organo-mineral associations (Oliveira et al., 2018). In addition, soil particle size distribution determines the soil surface area available to interact with organic matter and soil microorganisms (Borkovec et al., 1993; Hassink and Whitmore, 1997) controlling physical and biological processes that occur at or below the pore scale.

However, soils can be composed of a broad mixture of minerals and particle sizes, which results in the following challenges for laser diffraction PSA. Firstly, it is difficult to obtain a representative proportion of the coarser particles from the original sample due to particle size segregation in dry samples, and rapid sedimentation of large particles in liquid dispersed samples. Secondly, once a sample is obtained, it is difficult to disperse all the particles in the sample into a stable suspension to interact with the laser source. Thirdly, it has not been possible to match results from laser diffraction with standard soil texture determination methods without prior calibration based on the texture classification, organic matter and carbonate content, or the development of dataset specific conversion equations (Taubner et al., 2009; Di Stefano et al., 2010; Lamorski et al., 2014; Mako et al., 2017).

A critical step in making laser diffraction and the sieving, hydrometer and pipette methods comparable is identifying equivalent Stokes' and light scatter diameters for clay and silt fractions. Sedimentation, sieving, and laser diffraction PSA measure different particle properties. When sedimentation methods are used, the nominal particle size diameter measured is the Stokes' diameter, i.e. "the diameter of a sphere having the same settling rate as the particle under conditions of Stokes' law" (Merkus, 2009). The Stokes' diameter is different from the nominal sieve diameter, i.e. "the diameter of particles that just pass through the apertures of a sieving medium" measured by sieving, and the nominal light scatter diameter, i.e. "the diameter of a spherical particle with the same optical properties that produces the distinctive light scattering pattern" measured by laser diffraction (Merkus, 2009). The equivalent Stokes', sieve, and light scatter diameters for a homogeneous material vary depending on the density, shape, and optical parameters of the particles composing the material. Therefore, the nominal particle size distribution varies depending on the method used, as stated in the International Standard for Particle Size Analysis - Laser Diffraction Methods ISO:13320 (International Organization for Standardization, 2009).

The soil texture classification from the USDA-NRCS uses 2 µm as the nominal equivalent Stokes' diameter to differentiate between the clay and silt fractions when using standard sedimentation methods. Estimates for the equivalent light scatter diameter have varied between 6 µm (Miller and Schaetzl, 2012), 8 µm (Konert and Vandenberghe, 1997), and 9 µm (Fisher et al., 2017). Makó et al. (2017) detected a small variation in this threshold, ranging from 6.6 to 5.8 µm in soils with and without organic matter. Arriaga et al. (2006) used the USDA-NRCS 2 µm threshold and modified the refractive index and absorption index to match pipette method analysis results. However, Eshel and Levy (2007) warned against this approach, arguing that the refractive index that produced the best results (1.42) was below the ranges of accepted values for soil minerals (1.54 for quartz and 1.49 for calcite), and would produce distorted particle size distributions.

After an analysis of 41 soils samples from California, Eshel et al. (2004) stated that relationships between particle size distribution obtained with laser diffraction and standard sedimentation methods varied across textural classes and no consistent relationship could be formulated. Other studies have shown relationships between particle size data obtained with laser diffraction and sedimentation methods for different regions, but correlations differed between datasets, and high deviations from the 1:1 regression line were observed in the smallest size class (Konert and Vandenberghe, 1997; Buurman et al., 2001). Taubner et al. (2009) used sieving to exclude coarse particles from the suspension, improving the collection of homogeneous aliquots, but concluded that laser diffraction analysis could not be used for texture classification of soils without regression-transformed size fractions and validation using a sedimentation method. Miller and Schaetzl (2012) showed that 11.5% of their 1,485 soil samples changed textural class when the laser diffraction analyses were repeated, attributing the changes to subsampling errors. They concluded that the putative precision of laser-generated particle size data decreased with coarser particles due to misrepresentation of the complete population of particles in the sample and the effect of large particles on the sand percentage volume. Hence, reducing the particle size range of the sample could increase precision by reducing measurement variability.

Even though there are international standards associated with both laser diffraction and standard sedimentation methods, difficulties in making the results of both methods compatible has hindered the adoption of laser diffraction PSA method by the soil science community (Di Stefano et al., 2010; Lamorski et al., 2014; Bieganowski et al., 2018). Therefore, the objective of this study was to develop a laser diffraction protocol without the need for empirical transformations for soil PSA that produced results comparable to those obtained by standard USDA-NRCS sedimentation methods (Blake and Steinhardt, 2008; USDA, 2017). The protocol developed is based on two key methodological improvements: separation of the sand fraction through wet sieving after dispersion of the soil sample and before laser diffraction analysis, as suggested by Taubner et al. (2009), and the use of a laser diffraction instrument that overcame accuracy limitations of the instrument used by Taubner et al. in 2009.

2.2 Materials and Methods

2.2.1. Selection of Soil Samples

Standard soil samples from the North American Proficiency Testing (NAPT) Program, which operates under the Soil Science Society of America (SSSA) assisting inter-laboratory evaluation of analytical data, and the Agriculture Laboratory Proficiency (ALP) Program managed by Collaborative Testing Services Inc, were used to compare laser diffraction PSA results with soil texture results obtained with the sieve/pipette and the hydrometer methods as described by Gee and Bauder (1986). Both programs used the Soil, Plant, and Water Reference Methods for the Western Region (Gavlak et al., 2013), the Recommended Soil Testing Procedures for the Northeastern United States (NECC-1312, 2011), the Recommended Chemical Soil Tests Procedures for the North Central Region (NCERA-13, 2015), and the Soil Test Methods from the Southeastern United States (Sikora and Moore, 2014). NAPT quarterly soil analysis reports from 1998 to 2017, comprising 400 soil samples analyzed by 115 analytical testing laboratories (NAPT, 2018) and ALP quarterly soil analysis reports from 2013 to 2017, comprising 70 soil samples analyzed by 104 analytical testing laboratories (ALP, 2018), were digitized and assembled into a database using R statistical software (R Core Team, 2018). The reports provided a robust statistical summary of soil test results that included the median and the median absolute deviation (MAD) for each of the 470 soil samples. The median for clay, silt, and sand were used to assign each sample to a textural class of the USDA-NRCS textural classification using the ‘Soiltexture’ Package in R (Moeys et al., 2018). A total of 54 of these soils standards, comprising six to eight soil samples from each USDA-NRCS textural class in the database, were requested to the Penn State Ag Analytical laboratory soil standards repository for laser diffraction PSA. The properties of these samples are presented in Figure 2.1 and Table 2.1.

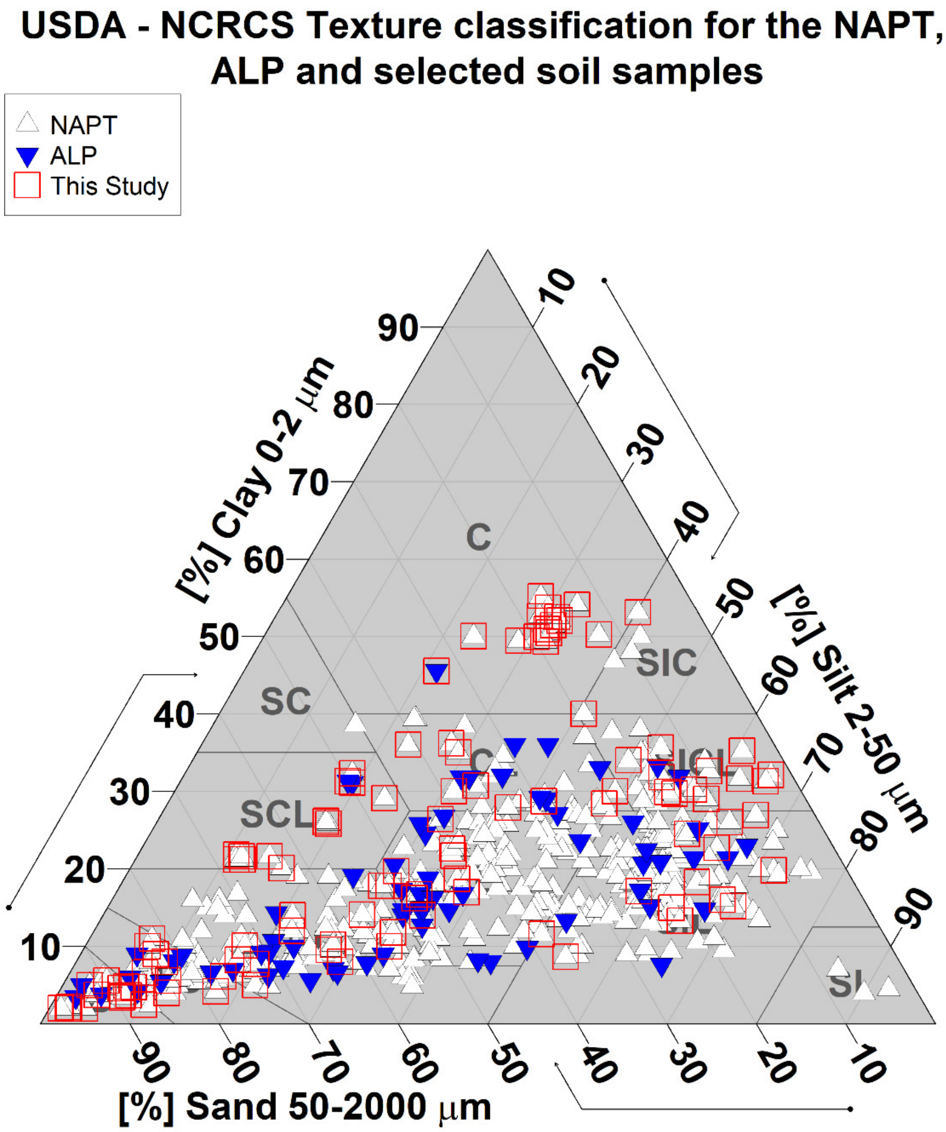


Figure. 2.1. Textural composition of soil samples according the USDA-NRCS texture triangle. The white triangles pointing up represent the soil texture classification corresponding to the median Clay, Silt and Sand content reported for each sample in the quarterly NAPT report; the blue triangles pointing down represent the soil texture classification corresponding to the median Clay, Silt and Sand content reported for each sample in the quarterly ALP report. The red squares surrounding triangles identify the samples selected for this study.

Table 2.1: Information about the standard soil samples used in the laser PSA; sample identification, soil classification, and median values for clay, sand, total organic carbon (TOC) and carbonate ($CaCO_3$) as stated in the NAPT and ALP quarterly reports used in this study. The number of analytical laboratories analyzing the sample resulting in the reported median is reported under the "n" column heading.

Sample	Location	Soil classification	Sieve/Pipette Method Sand	Silt	Clay	n	Hydrometer Method Sand	Silt	Clay	n	TOC	$CaCO_3$
			----------%----------				----------%----------				-----%-----	
2011-116	Antigo, WI	Coarse-loamy over sandy or sandy-skeletal, mixed, superactive, frigid Haplic Glossudalfs	37.0	54.2	8.7	4	38.2	50.6	11.6	30	1.1	0.1
2011-117	Umatilla, OR	Coarse-loamy, mixed, superactive, mesic Xeric Haplocalcids	82.9	12.9	5.6	4	76.5	17.5	6.1	30	0.5	0.4
2011-118	Fresno, CA	Coarse-loamy, mixed, superactive, mesic Ustic Haplocalcid	78.3	17.5	4.2	4	73.5	22.0	5.0	30	0.9	0.4
2011-119	Sturgeon Bay, WI	Coarse-loamy, mixed, superactive, frigid Typic Haplorthods	54.7	33.1	11.8	4	56	33.7	10.0	30	2.8	1.3
2011-120	San Juan, UT	Clayey, mixed, active, thermic, shallow Abruptic Durixeralfs	50.1	30.7	16.2	4	43.9	38.4	17.0	30	0.9	5
2012-101	San Luis Obispo, CA	Fine-loamy, mixed, superactive, thermic Calcic Haploxerolls	12.5	37.3	50.2	5	17.0	30.0	51.4	43	3.1	12.1
2012-102	Monmouth, NJ	Fine-loamy, mixed, active, mesic Typic Hapludults	65.9	21.9	12	5	64.8	21.0	14.0	43	0.7	0.5
2012-103	Riley, KS	Coarse-silty, mixed, superactive, nonacid, mesic Typic Udifluvents	72.0	20.1	7.7	5	62.5	29.6	8.0	43	0.6	1.7
2012-106	Fresno, CA	Coarse-loamy, mixed, superactive, thermic Fluvaquentic Haploxerolls	87.2	10.3	2.5	5	83.9	12.0	4.0	38	0.5	0.3
2012-108	Door, WI	Fine, mixed, active, mesic Typic Hapludalfs	49.3	34.2	16.7	5	50.4	30.2	19.7	38	2.5	1.1
2012-109	Farmington, UT	Fine-loamy, mixed, superactive, mesic Cumulic Haploxerolls	44.1	35.9	18.7	5	43.0	34.9	21.7	38	2.8	3.4
2012-110	San Patricio, TX	Fine-loamy, mixed, superactive, hyperthermic Typic Argiustolls	67.5	10	21.2	5	66.8	11.7	21.2	38	0.5	0.4

Sample	Location	Soil classification	Sieve/Pipette Method Sand	Silt	Clay	n	Hydrometer Method Sand	Silt	Clay	n	TOC	$CaCO_3$
			----------%----------				----------%----------				-----%-----	
2012-112	Grand, UT	Fine-loamy, mixed, superactive, calcareous, mesic Typic Torrifluvents	42.7	34.9	22.6	5	42.1	31.2	26.4	40	1.5	9.1
2012-113	Grand Forks, ND	Fine-loamy, mixed, superactive, frigid Calcic Hapludolls	33.8	39.1	27.9	5	38.8	32.0	30.0	40	2.7	0.6
2012-114	Kent, DE	Fine-loamy, siliceous, semiactive, mesic Typic Hapludults	88.3	8.03	3.7	5	87.2	8.0	4.75	40	0.6	0.3
2012-115	Baxer, TX	Clayey-skeletal, smectitic, thermic Lithic Haplustolls	96.7	1.6	2.03	5	95.7	2.8	2.2	40	0.6	0.3
2012-116	Caldwell, KY	Fine-silty, mixed, active, mesic Oxyaquic Fragiudalfs	15.0	69.8	15.2	2	17.5	64.5	18.3	36	1.1	0.7
2012-117	Linn, OR	Fine-silty, mixed, superactive, mesic Cumulic Ultic Haploxerolls	73.8	18.0	8.3	2	72.1	18.0	10.1	36	0.4	0.7
2012-118	Arlington, WI	Fine-silty, mixed, superactive, mesic Typic Argiudolls	8.2	72.0	19.8	2	13.1	63.8	22.7	36	2	0.8
2012-119	Waushara, WI	Mixed, mesic Typic Udipsamments	89.2	7.3	3.4	2	88.7	6.4	4.62	36	0.4	0.5
2013-102	San Luis Obispo, CA	Fine, smectitic, thermic Vertic Haploxerolls	17.9	33.0	52.6	5	16.0	31.5	52.0	40	2.8	11.3
2013-105	Wilacy, TX	Fine-loamy, mixed, superactive, hyperthermic Udic Argiustolls	55.1	18.3	26.0	5	54.9	19.6	25.8	40	0.6	4.2
2013-109	San Luis Obispo, CA	Fine-loamy, mixed, superactive, thermic Calcic Haploxerolls	18.9	31.8	49.3	4	16.4	29.3	53.7	34	2.6	18.5
2013-111	Bailey, TX	Fine-loamy, mixed, superactive, thermic Aridic Paleustalfs	89.8	5.6	5.6	4	85.0	8.4	6.6	39	0.9	0.5
2013-114	San Luis Obispo, CA	Fine, smectitic, thermic Aridic Haploxererts	21.9	32.0	49.4	4	26.6	22.5	50.0	39	1.8	2
2013-119	Allegheny, PA	Fine-loamy, mixed, semiactive, mesic Typic Hapludults	57.0	34.2	14.1	4	50.3	35.0	14.0	37	1.2	0.8
2014-103	Cache Junction, UT	Fine, mixed, superactive, mesic Typic Natrixerolls	4.0	56.8	35.2	3	12.9	51.3	35.6	36	1.4	5.3
2014-111	Larimer, CO	Fine-loamy, mixed, superactive, mesic Aridic Argiustolls	36.0	30.9	30.7	5	36.0	28.4	36.2	37	1.3	6.6

Sample	Location	Soil classification	Sieve/Pipette Method Sand	Silt	Clay	n	Hydrometer Method Sand	Silt	Clay	n	TOC	$CaCO_3$
			----------%----------				----------%----------				-----%-----	
2014-119	Riley, KS	Fine, smectitic, mesic Pachic Argiustolls	14.7	57.1	31.8	3	20.8	48.5	30	39	1.8	0.5
2015-101	Linn, MO	Fine, smectitic, mesic Aquertic Argiudolls	2.3	64.2	32.1	1	14.3	55.7	29.7	41	2.1	0.6
2015-103	San Luis Obispo, CA	Fine-loamy, mixed, superactive, thermic Calcic Pachic Haploxerolls	6.1	57.4	31.6	1	18.0	31.0	50.4	41	2.6	9.7
2015-108	Linn, MO	Fine, smectitic, mesic Aquertic Argiudolls	6.7	66.5	26.9	3	15.0	56.0	29.9	39	2.1	0.5
2015-109	Felton, DE	Fine-loamy, siliceous, semiactive, mesic Typic Hapludults	89.0	7.45	3.6	3	88.0	7.3	4.8	39	0.6	0.3
2015-113	San Patricio, TX	Fine-loamy, mixed, superactive, hyperthermic Typic Argiustolls	66.7	11.5	21.6	5	67.2	11.2	21.8	36	0.5	0.4
2015-115	Linn, MO	Fine-silty, mixed, semiactive, thermic Typic Paleudults	9.0	63.5	32.6	5	11.1	57.5	29.0	36	2.1	0.5
2015-118	Linn, MO	Loamy, kaolinitic, thermic Arenic Kandiudults	3.3	64.4	31.3	4	11.9	57.3	30.2	36	2.1	0.5
2016-111	Sao Luis Obispo, CA	Fine-loamy, mixed, superactive, thermic Calcic Haploxerolls	13.0	32.8	54.1	6	16.0	30.3	52.5	34	2.7	17.2
2016-114	Cache, UT	Fine-silty, mixed, superactive, mesic Calcic Pachic Argixerolls	22.8	45.4	28.4	6	29.4	44.0	28.7	34	3	1.3
2017-101	Centre, PA	Fine, mixed, semiactive, mesic Typic Hapludalfs	91.8	2.0	3.76	7	16.3	58.0	24.0	35	1.7	0.8
2017-102	Grand Forks, ND	Sandy, mixed, frigid Oxyaquic Hapludolls	82.0	7.0	11.0	7	82.5	9.2	8.01	35	1.8	0.7
2017-103	Penobscot, ME	Sandy, isotic, frigid Typic Haplorthods	40.9	27.0	36.0	7	63.9	27.0	9.0	35	2.5	0.6
2017-104	Gallatin, MT	Loamy-skeletal over sandy or sandy-skeletal, mixed, superactive, frigid Typic Argiustolls	19.3	48.0	40.0	7	40.2	41.6	17.5	35	3.7	2.8
2017-105	Grand, UT	Mixed, mesic Typic Torripsamments	53.0	29.2	17.8	7	92	3.9	5.0	35	0.4	0.6
2017-107	Grand Forks, ND	Sandy, mixed, frigid Oxyaquic Hapludolls	10.0	64.0	26.0	3	82.6	9.0	9.0	35	1.9	0.6
2017-108	Larimer, CO	Fine-loamy, mixed, superactive, mesic Aridic Argiustolls	62.2	28.0	10.2	3	35.8	28.7	35	35	1.3	5.5
2017-109	Cache, UT	Fine-silty, mixed, superactive, mesic Typic Calcixerolls	83.0	7.2	10.0	3	17.3	49.6	34.0	35	2.5	5.8

Sample	Location	Soil classification	Sieve/Pipette Method Sand	Silt	Clay	n	Hydrometer Method Sand	Silt	Clay	n	TOC	$CaCO_3$
			----------%----------				----------%----------				-----%-----	
2017-111	Cache, UT	Loamy-skeletal, micaceous Ustic Dystrocryepts	53.0	29.2	17.8	5	52.2	31.2	17.8	38	2.5	2.7
2017-112	Minnehaha, SD	Fine-silty, mixed, superactive, mesic Udic Haplustolls	10.0	64.0	26.0	5	15.5	61.1	24.5	38	2.9	1
2017-113	Caroll, NH	Coarse-loamy, mixed, active, frigid Aquic Dystrudepts	62.2	28.0	10.2	5	63	27.5	9.55	38	4.7	0.5
2017-114	Grand Forks, ND	Sandy, mixed, frigid Oxyaquic Hapludolls	83.0	7.2	10.0	5	82.1	9.0	8.0	38	1.7	0.6
2017-115	Cumberland, IL	Fine, smectitic, mesic Mollic Albaqualfs	15.8	68.0	16.0	5	22.0	63.3	15.0	38	1.3	0.4
SRS-1508	Pinal County, AZ	Fine-loamy, mixed, superactive, calcareous, hyperthermic Typic Torrifluvents	-	-	-	0	49.6	17.8	31.1	26	1.7	1.8
SRS-1604	Sonoma County, CA	Fine, mixed, semiactive, mesic Typic Haploxerults	-	-	-	0	50.0	18.5	31.3	30	2.2	0.2
SRS-1709	Sonoma, CA	Loamy, mixed, superactive, thermic Lithic Haploxerepts	-	-	-	0	33.0	22.0	45.0	28	5.4	0.6

Source: North American Proficiency Testing Program (NAPT, 2018), Agriculture Laboratory Proficiency (ALP) Program (ALP, 2018), University of California Davis California soil resource Lab SoilWeb (O'Geen, Walkinshaw, and D. Beaudette; 2017).

2.2.2. Sample Preparation and Sieving

A representative, well-mixed and dry 5-g soil material (< 2 mm) sample was collected from each of the 54 selected standard materials according to the best fundamental sampling error calculation proposed by Rawle (2015). The 5-g material sample was placed in a 470-mL container with 100 mL of a 5% sodium hexametaphosphate solution, vigorously mixed, and left to soak overnight to disperse the soil particles. The following day, distilled water was added to make up 300 mL of solution, after which samples were mixed for 5 minutes in a Triple-Spindle Drink Mixer HMD400 (Hamilton Beach Brands Inc.) to obtain a stable soil particle suspension sample (Polakowski et al., 2015). After mixing, the soil solution was sieved through a 53-µm mesh to separate sand-sized particles and to determine the sand fraction (f_{sa}, kg kg^{-1}). The sieve-removed particles were oven-dried at 105 °C for 24 h, and f_{sa} calculated as the ratio of the mass of the 53-µm sieved dried particles (M_{sa}, kg) and the total dried soil sample mass (M_T, kg).

2.2.3. Laser Diffraction PSA

Laser diffraction PSA used the Malvern Mastersizer 3000 laser diffractometer equipped with a He-Ne red light at 632.8 nm wavelength and a LED blue light at 470 nm wavelength, a 600 mL Hydro LV dispersion unit, and 101 size bins covering particle sizes from 0.01 µm to 3,500 µm (Malvern Panalytical Inc.). This is in contrast with the Analysette 22 (Fritsch GmbH) instrument used by Taubner et al. in 2009, which was equipped with a 638 nm laser source and measurement range of 0.290 to 295 µm distributed into 62 bins.

A subsample of the suspension of the fractions passing the 53 µm mesh sieve was taken with a wide mouth transfer pipette and added to the wet dispersion unit of the Mastersizer

3000. Enough suspension was added to increase the obscuration level to approximately 10%. A maximum stirring speed of 3500 rpm and 100% sonication power were applied for the duration of each measurement event (approximately 2 minutes). Some samples were replicated three times to test the reproducibility and consistency of the subsample grabbing method. From the dispersion unit, the sample was circulated in the measurement cell where the interaction of particles and light occurred. Sample replication showed very low variability (coefficient of variation ranged from 0.6 to 5.8% when sonication was applied) and therefore, only one reading per sample was taken for the selected NAPT and ALP sample analyses. Sample analyses used the Mie scattering general purpose model for quartz material with non-spherical shape mode, a particle refractive index of 1.543, a particle absorption index of 0.01, and a water refractive index of 1.33. After each measurement, the Hydro LV cell was washed with distilled water twice before a new sample was added, and the analyses were always performed with degassed water. Background scattering by the solution was measured periodically after every 25 samples to verify the cleanliness of the measurement cell. The laser diffraction analyses were carried out at the Materials Characterization Laboratory (MCL) of Penn State, which performs nominal particle size calibration with Duke Standards TM Polymer Microspheres NIST traceable diameter 8.9 µm (+/- 0.5 µm) on a monthly basis or on demand.

Clay and silt contents, as a mass fraction of the sample, were obtained by subtracting the amount of sand from each sample (M_T - M_{sa}), multiplying the remaining mass of the sample by the volume fraction of clay or silt obtained from laser diffraction analysis, and then dividing by the total mass of sample (Equations 2.1 and 2.2):

$$f_{cl} = \frac{(M_T - M_{sa}) \times f_{cl-LD}}{M_T} \qquad (2.1)$$

$$f_{si} = \frac{(M_T - M_{sa}) \times f_{si-LD}}{M_T} \qquad (2.2)$$

where f_{cl} is the mass fraction of clay in the sample, $f_{cl\text{-}LD}$ is the percent cumulative volume of particles less than a clay-silt cutoff of 6 µm (discussed below), f_{si} is the mass fraction of silt in the sample and $f_{si\text{-}LD}$ is the percent cumulative volume of particles greater than the clay-silt cutoff. This approach assumes spherical particles and equal particle density to partition the clay-silt mass into clay and silt fractions, the same assumptions used in sedimentation methods.

2.2.4. Comparing Methods

The clay-silt cutoff was selected through an optimization routine developed in Microsoft Excel to minimize the difference between the standard sample clay and silt fractions obtained using the proposed laser diffraction PSA protocol, and the median clay and silt fractions reported by the NAPT and the ALP programs (Table 2.1). The optimization routine searched for the clay-silt particle size threshold over a similar range to the 2 - 9 µm threshold range reported in the literature and discussed above (USDA-NRCS, 2017; Arriaga et al., 2006; Miller and Schaetzl, 2012; Makó et al., 2017; Konert and Vandenberghe, 1997; Fisher et al., 2017), using the bin sizes of 1.88, 2.13, 2.42, 2.75, 3.12, 3.55, 4.03, 4.58, 5.21, 5.92, 6.72, 7.64 and 8.68 µm reported by the Mastersizer 3000.

To check the stability of the clay-silt cutoff, a 3-Fold Cross-Validation (James et al., 2013) was conducted by randomly splitting the dataset in three groups, calculating the clay content with two thirds of the data, and validating the results against the remaining third of the data.

The cross validation was performed three times - using the three different two thirds of the 54-observation dataset as training models, and the other three respective one thirds of the dataset as validation (Table 2.2).

Sand, silt and clay fraction results obtained using the laser diffraction protocol were compared with NAPT and ALP sieve/pipette, and hydrometer reported medians using linear regression analysis. The 1:1 regression line provides a visual assessment of the magnitude of the errors, and the coefficient of the determination, the slope and the intercept provide quantitative measures of the bias between PSA methods.

2.3. Results

The clay-silt particle size cutoff that yielded the best agreement between the laser diffraction PSA and the NAPT and ALP reported results was the 5.92 µm Mastersizer 3000 size bin (Tables 2.2 and 2.3). As expected, the standard USDA-NRCS 2 µm clay-silt cutoff produced inferior results, which agrees well with prior reports (Miller and Schaetzl, 2012; Makó et al., 2017). Using 6-µm as the clay-silt threshold produced robust results in the 3-fold cross validation and good agreement with the NAPT and ALP reported data, with values of the regression intercept and slope close to the 1:1 line, high coefficient of determination (R^2) and low root mean square error (RMSE, Table 2.2). Furthermore, the magnitude of the RMSE between laser diffraction PSA results and the reported NAPT and ALP data ranged between 0.04 and 0.07, which is very close to the magnitude of the regression RMSE between pipette and hydrometer methods, 0.03 to 0.06 (Table 2.3, Figure 2.2). Analysis of the regression residuals indicated no significant correlation with total organic carbon or carbonate content, which agrees with prior reports by Fisher et al. (2017).

Table 2.2. 3-Fold cross validation statistics for clay content determined by randomly dividing the dataset in thirds. Two thirds of the dataset were used in the clay-silt cut-off optimization routine and the remaining third was used for validation.

Statistic	Training Set 1	Validation Set 1	Training Set 2	Validation Set 2	Training Set 3	Validation Set 3
Intercept	-0.01	-0.01	-0.001	-0.004	-0.006	-0.002
Slope	1.01	0.93	0.98	1.14	0.97	0.94
RMSE, g g^{-1}	0.05	0.02	0.04	0.06	0.04	0.04
R^2	0.89	0.99	0.95	0.89	0.92	0.92
n	36	18	36	18	36	18
Threshold, µm	6		7		6	

Table 2.3. Comparison of the coefficient of determination and root mean square error for the fraction of clay and silt using the standard clay-silt cutoff of 2 µm and the previously recommended 6 and 9 µm.

Cutoff, µm	Methods	Clay		Silt	
		R^2	RMSE	R^2	RMSE
2	Hydrometer vs Pipette	0.96	0.03	0.93	0.06
2	Laser diffraction vs Hydrometer	0.75	0.18	0.86	0.22
2	Laser diffraction vs Pipette	0.82	0.17	0.91	0.19
6	Laser diffraction vs Hydrometer	0.92	0.04	0.92	0.07
6	Laser diffraction vs Pipette	0.90	0.05	0.94	0.06
9	Laser diffraction vs Hydrometer	0.90	0.07	0.93	0.05
9	Laser diffraction vs Pipette	0.88	0.08	0.91	0.07

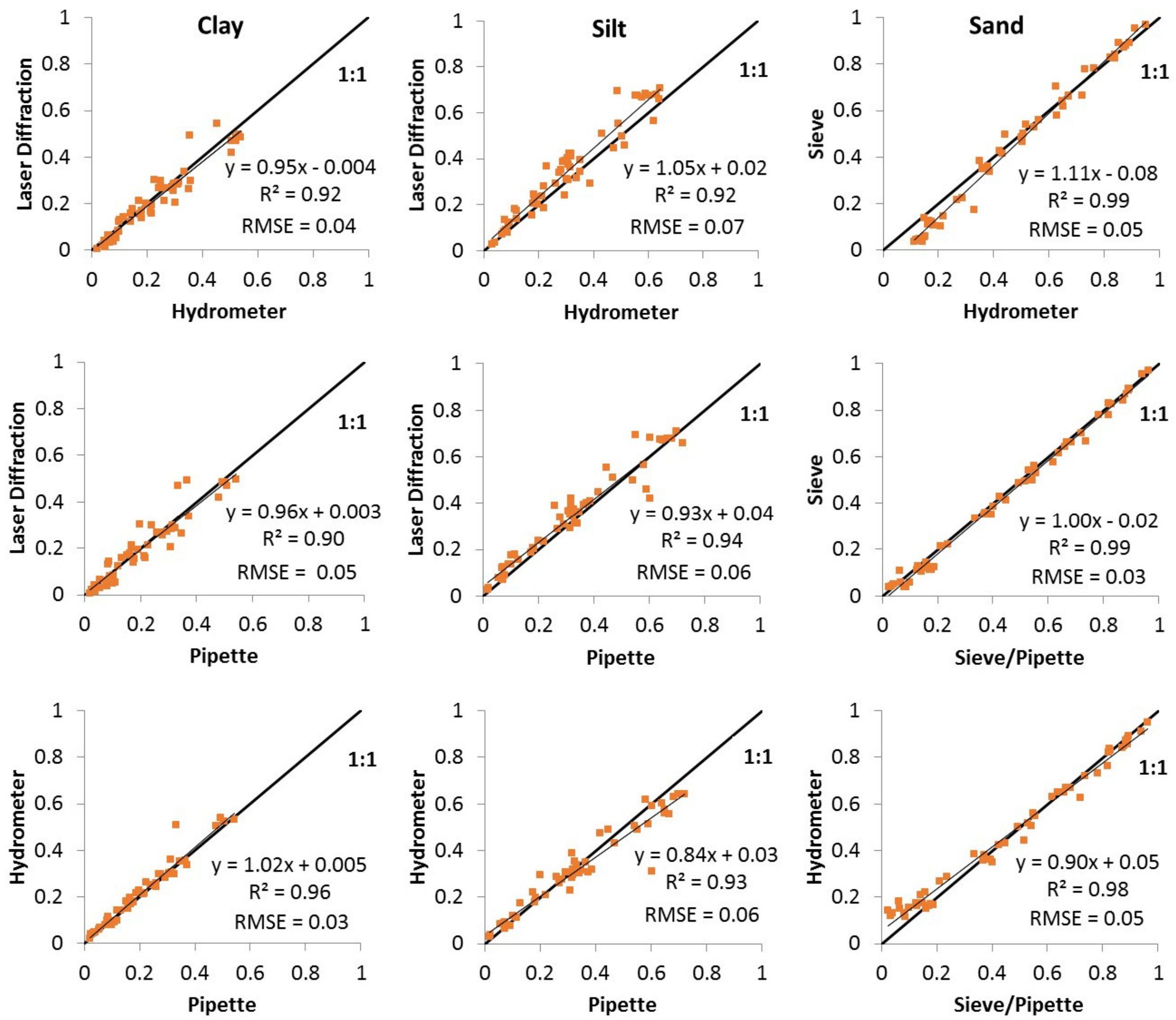


Figure 2.2. Regression analysis comparing the proposed laser diffraction protocol and the reported NAPT and ALP sieve/pipette and hydrometer for the 54 standard samples selected.

This study used a refractive index of 1.54 (corresponding to quartz) and an absorption index of 0.01. However, the Mastersizer 3000 allows recalculation of results using different scattering parameters, and we also recalculated our results using the refractive index values of 1.52 and absorption index of 0.1 proposed by Bieganowski et al. (2018). The major difference was a shift in the clay-silt cutoff from the 5.92 μm to the adjacent 5.21 μm bin. This was a very small change with minor impact on the texture classification corresponding to the standard sedimentation results reported by NAPT and ALP.

2.4. Discussion

Eshel and Levy's 2007 statement that 'there is no room to match particle size distribution data obtained by the LD [laser diffraction] to those obtained by the pipette' refers to the difficulties in obtaining laser diffraction PSA results for soils with different particle sizes, densities, shapes, and optical material properties that are consistent with sedimentation methods. The laser diffraction protocol presented in this work overcomes some of these limitations and is able to obtain results comparable with standard soil texture determination methods from a broad geographic area of the United States, representative of most soil textural classes, and varying substantially in soil taxonomic classification, total organic carbon and carbonate content. Implementing the idea first proposed by Taubner et al. (2009) of limiting the particle size range to obtain consistent representative soil particle suspensions, in combination with technological improvements on laser diffraction instrumentation, allowed consistent estimations of particle size distribution for clay and silt fractions. The protocol presented is robust with regards to variation in laser diffraction analytical parameters such as the refractive index and the absorption index. Varying the refractive index within reasonable bounds produced small changes in the particle analysis. Similarly, varying the clay-silt size cutoff from 2 to 9 µm produce PSA results that remained close to those reported by NAPT and ALP (Table 3.3).

With consistent soil laser diffraction PSA results, the issue of equating laser diffraction and sedimentation results is transformed into an empirical problem with various practical solutions, as has been demonstrated by Fernlund et al. (2007) for sieving and image analysis methods, and by Garboczi et al. (2017) for laser diffraction, sieving, and a combination of X-ray Computer Tomography and spherical harmonic analysis. The solution chosen in this work was based on three steps: 1) separation of the sand fraction via sieving, as in the sieve/pipette method; 2) choice of a nominal particle laser diffraction diameter that optimized the matching of clay and silt fractions between the two methods; and 3) use of the results of the laser diffraction PSA to describe the nominal particle size distribution- that is, the relative proportion of nominal light scatter particle diameter distribution within the clay and silt fractions.

As indicated by Eshel et al. (2004) and Merkus (2009), one of the advantages of laser diffraction is the rich information of particle size distribution (Figure 2.3). While textural classes provide a useful indication of the particle size distribution, it is well known that soils that have similar fractions of clay, silt, and sand may have contrasting particle size distributions. This is shown in Figure 2.3, where one of the samples has a particle size distribution with a large fraction in the finer portion of the clay range. An important additional advantage of laser diffraction over sedimentation methods is the speed of the analysis and reduction of the error introduced by the time of reading and the operator reading the hydrometer level (Allen, 1997; Syvitski et al., 2007). With the described set up, the Mastersizer apparatus throughput was 15 samples per hour, which allowed analysis of 400 soil samples in 2 weeks. It would have taken more than two months to do the same analyses using the current lab setup for the hydrometer technique with 11 Bouyoucos cylinders. In addition, by wet sieving the sand from the soil particle suspension, segregation and sedimentation errors are minimized, facilitating the collection of a representative suspension sample as suggested by Taubner et al. in 2009.

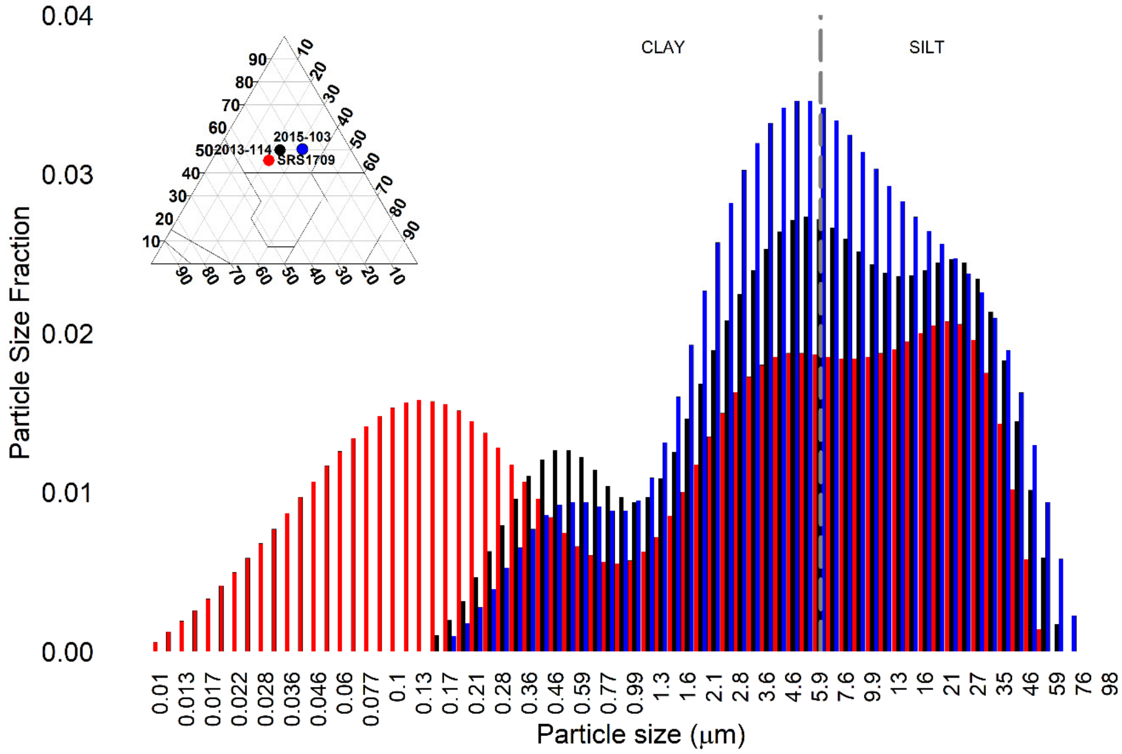


Figure 2.3. Particle size distribution determined by laser diffraction of samples 2013-114, 2015-103, and SRS-1709, with the same clay texture, but very different particle size distributions (See Table 1 for detailed sample description).

Eshel and Levy (2007) advocated for building a direct link between laser diffraction PSA results soil properties, as is currently used for sedimentation-based methods, bypassing the need for calibrating results of these methods. The work presented in this study supports that approach. However, there has been minimal progress towards building a direct link between laser diffraction PSA and soil properties since 2007, and it seems that an intermediate matching step is necessary to progress towards that goal.

The laser diffraction protocol presented in this research produced soil PSA results that match standard sedimentation methods within their expected error. Laser diffraction soil PSA is information rich, fast, and robust. Furthermore, the current average texture analysis operating cost of US$ 22 ± 11 (based on informal surveys of 10 US soil laboratories) could be reduced significantly once the initial investment in the laser diffraction equipment is discounted. Additionally, while the potential of laser diffraction and particle imaging methods will continue to expand with advances in sensor technology and machine learning techniques for data mining (Merkus, 2009), there is little room for further technical advancement using standard sedimentation methods. Instead of developing functions to convert laser diffraction analysis results to sedimentation equivalent data (Makó et al., 2017), pedotransfer functions could be developed *de novo* using laser diffraction PSA results.

2.5. Conclusions

The laser diffraction protocol for soil PSA proposed in this work uses a small soil sample, is more robust, simpler, and faster than the current sedimentation methods, and significantly expands the quality of the data collected from soil texture analysis into a detailed particle size distribution. Limiting the particle size range of the samples by wet sieving the sand fraction overcame the difficulties inherent in obtaining representative samples and stable soil dispersed suspensions, allowing accurate estimation of clay and silt fractions. The assumptions that form the basis of sedimentation methods were used to develop a protocol that matches results from laser diffraction and standard sedimentation methods for a wide range of soils. Rather than defaulting to standard sedimentation methods, results obtained with the protocol presented here encourage further adoption of laser diffraction methods in PSA.

Chapter 3. Soybean Yield in Relation to Environmental and Soil Properties

CORE IDEAS

- Solar radiation and precipitation over the growing season were associated with planting date and were the main drivers of soybean yield.
- The soil respiration to soil organic carbon ratio correlated positively with soybean yield.
- *In-situ* measured saturated hydraulic conductivity was positively correlated to soybean yield and can be a promising indicator of soil condition.

SUMMARY

Our goal was to identify soil, plant and climate attributes that are most closely related to soybean [*Glycine max* (L.) Merr.] yield variation in Pennsylvania. We studied 22 site-years over the 2016 and 2017 growing seasons in two regions. The average yields were 3.4 (ranging from 1.4 to 5) Mg ha^{-1} in 2016 and 5.5 (ranging from 3.5 to 7.4) Mg ha^{-1} in 2017. Solar radiation capture and water capture, both controlled by planting date, were the main predictors of soybean yield. Principal component analysis and Random Forest analysis revealed that the soil predictors of soybean yield were the content of zinc, copper, phosphorus, sulfur, potassium, as well as A horizon and total soil depth. The yield response to nutrients is likely a surrogate for a more complex response to animal manure additions. The physical and biological soil metrics in the comprehensive Cornell Assessment of Soil Health (CASH) did not correlate to soybean yields individually; however, the ratio of soil respiration to soil organic matter positively did so. Saturated hydraulic conductivity (K_{sat}) and root depth correlated with both soybean yield and each other. Thus, while planting date sets the maximum achievable yield, only soils having the

most water and nutrient availability (manured soils with high K_{sat}) expressed yields exceeding 7 Mg/ha. The K_{sat} appears to be a valuable indicator of soil condition.

3.1. Introduction

Average soybean [*Glycine max* (L.) Merr.] yield has increased steadily in the United States. Each year, the average yield for a region reflects a wide range of within field and among fields yield variation. These yields are obtained frequently in seemingly uniform fields that are managed similarly. In Pennsylvania, producers report yields ranging from 3 to 6 Mg ha^{-1} (Voight, 2016). In some fields, exceptional yields above 7 Mg ha^{-1} are obtained and documented in yield contests (Frankenfield, 2017). Understanding the causes of the yield variation as well as the factors that contribute to high yields can help charting pathways for increased productivity, profitability and environmental care.

Identifying the drivers of yield variation can be challenging due to management x environment interactions. Frequently, soil water holding capacity explains year-to-year crop yield variation (Williams et al., 2016). Nonetheless, Rattalino Edreira et al. (2017) indicated that planting date was the most consistent soybean yield predictor when considering different regions and years. The negative response of soybean yield to delaying planting dates is well understood (Mooers, 1908; Egli and Cornelius, 2009). In summary, soybean yield decreases due to the hastening in development caused by shorter daylengths and warmer temperatures in the summer, which leads to lower availability and capture of solar radiation for photosynthesis. Therefore, earlier planting can set a higher yield potential, and a key for realizing it is increasing our knowledge of local soil environments.

The relationship between nutrient levels and yield vary depending on other conditions. For example, Sawchik and Mallarino (2008) found that soybean yield in Iowa was positively correlated to soluble soil P and K, while Cox et al. (2003) in Mississippi did not, suggesting that in the latter case factors other than P and K limited yield. In an environment known for low soil P availability such as in Brazil, Santi et al. (2012) used Principal Component Analysis (PCA) to evaluate the effect of 63 chemical and physical variables on soybean yield and suggested that K content and soil infiltration rates were, respectively, the greatest chemical and physical soybean yield limiting factors. Certainly, soil-plant-climate interactions differ regionally, resulting in yields being most responsive to different soil variables depending on the location.

The soil quality concept, originally conceived as a measure of the soil's ability to yield crops (Mausel, 1971), has been extended to include the broader ecosystems services concept (Doran and Parkin, 1994) and referred to as soil health (Karlen et al., 1997). Laboratories are now offering soil testing packages that aim at evaluating comprehensively soil chemical, physical and biological properties. Among these soil testing packages is the Cornell Analysis of Soil Health (CASH, Moebius-Clune et al., 2016). Bunemann et al. (2018) showed in their review paper about soil quality that most studies have not tested or reported how soil biological and physical indicators relate to crop yield. For example, Karlen et al. (2017) summarized results from the on-farm Soil Health Partnership (65 farms), but without including crop yield. When researchers report the response to yield, it can be subdued or applicable to a narrow slice of the sampling space. Nunes et al. (2018) found some CASH indicators that were positively influenced by no-till management and plant diversification strategies which related to crop yield, but the yield response was noticeable in loamy sand and silt loam soils but not in clay loam soil.

Our goal was to explore the relationship between soybean yield, climate and soil properties in two regions of Pennsylvania. The southeastern region (deep soils, low elevation) is broadly representative of soil-climate clusters in Ohio, Indiana, Illinois and part of Iowa and Missouri, while the central region (variable soil depths, higher elevation) is representative of more northern latitudes in the Midwest (Rattalino Edreira et al., 2018; Kukal and Irmak, 2018). Our specific objective was to distill soil and climate attributes closely related to soybean yield while accounting for interactions with management. To fulfill this objective, we did an observational study of 22 site-years where, in addition to soybean yield, we collected descriptive attributes of soil profiles and measured a suite of environmental, physical, chemical and biological indicators in individual sampling units per field. Observational studies are an alternative to controlled experiments when the conditions of interest are not in place in experiments across regions (Seddaiu et al., 2013; Ernst et al., 2016).

3.2 Materials and Methods

We collected field data in two regions of Pennsylvania (Region 1, Lancaster and Lebanon counties, and Region 2, Centre county) during the 2016 and 2017 growing seasons. In 2016, we included double-cropped soybean systems with a wide range of planting dates, with experiments conducted in both research station fields and commercial farm fields. In 2017, we targeted top yielding farms in each region. Within each farm, we sampled pairs of commercial fields with similar soil, planting date, soybean variety and corn as preceding crop, but a divergent record of soybean yields. Overall, we worked with 8 fields in 2016 and 14 fields in 2017 from 10 producers, totaling 22 site-years (Table 3.1). Fields were labeled first with the region digit, followed by the yield ranking (e.g. 1.1 is the field from Region 1 with the highest soybean yield). Region 1 is a high crop yielding environment of Pennsylvania, and some of the commercial fields studied have consistently ranked among the top three in the Pennsylvania Soybean Yield Contest and the Five Acre Corn Club.

The 2016 research station experiments were conducted at the Southeast Agricultural Research and Extension Center in Landisville – Region 1, and at the Russell E. Larson Agricultural Research Farm at Rock Springs – Region 2. In 2017, all fields were on commercial farms. To facilitate sampling, commercial farm fields were located within a 20 km radius from each research station in both Regions. The distance between the two research stations is approximately 200 km. Of the 22 site-years, 18 used no-till for at least 5 years, and 4 used conventional tillage. All fields in Region 1, and 2 fields in Region 2, received manure. All soils are well drained and considered prime farmland. The most common parent material was limestone and siltstone. The soils were Hagerstown silt loam, fine, mixed, semiactive, mesic Typic Hapludalfs, or similar (Duffield silt loam, fine-loamy, mixed, active, mesic Ultic Hapludalfs; Hublesburg silt loam, clayey, illitic, mesic Typic Hapludults; Clarksburg silt loam, fine-loamy, mixed, superactive, mesic Oxyaquic Fragiudalfs; Morrison sandy loam, fine-loamy, mixed, active Ultic Hapludalfs; and Murrill fine-loamy, mixed, semiactive, mesic Typic Hapludults). The sampled areas had gentle slopes (0 to 3%). Average sand (clay) content varied from 4% (8%) to 77% (75%) in the whole soil profile, and from 12% (8%) to 77% (49%) in the A horizon.

Table 3.1. Elevation, soil type, parent material, previous crop, tillage, relative maturity group (MG) and row spacing of the studied fields from Region 1 and Region 2 in 2016 and 2017.

Year	Field	Elevation	Soil Type	Previous Crop	Tillage	MG	Row Spacing
		m					cm
2017	1.1	139	Duffield Silt Loam	Corn	Yes	3.6	38
2017	1.2	139	Duffield Silt Loam	Corn	No	3.6	38
2017	1.3	109	Hagerstown Silt Loam	Corn	No	3.5	38
2017	1.4	109	Clarksburg Silt Loam	Corn	No	3.8	38
2017	1.5	139	Duffield Silt Loam	Corn	Yes	3.6	38
2017	1.6	109	Hagerstown Silt Loam	Corn	No	3.5	38
2017	2.1	400	Murrill Channery Silt Loam	Corn	No	3.1	76
2017	2.2	344	Morrison Sandy Loam	Corn	No	3.1	76
2017	2.3	316	Hagerstown Silt Loam	Corn	No	3.5	38
2016	1.7	125	Hagerstown Silt Loam	Corn	Yes	3.6	38
2016	1.8	139	Duffield Silt Loam	Wheat	No	3.6	19
2017	1.9	109	Hagerstown Silt Loam	Corn	No	3.4	38
2017	2.4	344	Morrison Sandy Loam	Corn	No	3.1	76
2017	2.5	334	Hublersburg Silt Loam	Corn	No	3.6	76
2017	2.6	334	Hagerstown Silt Loam	Corn	No	3.6	76
2016	2.7	334	Hagerstown Silt Loam	Corn	No	3.5	76
2017	2.8	316	Hagerstown Silt Loam	Corn	No	3.5	38
2016	1.10	109	Duffield Silt Loam	Wheat	No	3.6	38
2016	2.9	329	Hagerstown Silt Loam	Barley	No	3.6	38
2016	2.10	329	Hagerstown Silt Loam	Sorghum	No	3.6	38
2016	1.11	125	Hagerstown Silt Loam	Wheat	No	3.6	38
2016	1.12	125	Hagerstown Silt Loam	Wheat	No	3.6	38
2016	2.11	329	Hagerstown Silt Loam	Barley	No	3.6	38

3.2.1. Plant Measurements

At the two Penn State research stations in 2016, plot size was 1.9 m (five rows) x 4.5 m in length. Three 1-m long sampling units were flagged after soybean establishment in each of the three adjacent mid-rows of every plot. All measurements were done in each 1-m sampling unit of every plot, totaling 3 m per plot (1.1 m^2). Soybean population was measured at V2 and R8, and phenology was recorded from VE to R8 following Fehr and Caviness (1977). Plant height and lodging were recorded prior to harvest at R8 stage. Grain was harvested using an experimental Wintersteiger AG combine. Moisture and test weight were measured using a Dickey-john GAC 2100 grain moisture tester, and grain yield was corrected to 13% moisture.

At all the other locations in both years, five subsamples were collected per commercial field after soybean establishment and the locations were fixed using flags and a global positioning system to assure that the plant and the soil measurements were conducted over the same individual land unit (1-2 m^2). From a location (mid-point) that was initially randomly selected on areas with adequate plant stands and anticipated soil type, we flagged four additional sampling units at fixed distances (7, 19, 37, and 56 m) and radially away from the mid-point. In each of the five sampling units, two 1-m lengths in adjacent rows were flagged and measurements taken in a similar fashion to the procedures used on the research farms' plots. Soybean population was counted at V2 and R8, and dates at which plants reached VE, R1 and R8 stages were recorded. Height, lodging and aboveground biomass were measured at the R8 stage prior to harvest. Soybean aboveground biomass was dried at 50°C until constant weight, and yield was estimated by threshing the dried aboveground biomass sampled at R8 using a plot combine in stationary mode and weighing the grain mass.

3.2.2. Soil Measurements

Soil cores were taken from the center of each sampling unit using a tractor-mounted hydraulic soil coring system (Giddings Inc.) that allowed obtaining up to 1.2 m long x 42 mm in diameter soil cores inside plastic liners. Given that there were shallow stones with diameters > 42 mm, when shallow rocks impeded deep sampling, we tried two additional coring attempts per sampling unit and retained the longest core. Soil samples were collected immediately after soybean harvest. The intact soil cores were laid out for observation in the laboratory. In 2016, the soil layers were separated by horizon, unless the horizon thickness exceeded 30 cm. In that case, the horizon was split in half for subsampling purposes related to chemical analysis. In 2017, the thicknesses sampled were fixed: 0-6 cm, 6-15 cm, 15-30 cm, 30-60 cm, 60-90 cm, and 90-120 cm. Depth of A horizon, maximum root depth and core length (a proxy for soil depth) were recorded. All samples were air-dried and sieved (2-mm mesh) for soil testing, soil organic matter (SOM) analysis, and particle size analysis. Sub-samples from each soil layer were oven-dried at 105° C for 24 h for gravimetric water content and bulk density (BD) determinations. In 2017, an undisturbed sample was also collected in every sampling unit using a stainless-steel cylinder of 7.5-cm diameter and 6-cm height to estimate soil water holding capacity.

Clay and silt content were measured in each soil layer using the laser diffraction method (Faé et al., 2019), and sand was estimated using the sieve method (Gee and Or, 2002) following the USDA classification system (USDA, 2017). Other soil tests were done at the Penn State Agricultural Analytical Services laboratory. Soil pH was determined in 1:1 water extracts (Eckert and Sims, 2011), extractable nutrients (P, K, Ca, and Mg) were determined using the Mehlich-3 (ICP) extractant (Wolf and Beegle, 2011), cation exchange capacity (CEC) was determined by summation (Ross and Ketterings, 2011), SOM by loss on ignition (Schulte and Hoskins, 2011), and total sorbed Zn and Cu using the EPA Method 3050B/3051 + 6010 (USEPA, 1986). Nutrient mass content (kg ha^{-1}) per sampling unit was calculated by multiplying bulk densities by the sampled soil layer depth and the elemental concentrations.

Saturated hydraulic conductivity was measured with an automated field dual-head infiltrometer (SATURO, METER Group Inc., formerly Decagon Devices Inc.). This instrument provides K_{sat} using the two-ponding head approach (Reynolds and Elrick, 1990) and simplifications described in Nimmo et al. (2009). The infiltrometer ring has a diameter of 14.4 cm with an insertion depth of 5 cm. A control unit regulates the pressure heads and measures infiltration rates over complete pressure cycles, determining field K_{sat} over different soil moisture conditions. It allows infiltration measurements from 0.0038 to 115 cm h^{-1} with a resolution of 0.0038 cm h^{-1} and accuracy of ± 5%. Measurements were done across sites within a one-month period in June of 2017. Extreme care was taken to avoid the formation of soil cracks while inserting the ring in the soil. When the infiltration flux showed significant fluctuations after the saturation stage, we discarded the measurement and repeated the procedure. Approximately 30% of the measurements were repeated at least once for this reason.

Water content at saturation, field capacity (-33 kPa) and permanent wilting point (-1500 kPa) were measured on undisturbed soil cores of 7.5 cm diameter and 6 cm depth per sampling unit using the soil moisture PM compressor FSM Jenny Pressure Plate pressure plate extractor (Dane and Hopmans, 2002; Burt, 2004). Samples were dried at 105˚C for 24 h and BD was calculated to convert the data to volumetric water content. Rock content was estimated in the 0-6 and 6-15 cm soil layers by collecting, washing and drying the sample sieved at 2 mm (water displacement method).

In 2017, we sent 15-cm topsoil samples for CASH testing to the Cornell Soil Lab Testing, following procedures determined by their guidelines (Moebius-Clune et al., 2016). For this test, composite samples were derived by proportionally combining well mixed soil samples (0-6 cm and 6-15 cm samples) for the five sampling units in each field. Soil samples at field soil water content were kept in a cold room at 4˚C until all samples were collected prior to shipping. The full CASH assessment includes particle size analysis, physical analyses (available water capacity, aggregate stability), biological analyses (SOM, ACE soil protein index, soil respiration, active carbon), and chemical analyses (pH, P, K, Mg, Fe, Mn, Zn). The following methods were used by the CASH test: Soil particle size analysis was done by the sedimentation method developed by Kettler et al. (2001). Wet aggregate stability was determined using a rainfall simulator and a set of sieves shaken on a mechanical shaker (Moebius et al., 2007). Available water capacity was gravimetrically assessed calculating the difference between water content at -10 and -1500 kPa using ceramic pressure plates in air pressure chambers (Reynolds and Topp, 2008). Soil organic matter content was determined by mass loss on ignition in a furnace at 500 ˚C for 2 hours (Broadbent, 1965). Soil respiration was measured using the incubation method (Zibilske, 1994). Autoclaved-Citrate Extractable (ACE) protein content was determined using sodium citrate to extract the soil and a standard curve for soil protein concentration after centrifugation and autoclaving steps (Wright and Upadhyaya, 1996). The ratios of soil respiration and active carbon to SOM were calculated to consider indicators of SOM quality in our analysis. Soil pH was measured in a suspension of 2 parts of water to 1 part of soil. Soil nutrients were extracted using a modified Morgan extractant (ammonium acetate plus acetic acid solution buffered at pH 4.8) and the filtrate was analyzed in an inductively coupled plasma emission spectrometer (ICP, SPECTRO Analytical Inc.).

The CASH has a scoring system based on sigmoid functions to interpret the measurements. The functions convert individual indicators to ratings ranging between 0 and 100. The functions are in some cases specific for coarse, medium and fine textured soils. The rating is based on scoring curves developed with their database for each indicator by estimating the cumulative normal distribution of samples from the CASH database. Later, a CASH overall quality score is calculated as the unweighted average of all individual scores. The CASH considers non-limiting level of AWC for coarse and medium plus fine textural classes of 0.13 and 0.16 g g^{-1}, respectively; aggregate stability for coarse, medium and fine textural classes of 400, 310 and 350 g kg^{-1}, respectively; ACE for coarse, medium and fine textural classes of 7.4, 6.5 and 5.9 mg g^{-1}, respectively; soil respiration for coarse + medium + fine textural classes 0.60 mg CO_2 g^{-1}; and active carbon for coarse, medium and fine textural classes 450, 500 and 575 mg kg^{-1}. The test could also cover surface and subsurface hardness if penetrometer readings are submitted with the samples. However, we did not use the penetrometer due to variable soil moisture at the time of sampling and presence of rocks in some fields.

3.2.3. Climate Measurements

In the absence of water stress, plant growth is driven primarily by the amount of photosynthetically active solar radiation intercepted by the canopy over a wide optimum temperature range. To account for the effect of temperature and the same time evaluate the effect planting date, we calculated a new variable, the cumulative solar radiation corrected with a temperature function (S_{fT}). This new variable was obtained by multiplying daily solar radiation times a temperature function f_T (Equation 1)

$$f_T = \frac{(T-T_n)^q \; x \; (T_x-T)}{(T_{op}-T_n)^q \; x \; (T_x-T_{op})} \qquad (1)$$

$$q = \frac{(T_n-T_{op})}{(T_{op}-T_x)} \qquad (2)$$

where T_n = 0˚C, T_{op} = 25˚C and T_x = 45˚C. If temperature (T, ˚C) is lower than the minimum temperature (Tn) or higher than the maximum temperature (Tx), then f_T = 0. The f_T not only sets the daily temperature limits, but also fine tunes for solar radiation availability by adjusting for a general optimum temperature (T_{op}) for growth and development.

Weather data were obtained from the NASA Land Data Assimilation Systems (NLDAS) reanalysis database at the closest grid point to each field. To characterize the weather behavior of Region 1 and Region 2 in 2016 and 2017 we used the calculated Standardized Precipitation Evapotranspiration Index (SPEI) described by Vicente-Serrano et al. (2010). The SPEI considers the difference between precipitation and potential evapotranspiration representing a multi-scalar index of drought. The reference evapotranspiration was calculated using the Penman-Monteith equation based on FAO56 (Allen et al, 2006), and the R code provided by the authors to calculate a monthly SPEI for the 2016 and 2017 seasons.

The warmer climate of Region 1 inherently allows producers to plant earlier than in Region 2. Due to the distinct temperature regimes and growing season onset date in these two regions, we re-scaled all planting dates in each region by creating a new variable called planting date offset (PDO) calculated as difference between the actual planting date per field and the first possible planting date based on temperature. The first possible planting date was defined as the day of the year when the 15-day central moving average temperature was greater than 13.5˚C, using a 38-year weather dataset representative of each region. On average, the first possible planting date considering the 38-year weather analysis was 1 May for Region 1 and 10 May for Region 2.

3.2.4. Statistical Analysis

Parametric and non-parametric regressions were used to identify the best models to predict soybean yield for each group of variables. For parametric analyses, we used SAS v. 9.4 (SAS Institute Inc.). In simple and multiple regression analyses, the SAS REG, RSQUARE, and STEPWISE procedures were used to generate candidate models. PROC GLM was used to test interactions. The criteria used to select the best agronomically sound model were the coefficient of determination (R^2), p-value, error variance, Mallow's Cp statistic, and PRESS statistic generated for each candidate model. PROC NLIN was used to estimate the parameters of linear-plateau functions.

Principal component analysis (PCA) with PROC FACTOR was used to deal with correlated predictor variables. Factor loadings close to or greater than 0.7 were used to interpret what each statistically significant factor represents. The principal components or factors were regressed against soybean yield using PROC GLMSELECT to identify factors significantly related to soybean yield. PROC REG was used to estimate the percentage soybean yield variability explained by the significant factors.

For non-parametric regression we used Random Forest (Breiman, 2001) from the R statistical software v. 3.5.1 (R Development Core Team, 2018). Random Forest is a diagnostic machine learning technique. For this relatively small data set, Random Forest allows exploring responses that do not fit simple linear or quadratic responses (Hoffman et al. 2017), which are diagnosed using partial dependence plots. The method is an aggregate of classification and regression trees which are created by an iterative partitioning of the data (Breiman et al., 1983). Analysis with the R Random Forest package starts with the full dataset in a single root node which then is recursively sliced into two nodes by the single predictor variable that explains the greatest variation in the response variable, and this slicing process continues until nodes cannot be sliced anymore or hold 1 % of total data (Breiman et al., 1984). In Random Forest, only a randomly selected subset of the predictor variables is used in each slice following the idea of bagging and resulting in independent trees (Breiman, 2001).

3.3. Results

3.3.1. Soybean Performance

In 2016, soybean yields ranged from 1.4 to 5.0 Mg ha^{-1}, mostly due to the variation in planting dates (Table 3.2). In 2017 and in contrast with 2016, precipitation was timely in most fields and yields were higher, from 3.5 to 7.4 Mg ha^{-1}. The highest yields occurred in Region 1. The average yields in Region 1 and Region 2 were 6.5 and 4.0 Mg ha^{-1}, respectively. In 2016, planting dates varied from 18 May to 13 July. In 2017, planting dates for Region 1 and Region 2 were on average 27 April (from 17 April to 4 May) and 20 May (from 13 to 27 May), respectively. Soybean RM groups varied from 3.1 to 3.8, with 80% of fields using RM group >

3.5. No yield response to soybean RM or population density was detected. Except for one field with low plant establishment in Region 2 in 2016, all other fields had adequate plant density.

3.3.2. Environment and Planting Date

The SPEI graphs indicate the monthly onset (negative) and end (positive) of drought events. In Region 1, the SPEI fell below zero in July and again in September of 2016 (Figure 3.1). In Region 2, the SPEI indicated that the drought started in March of 2016, reaching the historical low twice before it became positive in August. The latest planted plots (mid-July) in Region 2 were frost-killed on 11 October 2016 during grain filling. In 2017, fields from Region 1 benefited from timely precipitation throughout the entire season, while in Region 2 there was a drought during late summer, affecting the grain filling phase.

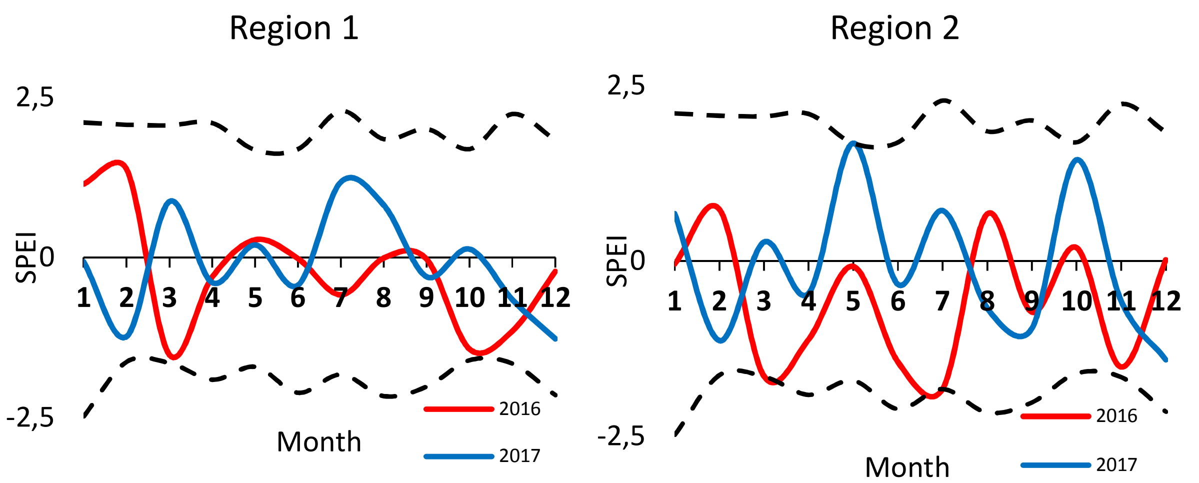


Figure 3.1. Standardized Precipitation Evapotranspiration Index (SPEI) of Region 1 and Region 2 for 2016 and 2017 weather data. Dashed lines are the minimum and maximum SPEI over a 38-year weather period, and the x-axis represent the months of the year.

The growing season cumulative precipitation and S_{fT} were positively correlated with soybean yield (R^2 of 0.57 and 0.67, respectively; *P*<0.0001, Table 3.4). Both S_{fT} and precipitation were associated with PDO (R^2 of 0.90 and 0.75, respectively). The warmer climate of Region 1 inherently allowed producers to plant earlier than in Region 2. Therefore, to assess planting date as a management strategy we used PDO in all analyses. The PDO explained 56% of the combined soybean yield variation.

Table 3.2. Average yield, planting date, onset planting date offset (PDO), S_{fT}, precipitation (PP) and soybean population. The same weather data was used in fields located in the same NLDAS grid cell.

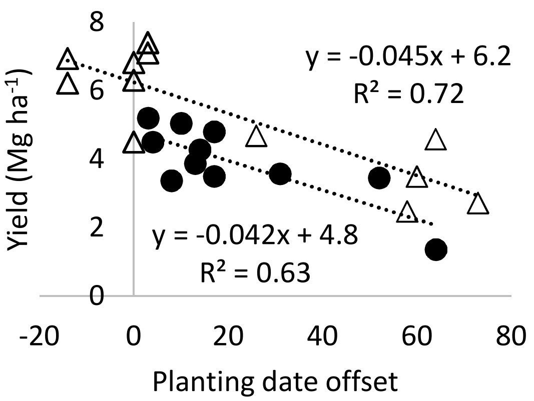
Region	Yield	Planting Date	Planting Date Offset	S_{fT}	PP†	Population
	Mg ha^{-1}			MJ m^{-2}	mm	pl m^{-2}
1.1	7.4	5/4/17	3	3088	645	33
1.2	7.1	5/4/17	3	3088	645	25
1.3	7.0	4/17/17	-14	3398	681	47
1.4	6.8	5/1/17	0	3176	661	36
1.5	6.3	5/1/17	0	3280	685	37
1.6	6.0	4/17/17	-14	3398	681	29
2.1	5.2	5/13/17	3	2939	605	32
2.2	5.0	5/20/16	10	2975	536	36
2.3	4.8	5/27/17	17	2545	515	29
1.7	4.7	5/26/16	26	2947	513	38
1.8	4.6	7/4/16	65	1975	400	45
1.9	4.5	5/1/17	0	3176	661	31
2.4	4.5	5/14/17	4	2935	605	23
2.5	4.4	5/24/17	14	2576	516	27
2.6	3.9	5/23/17	13	2595	516	21
2.7	3.6	6/10/16	31	2360	379	36
2.8	3.5	5/27/17	17	2545	515	30
1.10‡	3.5	6/30/16	61	2081	450	.
2.9	3.5	7/1/16	52	1896	310	47
2.10	3.4	5/18/16	8	2822	408	16
1.11	2.7	7/12/16	73	1801	357	48
1.12	2.5	6/27/16	58	2172	405	42

2.11	1.4	7/13/16	64	1611	267	36

†Cumulative, from one month prior to planting until October 1st for full season, and October 15th for double-cropping plantings.

‡Final plant population was not recorded.

All top yielding fields had higher S_{fT} availability and therefore a higher yield potential (Figure 3.2). The regression model for PDO showed that soybean yields were reduced linearly by approximately 45 and 42 kg ha^{-1} per day of planting delay on average for Region 1 and Region 2, respectively (P < 0.0001). The yield variation explained by PDO was 72% in Region 1 and 63% in Region 2. There were no interactions between S_{fT} or PDO with region and the slopes were similar between the two regions. The intercepts of the two regressions, 6.2 Mg ha^{-1} in Region 1 and 4.8 Mg ha^{-1} in Region 2, reveal a yield gap of 1.4 Mg ha^{-1} between these Regions, owing to the earlier absolute planting date in Region 1 afforded by a warmer climate.



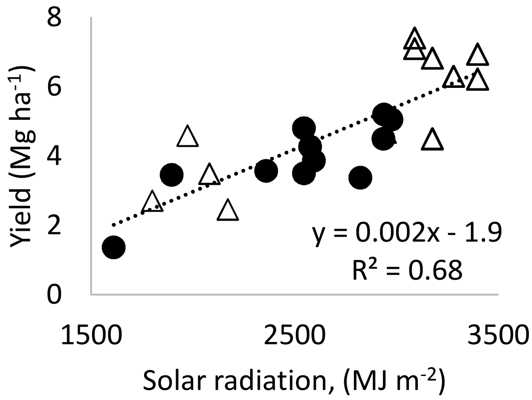


Figure 3.2. Simple linear regression of planting date offset and cumulative solar radiation corrected by temperature (S_{fT} in the text) with soybean yield (*P* < 0.0001) from all site-years studied in 2016 and 2017 in Regions 1 (triangle) and 2 (circle).

The number of days to physiological maturity and thus cumulative solar radiation from VE to R8 were strongly affected by planting date (both R^2s were higher than 0.95), which controlled the positive linear yield response to S_{fT} (R^2 = 0.68, Figure 3.2).

3.3.3. Soil and Environmental Factors

Overall, we collected data from 110 profiles and more than 600 soil layers (Table 3.3). Soil depth varied from 42 to 123 cm. Although soil depth was a statistically significant yield predictor (*P* = 0.02), it only explained about 5% of the total soybean yield variation. Thickness of the A horizon varied from 17 to 30 cm, except in one field that registered an uncommon thickness of 50 cm. Bulk density and SOM were predictably influenced by texture; for instance, the field with the highest sand content had the highest BD (1.7 Mg m^{-3}) and the lowest SOM content in individual soil layers (6 g kg^{-1}). Nutrient concentrations were mostly at or above optimum levels for phosphorous (P), potassium (K), magnesium (Mg), calcium (Ca) in the A horizon as defined by the PSU Ag Analytical Lab with only a few exceptions. In general, pH was close to neutral within the entire soil profile. Nutrients with low soil mobility such as P, Zn and

Cu presented the expected stratification of no-till managed fields. Although no symptom of nutrient deficiency was visually detected, the two research stations at Landisville and Rock Springs had on average the lowest soil nutrient concentrations.

Table 3.3. Depth of A horizon (Depth A), total soil depth (Depth), profile weighted averages of bulk density (BD), pH, soil organic matter (SOM), cation exchange capacity (CEC), and nutrient stocks of phosphorous (P), potassium (K), magnesium (Mg), calcium (Ca), zinc (Zn), copper (Cu), and sulfur (S) for the total soil depth.

Field	Depth A	Depth	BD	pH	SOM	CEC	P	K	Mg	Ca	Zn	Cu	S
	cm	cm	Mg m^{-3}		g kg^{-1}	meq $100g^{-1}$	kg ha^{-1}						
1.1	26	115	1.57	7.1	14	10.6	264	1638	5505	27344	25	39	221
1.2	24	108	1.45	6.9	19	9.1	432	3031	3080	19837	27	32	431
1.3	30	111	1.59	7.1	15	7.6	274	2100	3311	19635	41	27	223
1.4	50	107	1.50	6.9	20	8.4	492	4650	2795	14990	33	26	360
1.5	26	89	1.58	6.9	16	8.6	667	1757	2226	15971	42	26	167
1.6	28	104	1.55	6.9	17	9.8	152	1859	3076	23533	31	30	222
2.1	28	96	1.72	6.3	6	5.7	371	1328	1901	9110	18	29	419
2.2	21	94	1.46	6.2	16	8.0	446	1637	1794	11825	20	19	310
2.3	30	98	1.50	6.1	21	10.4	161	1095	1883	16974	15	14	986
1.7	22	72	1.37	6.6	17	8.7	122	864	1892	11268	11	12	197
1.8	30	117	1.32	7.0	16	8.3	136	1193	2959	16853	20	21	255
1.9	26	100	1.55	6.8	16	9.1	111	1325	2091	20927	16	16	370
2.4	17	102	1.68	5.4	9	6.3	342	2472	1246	6623	23	21	1595
2.5	27	97	1.53	6.5	14	8.8	463	2064	2417	15460	26	17	720
2.6	20	103	1.54	6.5	15	10.7	241	1403	2779	21210	15	22	468
2.7	24	98	1.41	6.5	15	6.9	188	1148	2137	16235	14	22	370
2.8	24	89	1.53	5.5	16	9.7	200	1202	1636	10982	10	15	927
1.10	26	114	1.36	6.9	17	8.4	196	1913	2989	17934	22	17	290
2.9	28	86	1.32	7.2	15	10.2	120	972	2702	16020	7	12	145
2.10	26	75	1.46	6.6	12	10.5	77	898	2620	13072	11	10	136
1.11	21	118	1.38	6.7	16	8.8	101	1111	2888	20567	5	20	339
1.12	21	114	1.22	7.4	17	10.6	98	928	2611	18587	4	16	225
2.11	24	76	1.45	7.1	15	10.4	92	999	2409	15577	4	10	128

In addition to the main climatic yield drivers (S_{fT} and precipitation), the best soil predictors of yield were nutrient stocks of Zn (R^2 = 53), Cu (R^2 = 51) and P (R^2 = 42, Table 3.4).

Table 3.4. Random Forest analysis of the best possible environmental and soil models using field averages of variables described in Tables 3.2 and 3.3 (n = 22).

Variable	Model								
	1	2	3	4	5	6	7	8	9
S_{fT}		X	X		X				
Precipitation		X		X	X				
Zn		X				X			X
Cu		X					X		X
P		X						X	X
All variables	X								
Mtry†	4	2	1	1	1	1	1	1	1
R^2 (%)	62	79	62	57	61	53	51	42	73

† Number of variables tried at each split.

Since there were many soil variables correlated to each other in this study, we used PCA to simplify the dataset. Five components (or factors) explained 86% of the overall variation in the dataset. Of these 5 factors, 3 were significantly related to soybean yield (Table 3.5). Factor 1 represented S_{fT}, precipitation, BD, P, Zn and Cu ($P < 0.001$), factor 3 represented depth of soil profile ($P = 0.02$), and factor 4 represented depth of A horizon and K ($P = 0.004$). Based on standardized coefficients, factor 1 had approximately 4 times more impact on soybean yield response than factors 3 and 4. Combined, factors 1, 3 and 4 explained approximately 84% of the soybean yield variation (Table 3.5). Factors 2 and 5 were not significantly correlated with soybean yield.

Table 3.5. Principal component analysis of field average data from tables 3.2 and 3.3 showing the significance of each factor, and the factor loadings (correlation coefficients) of each soil predictor within factor (n = 22). P-values represent the significance of each factor regressed against soybean yield.

	Factors				
	1	**2**	**3**	**4**	**5**
P-value	< 0.001	NS	0.02	0.004	NS
Variables	**Factor Loadings**				
S_{fT}	**0.91**	-0.06	0.07	0.15	0.01
Precipitation	**0.93**	-0.09	0.13	0.16	0.04
Depth of A horizon	0.21	0.24	-0.02	**0.77**	0.009
Soil depth	0.05	-0.007	**0.96**	0.16	-0.03
BD	**0.81**	-0.28	-0.09	-0.22	-0.24
pH	-0.16	0.88	0.21	0.18	0.16
SOM	-0.15	0.02	0.10	0.63	0.67
CEC	-0.22	0.25	-0.06	-0.12	0.86
P	**0.65**	-0.08	-0.04	0.40	-0.32
K	0.48	-0.10	0.24	**0.72**	-0.13
Mg	0.18	0.64	0.58	-0.06	0.27
Ca	0.12	0.51	0.59	-0.08	0.56
Zn	**0.80**	0.11	0.17	0.39	-0.12
Cu	**0.69**	0.23	0.59	0.02	-0.15
S	0.13	-0.94	0.09	-0.05	-0.08

In addition, we analyzed the data focusing on the nutrient concentration in the 0 - 15 cm soil top layer (Tables 3.6 and 3.7), a layer most commonly and easily sampled. Most fields had adequate levels of pH and nutrient content, considering critical levels of pH, Mg, P and K of 6.5, 60, 30 and 100 mg kg^{-1}, respectively. Both research farms and one field from Region 1 had P and K content below the critical level. Region 2 had one field with low pH and Mg content and another with K content below the critical level. Soil pH was below 6 in the top 15-cm soil layer only in 4 fields. The PCA for this soil layer did not differ from that of the entire soil profile.

Table 3.6. Minimum, average and maximum clay, silt, sand, BD, SOM, pH, CEC and concentration of soil nutrients determined with Mehlich-3 extractant in the 15-cm of topsoil of all sampling units in both years (n=110).

Variable	Unit	Minimum	Mean	Maximum	Standard Deviation
BD	Mg m^{-3}	0.9	1.4	1.6	0.1
Clay	g kg^{-1}	90	210	370	70
Silt		150	480	620	100
Sand		100	310	760	140
SOM		10	24	39	6
pH		4.3	6.4	7.6	0.7
CEC	meq 100 g^{-1}	2	10	17	3
P	mg kg^{-1}	5	68	392	63
K		39	181	640	135
Mg		29	158	521	78
Ca		561	1243	3061	442
Zn		0	5	36	4
Cu		1	3	11	2
S		2	11	21	4

Random Forest analysis showed that models combining Zn, Cu, S and P within the top 15-cm soil layer explained from 50 to 65% of the total yield variability, and the most important individual yield soil predictor was Zn (R^2 = 0.47, Table 3.7). The climate variables S_{fT} (R^2 = 0.85) and precipitation (R^2 = 0.82) were still more important predictors of soybean yield than any soil variable.

Table 3.7. Random Forest analysis showing the best possible soil models using the 0 – 15 cm soil layer dataset (n = 110). Mtry is the number of variables randomly tried to do each split.

Variables	Models																				
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
S_{fT}	X	X																			X
Precipitation	X		X																		X
Zn	X			X	X	X	X	X	X	X	X	X	X		X		X				X
Cu	X			X	X	X	X	X	X	X	X	X	X	X		X			X		X
S	X			X	X	X	X	X	X	X	X	X		X	X			X			X
P	X			X	X	X	X	X	X	X	X					X				X	X
pH	X			X	X	X	X	X	X	X											
Mg	X			X	X	X	X	X	X												
K	X			X	X	X	X	X													
BD	X			X	X	X	X														
SOM	X			X	X	X															
Ca	X			X	X																
CEC	X			X																	
Mtry	4	1	1	4	3	3	3	3	3	3	2	2	1	1	1	1	1	1	1	1	2
R^2 (%)	81	85	82	69	70	70	70	71	71	69	65	65	64	62	52	50	47	30	29	24	82

Random Forest variable importance plots from analysis presented in Tables 3.4 and 3.7 showed a similar importance pattern, with S_{fT} explaining the most soybean yield variability and P the least (Figure 3.3). The S signal was not captured when analyzing the entire soil profile (Panel A, Figure 3.3).

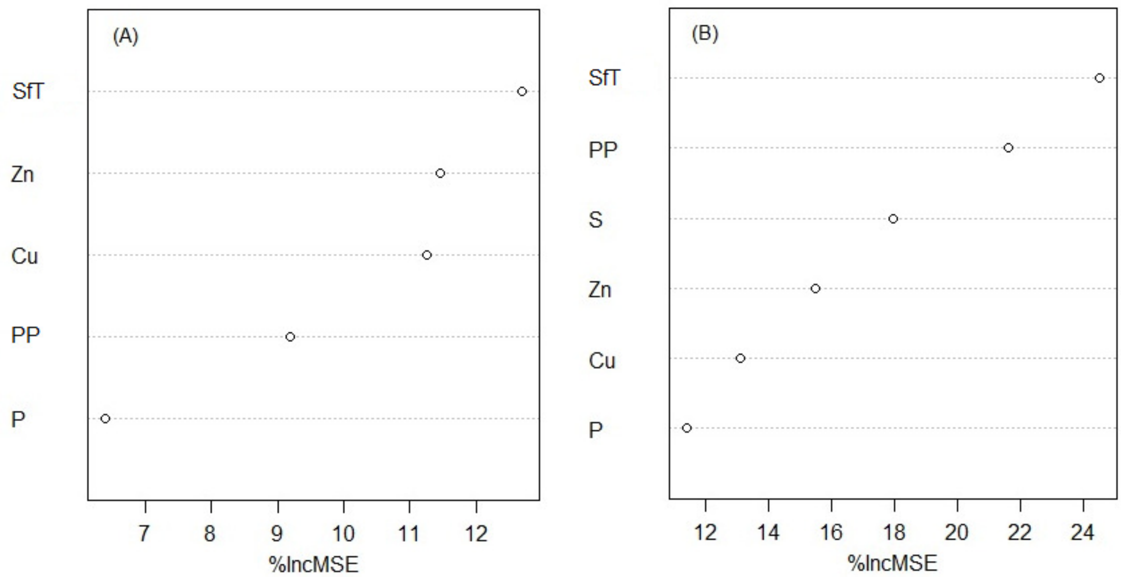


Figure 3.3. Variable importance plots from Random Forest regression analysis presented in Table 3.4 (A, $R^2 = 0.79$) and Table 3.7 (B, $R^2 = 0.82$). Number of trees: 500. Number of variables tried in each split: 2.

Analyzing individual data from the 65 sampling units collected in 2017, we found that SOM was positively related to gravimetric soil water content at - 0.3 bar ($y = 0.04x + 0.11$, $R^2 = 0.41$) and - 15 bar ($y = 0.03x + 0.02$, $R^2 = 0.61$), but no effect was found in AWC ($R^2=0.02$). There is evidence that the amount of water a soil can hold between field capacity and permanent wilting point is a good crop yield predictor (Yang et al., 2014; Williams et al., 2016), but we did not find a strong relationship between AWC and soybean yield. Available water capacity was significantly related to soybean yield (P = 0.01, 65 observations) and it explained 9.5% of the soybean yield variation in 2017.

3.3.4. Cornell Assessment of Soil Health

We used the CASH test to determine how each field would rank relative to soil heath. In this study, 10 out of 13 fields analyzed were rated excellent (rating between 60 and 80), which interpret as soil having no limitation to express the yield or soil without soil physical, biological or chemical limitations. (Table 3.8). We did not find any relationship of soybean yield with the CASH score nor with individual indicators, possibly because most fields were in the optimum fertility range (Figure 3.4).

Table 3.8. Field averages of the Cornell overall quality score, available water capacity (AWC), aggregate stability, ACE protein index, soil respiration, active carbon, and textural class.

Region	Cornell Score	AWC	Aggregate Stability	ACE Protein	Soil Respiration	Active Carbon	Textural Class
	%	$g\ g^{-1}$	$g\ kg^{-1}$	$mg\ g^{-1}$	mg	$mg\ kg^{-1}$	
1	59	0.33	58	4.1	0.5	440	Silt Loam
1	65	0.32	114	6.1	0.6	586	Silt Loam
1	71	0.26	242	5.3	0.6	443	Silt Loam
1	71	0.30	141	5.3	0.6	471	Silt Loam
1	62	0.28	236	4.9	0.5	517	Silt Loam
1	77	0.33	327	6.8	0.5	517	Silt Loam
2	55	0.15	272	4.5	0.3	312	Sandy Loam
2	71	0.23	308	6.2	0.6	462	Silty Clay Loam
1	66	0.23	343	5.1	0.4	451	Silty Clay Loam
2	72	0.20	334	6.5	0.5	445	Sandy Loam
2	79	0.32	262	8.7	0.6	718	Silt Loam
2	63	0.30	174	4.1	0.4	401	Silt Loam
2	53	0.21	162	5.0	0.4	408	Silt Loam

The ratio of soil respiration to SOM was the only calculated variable with a relationship with yield, albeit with a different slope and intercept depending on the region (Figure 3.4). Available water capacity ($R^2 = 0.41$, $P = 0.02$) and soil respiration ($R^2 = 0.46$, $P = 0.01$) were both positively related to active carbon. In addition, AWC was related to soil respiration ($R^2 = 0.32$, $P = 0.04$).

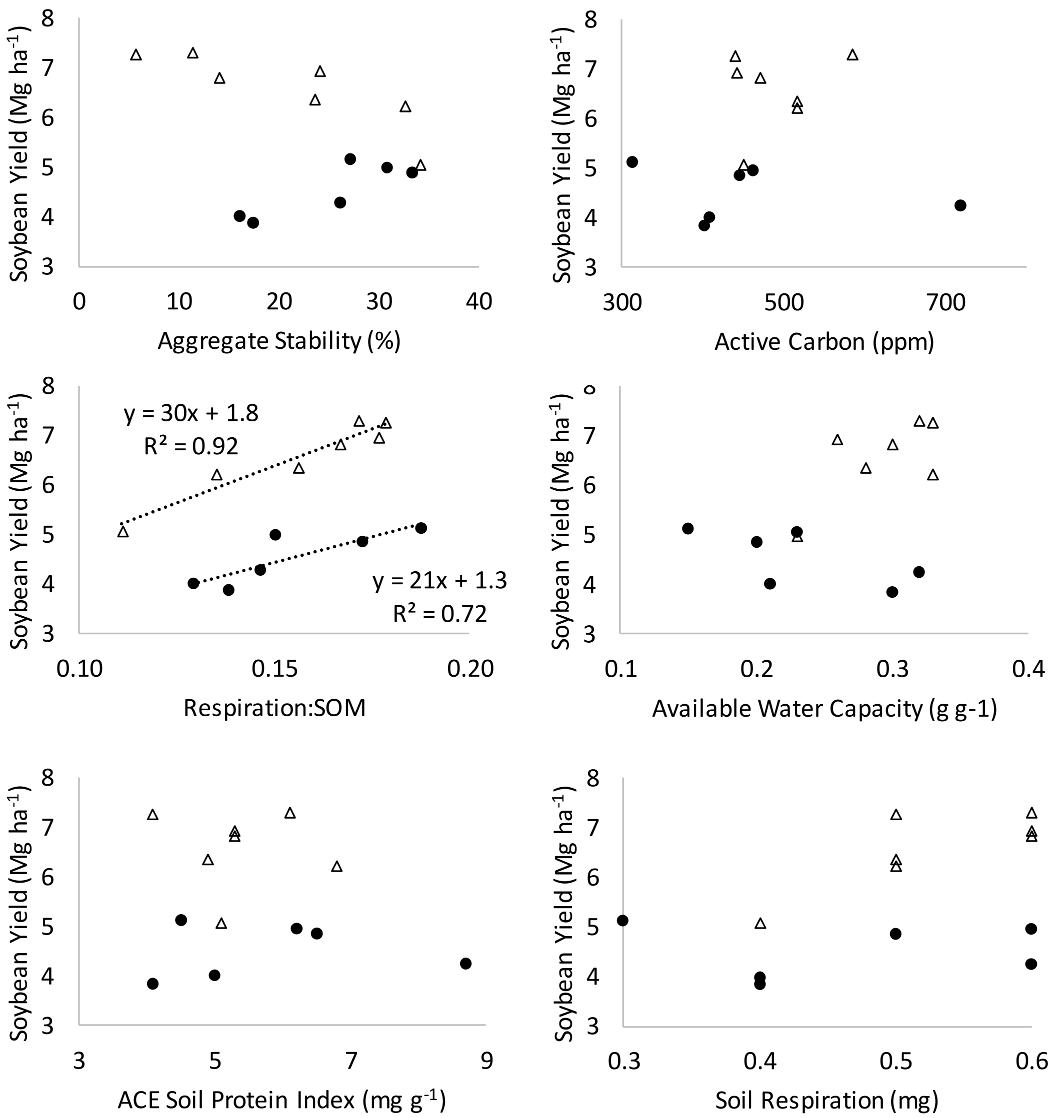


Figure 3.4. Simple linear regression of soybean yield against the CASH variables measured in 2017 in Region 1 (triangles) and Region 2 (circles).

Even though soybean yield showed no response to aggregate stability, it was rated low in some of the highest yielding fields that we studied. For instance, CASH scored aggregate stability 17 out of 100 in a field from Region 1, suggesting potential constraints to aeration, water infiltration, rooting, crusting, sealing, erosion, and runoff. However, this field attained the fourth largest yield (6.8 Mg ha^{-1}), had the third highest K_{sat} (807 cm d^{-1}), and had the fifth longest rooting depth (85 cm) of all fields studied.

3.3.5. Saturated Hydraulic Conductivity and Root Depth

Root depth and K_{sat} were positively correlated (P = 0.001, R^2 = 0.71) and exhibited great measurement variability, ranging from 30 to 114 cm and 31 to 2143 cm d^{-1}, respectively (Table 3.9).

Table 3.9. Minimum, mean, maximum and standard deviation of measured K_{sat} (K_{sat} SATURO) and root depth of 14 fields evaluated in 2017, and the calculated K_{sat} using Saxton and Rawls (2006) model (K_{sat} S&R).

Region	K_{sat} S&R	K_{sat} SATURO				Root Depth			
		Min	Mean	Max	SD	Min	Mean	Max	SD
	-------------------------- cm d^{-1} --------------------------					--------------- cm d^{-1} -------------			
1	19	196	366	533	162	90	95	114	11
1	29	419	888	1909	285	60	92	110	23
1	23	574	928	1173	238	90	108	115	10
1	17	272	807	2143	568	60	85	90	14
1†	.	.	.	.	.	46	87	109	26
1	20	98	196	239	77	60	80	101	19
2	119	71	337	571	111	60	78	90	16
2	23	125	306	672	304	60	80	114	23
1	19	570	703	948	224	60	90	110	21

2	55	110	442	907	168	30	72	90	27
2†	.	.	.	.	.	60	75	90	17
2†	.	.	.	.	.	30	79	113	35
2	26	90	193	380	60	50	75	90	19
2‡	40	31	75	119	55	.	.	.	.

† K_{sat} not measured. ‡ Root depth was not estimated.

Simple regression analysis of root depth showed a good positive quadratic response to soybean yield (P = 0.002, R^2 = 0.60), whereas K_{sat} explained 47% of the yield variability. Both variables presented a curvilinear pattern, similarly to nutrient response curves, where the yield increases until a critical point after which it plateaus. The critical K_{sat} in this dataset was 236 cm d^{-1}, and the linear-plateau equation explained 47% of the yield variation with a maximum soybean yield of 6 Mg ha^{-1} (Figure 3.5).

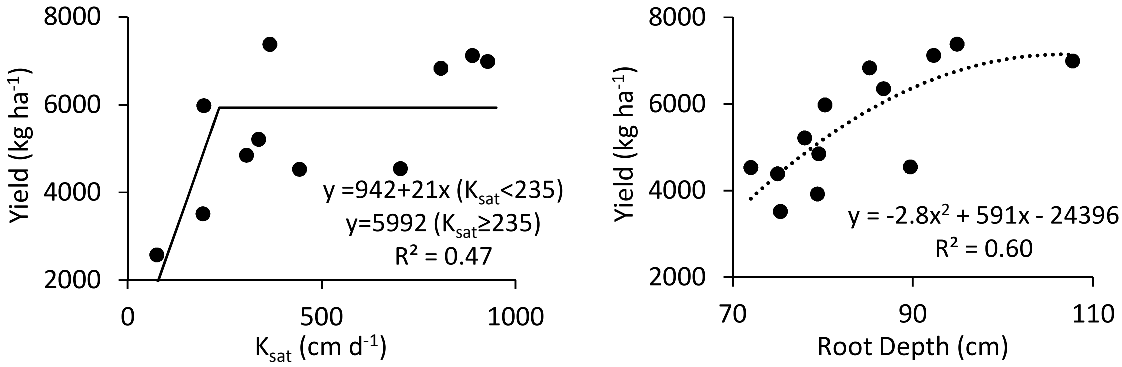


Figure 3.5. Regression of soybean yield against K_{sat} (P < 0.01) and root depth (P < 0.002).

Although, as expected, clay and sand were statistically significant predictors of soil gravimetric water content at - 30 kPa (R^2 = 0.46 and 0.51, respectively; P < 0.001, n = 65) and - 1500 kPa (R^2 = 0.64 and 0.58, respectively; P < 0.001, n = 65), soil texture did not influence K_{sat} in our study.

The best measured soil predictor of K_{sat} was Ca concentration (R^2 = 0.34, P = 0.059). The fields with the highest K_{sat} frequently showed earthworm activity, whereas the fields with the lowest K_{sat} were compacted or surface-crusted soils. Our measured K_{sats} were on average 13-fold greater than that calculated with Saxton and Rawls (2006) pedotransfer functions.

3.4. Discussion

While as expected planting date was the main control of soybean yield (Carter and Hartwig, 1963), there was substantial yield variability at a given planting date. Most yield responses to planting date in the U.S. vary at rates between 0.09 and 1.7% per day of planting delay (Beuerlein, 1988; Egli and Cornelius, 2009; Salmerón et al., 2016). In this study, the yield loss rate was 0.6% per day, or 0.2 g MJ^{-1} when expressed per unit of temperature corrected solar radiation (S_{FT}) over the growing season; however, yield can vary by ± 1 Mg ha^{-1} for a given level of growing season S_{FT} (Fig. 2).

Soil depth is normally a yield limiting factor in dry years in Pennsylvania, and it is also known to be responsible for large yield variations (Sadras and Calviño, 2001). However, in our study, the response to soil depth and AWC was probably subdued because the pattern of precipitation did not allow an expression of soil-depth and water-storage effect: late planting dates in 2016 and timely precipitation events in 2017.

In Pennsylvania, deficiencies of Cu or Zn in soybean are rare and therefore yield response curves for these micronutrients were not established. Normal ranges of Zn and Cu content in Pennsylvania determined using Mehlich-3 extractant are 1.1 to 9.4 and 1.2 to 5.5 mg kg^{-1} (Beagle et al., 2014). The positive relationship between yield and these two micronutrients is likely not a response to nutrient supply but an artifact of a history of manure applications. Several studies demonstrated that both Zn and Cu accumulate in soils that are manured yearly (McBride and Spiers, 2001; Mantovi et al., 2003; Brock et al., 2006; Benke et al., 2008; Berenguer et al., 2008; Sheppard and Sanipelli, 2012). We calculated the mass of Zn and Cu addition using the median concentration of Zn and Cu of 1,100 to 2,600 dairy, swine and poultry manure sample analyses provided by the Penn State Ag Analytical laboratory, the average reported manure application rates, and the mass of nutrient extracted by the grain harvest using the soybean grain Cu and Zn content described by Reddy et al., 1989. Based on these figures, each application of dairy, swine and poultry manure adds 0.6, 1 and 3 kg ha^{-1} of Zn and 0.16, 0.21 and 0.54 kg ha^{-1} of Cu, respectively. Soybean removal of Zn and Cu for a 5 Mg ha^{-1} grain yield is 0.3 and 0.1 kg ha^{-1}, respectively. McBride and Spiers (2001) estimated an annual application of 0.9 and 0.35 kg ha^{-1} of Zn and Cu to New York farmlands for a median dairy manure composition and application rate. These results indicate that manure application can result in an accumulation of Zn and Cu in soils cultivated with soybeans. Frequent manure applications can affect physical, chemical and biological properties of soils and ultimately yield. For example, Bandyopadhyay et al. (2010) found lower soil bulk density and penetration resistance, and greater hydraulic conductivity, size of aggregates, SOM, root length, and soybean yield after four years of manure application; and Hati et al. (2007) showed improvements in AWC and crop yields after 28 years of manure application. While excessive manure applications can lead to toxic levels and environmental concerns (Petersen et al., 2007), a study in the northeastern U.S. found that current Cu and Zn levels in agricultural soils were not toxic (Brock et al., 2006).

The role of SOM in agricultural sustainability is recognized, but SOM is not always related to crop productivity (Sojka and Upchurch, 1999). The stock of SOM alone may not be a good indicator of soil condition, but it has been proposed that stratification ratios of soil organic carbon and nitrogen pools (e.g., particulate organic carbon, microbial biomass and potential carbon and nitrogen mineralization) could be indicators of soil quality, impacts of soil management and crop productivity (Franzluebbers, 2002; Hurisso et al., 2016). The potential nutrient mineralization can be estimated indirectly via quantification of microbial activity by soil respiration (Haney et al., 2008), and there is evidence that the soil respiration rate is determined more by the amount of substrate available rather than by the size of the microbial biomass (Wang et al. 2003). The significant yield response to the ratio of soil respiration to SOM indicates that rather than the absolute individual SOM or soil respiration rate, a potential soil indicator of relevance to crop yield is the relative biological activity of the soil. Since the ratio of microbial activity to SOM benefits plant growth through mineralization of nutrients (Gupta and Germida, 2015), it can be considered an indicator of SOM quality. In our study, however, the intercept of the response to yield was dependent on the region. Generalizing this indicator can be challenging.

One of the simplest indicators of soil condition in agricultural fields is crop yield (Bünemann et al., 2018); it is perhaps the only single indicator that combines chemical, physical and biological aspects. The weakness of crop yield as an indicator is that different plant species have different sensitivity to soil properties and that the yield potential varies with local agroclimatic conditions. But even accounting for agroclimatic conditions, the many abiotic and biotic environmental interacting factors that determine yield makes it challenging to isolate the relationships among CASH variables and crop yield, which could lead to seemingly contradictory reports of the relationship between CASH metrics and crop yields (Svoray et al., 2015; Roper et al., 2017; van Es and Karlen 2019). These results, rather than diminishing the importance of CASH tests, underscore that it needs to be interpreted within a broader context of factors that influence crop yield. Soil health is not an intensive property like temperature or water potential that can be measured with standards and related to thermodynamic properties, but a holistic assessment of the soil condition in a given context.

Even though we did not find any relationship between soybean yield and soil physical variables measured with the CASH methodology, soil physical properties can be the ultimate driver that limits nutrient and water capture via its control on water infiltration, water storage, and root exploration of the soil volume. Field-measured K_{sat} values can be indicators in the true sense of the word, collecting multiple properties in one variable. The theoretical predictions of K_{sat} using Saxton and Rawls (2006) pedotransfer function suggest K_{sat} differences from a sandy to a clayey soil of approximately 190-fold. However, our K_{sat} data did not show any relationship with soil particle size and the measurements were much higher than the K_{sat} predictions using Saxton and Rawls (2006). Clothier and Smettem (1990) also did not find a relationship between particle size and K_{sat} and suggested that K_{sat} was dominated by biogenic macroporosity, which is not detected in laboratory measurements that capture mainly the matrix-dominated water flow. Field measurement of K_{sat} does capture this macroporosity. The K_{sat} measurements were high when compared with the K_{sat} estimated from the Saxton and Rawls (2006) pedotransfer function, but our readings were similar to other field-measured K_{sat} (Moore et al., 1986; Blanco-Canqui et al., 2017; Gonzales et al., 2018). Infiltration rate was also related to wheat yield (Ernst et al., 2018). Clearly, these results suggest that macropore flow was a main component of the field K_{sat} variability, and both an indicator and cause of soil condition and soybean yield.

Roots normally grow through cracks, holes, or between soil aggregates following the path of least resistance in the soil to root elongation (Russell, 1977; Stirzaker et al., 1996), and increase in diameter when physically obstructed (Bengough and Mullins, 1990). It is hard to establish a cause and effect relationship between K_{sat} and root depth in our field observational study. Yet, infiltration measurements have been recommended as an indirect method to quantify macroporosity (Edwards et al., 1993) which in turn can facilitate root growth. The warmer climate from Region 1 not only allowed roots to grow for a longer period compared to Region 2, but also to maximize yields in double-cropping systems.

Region 1 is naturally a high crop yielding environment of Pennsylvania with longer growing seasons, deeper soils with good water holding capacity and high biogenic activity promoted by yearly animal manure applications that facilitate nutrient mineralization potential and deeper root growth. The high solar radiation availability of Region 1 maximizes the soybean yield potential while the exceptional biophysical soil properties allow for the expression of top soybean yields.

3.5. Conclusions

In this study, cumulative solar radiation over the growing season and available precipitation were the main drivers of soybean yield. Our data confirmed that planting date is the main management practice to control soybean yield potential in Pennsylvania, but only soils with certain properties enable realizing this potential. Our results showed that current CASH metrics did not relate to soybean yield, and that defining soil indicators of soil “health” can be challenging. However, *in-situ* measurements of K_{sat} more better related to soybean yields than any laboratory test. While the soybean yield responses to field K_{sat} can vary with the production environment, our results suggest that K_{sat} can be a valuable indicator of soil productivity.

Chapter 4. A Comparative Analysis of Soybean Yield Potential in the Mid-Atlantic United States and Southern Brazil

CORE IDEAS

- The simulation model Cycles allowed quantifying soybean yield gaps and agricultural intensification potential in four distinct regions.
- Soybean yield gaps due to water and management in the mid-Atlantic U.S. and southern Brazil exist and can be remediated.
- It is possible to improve solar radiation and water capture efficiencies by double-cropping in all regions and by producing a third crop per year in Brazil.
- Double-cropping soybean yields were greater than full season yields in Brazil.

ABSTRACT

The first step towards increasing sustainable soybean production may be to assess how close the current yields are to the yield potential and how efficient we are using the available solar radiation and water. Field data were collected in four regions, two in Pennsylvania and two in Southern Brazil. The simulation model Cycles was used to quantify the biophysical soybean yield potential and indicators of resource capture were calculated. The potential and water-limited soybean yields averaged for the four environments studied and from 2008 to 2017 were 5.8 and 4.8 Mg ha^{-1} (dry weight). The total measured yield gap varied from 5 to 48% within regions. There is great potential to increase soybean yields with the available solar radiation and water resources through improved management tactics in the 3 of the 4 regions studied. Water capture efficiency, or the cumulative soybean transpiration divided by the available soil

water over the growing season, of full season soybean systems varied from 47 to 67%. Even though soybean yields were limited by water availability due to a non-uniform distribution of precipitation during the growing season in some regions, there was enough water for a second crop per year in all regions. In full season soybean systems, 50 to 74% of the solar radiation available was used compared to 77 and 87% with double-cropping systems in Brazil and the U.S., respectively. In Pennsylvania, agriculture intensification is limited to double-cropping due to low temperatures that limit the usage of available solar radiation, while in some regions in Brazil it is possible to produce a third crop per year.

4.1 Introduction

Soybean [*Glycine max* (L.) Merr.] is one of the most important crop commodities in the U.S. and Brazil, and both countries together produce around two-thirds of the world supply. Technological improvements in soybean production that reduce yield losses from nutrient limitations, weeds, diseases and pests have resulted in impressive improvements in yields during the past decades (Specht et al., 1999; Cooper, 2003). As these management limitations have been addressed, biophysical constraints to soybean production have become more limiting, making it valuable to understand solar radiation and water limitations to yield in local environments.

The yield potential, or the yield of a non-stressed crop, is determined by the available environmental resources and the ability of the plant to capture and convert them to biomass (Monteith, 1981). Soybean yields in both Brazil and the U.S. vary under similar management regimes, with some fields producing exceptional grain yields (> 6 Mg ha^{-1}) and others moderate to low yields. Understanding the environmental conditions that limit these yields underpins our ability to continue expanding productivity barriers and to realize the yield potential determined by locally dominant yield drivers (de Wit, 1965; Fischer et al., 2014).

A benefit of assessing the biophysical yield potential and natural resource limitations to plant growth is the ability to estimate yield gaps in various production systems. Yield gap is defined as the difference between average and the local potential yield (Lobell et al., 2009). Yield gaps often arise due to management defects that can be addressed. In the tropics, there is evidence that yield gaps are more related to poor soil fertility and severe weeds, diseases and insect pressure than in temperate regions (Affholder et al., 2013; Tay et al., 2013; Godoy et al., 2016). The term water-limited yield has been proposed to refer to the yield producers can reach under rainfed conditions by managing stresses such as nutrients, weeds, pests and diseases (Lobell et al., 2009). Water-limited yields will always be lower than potential yields, and the yield gap determined by water is a measure of the water stress of that particular environment. Finding current yield gaps locally is imperative to identify management strategies to either reduce water stress or improve pest or nutrient management.

Another benefit of the characterization of the biophysical resource use is to estimate the potential for sustainable agricultural intensification of local cropping systems. This could include double or triple cropping if enough resources are available. Double-cropping can increase land productivity by improving resource use compared to full season systems (Caviglia et al., 2010; Andrade et al., 2015). In temperate regions that can accommodate a winter grain crop and a summer crop, one of the most prevalent double-cropping systems is wheat (*Triticum aestivum* L.) or barley (*Hordeum vulgare* L.) followed by soybean. In these systems, the soybean planting date is determined by the maturity and harvest of the winter cereal. In northern latitudes, this planting date often falls outside the optimum time window to maximize soybean yields (Beuerlein, 1988). However, the combined production and profit of double cropping system can be larger than that of wheat or soybean alone (Burton et al., 1996; Kelley, 2003; Kyei-Boahen and Zhang, 2006), and yields are more stable than single crops (Andrade and Satorre, 2015). The task of assessing the cascade of effects associated with increases in agricultural output can be simplified and accomplished with efficiency by using agricultural systems simulation models.

Simulation models are the best tool available to estimate crop yield potential based on biophysical data, and therefore assess yield gaps and possible yield limiting factors (Van Ittersum et al., 2013). Crop models allow the evaluation of crop performance under different environments and can assess how efficient different production systems use local resources (Van Opstal et al. 2011; Grassini et al., 2015; Zanon et al., 2016; Rattalino Edreira et al., 2018). Multiple year field studies to verify crop management and weather interactions can be costly. An accurate model supported with reliable soil and long-term weather data can be an effective tool to explore soil-climate-management interactions, determine tradeoffs of management strategies, and assess the soybean yield response to planting dates in different environments rapidly (Whisler et al., 1986; Boote et al., 1996; Meinke et al., 2001; Mercau et al., 2007). Models can also be useful in assessing the potential impacts of climate change over the long term (Prasad et al., 2018).

The objective of this research is threefold: first, to evaluate the biophysical potential for soybean production in two contrasting regions of the world, the mid-Atlantic United States and subtropical southern Brazil; second, to estimate yield gaps in these distinct environments; and third, to estimate the potential for double or triple cropping in these environments based on solar radiation and water availability.

4.2. Materials and Methods

To accomplish the project objectives, there were three phases to this research. First, the predictive accuracy of the simulation model Cycles was tested across all the U.S. and Brazilian environments for soil water content and yield. These environments included multiple planting dates and years at each of the two research stations in Brazil. In the U.S., eleven site-years of data were used for each of the two regions, consisting of different locations and planting dates. Secondly, the biophysical yield potential for each of the four environments using representative fields, management and planting dates were calculated and yield gaps due to water stress and management were estimated. In the third phase, the potential of double and triple cropping production systems was evaluated using the representative field environments with the Cycles model by assessing potential resource capture efficiencies.

4.2.1. Field Data

Soil, weather and crop data were collected from 39 field studies at or near four research stations, two in Pennsylvania at the Penn State Russell E. Larson Agricultural Research Farm at Rock Springs (US1) and the Penn State Southeast Agricultural Research and Extension Center in Landisville (SEAREC) (US2), and two in Brazil, at the Brazilian Agricultural Research Corporation (Embrapa Wheat) in Passo Fundo, in the state of Rio Grande do Sul (BR1), and at the Agrária Foundation for Agricultural Research (FAPA) in Guarapuava, in the state of Paraná (BR2, Table 4.1).

Table 4.1. Location, soil and climate of the four regions studied.

Region	Latitude	Longitude	Elevation	Climate†	Soil
			m		
BR1	28˚15’ S	52˚24’ W	650	Cfa	Rhodic Hapludox (Clayey Oxisol) or Distroferric Red Latosol according to the Brazilian system soil classification (Santos et al. 2006)
BR2	25˚33’ S	51˚29’ W	1100	Cfb	Hapludox (Clayey Oxisol) or Brown Latosol according to the Brazilian system soil classification (Santos et al. 2006)
US1	40˚51’ N	77˚50’ W	330	Dfb	Hagerstown silt loam, fine, mixed, semiactive, mesic Typic Hapludalfs; Hublesburg silt loam, clayey, illitic, mesic Typic Hapludults; Morrison sandy loam, fine-loamy, mixed, active Ultic Hapludalfs; and Murrill fine-loamy, mixed, semiactive, mesic Typic Hapludults
US2	40˚16’ N	77˚31’ W	110	Cwa	Hagerstown silt loam, fine, mixed, semiactive, mesic Typic Hapludalfs; Duffield silt loam, fine-loamy, mixed, active, mesic Ultic Hapludalfs; Clarksburg silt loam, fine-loamy, mixed, superactive, mesic Oxyaquic Fragiudalfs

† Köppen-Geiger climate classification system

According to the Köppen-Geiger climate classification system, the US1 and US2 regions have a temperate climate classified as humid continental (Dfb) and mild temperate (Cwa), respectively, and BR1 and BR2 have a subtropical climate classified as humid subtropical (Cfa) and highland humid subtropical (Cfb), respectively.

In Pennsylvania, data were collected from 9 fields in 2016 and 13 in 2017 from 10 producers, totaling 22 site-years equally balanced between regions US1 and US2. All fields were commercially managed by producers, except in 2016 at Rock Springs and at the SEAREC, where data were collected from research plots. Commercial fields were located within a 20 km radius from each research farm in both regions. The distance between regions US1 and US2 is approximately 200 km.

In Brazil, data were collected from replicated research trials conducted from 2012 to 2015. These included different soybean varieties and planting dates for 3 years in each region. The field studies were conducted from 2012 to 2014 at BR1 and from 2013 to 2015 at BR2. The distance between regions BR1 and BR2 is approximately 500 km. Data from the same soybean variety, BMX Apolo RR, was selected for the model simulations in Brazil.

Emergence, flowering and physiological maturity dates were recorded following Fehr and Caviness (1977). Five sampling units were selected per commercial field after soybean establishment and the plant and soil measurements were conducted over the same individual sampling unit (1-2 m^2) where all plant measurements were done in three 1-m row sections of plants from the 3 middle soybean rows. Soybean aboveground biomass was dried at 50˚C until constant weight, and yield was estimated by threshing the dried aboveground biomass sampled at R8 and weighing the grain mass. Harvest index at R8 was calculated in the U.S. regions using the dried aboveground biomass and grain mass. In all research plots, soybean grain was harvested using a research scale Wintersteiger combine by cutting the middle 3 soybean rows.

Soil cores were taken from the center of each sampling unit using a tractor-mounted hydraulic soil coring system (Giddings Inc.) that allowed obtaining up to 1.2 m long x 42 mm in diameter soil cores inside plastic liners. Soil samples were collected immediately after soybean harvest. The intact soil cores were laid out for observation in the laboratory and multiple soil layers were separated in each soil sample. All samples were air-dried and sieved (2-mm mesh) for soil organic matter (SOM), and particle size analyses. Sub-samples from each soil layer were oven-dried at 105°C for 24 h for gravimetric water content and bulk density determinations. In 2017, at regions US1 and US2, root depth was visually estimated using these soil cores, and an undisturbed sample was collected in every sampling unit using a stainless-steel cylinder of 7.5-cm diameter and 6-cm height to estimate water content at field capacity and permanent wilting point of the top 6 cm soil layer.

In the U.S., clay content was measured in each soil layer using the laser diffraction method (Chapter 2; Faé et al., 2019). In Brazil, clay was determined by the hydrometer method (Gee and Or, 2002). In both regions, the USDA classification system was followed (USDA, 2017). Sand was estimated using the sieve method (Gee and Or, 2002). Soil organic matter content was analyzed by loss on ignition (Schulte and Hoskins, 2011). In the U.S. and in 2017, saturated hydraulic conductivity was measured with an automated field dual-head infiltrometer (SATURO, METER Group Inc.), and water content at field capacity (fc, -33 kPa) and permanent wilting point (pwp, -1500 kPa) were measured using the soil moisture PM compressor FSM Jenny Pressure Plate pressure plate extractor (Dane and Hopmans, 2002; Burt, 2004).

Weekly soil water content measurements were taken from planting to maturity at SEAREC using a capacitance probe (Diviner 2000, Sentek Pty Ltd, Stepney, Australia) that reported data at 10-cm soil depth intervals. The Diviner access tubes were inserted in the same soil profile where the samples were taken with the Giddings probe to measure particle size and SOM. Since a reliable calibration equation for the Diviner was not found for the research site, the fc and pwp water content of each soil layer were calculated with the Saxton and Rawls (2006) pedotransfer function and used to scale the field scaled frequency measurements in between these boundaries (Equation 1) as follows:

$$\Theta = \Theta_{\mathrm{pwp}} + \left(\Theta_{\mathrm{fc}} - \Theta_{\mathrm{pwp}}\right) x \left[\frac{(R-R_n)}{R_x-R_n}\right]^5, \qquad (1)$$

where Θ is soil water content, R is the raw measured scaled frequency reading, R_n is the minimum scaled frequency reading in the layer, R_x is the maximum scaled frequency reading in that layer. The R_n and R_x considered the readings from the entire growing season. This approach was only appropriate because 2016 was a dry year that allowed the soil to dry until the Θ_{pwp}. The power of 5 accounts for the non-linear change in the signal with soil moisture and was selected to match observed and modeled soil moisture patterns. The goal with this approach was to compare the measured and simulated soil moisture fluctuations to investigate if Cycles can capture the seasonal soil moisture variability. Measurements were performed once a week in one plot in each of the 5 replications in two soybean planting dates (June 26 and July 12).

4.2.2. The Cycles Model

Cycles is a multi-crop, multi-year, process-based model with daily time step simulations of crop production and the water, carbon and nitrogen cycles. The model is an evolution of C-FARM (Kemanian et al., 2010) and is closely related to CropSyst (Stöckle et al., 2003). The hydrology is simulated with an adaptive sub-daily time step. The algorithms of heat and water transport were adapted from Campbell (1985). The reference evapotranspiration is calculated using the Penman-Monteith equation described in FAO56 (Allen et al, 2006). Daily plant growth is based either on the radiation capture (light limited) and or on the realized transpiration (water limited), whichever is less, an approach that is a surrogate for a coupled transpiration and photosynthesis model (Kremer et al., 2008). In Cycles, the stomatal conductance is determined by temperature and the leaf water potential. Crop development is calculated using thermal time, and grain yield is calculated using the biomass accrued and the harvest index (Kemanian et al., 2007). The minimum inputs to the model are: latitude, daily weather (minimum and maximum temperature, precipitation, solar radiation, minimum and maximum relative humidity, and wind speed), soil description (layer thickness, clay, sand and organic matter content), cropping sequence, and management information.

The model can simulate the effects of management on biogeochemical processes of agronomic practices such as tillage, irrigation, organic and inorganic nutrient applications, annual and perennial crops, grain and forage harvest, polycultures, relay cropping and grazing. Cycles allows unlimited crop species to be specified by the user, because growth is represented with a general framework of resource capture and resource use efficiency.

4.2.3. Cycles Simulations

The Cycles model was used to simulate water content and crop production in the study using biophysical and crop management inputs from each environment. First, the observed yields from 17 Brazilian and 22 U.S. environments were compared to the simulated yields. Second, the biophysical yield potential, water-limited and reported soybean yield were calculated in two representative environments each in Brazil and the U.S. From this, yield gaps due to water and management were estimated. Third, the potential for cropping systems intensification was assessed in each of these 4 representative environments based on estimates of potential available water and solar radiation.

Air temperature, relative humidity, precipitation, wind speed and solar radiation were obtained from the NASA Land Data Assimilation Systems (NLDAS) reanalysis database at the closest grid point from each field. Soybean phenology dates (VE, R1 and R8) and maximum root depth (only in 2017 in the U.S.) were used to adjust parameters in the crop input files for root depth, and thermal time to emergence, flowering and physiological maturity. Saturated hydraulic conductivity and available water capacity were used to parameterize the soil input files in the U.S. regions in 2017. Soybean planting dates varied from 17 April to 13 July in the U.S., and from 10 October to 8 December in Brazil. All management operations were entered in the model to emulate actual field management. Relative maturity (RM) groups varied from 3.1 to 3.9 in the U.S.; in Brazil, a 5.5 group was used in both regions.

Cycles was used to simulate water content at SEAREC in 2016 at two planting dates to compare modeled water content with that measured with the Diviner. In all the other 39 environments Cycles was only used to predict soybean yields. The goodness of fit of Cycles was evaluated with regression analysis between observed and simulated data. The 1:1 reference line, p-value, coefficient of determination (R^2), intercept, and slope were used to assess model performance against the observed data.

In 2016, the soybean harvest index (HI) in regions US1 and US2 was measured, and this data was used to compare the final simulated HI and the observed HI. Cycles uses the pre- and post-anthesis phases growth to estimate HI (Kemanian et al., 2007); the default HI asymptote is 0.40 for soybean. In Cycles, the HI approaches an asymptote as the post anthesis phase growth increases. Because the simulated HI was underpredicted (0.36), the HI asymptote was manually changed until a final HI closer to the average observed value (0.42) was reached. Thus, the asymptote, originally set to 0.40, was increased to 0.49 to match the maximum yields (i.e. those likely representing the yield potential).

To compare the biophysical yield potential and the yield gap of the representative U.S. and Brazilian environments, one field per region that represented the average yield and environment was selected to perform the simulations. In each of these environments, the input files were based on data measured in the field. The minimum soil input dataset necessary to perform a simulation in Cycles was used to compare the four regions (Table 4.2).

Table 4.2. Clay, sand and SOM content in each soil layer of the four regions studied.

Location	Layer	Thicknes	Clay	Sand	SOM
		m	g kg^{-1}		
US1	1	0.06	203	320	44
	2	0.09	238	279	29
	3	0.15	270	250	17
	4	0.30	315	221	10
	5	0.26	424	145	8
	6	0.16	411	178	6
US2	1	0.06	317	153	39
	2	0.09	353	131	25
	3	0.15	348	129	21
	4	0.20	345	140	20
	5	0.10	345	140	20
	6	0.30	365	129	16
	7	0.17	396	133	17.5
BR1	1	0.025	440	310	39
	2	0.025	440	310	39
	3	0.05	530	283	30
	4	0.10	530	275	30
	5	0.20	590	245	27
	6	0.30	750	170	24
	7	0.30	740	135	16

BR2	1	0.025	400	270	51
	2	0.025	400	270	51
	3	0.05	400	270	51
	4	0.10	590	140	41
	5	0.20	670	100	32
	6	0.20	740	70	25
	7	0.20	630	170	24
	8	0.20	670	140	17
	9	0.20	700	110	10

For each simulation, commonly used planting dates were selected in each region (Table 4.3). Soybean RMs were 3.6 and 5.5 in the U.S. and Brazil, respectively. Since the goal was neither to validate nor to calibrate the wheat simulations, general wheat parameters that matched the expected flowering and maturity dates in each region were used.

Table 4.3. Planting, maturity dates and thermal times (TT) of full season and double cropping soybeans in each region of the U.S. and Brazil.

Crop / Region	Planting Date	Maturity Date	TT	TT
Soybean Full Season			VE-R1 ˚C d^{-1}	R1-R8 ˚C d^{-1}
US1	05/22/2017	10/03/2017	702	1690
US2	05/01/2017	10/04/2017	840	1976
BR1	11/08/2012	03/24/2013	839	1853
BR2	11/12/2012	04/02/2013	904	1833
Wheat Double-Crop				
US1	10/14/2016	06/20/2017	1410	2040
US2	10/14/2016	06/09/2017	1410	2040
BR1	06/06/2011	10/24/2012	1061	1691
BR2	06/06/2011	10/25/2012	1061	1691
Soybean Double-Crop				
US1	07/13/2017	11/07/2017	600	1327
US2	07/06/2017	10/16/2017	562	1429
BR1	11/18/2012	03/28/2013	741	1754
BR2	12/03/2012	04/18/2013	798	1763

To calculate the soybean yield potential (no water stress), the soil was automatically irrigated when the plant available water fell below 90% of the water hold between field capacity and permanent wilting point.

4.2.4. Biophysical Quantification

The soybean yield gap was estimated using data from 2013 in Brazil and 2017 in the U.S. Yield potential and water-limited (rainfed) yield were quantified using Cycles and observed yields were averaged for each region. Cycles allowed the estimation of total yield gap (Y_{gt}), yield gap due to water (Y_{gw}) and yield gap due to other abiotic and biotic factors (Y_{gx}). The relative yield gap due to water (RY_{gw}) is the percent difference between the potential and water-limited yields, whereas the relative yield gap due to other abiotic and biotic factors (RY_{gx}) is the percent difference between water-limited and observed yields. The cumulative evaporation, runoff, drainage, infiltration and transpiration from planting to physiological maturity, and plant available water (PAW) at planting and residual water at maturity were estimated with Cycles. Water capture efficiency was calculated by dividing the cumulative transpiration by the amount of water available from planting to maturity in the top rootable 0.9 m soil layer (PAW plus the difference between infiltration and residual water).

To assess the potential of cropping systems intensification, full season soybean and double-cropping wheat and soybean yields were simulated from 2008 to 2017 in each region. Means and standard deviations were used to compare the cropping systems and regions. The percent of potential solar radiation captured in each cropping system was calculated by dividing the cumulative solar radiation available from planting to maturity in each system by the total available solar radiation in one year.

The cumulative daily solar radiation (S_t) over the growing season in each location was normalized or corrected using both a temperature (T, °C) function (f_T) and a vapor pressure deficit (*D*, kPa) function (f_D) (Kemanian et al., 2004). The temperature correction was done by multiplying S_t times f_T:

$$f_T = \frac{(T - T_n)^q \; x \; (T_x - T)}{\left(T_{op} - T_n\right)^q \; x \; \left(T_x - T_{op}\right)} \qquad (2)$$

$$q = \frac{\left(T_n - T_{op}\right)}{\left(T_{op} - T_x\right)} \qquad (3)$$

where $T_n = 0$, $T_{op} = 25$ and $T_x = 45$ ˚C and q = (Equation 3). If temperature (T, ˚C) is lower than the minimum temperature (Tn) or higher than the maximum temperature (Tx), then $f_T = 0$. The radiation term was further adjusted by dryness of the atmosphere by dividing by the square root of *D* if *D* >1 kPa (Equation 4):

$$S_{tc} = \frac{S_t \; x \; f_T}{\sqrt{D}} \qquad (4)$$

Total biomass synthesis is better quantified in terms of primary substrate production because the energy composition of soybean and wheat grain differ. Therefore, to compare the total production of full season and double-cropping systems in one calendar year, the primary sugar or glucose requirement was quantified. The amount of glucose produced in each environment and production system was calculated as a measure of potential energy produced from grain as described by McDermitt and Loomis (1981). We used the following conversions: 1 kg of glucose generates 0.7 kg of wheat grain and 0.45 kg of soybean grain. These figures are not constant and depend on the source of nitrogen, protein, carbohydrate and lipid content of the grain, but the figures selected reasonably normalize biomass sources of contrasting composition.

4.3. Results

4.3.1. Cycles model performance

Cycles matched the sensor daily Θ variation pattern down to 60 cm in both planting dates throughout the entire growing season well (Figure 4.1). The soil surface layer Θ is apparently overestimated by Cycles but it is likely that this error reflects difficulties getting a correct reading from the device close to the soil surface, as the air layer above the soil may interfere with the signal. The standard error of the measurements increased with depth, likely reflecting more heterogenous soils conditions and root exploration in the subsoil (prismatic peds, rock fragments). The water drawdown as well as recharge-events were also well simulated by the model.

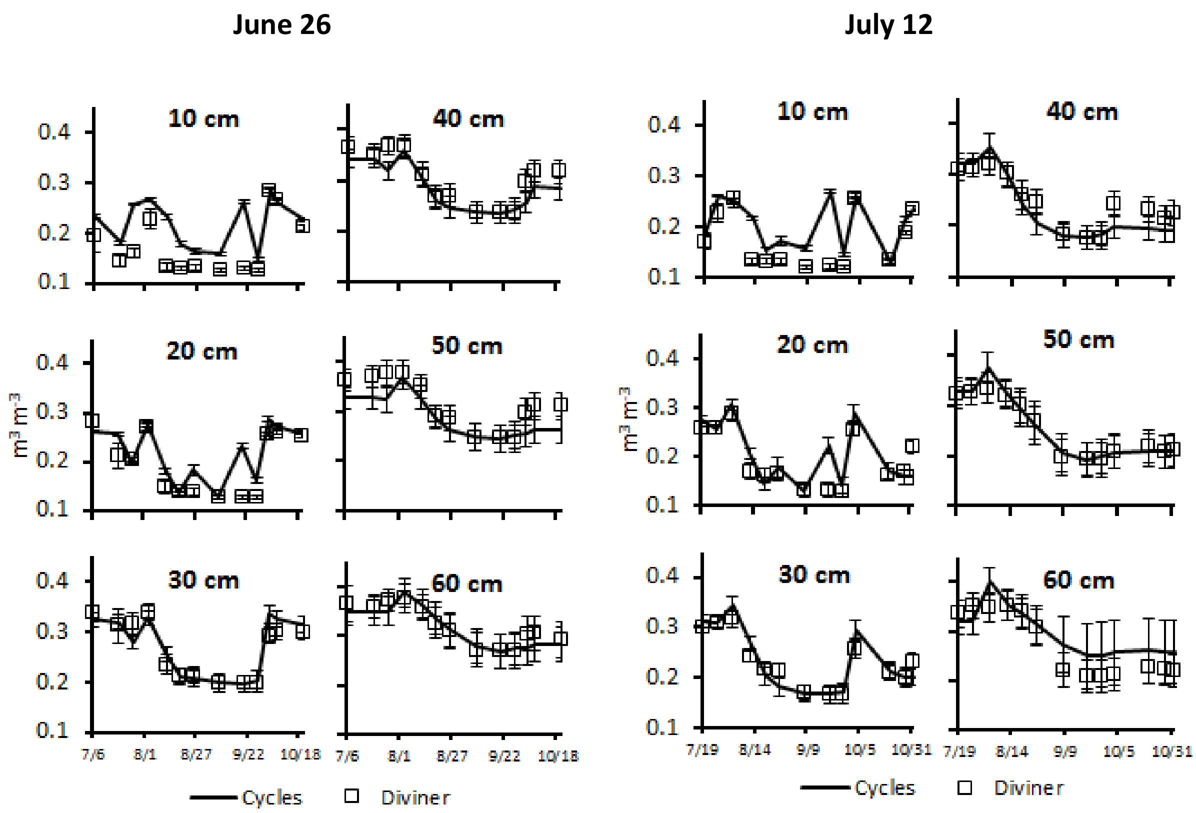


Figure 4.1. Measured (Diviner) and simulated (Cycles model) soil water content from soybean planting to harvest at the SEAREC research station in Pennsylvania for the planting dates of 26 June and 12 July. Error bars indicate the standard deviations of five replications.

Soybean yield predictions agreed well with the observed yields using the model default parameters for soybean (Figure 4.2). However, the model slightly underpredicted the highest yields and overpredicted the lowest yields, and overall underestimated the HI (0.36 vs 0.42). This change improved the slope of the simulated vs observed yield regression in the U.S. (from 0.69 to 0.91) and slightly so in Brazil (from 0.9 to 1.08).

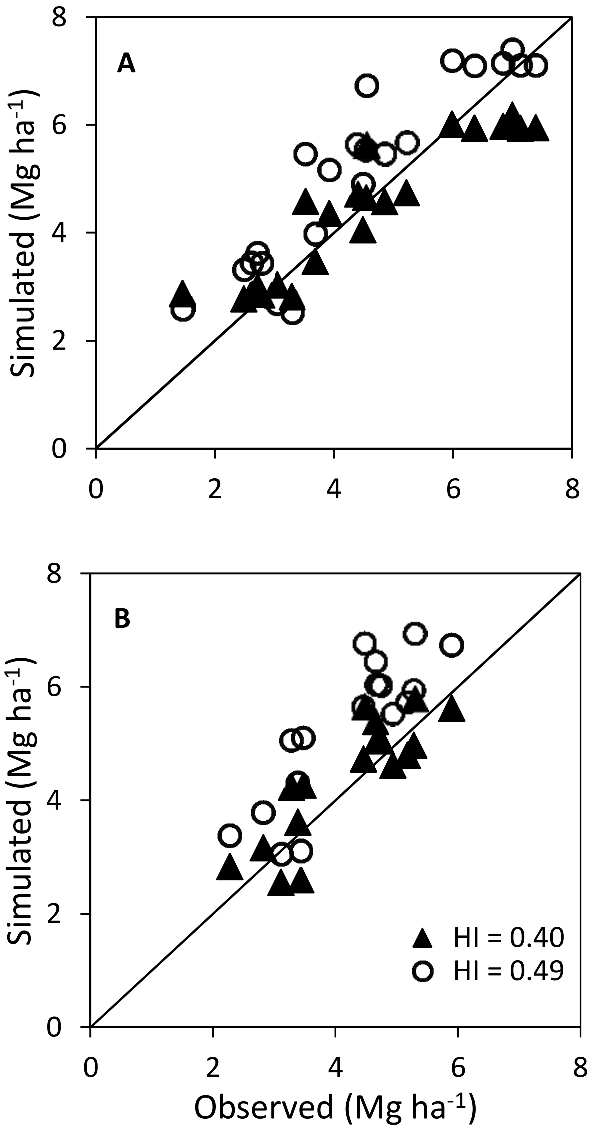


Figure 4.2. Simulated and observed soybean yields in the U.S (panel A, regions US1 and US2) from 2016 and 2017 and Brazil (panel B, regions BR1 and BR2) from 2012 to 2015 before and after changing the HI asymptote from 0.40 to 0.49.

The simulated and observed soybean yields also agreed well within individual regions in the U.S. and Brazil (Table 4.4). The R^2s, slopes and intercepts varied from 0.66 to 0.90, 0.66 to 1.28, and -0.1 to 2.8, respectively.

Table 4.4. Regression models of observed x simulated soybean yield in each region of the U.S. and Brazil.

Region	**n**	**Slope**	**Intercept**	**R^2**	***P***
US1	10	1.04	0.5	0.66	0.004
US2	12	0.86	1.4	0.90	<0.0001
BR1	8	1.28	-0.1	0.71	0.009
BR2	9	0.66	2.8	0.73	0.003

The most critical parametrization to correctly predict yields was to adjust thermal time for flowering and physiological maturity in every location, maturity group and planting date. Thermal times from planting to emergence, flowering and maturity were calculated based on measured phenology data in each location and adjusted based on Cycles crop outputs.

4.3.2. Biophysical yield potential and yield gap

The four regions varied considerably in terms of solar radiation, precipitation and temperature during the growing season. The southern Brazil regions receive more solar radiation, precipitation and have greater cumulative degree days than those in Pennsylvania (Table 4.5). Region US2 is warmer and receives more precipitation and solar radiation than Region US1, and Region BR2 is colder and receives more precipitation and solar radiation than Region BR1.

Table 4.5. Average cumulative precipitation, cumulative temperature and daily available solar radiation data at each of the 4 regions studied. Weather data was averaged from 2008 to 2017.

Month	Precipitation				Cumulative Degree Days				Solar Radiation			
	mm				˚C above 0				MJ m^{-2} day^{-1}			
	US1	US2	BR1	BR2	US1	US2	BR1	BR2	US1	US2	BR1	BR2
January	60	71	159	199	29	44	713	649	7	7	22	22
February	59	73	153	202	41	58	659	598	9	10	20	20
March	78	85	45	173	142	179	663	620	14	14	18	19
April	82	90	155	149	320	354	580	554	18	19	15	16
May	113	118	150	137	488	529	488	472	20	21	11	12
June	105	114	168	237	603	651	396	398	21	23	10	11
July	103	120	175	179	700	758	422	424	22	24	11	13
August	97	111	166	126	667	721	481	468	21	21	13	16
September	98	134	182	151	562	610	497	496	16	16	15	18
October	99	116	235	211	378	415	581	562	11	12	18	19
November	55	57	147	148	178	208	635	584	8	8	22	22
December	83	94	153	237	74	105	705	644	6	6	22	21
Total	1032	1182	1990	2150	4183	4631	6820	6469	5279	5561	6017	6366

The four environments selected for this study had soybean yield potentials based on the Cycles simulation ranging from 4.9 to 6.2 Mg ha^{-1} in 2013 in Brazil and 2017 in the U.S. (Table 4.6). Region US2 had a relatively stress-free soybean season in 2017, and it achieved 95% of its biophysical yield potential. Regions US1, BR2 and BR1 were 13/22, 23/11 and 6/42% limited by water/other factors, respectively. These other factors represent yield gaps due to management. Region US1 was affected by water stresses during the grain filling phase according to Cycles. Region BR1 was mostly limited by other factors such as nutrients, weeds, pests and diseases rather than water stresses according to the simulations.

Region BR2 had a high precipitation from planting to maturity (830 mm), but with a non-uniform distribution during the growing season. Low precipitation early in the season caused water stress and limited soybean growth during the first 77 days after emergence in region BR2, which resulted in a maximum solar radiation interception of 83% according to our simulations. Later in the season though, heavy rain events caused runoff and drainage losses that added up to 386 mm (Table 4.6).

Table 4.6. Soybean yields and water metrics in Brazil in 2013 and in the U.S. in 2017.

Variable	BR1	BR2	US1	US2
Soybean Yield (Mg ha^{-1} @ 0%)				
Potential	5.0	6.1	5.6	6.2
Water-limited	4.7	4.6	4.9	6.2
Observed	2.7	4.1	3.8	5.9
RY_{gw} (%)	6	23	13	1
RY_{gx} (%)	42	11	22	4
RY_{gt} (%)	48	34	35	5
Water (mm)†				
Evaporation from PD to R8	133	158	133	151
Runoff from PD to R8	87	187	3	15
Drainage from PD to R8	95	199	68	56
Plant available water at PD	404	392	294	329
Cumulative infiltration from PD to R8	551	645	402	525
Residual water at R8	410	387	190	252
Cumulative transpiration	323	304	310	406
Water capture efficiency (%)	59	47	61	67

† 90 cm root zone soil profile.

Water capture efficiencies varied from 47 to 67% (Table 4.6). Region US2 had the highest water capture efficiency probably due to the timely precipitation events. The relatively low water capture efficiency of Region BR2 was related to large precipitation events. For instance, Cycles estimated runoff and drainage volumes at Region BR2 of 187 mm (145 mm in 39 days with daily runoffs reaching of 47 mm day^{-1}) and 199 mm from planting to maturity, respectively.

4.3.3. Potential for Agricultural Intensification

Comparing the soybean yield gap using Cycles over a period of 10 years, the loss due to water is higher in full season soybean than in double-cropping systems (Table 4.7). Average soybean yields can be increased 17 and 12% with water management in the 4 regions studied in full season and double-cropping systems, respectively. The U.S. regions had lower potential soybean yield in double-cropping systems. However, in Brazil, potential and water-limited double-cropping yields were similar to full season soybean yields. In the U.S., soybean yields were significantly lower in later plantings after wheat harvest. Region BR2 had higher soybean yields than Region BR1, and Region US2 had higher soybean yield than US1 due to greater solar radiation loads and precipitation volumes. The standard deviations of water-limited soybean yields were larger in full season (0.7 Mg ha^{-1} in average of the four regions) than in double cropping systems (0.4 Mg ha^{-1} in average of the four regions). The standard deviations of the soybean yield potential were the same (0.2 Mg ha^{-1}) for all regions in both systems. These smaller differences in standard deviations under irrigated conditions show that water resources are the main source of season yield variability in these regions.

Table 4.7. Average wheat, soybean and glucose yield, and cumulative solar radiation indicators from 2008 to 2017 in full season (FS) and double-cropping (DC) wheat-soybean systems in the U.S. and Brazil.

Variable	BR1	BR2	US1	US2
Yield Mg ha^{-1} @ 0%				
Soybean FS_Potential	5.7 ± 0.2	5.9 ± 0.2	5.5 ± 0.3	6.1 ± 0.2
Soybean FS_Water-limited	4.6 ± 0.7	5.0 ± 0.6	4.4 ± 0.7	5.1 ± 0.7
Wheat DC_Potential	5.9	6.7	7.7	7.2
Wheat DC_Water-limited	5.4	4.6	7.6	7.2
Soybean DC_Potential	5.5 ± 0.2	5.7 ± 0.2	3.3 ± 0.2	3.6 ± 0.2
Soybean DC_Water-limited	4.7 ± 0.4	5.1 ± 0.5	2.8 ± 0.4	3.2 ± 0.4
% of yield gap due to water_FS	20	15	20	16

% of yield gap due to water_DC	14	11	14	11
Variable	**BR1**	**BR2**	**US1**	**US2**
Simulated Glucose Yield Mg ha^{-1} @ 0%				
FS_Soybean	10.2	11.2	9.8	11.4
DC_Wheat + Soybean	18.3	17.8	17.1	17.5
Variable	**BR1**	**BR2**	**US1**	**US2**
Solar Radiation (MJ m^{-2}yr^{-1})				
Total in one year	6017	6366	5279	5560
Corrected for Temperature in one year	5591	5863	3673	4018
Corrected for Temperature and VPD in one year	5084	5441	3546	3747
FS_Total from PD to R8	2903	2958	2747	3278
FS_Corrected for Temperature from PD to R8	2862	2887	2623	3129
FS_Corrected for Temperature and VPD from PD to R8	2526	2671	2505	2867
(Full Season) % of Potential Radiation Capture	50	49	71	77
DC_Total from PD to R8	4599	4933	4993	4947
DC_Corrected for Temperature from PD to R8	4279	4552	3312	3411
DC_Corrected for Temperature and VPD from PD to R8	3899	4235	3198	3176
(Double-Cropping) % of Potential Radiation Capture	77	78	90	85

After correcting the available solar radiation in one year for temperature and water, the average potential use of solar radiation available for agricultural production in full season soybean systems were 50% and 74% in Brazil and the U.S., respectively (Table 4.7). In double-cropping systems, the potential use of available solar radiation increased in average to 77 and 87% in Brazil and the U.S., respectively, while increasing potential production of glucose in the same area per year from 54 to 79% depending on the region studied (Table 4.7).

4.4. Discussion

4.4.1. Multiple Environments Cycles Simulations

The excellent agreement between daily simulated and observed soil water content variations over the entire soybean growing season demonstrated Cycles' ability to correctly predict water movement within the soil-plant-atmosphere continuum. The Cycles Θ overestimation in the top layers could be due to errors in field measurements of Θ near the soil surface and to some observed daily inconsistencies in the weather data from NLDAS. Eitzinger et al. (2004) also found an overestimation pattern of soil water depletion in shallow layers and greater difference between observed and simulated values in deeper layers. Inconsistencies in root distribution within the soil profile could be a factor influencing the greater variability in the deeper measurements of soil water content. Finally, the water balance predictions were only evaluated in a silt loam soil of Pennsylvania, and it is possible these results can vary for other soil textures or environments.

One improvement of modern soybean varieties that guided higher yields over time was the greater partitioning of biomass into seed. Koester et al. (2014) analyzed 24 soybean varieties released from 1923 to 2007 and found a range of HI from 0.3 to 0.55 with the newest varieties approaching 0.60. The HI varies within varieties and environments, but the Cycles HI adjustment situated the soybean HI closer to recent measured values. Additionally, the better agreement with the 1:1 line between observed and simulated soybean yields after calibrating HI improved the ability of the model to predict potential yields and to assess plant interactions with soil and weather.

Cycles uses a pedotransfer function to calculate soil hydraulic properties that was developed for temperate soils (Saxton and Rawls, 2006). So, possibly part of the weaker predictions in Brazil compared to the U.S. simulations could be improved with a pedotransfer function developed for the highly weathered soils of Brazil (Tomasella et al., 2000; Hodnett and Tomasella, 2002).

4.4.2. Biophysical Yield Potential and Yield Gaps

Strategies to reduce the gap between potential and water-limited yields can be expensive or only achievable in the long-term. In the short term, irrigation systems can be a viable option in some locations, and crop models can assist to quantify the return of this investment. Another potential alternative is improving the soil conditions to store more water and to allow deeper and better distributed rooting systems in the soil profile with time (Taylor, 1983; Cairns et al., 2011; Sakschewski et al., 2014). For instance, Faé et al. (Chapter 4) found that greater saturated hydraulic conductivity in Pennsylvania soils was related to deeper rooting systems and higher soybean yields.

Alternatively, the difference between the observed and water-limited yields indicated a gap that can be reduced by managing other factors such as nutrient deficiencies, weeds, diseases and pests (Affholder et al., 2013). Rattalino Edreira et al. (2018) found non-water stresses were the main causes of wheat and corn yield reductions in about half of the 26 countries they studied. Similar to the significant yield gap found in region BR1, Sentelhas et al. (2015) suggested that the southern region of Brazil had yield gaps due to water deficit and crop management greater than 2 Mg ha^{-1}. Based on Cycles simulations, regions BR1 and US1 could have increased yields by 42 and 22% in the years studied with adjustments in soil and crop management.

Some of the yield gap due to other factors could be related to water stresses not captured by the model because of variations in actual soybean root depths (root depth was not measured in Brazil and the 100 cm default was used). The available soil data from Region BR1 showed that the 40-cm soil layer had some restrictions to root growth (75% clay, pH 5.0 and 54% Aluminum saturation) that possibly limited the root depth to a maximum of 40 cm. Forcing Cycles' maximum root depth to 40 cm in Region BR1 reduced the water-limited yield by 16% from the reported result. This could help explain part of the 42% yield gap caused by other factors in this region. In addition, Nunes (2018) showed that some crop fields from region BR1 can have an impermeable soil layer ranging from 7 to 20 cm depth with high resistance to root growth and low soil fertility, which could have further limited root depth and consequently reduced yields. A detailed description of soybean yield response to soil, plant and climate from Region US1 and Region US2 can be found in Fae et al. (Chapter 3). However, explaining the 22% yield gap in Region US1 due to management is quite challenging. Traditional soil tests and the Cornell Assessment of Soil Health did not indicate the possible causal effects to this yield gap. One factor that could be limiting soybean yields in Region US1 is the frequent use of planters with row spacings of 76 cm in the region to reduce planting time. Wider row spacings associated with unfavorable environmental conditions can delay canopy closure and limit solar radiation interception which ultimately can impact yields (Andrade et al., 2019; Van Roekel et al., 2015). On the other hand, Region US2 has the lowest manageable yield gap and an average root depth of 85 cm. Fae et al. (Chapter 3) showed that soils from region US2 have a physical profile that allows deep roots and therefore stable high yields.

The highest water capture efficiency in this study was found in the field with the lowest yield gap due to water, and vice versa. However, the region (BR2) with the lowest water capture efficiency had the greatest cumulative infiltration from all regions. This distinct pattern occurred mainly due to a non-uniform precipitation distribution that caused water stresses earlier in the growing season, and excessive precipitation events during seed filling stages that caused losses through runoff and drainage. Besides the waste of a photosynthetic resource, the water that is not used for crop production can be directly involved in environmental pollution or soil erosion (Gregory et al., 1992; Nosetto et al. 2012). All regions studied can increase the effective use of the water available, that is improving soil water capture for transpiration (Blum, 2009). Enhanced management practices can help to increase soil water holding capacity to improve water use in seasons facing droughts or non-uniform precipitation distributions in the long-term, but strategies to increase infiltration and reduce losses through runoff and evaporation should not be ignored in the short-term.

A single crop per year did not use all the water available in the four regions studied. Intensifying and diversifying cropping systems with multiple crops per year can increase resource capture and therefore land productivity (Trenbath, 1986; Hook and Gascho, 1988; Fukai, 1993). The inclusion of crops such as wheat or corn in the system can also help to improve the efficient resource use because they have more efficient photosynthetic metabolism (Caviglia and Andrade, 2010; Van Opstal et al., 2011).

4.4.3. Potential for Cropping Systems Intensification

The solar radiation availability varies per year and region, but probably the easiest route to improve this resource capture is through a cropping systems approach. Double-cropping soybeans after wheat harvest is a widely adopted system around the world probably because the combined system increases land productivity, yields are more stable, net-returns are potentially greater, and aids environmental benefits compared to single crops (Burton et al., 1996; Kyei-Boahen and Zhang, 2006; Calviño and Monzon, 2009; Fischer et al., 2014; Andrade et al., 2015). In this study, the amount of energy (measured as glucose) produced per unit of solar radiation available and per calendar year was 66% greater in double cropping than full season systems.

In general, crop models predict higher yields in longer growing seasons driven by earlier plantings that will be associated with higher accumulation of solar radiation capture (Adam et al., 2011). However, actual yield responses to planting date are prone to other stresses that can determine different results in fields where management is not optimum. For instance, both regions in Brazil are susceptible to significant yield declines due to soybean rust, and planting date is also a factor that influences this disease management (Godoy, et al. 2016). Similar to the greater measured double-cropping soybean yield followed by wheat in comparison to the earlier planted soybean after a cover crop [black oat (*Avena strigosa* Schreb.)] found by Pires et al. (2016), the results of this study also indicated that double-cropping systems in southern Brazil do not have the yield penalty due to later planting such as in the U.S. regions. Pires et al. (2016) attributed this positive yield response in double-cropping systems to genotype x weather interactions. Here, similarly, the greater soybean yield after wheat found in comparison to full season system in Brazil was due to lower water stresses in later planting dates.

Even with the estimated increase in resource capture with double-cropping systems, in some regions such as BR1 there is still water and solar radiation available for an extra cover crop growth per year that could add profits with ecosystems services or as a forage crop for animal production (Fae et al., 2009; Schipanski et al., 2014). To test this theory, Cycles was used to predict cover crop biomass production (using corn parameters) in the fallow window between soybean harvest and wheat sowing given in the double-cropping setup of Region BR1. In those conditions, and delaying wheat sowing to 1 July, the simulated aboveground biomass production was 4 Mg ha^{-1} (DM) and the root biomass growth was 1.4 Mg ha^{-1} (DM) of cover crop planted on 1 April and killed 1 July. In this scenario, wheat harvest is pushed back to mid-October and soybean planting would not change from the previous setup.

Cycles simulations demonstrated that the U.S. regions studied cannot exploit every year around 29% of the total available solar radiation for photosynthesis due to low temperatures, whereas the Brazilian regions only lose around 7.5% of this photosynthetic resource due to temperature. In addition to the direct solar radiation losses due to temperature, droughts reduce the crop photosynthetic capacity and cause further inefficiencies in solar radiation use (Zou and Kahnt, 1988). Occasionally, even in well-watered conditions, daily imbalances in evaporation and water supply can cause water stresses too (Hanson and Hitz, 1982). Using the *D* approach (Stöckle and Kiniry, 1990; Kemanian et al., 2004) to further correct S_{tc}, additional losses in solar radiation availability due to water stresses are in average around 5 and 8% per year in Pennsylvania and Southern Brazil, respectively. Among the many negative agricultural impacts of global warming, Region US1 and Region US2 may be benefited by an expansion of the growing season (Prasad et al., 2018). In this study, the estimated available solar radiation increase for each degree-day increase in Pennsylvania was 0.76 MJ m^{-2} yr^{-1}.

Considering all the benefits of double-cropping wheat-soybean systems, in theory it would be logical to see greater use of this production system in the regions studied, but in practice its adoption in these regions is quite low. According to CONAB (2019), in Southern

Brazil, more specifically in the states of Rio Grande do Sul (Region BR1) and Paraná (Region BR2), from a total area of 19.5 M ha^{-1} planted with cash crops in the summer of 2018/19, only 25% was cultivated with grain crops during the winter. The total area of wheat and soybean were 1.7 and 11.9 million hectares in the same year, respectively. In Pennsylvania, only 11% of the planted soybean area was double cropped in 2018 (USDA-NASS, 2019). The reasons for this low adoption in the regions studied are various, but mainly it is due to grain prices that are driven by both macroeconomic decisions and abiotic and biotic factors that limit grain quality. Researchers are working to overcome the factors that reduce wheat grain quality but opposing macroeconomic decisions may remain. Producers have other alternatives rather than the traditional wheat-soybean system to sustainably intensify cropping systems in the U.S. and Brazil though. One promising alternative of agricultural intensification and an excellent strategy to improve solar radiation and water capture throughout the growing season is to integrate crop and livestock in the same crop area (Sulc and Franzluebbers, 2014; de Moraes et al., 2019).

4.5. Conclusions

The accurate soybean yield predictions of Cycles allowed quantifying yield gaps and the biophysical potential for agriculture intensification in four distinct regions. The yield gaps found in this study show that there is potential to increase soybean yields with the available solar radiation and water resources through improved management tactics. Total yield gaps ranged from 5 to 46% in the regions and years studied. However, attaining this potential is contingent first on recognizing the main non-water stresses in each region. Definitive yield gap causes may not be known, but these estimations are valid to show the need for more field research to better understand yield limiting factors. Increases in crop productivity are necessary to meet the current global food demand, but the better exploitation of available resources is also critical. The U.S. regions almost use all the available solar radiation in full season systems (74%), but it is still possible to extend the growing season by 13% with successful double cropping systems. In Southern Brazil, the potential capture of solar radiation increases from 50 to 77% from full season to double cropping systems, and it is still possible to yield a decent cover crop production in the planting window between the soybean and the wheat growing season. The promotion of more diverse cropping systems appears to be the best solution to increase crop production in the same land per year, but there are management strategies to consider in order to be successful.

Chapter 5. Designing and Implementing an International Extension Tour

ABSTRACT

International extension experiences can provide valuable outcomes to clientele. However, expectations can be high due to the cost and the length of the activity. Consequently, careful planning is necessary to maximize the benefits to participants and the potential impacts of the tour. Here, we describe the main organizational steps and the lessons we learned planning and executing a comprehensive tour program to Brazil.

5.1. Introduction

International tours can provide significant lifelong impacts to extension clientele (Andrews et al., 2001). They can offer insights into alternative approaches and technologies, develop linkages with foreign collaborators, and provide cultural development. Treadwell et al. (2013) reported that extension participants improved their abilities in dealing with comparable technological issues after participating in a tour to Nicaragua. International field tours are also a great extension tool to exchange information with progressive growers (Hawkins & Southard, 2001). Considering this, we organized an international tour to study sustainable soybean production systems in Brazil. A group of 14 participants including growers and extension personnel from Pennsylvania traveled to Brazil from February 22nd to March 2nd of 2018.

We chose Brazil because the country has been overcoming the lack of agricultural subsidies and poor infrastructure by increasing soybean production efficiency. Brazilian producers have also progressively adopted greater integrated crop and livestock systems over the past decade as a sustainable method of intensifying agricultural production on the same land base. Also, we used the local experience of an employee from the Brazilian Agricultural Research Corporation (Embrapa) who is pursuing PhD at Penn State.

We prospected potential participants during extension meetings with the Pennsylvania Soybean Network by discussing production similarities between the two countries. As we became aware during these meetings, soybean growers from Pennsylvania rarely take advantage of international opportunities to talk to peers facing different production scenarios. The Pennsylvania Soybean Board supported this trip and promoted the idea among leading growers as a great opportunity to enlighten their members about our biggest international competitor in soybean production.

We included visits to the biggest soybean production region of Brazil in the Cerrado region, and to the most southern part of Brazil where topography and farm size are similar to Pennsylvania. The tour was planned for late February because it was the beginning of harvest in the Cerrado and two months before planting season in Pennsylvania. Most expenses were paid by the participants. However, we obtained financial support from the Pennsylvania Soybean Board checkoff program to evaluate trade and production economics, develop a blog, and share our experiences at post-tour conferences and farm press interviews.

Because of the significant expense and high participant expectations of an international tour, careful planning was necessary to maximize the benefit to participants and the potential impacts. Therefore, the objective of this publication is to share our main tour planning steps, the lessons we learned organizing the trip, and to encourage extension educators and specialists to develop successful international extension tours.

5.2. Tour Planning and Implementation

We initiated our planning approximately one year prior to the tour by meeting with Penn State international program staff and other extension educators who had led international tours. This guided key planning and implementation steps for the tour (Figure 5.1).

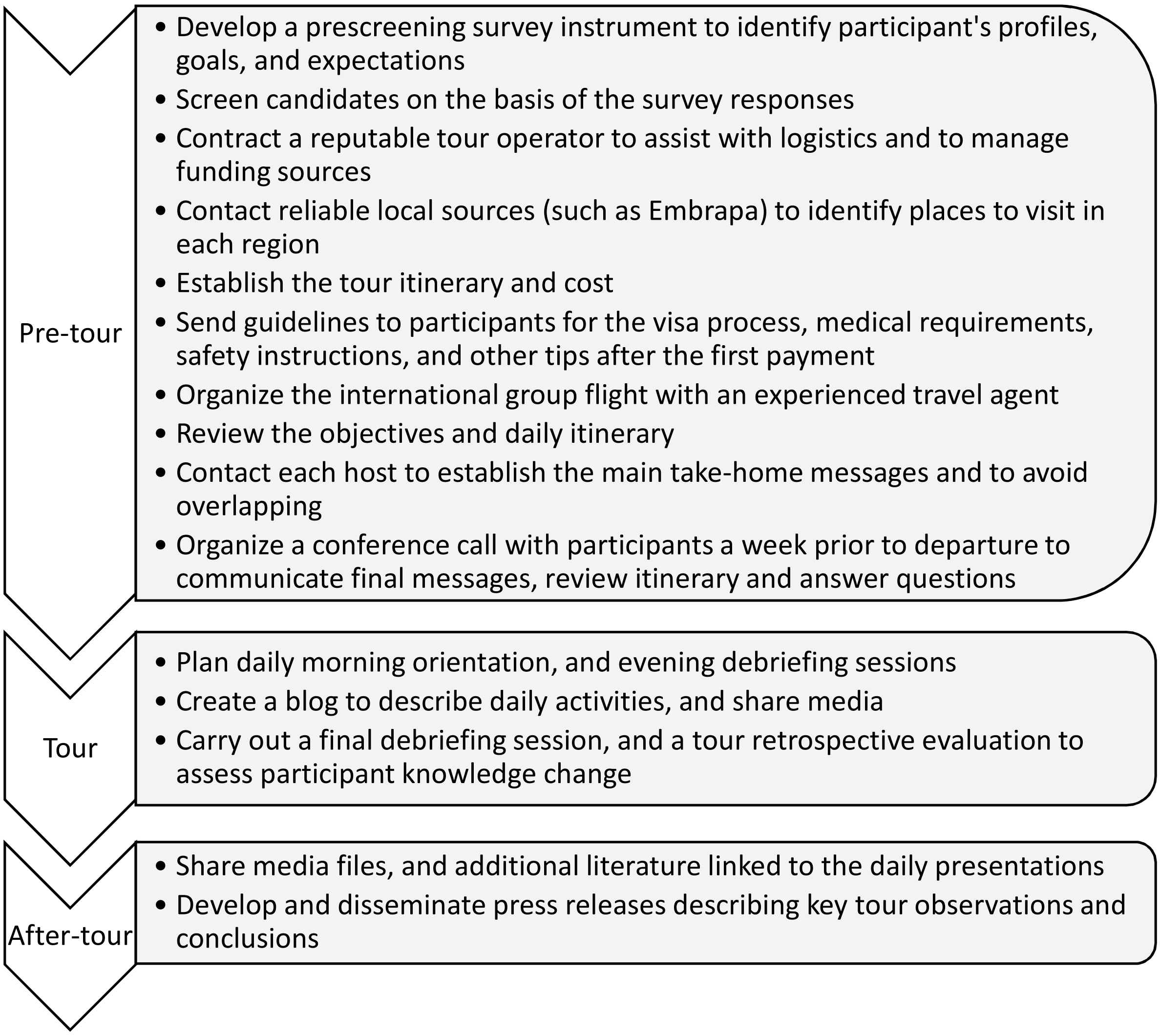


Figure 5.1. Critical steps in developing a successful international tour.

5.3. Participant Outcomes and Lessons Learned

The results of our evaluation showed that the twelve participants increased their knowledge in each of our key planned educational objectives (*Mean* = 96%, Table 5.1). Participants also rated the value, logistics, timing and food of the trip as high (*Mean* = 94%). This indicated the tour was successful in meeting our objectives. The success of the tour was likely due to the pre-trip planning and our focus on the educational objectives during the trip.

Table 5.1. Average tour retrospective evaluation scores from 0 (*not satisfied*) to 5 (*completely satisfied*).

Topic	Score[a]	*SD*
Educational Objectives		
Improving your knowledge of Brazilian culture and customs	5.0	0.6
Knowledge of the economics of soybean production	4.8	0.6
Understanding Brazilian cropping systems in different regions	4.9	0.6
Understanding the role of cooperatives for producers in Brazil	4.8	0.5
Understanding soybean quality issues in Brazil	4.7	0.7
Understanding some of the key insect and disease issues in Brazil	4.8	0.5
Understanding how Brazil is trying to improve sustainability of soybean production	4.9	0.5
Mean Education	4.8	0.1
Logistical Issues		
Food	5.2	0.4
Organization and logistics of the trip	4.6	0.7
Ratio of educational time to leisure time	4.0	1.3
Timing of the trip	4.7	0.7
Value of the trip considering cost, overall knowledge and usefulness	4.9	0.8
Mean Logistical	4.7	0.4
Overall Mean	**4.8**	**0.3**

[a] Some topics were rated 6 by two participants.

Each day we conducted a morning review of activities and an evening debriefing that were critical to retain a consistent and accurate message in the group. The final debriefing session was important to review take-home messages and to share different points of view among the participants. At this session, we surveyed the group about the key learning objectives, and carried out an open discussion on topics such as sustainability, economics, technological compatibility, take-home messages, and others.

The tour company was important for managing participant payments, in-country logistics, liability issues, tour guide, and interpreter. This allowed us to focus on our educational objectives. Defining the expectations before the trip with each participant was important to optimize the daily visits. Certainly, having a group with shared interests made the whole educational process easier.

The daily blogging was a stimulating tool to expand the outreach benefits to the local community in Pennsylvania. During the tour, the blog had more than 4,000 visitors among growers, extension educators, participants' family members, media personnel, and others. Articles developed from our post trip interviews resulted in excellent tour visibility both in Brazil and U.S. (Cotrijal, 2018; Embrapa, 2018; Lancaster Farming, 2018; Pennsylvania State University, 2018). We provided resources to participants following the tour to assist them in developing presentations for their peer groups, which included local farm organizations, industry colleagues, and extension and academic audiences. The presentations were well received.

Adult learning can be challenging during full day activities, especially when the message is being translated through an interpreter. Even though most participants appreciated the technical agenda, three participants felt it was excessively intense, and that it affected the learning process (Table 5.1). Depending on the group profile, increasing leisure time may be advised.

We documented other positive impacts that happened after the tour, such as various social media connections between industry participants and their peers in Brazil, PA extension specialists and Brazilian growers, and potential Brazilian graduate students and Penn State professors. After the trip, one participant was inspired to host a tour at his farm for a group of Brazilian growers he met while in Brazil. It also inspired new research ideas such as testing new inoculant technologies and evaluating the timing of interseeding cover crops. Finally, it fostered stronger social and professional relationships among the tour participants.

5.4. Recommendations

International extension tours can be successful and there is potential for increasing this type of program. To be successful and maximize impact, extension educators planning an international tour should consider the planning and implementation steps described in this publication. Often, international students or scholars can also contribute to create an effective tour. Developing relationships with commodity groups can help to defray some expenses and greatly increase the impacts of the tour.

Chapter 6. Summary and Conclusions

This PhD program developed from 2015 to 2019 was mostly successful by reaching the established research goals and interesting positive outcomes emerged from it. We first refined a laser diffraction method that will benefit many researchers by performing particle size analysis faster and more uniformly in comparison to the cumbersome sedimentation methods. Then, we showed that the individual CASH metrics did not correlate to soybean yield, but K_{sat} on the other hand arouse as a promising indicator of soil condition that is correlated with root depth and yield. We also demonstrated that Cycles can predict soil water content and soybean yield accurately. Then, we estimated soybean yield gaps that can be reduced with enhanced soil management tactics and showed that Pennsylvania has potential to increase production with double-cropping systems, while southern Brazil has sufficient water and solar radiation for a third cover crop production in between the soybean harvest and wheat sowing time. Finally, the 10 days that we spent in Brazil visiting topnotch farms and interacting with progressive producers yielded several positive outcomes for the group, such as increasing agronomic knowledge in soybean production, networking with international peers, new ideas for research, and others. Throughout the entire PhD period, we established several connections with producers and extension personnel in Pennsylvania, and we were invited to share research results in numerous talks, field days and diagnostic clinics during these four years. We believe that the soil and plant sampling methodology of Chapter 3 was also creative and can be used by others in future on-farm research projects. Lastly, it is likely that a memorandum of understanding will be signed to formalize the collaboration between Penn State and Embrapa to continue the crop modelling research started in this PhD.

In chapter 2, we developed a laser diffraction protocol for soil PSA that uses a small soil sample, is more robust, simpler, and faster than the current sedimentation methods, and significantly expands the quality of the data collected from soil texture analysis into a detailed particle size distribution. The assumptions that form the basis of sedimentation methods were used to develop a protocol that matches results from laser diffraction and standard sedimentation methods for a wide range of soils. Rather than defaulting to standard sedimentation methods, results obtained with the protocol presented here encourage further adoption of laser diffraction methods in PSA.

In chapter 3, we showed that cumulative solar radiation over the growing season and available precipitation were the main drivers of soybean yield. Our data confirmed that planting date is the main management practice to control soybean yield potential in Pennsylvania, but only soils with certain properties enable realizing this potential. Our results showed that current individual CASH metrics did not relate to soybean yield, and that defining soil indicators of soil "health" can be challenging. However, *in-situ* K_{sat} measurements were more predictive of soybean yields than the laboratory tests. While the soybean yield responses to field K_{sat} can vary with the production environment, our results suggest that K_{sat} can be a valuable indicator of soil condition and productivity. However, increasing soil macropore flow can increase the risk of subsurface water contamination with nutrients and pesticides (Bouma, 1991). On the other hand, increasing infiltration can reduce the risk of runoff of soil, nutrients and other contaminants to surface water sources. Further research is still needed to assess sustainable outcomes of higher K_{sat} from a producer and environment perspective.

In chapter 4, we estimated soybean yield gaps that suggests that there is potential to increase soybean yields with the available solar radiation and water resources through improved management tactics. Total yield gaps ranged from 5 to 46% in the regions and years studied. However, attaining this potential is contingent first on recognizing the main non-water stresses in each region. The U.S. regions almost use all the available solar radiation in full season systems (74%), but it is still possible to extend the growing season by 13% with successful double cropping systems. In Southern Brazil, the potential capture of solar radiation increases from 50 to 77% from full season to double cropping systems, and it is still possible to produce a viable cover crop in the planting window between the soybean and the wheat growing season. Converting from full season to double cropping systems in the environments studied can allow in average a potential increase in glucose production of 67% in the same area per year.

In chapter 5, we showed that international extension tours can be successful and there is potential for increasing this type of program. To be successful and maximize impact, extension educators planning an international tour should consider the planning and implementation steps described in this publication. Often, international students or scholars can also contribute to create an effective tour. Developing relationships with commodity groups can help to defray some expenses and greatly increase the impacts of the tour.

There is need for future research in some topics that need more clarification or that were not covered here. For instance, there is need for more research to refine the understanding of K_{sat} as a soil condition metric. More data should be collected in different fields to refine the yield response curve to K_{sat}. Also, there are a few modelling opportunities that we would like to work on once I return to Embrapa: Cycles validation in predicting wheat yield in Brazil; explore the temperature effect in soybean yields and the potential adaptation of cropping systems in different scenarios of climate change; and predict the production response of commercial monocultures and diverse cropping systems (crop-livestock integrated systems) using long-term and projected weather files.

References

Adam, M., Van Bussel, L.G.J., Leffelaar, P.A., Van Keulen, H., Ewert, F. 2011. Effects of modelling detail on simulated potential crop yields under a wide range of climatic conditions. Ecological Modelling. 222:131–143.

Affholder, F., Poeydebat, C., Corbeels, M., Scopel, E., and Tittonell, P. 2013. The yield gap of major food crops in family agriculture in the tropics: Assessment and analysis through field surveys and modelling. Field Crops Res. 143:106–118. doi:10.1016/j.fcr.2012.10.021

Agrawal, Y.C., and Pottsmith, H.C. 2000. Instruments for particle size and settling velocity observations in sediment transport. Marine Geology. 168:89–114.

Andrade, J.F., Rattalino Edreira, J.I., Mourtzinis, S., Conley, S.P., Ciampitti, I.A., et al. 2019. Assessing the influence of row spacing on soybean yield using experimental and producer survey data. Field Crop Res. 230:98-106.

Allen, R.G., Pruitt, W.O., Wright, J.L., Howell, T.A., Ventura, F., Snyder, R., Itenfisu, D., Steduto, P., Berengena, J., Yrisarry, J.B., Smith, M., Pereira, L.S., Raes, D., Perrier, A., Alves, I., Walter, I., Elliott, R. 2006. A recommendation on standardized surface resistance for hourly calculation of reference ETo by the FAO56 Penman-Monteith method. Agriculture Water Management. 81:1-22.

Allen, T. 1997. Particle size measurement. London: Chapman & Hall. Vol. 1. 5th Edition. ISBN 04123570

ALP, 2018. Agricultural Laboratory Proficiency (ALP) Program. https://collaborative-testing.com/program-1.php accessed in 2018.

Andrade, J.F., and Satorre, E.H. 2015. Single and double crop systems in the Argentine Pampas: Environmental determinants of annual grain yield. Field Crops Research. 177:137-147.

Andrade, J.F., Poggio, S.L., Ermácora, M., Satorre, E.H. 2015. Productivity and resource use in intensified cropping systems in the Rolling Pampa, Argentina. Eur. J. Agron. 67:37–51.

Andrews, M.P., Place, N.T., Crago, N.E. 2001. A globally focused Extension service. In F.L. Brewer (Ed.), *Agricultural Extension systems: An international perspective* (pp. 125-151). North Chelmsford, Massachusetts: Erudition Books.

Arriaga, F.J., and Lowery, B. 2003. Soil physical properties and crop productivity of an eroded soil amended with cattle manure. Soil Science. 168:889-899.

Arriaga, F.J., B. Lowery, and M.D. Mays. 2006. A fast method for determining soil particle size distribution using a laser instrument. Soil Science 171:663-674.

Bandyopadhyay, K.K., Misra, A.K., Ghosh, P.K., Hati, K.M. 2010. Effect of integrated use of farmyard manure and chemical fertilizers on soil physical properties and productivity of soybean. Soil and Tillage Research. 110:115-125.

Bengough, A.G., and Mullins, C.E. 1990. Mechanical impedance to root growth: a review of experimental techniques and root growth responses. Journal of Soil Science. 41:341-358.

Benke, M.B., Indraratne, S.P., Hoa, X., Chang, C., and Goh, T.B. 2008. Trace element changes in soil after long-term cattle manure applications. J. Environ. Qual. 37:798–807.

Berenguer, P., Cela, S., Santiveri, F., Boixadera, J., and Lloveras, J. 2008. Copper and Zinc soil accumulation and plant concentration in irrigated maize fertilized with liquid swine manure. Agron. J. 100:1056-1061.

Beuerlein, J.E. 1988. Yield of indeterminate and determinate semidwarf soybean for several planting dates, row spacings, and seeding rates. J. Prod. Agric. 1:300-303.
Bieganowski, A., M. Ryżak, A. Sochan, G. Barna, H. Hernádi, M. Beczek, C. Polakowski, and A. Makó. 2018. "Laser diffractometry in the measurements of soil and sediment particle size distribution." In Advances in Agronomy. Academic Press. 151:1-65.
Bouma, J. 1991. Influence of soil macroporosity on environmental quality. Adv. Agron. 46:1-37.
Blake, G.R., and G.C. Steinhardt. 2008. Particle-size distribution. In Encyclopedia of Soil Science, 505–10. Springer, Dordrecht.
Blanco-Canqui, H., Wienhold, B.J., Jin, V.L., and Schmer, M.R. 2017. Long-term tillage impact on soil hydraulic properties. Soil & Tillage Research. 170:38-42.
Blum, A. 2009. Effective use of water (EUW) and not water-use efficiency (WUE) is the target of crop yield improvement under drought stress. Field Crops Research. 112:119-123.
Boote, K.J., Jones, J.W., Pickering, N.B. 1996. Potential uses and limitations of crop models. Agron. J. 88:704-716.
Borkovec, M., Q. Wu, G. Degovics, P. Laggner, and H. Sticher. 1993. Surface area and size distributions of soil particles. Colloids and surfaces A: physicochemical and engineering aspects, A collection of papers presented at the International Symposium on Colloids in the Aquatic Environment, organized by SCI and Surface Chemistry Group, 73:65–76.
Breiman, L. 2001. Random forests. Mach. Learn. 45:5-32.
Breiman, L., Friedman, J., Olshen, R., Stone, C., Steinberg, D., and Colla, P. 1983. CART: Classification and regression trees (p. 156). Belmont, CA: Wadsworth.
Breiman, L., Friedman J.H., Olshen, R.A. and Stone, C.J. 1984. Classification and regression trees. Wadsworth, Belmont, CA.
Broadbent, F.E. 1965. Organic Matter, Methods of Soil Analysis. Part 1, Physical and Mineralogical Methods. American Society of Agronomy Monograph No. 9. pp. 1397-1400.
Brock, E., Ketterings, Q.M., and McBride, M. 2006. Copper and zinc accumulation in poultry and dairy manure-amended fields. Soil Science. 171:388-399.
Bünemann, E.K., Bongiorno, G., Bai, Z.G., de Goede, R., Mäder, P., Sukkel, W., and Brussaard, L. 2018. Soil quality – a review. Soil Biol. Biochem. 120:105-125
Burt, R. 2004. Soil Survey laboratory methods manual. Soil Survey Inv. Report 42:105-131. Campbell, G.S. 1985. Soil physics with BASIC—Transport models for soil-plant systems. Elsevier Co., Amsterdam.
Burton, R.O., Crisostomo, M.F., Berends, P.T., Kenneth, W., Burton, R.O., Crisostomo, M.F., Berends, P.T., Kelley, K.W., and Buller, O.H. 1996. Risk/return analysis of double-cropping and alternative crop rotations with and without government programs. Rev. Agric. Econ. 18:681–696.
Buurman, P., T. Pape, J.A. Reijneveld, F. de Jong, and E. van Gelder. 2001. Laser-diffraction and pipette-method grain sizing of Dutch sediments: correlations for fine fractions of marine, fluvial, and loess samples. Netherlands Journal of Geosciences. 80:49-57.
Calviño, P., Monzon, J. 2009. Farming systems of Argentina: yield constraints and risk management. In: Sadras, V.O., Calderini, D.F. (Eds.), Crop Physiology: Applications for Genetic Improvement and Agronomy, vol. 51. Elsevier Academic Press, San Diego, CA, pp. 70.

Calviño, P.A., G.A. Studdert, P.E. Abbate, F.H. Andrade, and M. Redolatti. 2002. Use of non-selective herbicides for wheat physiological and harvest maturity acceleration. F. Crop. Res. 77:191–199. doi:10.1016/S0378-4290(02)00072-2

Campbell, G.S. 1985. Soil Physics with Basic, Elsevier, Amsterdam.

Carter, J.C., and Hartwig, E.E. 1963. The management of soybean pp. 161-226. In Norman, A. G. (ed). The soybean Academic Press, New York.

Caviglia, O.P., and Andrade, F.H. 2010. Sustainable intensification of agriculture in the Argentinean Pampas: capture and use efficiency of environmental resources. Am. J. Plant Sci. Biotechnol., 3:1-8.

Chung, H. S., and Hogg, R. 1985. The effect of Brownian motion on particle size analysis by sedimentation. Powder Technology. 41:211–16.

Clothier, B.E., and Smettem, K.R.J. 1990. Combining laboratory and field measurements to define the hydraulic properties of soil. Soil Sci. Soc. Am. J. 54:299-304.

Companhia Nacional de Abastecimento (CONAB). 2019. Séries Históricas. Available from http://www.conab.gov.br/conteudos.php?a=1252 (last consult: 03/31/2019).

Cooper, R.L. 2003. A delayed flowering barrier to higher soybean yields. Field Crops Research. 82:27-35.

Cotrijal. (2018, March 1). *Cotrijal recebe produtores da Pensilvânia* [Press release]. Retrieved from http://www.cotrijal.com.br/noticias/ver/4781/Cotrijal+recebe+produtores+da+Pensilv%C3%A2nia

Cox, M.S., Gerard, P.D., Wardlaw, M.C., and Abshire, M.J. 2003. Variability of selected soil properties and their relationships with soybean yield. Soil Sci. Soc. Am. J. 67:1296-1302.

Dane, J.H. and Hopmans, J.W. 2002. Pressure Plate Extractor. In: Dane, J.H. and Topp, G.C., Eds., Methods of Soil Analysis: Physical Methods, Part 4, Soil Science Society of America, Madison, 688-690.

de Moraes, A., Carvalho, P.C.F., Crusciol, C.A.C., Lang, C.R., Pariz, C.M., Deiss, L., Sulc, R.M. 2019. Integrated Crop-Livestock Systems as a Solution Facing the Destruction of Pampa and Cerrado Biomes in South America by Intensive Monoculture Systems. *In.* Agroecosystem Diversity: Reconciling contemporary agriculture and environmental quality. Academic Press. Pages 257-273. ISBN 978-0-12-811050-8. https://doi.org/10.1016/C2016-0-00198-5

de Wit, C.T. 1965. Photosynthesis of leaf canopies Agric. Res. Rep. 663, p. 57 Pudoc, Wageningen.

Di Stefano, C., V. Ferro, and S. Mirabile. 2010. Comparison between grain-size analyses using laser diffraction and sedimentation methods. Biosystems engineering. 106:205–215.

Doran, J.W., and Parkin, T.B., 1994. Defining and assessing soil quality. In: Doran, J.W., Coleman, D.C., Bezdicek, D.F., Stewart, B.A. (Eds.), Defining Soil Quality for a Sustainable Environment. SSSA, Madison, WI, pp. 3–21.

Eckert, D. and Sims, J.T. 2011. Recommended Soil pH and Lime Requirement Tests. p. 19-25. In J.T. Sims and A. Wolf (eds.) Recommended Soil Testing Procedures for the Northeastern United States. Northeast Regional Bulletin #493. 3rd edition. Agricultural Experiment Station, University of Delaware, Newark, DE.

Edwards, W.M., Shipitalo, M.J., and Owens, L.B. 1993. Gas, water, and solute transport in soils containing macropores: A review of methodology. Geoderma. 57:31-49.

Egli, D.B. 2011. Time and the productivity of agronomic crops and cropping systems. Agron. J. 103:743–750. doi:10.2134/agronj2010.0508

Egli, D.B., and Cornelius, P.L. 2009. A Regional analysis of the response of soybean yield to planting date. Agron. J. 101:330-335.

Eitzinger, J., Trnka, M., Hösch, J., Žalud, Z., Dubrovský, M. 2008. Comparison of CERES, WOFOST and SWAP models in simulating soil water content during growing season under different soil conditions. Ecological Modelling. 171:223-246.

Embrapa. (2018, March 3). *Produção de grãos no Brasil atrai americanos* [Press release]. Retrieved from https://www.embrapa.br/busca-de-noticias/-/noticia/32853234/producao-de-graos-no-brasil-atrai-americanos

Eriksen-Hamel, N.S., and Whalen, J.K. 2007. Impacts of earthworms on soil nutrients and plant growth in soybean and maize agroecosystems. Agr. Ecosyst. Environ. 120:442-448.

Ernst, O.R., Kemanian, A.R., Mazzilli, S.R., Cadenazzi, M., Dogliotti, S. 2016. Depressed attainable wheat yields under continuous annual no-till agriculture suggest declining soil productivity. Field Crops Research. 186:107–116. https://doi.org/10.1016/j.fcr.2015.11.005

Ernst, O.R., Dogliotti, S., Cadenazzi, M., Kemanian, A.R. 2018. hifting crop-pasture rotations to no-till annual cropping reduces soil quality and wheat yield. Field Crops Research. 217:180–187. https://doi.org/10.1016/j.fcr.2017.11.014

Eshel, G., and G.J. Levy. 2007. "Comments on 'A fast method for determining soil particle size distribution using a laser instrument' by F.J. Arriaga, B. Lowery, and D.W. Mays. Soil Science 171:663-674 (2006)." Soil Science. 172(5):413.

Eshel, G., G.J. Levy, U. Mingelgrin, and M.J. Singer. 2004. Critical evaluation of the use of laser diffraction for particle-size distribution analysis. Soil Sci. Soc. Am. J. 68:736–743.

Faé, G.S., Montes, F., Bazilevskaya, E., Añó, R.M., Kemanian, A.R. 2019. Making soil particle size analysis by laser diffraction compatible with standard soil texture determination methods. Soil Science Society of Agronomy Journal. doi: 10.2136/sssaj2018.10.0385

Faé, G.S., Sulc, R.M., Barker, D.J., Dick, R.P., Eastridge, M.L., and Lorenz, N. 2009. Integrating Winter Annual Forages into a No-Till Corn Silage System. Agron J. 101:1286-1296.

FAO. 2014. World reference base for soil resources 2014: International soil classification system for naming soils and creating legends for soil maps. Food and Agriculture Organization (FAO) Rome, Italy.

Fehr, W.R. and Caviness, C.E. 1977. Stages of soybean development. Special Report 80, Iowa Agricultural Experiment Station, Iowa Cooperative External Series, Iowa State University, Ames.

Fernlund, J.M.R., Zimmerman, R.W., and Kragic, D. 2007. Influence of volume/mass on grain-size curves and conversion of image-analysis size to sieve size. Engineering Geology. 90:124–37.

Fischer, T., D. Byerlee, D. and Edmeades, G. 2014. Crop yields and global food security: Will yield increase continue to feed the world? ACIAR Monogr. 158. Australian Centre for International Agricultural Research, Canberra, Australia. p. 634.

Fisher, P., Aumann, C., Chia, K., O'Halloran, N. and Chandra, S. 2017. Adequacy of laser diffraction for soil particle size analysis. PLoS ONE 12(5):e0176510.

Frankenfield, A. 2017. The Pennsylvania soybean contest report. The Pennsylvania State University, The Pennsylvania Soybean Board. University Park, PA. https://pasoybean.org/wp-content/uploads/2018/01/Soybean-Contest-Report-2017.pdf Last checked May 16th 2019.
Franzluebbers, A.J. 2002. Soil organic matter stratification ratio as an indicator of soil quality. Soil & Tillage Research. 66:95-106.
Fritsch GmbH, 2018. https://www.fritsch-international.com/
Garboczi, E.J., Riding, K.A. and Mohammadreza Mirzahosseini. 2017. Particle shape effects on particle size measurement for crushed waste glass. Advanced Powder Technology. 28:648–57.
Gavlak R., Horneck, D. and Miller, R. 2013. Soil, plant, and water reference methods for the western Region. 3rd ed. WREP. 125. https://www.naptprogram.org/files/napt/publications/method-papers/western-states-methods-manual-2013.pdf
Gee, G.W., and Bauder, J. W. 1986. Particle-size analysis. pp 383-411. In: Methods of soil analysis: Part 1 Physical and Mineralogical Methods, editor: Arnold Klute. AGRONOMY Book Series Number 9, Second Edition, American Society of Agronomy and Soil Science Society of America. Madison, WI.
Gee, G.W., and Or, D. 2002. Particle-size analysis. pp 255-293. In: Methods of soil analysis: Part 4 Physical Methods, eds. Dane, J.H., and G.T. Clarke. SSSA Book Series, 5.4. Madison, WI: Soil Science Society of America.
Godoy, C.V., Seixas, C.D.S., Soares, R.M., Marcelino‑Guimarães, F.C., Meyer, M.C., and Costamilan, L.M. 2016. Asian soybean rust in Brazil: past, present, and future. Pesq. agropec. bras. 51:407-421.
Gonzales, H.B., Ravi, S., Li, J., and Sankey, J.B. 2018. Ecohydrological implications of aeolian sediment trapping by sparse vegetation in drylands. Ecohydrology. 11:e1986.
Grassini, P., Torrion, J.A., Cassman, K.G., Yang, H.S., and Specht, J.E., 2014. Drivers of spatial and temporal variation in soybean yield and irrigation requirements in the western US Corn Belt. Field Crops Res. 163:32–46.
Grassini, P., Torrion, J.A., Yang, H.S., Rees, J., Andersen, D., Cassman, K.G., Specht, J.E. 2015. Soybean yield gaps and water productivity in the western U.S. Corn Belt. Field Crop Res. 179:150-163.
Green, W.H., and Ampt, G.A. 1911. Studies on soil physics: 1. Flow of air and water through soils. J. Agric. Sci. 4:1-24.
Gregory, P.J., Tennant, D., Hambiln, A.P., and Eastham J. 1992. Components of the water balance on duplex soils in Western Australia. Aust J Exp Agr 33: 845-855
Gupta, V.V.S.R., and Germida, J.J., 2015. Soil aggregation: influence on microbial biomass and implications for biological processes. Soil Biol. Biochem. 80, A3–A9.
Haney, R.L., Brinton, W.H., and Evans, E. 2008. Estimating soil carbon, nitrogen, and phosphorus mineralization from short-term carbon dioxide respiration. Communications in Soil Science and Plant Analysis. 39:2706–2720.
Hanson, A.D. and Hitz, W.D., 1982. Metabolic responses of mesophytes to plant water deficits. Annu. Rev. Plant Physiol., 33" 163-203.

Hassink, J., and Whitmore, A.P. 1997. A Model of the physical protection of organic matter in soils. Soil Sci. Soc. Am. J. 61:131–39.
Hati, K.M., Swarup, A., Dwivedi, A.K., Misra, A.K., Bandyopadhyay, K.K. 2007. Changes in soil physical properties and organic carbon status at the top soil horizon of a vertisol of central India after 28 years of continuous cropping, fertilization and manuring. Agr. Ecosyst. Environ. 119:127-134.
Hawkins, S.E., Southard, B. 2001. Field Tours-An Old Tool That Can Still Work. *Journal of Extension*, 39(1), Article 1TOT4. Available at: https://www.joe.org/joe/2001february/tt4.php
Hillel, D., and Hatfield, J.L. eds. 2005. Encyclopedia of Soils in the Environment. 1st ed. Oxford, UK; Boston: Elsevier/Academic Press.
Hodnett, M.G., Tomasella, J., 2002. Marked differences between van Genuchten soil moisture-retention parameters for temperate and tropical soils: a new water retention pedo-transfer function developed for tropical soils. Geoderma 108:155–180.
Hoffman, A.L., Kemanian, A.R., and Forest, C.E. 2018. Analysis of climate signals in the crop yield record of sub-Saharan Africa. Glob. Chang. Biol. 24:143-157
International Organization for Standardization, 2009. ISO 13320: Particle size analysis – Laser diffraction methods.
James, G., D. Witten, T. Hastie, and R. Tibshirani. 2013. An introduction to statistical learning. Springer Science + Business Media, New York.
Karlen, D.L., Goeser, N.J., Veum, K.S., and Yost, M.A. 2017. On-farm soil health evaluations: Challenges and opportunities. Journal of Soil and Water Conservation. 72:26-32.
Karlen, D.L., Mausbach, M.J., Doran, J.W., Cline, R.G., Harris, R.F., and Schuman, G.E. 1997. Soil quality: A concept, definition, and framework for evaluation. Soil Sci. Soc. Am. J. 61:4-10.
Kautz, T. 2014. Research on subsoil biopores and their functions in organically managed soils: A review. Renewable Agriculture and Food Systems. 30:318-327.
Kelley, K.W. 2003. Double-cropping winter wheat and soybean improves net returns in the eastern great plains. Crop Manag. 2:0–0. doi:10.1094/CM-2003-1112-01-RS
Kemanian, A.R., Stöckle, C.O. 2010. C-farm: a simple model to evaluate the carbon balance of soil profiles. European Journal of Agronomy, Montpellier. 32:22-29.
Kemanian, A.R., Stöckle, C.O., Huggins, D.R., 2004. Variability of barley radiation-use efficiency. Crop Sci. 44, 1662–1672.
Kemanian, A.R., Stöckle, C.O., Huggins, D.R., Viega, L.M. 2007. A simple method to estimate harvest index in grain crops. Field Crops Res. 103:208-216.
Kettler, T. A., Doran, J. W. and Gilbert, T. L. 2001. Simplified method for soil particle size determination to accompany soil-quality analyses. Soil Sci. Soc. Am. J. 65:849–852.
Koester, R.P., Skoneczka, J.A., Cary, T.R., Diers, B.W., and Ainsworth, E.A. 2014. Historical gains in soybean (*Glycine max* Merr.) seed yield are driven by linear increases in light interception, energy conversion, and partitioning efficiencies. Journal of Experimental Botany. 65:3311–3321.
Konert, M., and Vandenberghe, J. 1997. Comparison of laser grain size analysis with pipette and sieve analysis: A solution for the underestimation of the clay fraction. Sedimentology. 44:523–535.

Kremer, C., Stöckle, C.O., Kemanian, A.R., Howell, T. 2008. A Canopy Transpiration and Photosynthesis Modelfor Evaluating Simple Crop Productivity Models. *In.* Response of crops to limited water: understanding and modeling water stress effects on plant growth processes. Advances in Agricultural systems Modeling Series 1. ASA, CSSA, SSSA, 677 S. Segoe Rd., Madison, wi 53711. USA.

Kukal, M.S., and Irmak, S. 2018. U.S. Agro-climate in 20th century. Growing degree days, first and last frost, growing season length, and impacts on crop yields. Scientific Reports 8 (1), 6977

Kyei-Boahen, S., and Zhang, L. 2006. Early-maturing soybean in a wheat–soybean double-crop system: Yield and net returns. Agron. J. 98:295–301. doi:10.2134/agronj2005.0198

Lamorski, K., Bieganowski, A., Ryżak, M., Sochan, A., Sławiński, C. and Stelmach, W. 2014. Assessment of the usefulness of particle size distribution measured by laser diffraction for soil water retention Modelling. Journal of Plant Nutrition and Soil Science. 177:803–813.

Lancaster Farming. (2018, March 23). *Tour reveals brazil's bean bounty* [Press release]. Retrieved from https://www.lancasterfarming.com/farming/field_crops/tour-reveals-brazil-s-bean-bounty/article_6e146f42-13d6-55b1-b344-55a77f7574d8.html

Lobell, D.B., Cassman, K.G., and Field, C.B. 2009. Crop yield gaps: Their importance, magnitudes, and causes. Annu. Rev. Environ. Resour. 34:179–204.

Loveland P., and Whalley, R. 2000. Particle Size Analysis. In: Soil and Environmental Analysis: Physical Methods. Smith, Keith A., and Chris E. Mullins, editors. Second Edition. Baton Rouge, UNITED STATES: Chapman and Hall/CRC.

Makeschin F. 1997. Earthworms (Lumbricidae: Oligochaeta): important promoters of soil development and soil fertility. In: Benckiser, G, ed. Fauna in soil ecosystems. Dekker: New York, 173–223.

Makó, A., Tóth, G., Weynants, M., Rajkai, K., Hermann, T. and Tóth, B. 2017. Pedotransfer functions for converting laser diffraction particle-size data to conventional values. European Journal of Soil Science. 68:769–782.

Malvern Panalytical inc., 2018. https://www.malvernpanalytical.com/en.

Mantovi, P., Bonazzi, G., Maestri, E., and Marmiroli, N. 2003. Accumulation of copper and zinc from liquid manure in agricultural soils and crop plants. Plant Soil. 250:249–257.

Matthews, M. 2007. The effect of grain shape and density on size measurement. In: Principles, Particle Size Analysis. Syvitski, J. P. M editor. Reissue edition. Cambridge: Cambridge University Press.

Mausel, P.W., 1971. Soil quality in Illinois—an example of a soils geography resource analysis. The Professional Geographer. 23:127–136.

McBride, M.B., and Spiers, G. 2001. Trace element content of selected fertilizers and dairy manures as determined by ICP-MS. Communications in Soil Science and Plant Analysis. 32:139-156.

McDermitt, D.K., Loomis, R.S. 1981. Elemental composition of biomass and its relation to energy content, growth efficiency, and growth yield. Annals of Botany, 48: 275-290.

Meinke, H., Baethgen, W.E., Carberry, P.S., Donatelli, M., Hammer, G.L., Selvaraju, R., Stöckle, C.O., 2001. Increasing profits and reducing risks in crop production using participatory systems simulation approaches. Agric. Syst. 70:493–513

Mercau, J.L., Dardanelli, J.L., Collino, D.J., Andriani, J.M., Irigoyen, A., Satorre, E.H. 2007. Predicting on-farm soybean yields in the pampas using CROPGRO-soybean. Field Crops Research 100:200–209.

Merkus, H.G. 2009. Particle size measurements: fundamentals, practice, quality. Springer Particle Technology Series, v. 17. ISBN: 978-1-4020-9015-8.

Miller, B.A., and Schaetzl, R.J. 2012. Precision of soil particle size analysis using laser diffractometry. Soil Sci. Soc. Am. J. 76:1719–1727.

Moebius, B.N., van Es, H.M., Schindelbeck, R.R., Idowu, O.J., Thies, O.J., and Clune. D.J. 2007. Evaluation of laboratory-measured soil physical properties as indicators of soil quality. Soil Science. 172:895-910.

Moebius-Clune, B.N., Moebius-Clune, D.J., Gugino, B.K., Idowu, O.J., Schindelbeck, R.R., Ristow, A.J., van Es, H.M., This, J.E., Shayler, H.A., McBride, M.B., Kurtz, K.S.M., Wolfe, D.W., and Abawi, G.S., 2016. Comprehensive Assessment of Soil Health, 3th Edition.

Moeys, J., W. Shangguan, R. Petzold, B. Minasny, B. Rosca, N. Jelinski, W. Zelazny, R.M. Silva Souza, J.L. Safanelli, and A. ten Caten. 2018. Soiltexture: functions for soil texture plot, classification and transformation (version 1.5.1).

Monteith, J.L., 1981. Does light limit crop production? In: C.B. Johnson (Editor), Physiological Processes Limiting Plant Productivity. Butterworths, London, pp. 23-38.

Mooers, C.A. 1908. The soybean: A comparison with cowpea. Bull. 82. Tennessee Agric. Exp. Stn., Knoxville.

Moore, I.D., Burch, G.J., and Wallbrink, P.J. 1986. Preferential flow and hydraulic conductivity of forest soils. Soil Sci. Soc. Am. J. 50:876-881.

NAPT, 2018. North American Proficiency Testing (NAPT) Program. https://www.naptprogram.org/ accessed in 2018.

Nimmo, J.R., Schmidt, K.M., Perkins, K.S., and Stock, J.D. 2009. Rapid measurement of field-saturated hydraulic conductivity for areal characterization. Vadose Zone J. 8:142−149.

North Central Regional Research (NCERA-13). 2015. Recommended Chemical Soil Tests Procedures for the North Central Region. 221. http://extension.missouri.edu/explorepdf/specialb/sb1001.pdf.

Northeast Coordinating Committee for Soil Testing (NECC-1312). 2011. Recommended Soil Testing Procedures for the Northeastern United States. Cooperative Extension (blog). Accessed December 12, 2018. http://extension.udel.edu/lawngarden/soil-health-composting/recommended-soil-testing-procedures-for-the-northeastern-united-states/.

Nosetto, M.D., Jobbágy, E.G., Brizuela, A.B., Jackson, R.B. 2012. The hydrologic consequences of land cover change in central Argentina. Agric. Ecosyst. Environ. 154:2-11.

Nunes, M. 2018. Estrutura de solos altamente intemperizados cultivados sob plantio direto. Universidade de São Paulo. Piracicaba. Dissertation.

Nunes, M.R., van Es, H.M., Schindelbeck, R., Ristow, A.J., and Ryan, M. 2018. No-till and cropping system diversification improve soil health and crop yield. Geoderma. 328:30–43.

O'Geen, A., M. Walkinshaw, and D. Beaudette. 2017. SoilWeb: A multifaceted interface to soil survey information. Soil Sci. Soc. Am. J. 81:853-862.

Oliveira, N. C., A.R. Paschoal, R.J. Paula, I.C. Constantino, M.C. Bisinoti, A.B. Moreira, L.G. Fregolente, et al. 2018. Morphological analysis of soil particles at multiple length-scale reveals nutrient stocks of Amazonian Anthrosols. Geoderma. 311:58–66.

Pennsylvania State University. (2018, April 18). *Penn State Extension provides clients with 'study abroad' opportunities* [Press release]. Retrieved from https://news.psu.edu/story/517074/2018/04/18/study-abroad/penn-state-extension-provides-clients-study-abroad

Petersen, S.O., Sommer, S.G., Béline, F., Burton, C., Dach, J., Dourmad, J.Y., Leip, A., Misselbrook, T., Nicholson, F., Poulsen, H.D., Provolo, G., Sørensen, P., Vinnerås, B., Weiske, A., Bernal, M.-P., Böhm, R., Juhász, C., and Mihelic. R. 2007. Recycling of livestock manure in a whole-farm perspective. Livestock Science. 112:180–191.

Pires, J.L., Strieder, M.L., Pereira, P.R., Costamilan, L.M., Maciel, J.L.N., De Mori, C., Caierão, E., Guarienti, E., Carrão-Panizzi, M., Dalmago, G., Santos, H.P., Faé, G.S., Silva Junior, J.P., Santi, A., Cunha, G.R., Vargas, L., Pazinatto, A. 2016. Estratégias de sucessão trigo/aveia preta soja para sistemas de produção de grãos no Planalto Médio do Rio Grande do Sul. Circular técnica online 30. Passo Fundo, RS.

Polakowski, C., Ryżak, M., Bieganowski, A., Sochan, A., Bartmiński, P., Dębicki, R. and Stelmach, W. 2015. The reasons for incorrect measurements of the mass fraction ratios of fine and coarse material by laser diffraction. Soil Sci. Soc. Am. J. 79(1):30.

R Development Core Team. 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Rattalino Edreira, J.I., Guilpart, N., Sadras, V., Cassman, K.C., van Ittersum, M.K., Schils, R.L.M., Grassini, P. 2018. Water productivity of rainfed maize and wheat: A local to global perspective. Agricultural and Forest Meteorology. 259:364-373.

Rattalino Edreira. J.I., Mourtzinis, S., Conley, S.P., Roth, A.C., Ciampitti, I.A., Licht, M.A., Kandel, H., Kyveryga, P.M., Lindsey, L.E., Mueller, D.S., Naeve, S.L., Nafziger, E., Specht, J.E., Stanley, J., Staton, M.J., and Grassini, P. 2017. Assessing causes of yield gaps in agricultural areas with diversity in climate and soils. Agricultural and Forest Meteorology. 247:170–180.

Rawle, A.F. 2015. Representative sampling – another Cinderella of particle size analysis. Procedia Eng., 102:1707-1713. The 7th World Congress on Particle Technology (WCPT7).

Rawls, W.J., Brakensiek, D.L., and Longsdon, S.D. 1993. Predicting saturated hydraulic conductivity utilizing fractal principles. Soil Sci. Soc. Am. J. 57:1193-1197.

Reddy, M.R., Lameck, D., and Rezania, M.E. 1989. Uptake and distribution of copper and zinc by soybean and corn from soil treated with sewage sludge. Plant and Soil. 113:271-274.

Reynolds, W.D. and Elrick, D.E. 1990. Ponded infiltration from a single ring: I. Analysis of steady flow. Soil Sci. Soc. Am. J. 54:1233-1241.

Reynolds, W.D., and Topp, G.C. 2008. Soil water desorption and imbibition: tension and pressure techniques. Soil sampling and methods of analysis. 2nd ed. CRC Press, Boca Raton, FL, 981-997.

Van Roekel, R.J., Purcell, L.C., and Salmerón, M. 2015. Physiological and management factors contributing to soybean potential yield. Field Crops Research. 182:86-97.

Roper, W.R., Osmond, D.L., Heitman, J.L., Wagger, M.G., and Reberg-Horton, S.C. 2017. Soil health indicators do not differentiate among agronomic management systems in North Carolina Soils. Soil Sci. Soc. Am. J. 81:828–843

Ross, D., and Ketterings, Q. 2011. Recommended soil tests for determining soil cation exchange capacity. p. 75-86. In J.T. Sims and A. Wolf (eds.) Recommended Soil Testing Procedures

for the Northeastern United States. Northeast Regional Bulletin #493. 3rd edition. Agricultural Experiment Station, University of Delaware, Newark, DE.
Russel, R.S. 1977. Plant root systems: their function and interaction with the soil. McGraw-Hill. London.
Sadras, V.O., and Calviño, P.A. 2001. Quantification of grain yield response to soil depth in soybean, maize, sunflower, and wheat. Agron. J. 93:577–583.
Salmerón, M., E.E. Gbur, F.M. Bourland, N.W. Buehring, L. Earnest, F.B. Fritschi, B.R. Golden, D. Hathcoat, J. Lofton, A.T. McClure, T.D. Miller, C. Neely, G. Shannon, T.K. Udeigwe, D.A. Verbree, E.D. Vories, W.J. Wiebold, and L.C. Purcell. 2016. Yield response to planting date among soybean maturity groups for irrigated production in the US Midsouth. Crop Sci. 56:747–759. doi:10.2135/cropsci2015.07.0466
Santi, A.L., Amado, T.J.C., Cherubin, M.R., Martin, T.N., Pires, J.L., Della Flora, L.P., and Basso, C.J. 2012. Análise de componentes principais de atributos químicos e físicos do solo limitantes à produtividade de grãos. Pesq. Agropec. Bras. 47:1346-1357.
Santos, H.G, Jacomine, P.K.T., Anjos, L.H., Oliveira, V.A., Oliveira, J.B., Coelho, M.R., Lumbreras, J.F., Cunha, T.J.F. 2006. Brazilian system of soils classification. 3rd edn. Embrapa Solos: Rio de Janeiro.
Sawchik, J., and Mallarino, A.P. 2008. Variability of soil properties, early phosphorus and potassium uptake, and incidence of pests and weeds in relation to soybean grain yield. Agron. J. 100:1450-1462.
Saxton, K.E., and Rawls, W.J. 2006. Soil water characteristic estimates by texture and organic matter for hydrologic solutions. Soil Sci. Soc. Am. J., 70:1569-1578.
Schaap, M.G., F.J. Leij, and M.Th. van Genuchten. 1998. Neural network analysis for hierarchical prediction of soil hydraulic properties. Soil Sci. Soc. Am. J. 62(4):847.
Schipanski, M.E., Barbercheck, M., Douglas, M.R., Finney, D.M. Haider, K., Kaye, J.P., Kemanian, A.R., Mortensen, D.A., Ryan, M.R., Tooker, J., White, C. 2014. A framework for evaluating ecosystem services provided by cover crops in agroecosystems. Agricultural Systems. 125:12-22.
Schulte, E.E. and Hoskins, B. 2011. Recommended Soil Organic Matter Tests. p. 63-74. In J.T. Sims and A. Wolf (eds.) Recommended Soil Testing Procedures for the Northeastern United States. Northeast Regional Bulletin #493. 3rd edition. Agricultural Experiment Station, University of Delaware, Newark, DE.
Seddaiu, G, Porcu, G., Ledda, L. Roggero, P.P., Agnelli, A., Corti, G. 2013. Soil organic matter content and composition as influenced by soil management in a semi-arid Mediterranean agro-silvo-pastoral system. Agr. Ecosyst. Environ. 167:1-11
Seifert, C.A., and D.B. Lobell. 2015. Response of double cropping suitability to climate change in the United States. Environ. Res. Lett. 10:024002. doi:10.1088/1748-9326/10/2/024002
Sentek Environmental Technologies. 2001. Calibration of the Sentek Pty Ltd soil moisture sensors, Stepney, Australia.
Sentelhas, P.C., Battisti, R., Câmara, G.M.S., Farias, J.R.B., Hampf, A., Nendel, C. 2015.The soybean yield gap in Brazil – magnitude, causes and possible solutions fora sustainable production. J. Agric. Sci. 157:1394–1411, http://dx.doi.org/10.1017/S0021859615000313.
Sheppard, S.C., and Sanipelli, B. 2012. Trace Elements in Feed, Manure, and Manured Soils. Journal of Environmental Quality. 41: 1846-1856.

Sikora, F., and Moore, K. 2014. Soil test methods from the Southeastern United States. Southern Extension and Research Activity Information Exchange Group - 6 (SERA-IEG-6), Southern Cooperative Series Bulletin No. 419. http://aesl.ces.uga.edu/sera6/PUB/MethodsManualFinalSERA6.asp

Snedecor, G.W., Cochran, W.G. 1989. Statistical Methods, eight ed. Iowa State University Press.

Sojka, R.E., and Upchurch, D.R., 1999. Reservations regarding the soil quality concept. Soil Sci. Soc. Am. J. 63:1039–1054.

Specht, J.E., Hume, D.J., and Kumudini, S.V. 1999. Soybean Yield Potential—A Genetic and Physiological Perspective. Crop Sci. 39:1560–1570.

Stirzaker, R.J., Passioura, J.B., and Wilms, Y. 1996. Soil structure and plant growth: Impact of bulk density and biopores. Plant and Soil. 185:151-162.

Stöckle, C.O., Donatelli, M., and Nelson, R. 2003. CropSyst, a cropping systems simulation model. European Journal of Agronomy, Montpellier, 18:289-307.

Stöckle, C.O., Kiniry, J.R. 1990. Variability in crop radiation use efficiency associated with vapor-pressure deficit. Field Crops Res. 25, 171–181.

Sulc, R.M, and Franzluebbers, A.J. 2014. Exploring integrated crop–livestock systems in different ecoregions of the United States. European Journal of Agronomy. 57:21-30.

Svoray, T., Hassid, I., Atkinson, P.M., Moebius-Clune, B.N., and van Es., H.M. 2015. Mapping soil health over large agriculturally important areas. Soil Sci. Soc. Am. J. 79:1420–1434.

Syvitski, J.P.M, K.W. Asprey, and D.A. Clattenburg. 2007. Principles, design, and calibration of settling tubes. In: Principles, Particle Size Analysis. Syvitski, J. P. M editor. Reissue edition. Cambridge: Cambridge University Press.

Taubner, H., Roth, B. and Tippkötter, R. 2009. Determination of soil texture: comparison of the sedimentation method and the laser-diffraction analysis. Journal of Plant Nutrition and Soil Science. 172:161–71.

Tay WT, Soria MF, Walsh T, Thomazoni D, Silvie P, Behere GT, et al. (2013) A Brave New World for an Old World Pest: Helicoverpa armigera (Lepidoptera: Noctuidae) in Brazil. PLoS ONE 8(11): e80134. https://doi.org/10.1371/journal.pone.0080134

The Agronomy Guide. 2015. The Agronomy Guide (2015–2016). Penn State College of Agricultural Sciences. The Pennsylvania State University, University Park, PA.

Tomasella, J., Hodnett, M.G., and Rossato, L., 2000. Pedotransfer functions for the estimation of soil water retention in Brazilian soils. Soil Sci. Soc. Am. J. 69:649–652.

Treadwell, P., Lachapelle, P., Howe, R. (2013). Extension Learning Exchange: Lessons from Nicaragua. *Journal of Extension*, 51(5), Article 5IAW6. Available at:

USDA. 2017. Soil survey manual. Soil Science Division Staff. United States Department of Agriculture Handbook No. 18.

USDA-NASS. 2018. National Agricultural Statistics Service. Available at www.nass.usda.gov/index.asp (accessed 04 March 2019; verified 9 June 2019). USDA-NASS, Washington, DC.

USEPA. 1986. Test methods for evaluating solid waste. Volume IA: 3rd Edition. EPA/SW-846. National Technical Information Service. Springfield, Va.

van Es, H.M., and Karleen, D. 2019. Reanalysis validates soil health indicator sensitivity and correlation with long-term crop yields. Soil Sci. Soc. Am. J. doi: 10.2136/sssaj2018.09.0338

Van Ittersum, M.K., Cassman, K.G., Grassini, P., Wolf, J., Tittonell, P., and Hochman, Z. 2013. Yield gap analysis with local to global relevance—a review. Field Crops Res. 143:4–17.
Van Opstal, N.V., Caviglia, O.P., and Melchiori, R.J.M. 2011. Water and solar radiation productivity of double-crops in a humid temperate area. Aust. J. Crop Sci. 5:1760–1766.
Vicente-Serrano, S.M., Beguería, S., and López-Moreno, J.I. 2010: A multiscalar drought index sensitive to global warming: The Standardized Precipitation Evapotranspiration Index. J. Climate. 23:1696–1718.
Voight, D. 2016. Pennsylvania on-farm network reports: 2009-2015. Penn State Extension. The Pennsylvania State University. 1:1-100.
Wang, J., Wang, E., Yin, H., Feng, L. and Zhang, J. 2014. Declining yield potential and shrinking yield gaps of maize in the North China Plain. Agric. For. Meteorol. 195-196:89–101. doi:10.1016/j.agrformet.2014.05.004
Wang, W.J., Dalal, R.C., Moody, P.W., Smith, C.J. 2003. Relationships of soil respiration to microbial biomass, substrate availability and clay content. Soil Biology and Biochemistry. 35:273-284.
Whisler, F.D., Acock, B., Baker, D.N., Fye, R.E., Hodges, H.F., Lambert, J.R., Lemmon, H.E., McKinion, J.M., and Reddy, V.R. 1986. Crop simulation models in agronomic systems. Adv. Agron. 40:141-208.
White, R.G., and Kirkegaard, J.A. 2010. The distribution and abundance of wheat roots in a dense structured subsoil – implications for water uptake. Plant, Cell and Environment. 33:133-148.
Williams, A., Hunter, M.C., Kammerer, M., Kane, D.A., Jordan, N.R., Mortensen, D.A., Smith, R.G., Snapp, S., and Davis, A.S. 2016. Soil Water Holding Capacity Mitigates Downside Risk and Volatility in US Rainfed Maize: Time to Invest in Soil Organic Matter? PLoS ONE 11(8): e0160974.
Wolf, A.M., and Beegle, D.B. 2011. Recommended soil tests for macronutrients. p. 39-47. In J.T. Sims and A. Wolf (eds.) Recommended Soil Testing Procedures for the Northeastern United States. Northeast Regional Bulletin #493. 3rd edition. Agricultural Experiment Station, University of Delaware, Newark, DE.
Wright, S.F., and Upadhyaya, A. 1996. Extraction of an abundant and unusual protein from soil and comparison with hyphal protein of arbuscular mycorrhizal fungi. Soil Science. 161:575-586.
Yang, F., Zhang, G.L., Yang, J.L., Li, D.C., Zhao, Y.G., Liu, F. Yang, R., and Yang, F. 2014. Organic matter controls of soil water retention in an alpine grassland and its significance for hydrological processes. Journal of Hydrology. 519:3086–3093.
Zanon, A.J., Streck, N.A. and Grassini, P. 2016. Climate and management factors influence soybean yield potential in a subtropical environment. Agron J. 108:1447-1454.
Zibilske, L. 1994. Carbon mineralization. Methods of Soil Analysis: Part 2—Microbiological and -Biochemical Properties. Soil Science Society of America, Madison, WI, pp. 835-863.
Zou, D.S. and Kahnt, G. 1988. Effect of air humidity on photosynthesis and transpiration of soybean leaves. J. Agron. Crop Sci., 161:190-194.

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