Published July 11, 2019

Diagnosing, Ameliorating, and Monitoring Soil Compaction in No-Till Brazilian Soils

Devison Souza Peixoto, Bruno Montoani Silva,* Sérgio Henrique Godinho Silva, Douglas L. Karlen, Silvino Guimarães Moreira, Alessandro Alvarenga Pereira da Silva, Álvaro Vilela de Resende, Lloyd Darrell Norton, and Nilton Curi

Core Ideas

- One-time tillage increased soybean yield as a result of improving soil physical properties.
- Penetration resistance, air capacity, macroporosity, relative field capacity, and S index were the soil physical properties that best predicted soybean yield.
- The most sensitive soil physical properties for detecting structural related alterations were equally important for predicting soybean yield.
- Penetration resistance is the indicator that addresses no-tillage soil compaction and its effect on soybean yield.

D.S. Peixoto, B.M. Silva, S.H.G. Silva, and N. Curi, Dep. of Soil Science, Federal Univ. of Lavras, Av. Doutor Sylvio Menicucci 1001, CEP 37200-000, Lavras-Minas Gerais, Brazil; D.L. Karlen, USDA-Agricultural Research Service, National Laboratory for Agriculture and the Environment, 1015 N. University Blvd., Ames, IA 50011-3120; S.G. Moreira and A.A.P. Silva, Dep. of Agriculture, Federal Univ. of Lavras, Av. Doutor Sylvio Menicucci 1001, CEP 37200-000, Lavras- Minas Gerais, Brazil; A.V. Resende, Brazilian Agricultural Research Corporation (Embrapa), CEP 35700-029, Sete Lagoas-Minas Gerais, Brazil; and L.D. Norton, Purdue Univ., Dep. of Agricultural and Biological Engineering, West Lafayette, IN 47907-2053.

Received 6 Sept. 2018.
Accepted 28 May 2019.
*Corresponding author (brunom.silva@dcs.ufla.br).

Agrosyst. Geosci. Environ. 2:180035 (2019)
doi:10.2134/age2018.09.0035

ABSTRACT

Soil compaction can significantly reduce crop yield. Our objective was to identify the most sensitive soil physical property and process indicators related to crop yield using a Random Forest algorithm (RFA). This machine-learning, decision-making tool was used with field-scale data from five soil management treatments designed to ameliorate compaction in no-tillage (NT) fields. The treatments were: T1, NT for 10 yr (control); T2, NT with surface application of 3.6 Mg ha^{-1} of agricultural gypsum; T3, NT with subsoiling plus 1.44 Mg ha^{-1} of highly reactive limestone applied to a depth of 0.60 m; T4, NT planting following chisel plowing at a depth of 0.26 m; and T5, NT with subsoiling to a depth of 0.60 m plus 1.44 Mg ha^{-1} of surface-applied, highly reactive limestone. Fifteen soil physical properties and processes related to growth and yield of soybean [*Glycine max* (L.) Merr.] were measured. Mechanical intervention, specifically subsoiling, improved soil physical properties and increased soybean yield cultivated following occasional tillage. The RFA ranked penetration resistance (PR), air capacity, macroporosity, relative field capacity, and the Dexter-S index as the most sensitive soil physical indicators affecting soybean yield. Those indicators were also sensitive to changes in soil structure due to subsoiling. We conclude that the RFA was an effective tool for screening indicators and that those chosen can be effective for monitoring soil compaction and its effect on soybean yield. Penetration resistance may be used to guide on-farm decision-making regarding when and how NT soil compaction should be addressed.

Abbreviations: AC, air capacity; ACm, air capacity of soil matrix; ANOVA, analysis of variance; BD, bulk density; IE, integral energy; Inser1stpod, height of insertion of the first pod; Mac, macroporosity; Mic, microporosity; NT, no-tillage; PAWC, plant-available water capacity; PAWCip, plant-available water capacity using the inflection point as field capacity; PCA, principal component analysis; PHeight, plant height; PORp, porosity of soil macropore domain; PR, penetration resistance; RAW, readily available water; RAWip, readily available water using inflection point as field capacity; RFA, Random Forest algorithm; RFC, relative field capacity; TP, total porosity.

No-tillage (NT) has been adopted globally on more than 155 million ha (FAO, 2016) and is expanding at approximately 6 million ha yr^{-1} because of both economic and environmental benefits (Derpsch et al., 2010; Pittelkow et al., 2015). In Brazil, NT covers more than 32 million ha mostly used for soybean [*Glycine max* (L.) Merr.], but compaction is becoming a more frequently observed problem on clay-textured soils (Reichert et al., 2009; Nunes et al., 2014; Nunes et al., 2015). Mechanized operations are the primary cause for soil compaction, since wheel-traffic during as many as three cropping cycles per year may occur on 100, 60, and 30% of the soil surface with conventional-, minimum-, and no-tillage, respectively (Tullberg, 1990). Furthermore, although NT has many advantages, including trafficability, its implementation on wet soils can cause a progressive increase in compaction with every cropping cycle (Hamza and Anderson, 2005).

Soil compaction limits plant root development (Bengough et al., 2011; Lipiec et al., 2012) due to increased bulk density (BD), penetration resistance (PR), and reduced permeability (Hamza and Anderson, 2005), which collectively limit gas exchange (air and water vapor) as well as nutrient uptake by roots (Lipiec and Stepniewski, 1995). Mechanical strategies suggested to mitigate NT soil compaction include equipping seeders with fixed shanks or openers that disturb soil to a depth of ~0.17 m (Nunes et al., 2014; Nunes et al., 2015); chiseling to a depth of ~0.20 to 0.30 m every year or occasionally (Secco et al., 2009; Calonego and Rosolem, 2010; Calonego et al., 2017); combining tillage (disc plow and disc harrow to a depth of ~0.20 m) with lime application (Fidalski et al., 2015), or subsoiling diagonally across the field at a depth of ~0.60 m (Wang et al., 2014; Bobade et al., 2016).

Increasing observations of NT compaction coupled with the well-documented adverse effects of compaction are creating a soil and crop management dilemma for many Brazilian farmers. They adopted NT to reduce soil erosion and energy needs, increase soil organic matter, and improve soil structure and soil biological attributes (Grandy et al., 2006; Lal et al., 2007; Derpsch et al., 2010; Soane et al., 2012). Now, the need (real or perceived) to mitigate NT compaction is threatening to destroy many of the long-term NT benefits (Caires et al., 2006; Stavi et al., 2011; Zhang et al., 2017).

To determine the best course of action, on-farm field-scale studies and detailed monitoring of soil physical properties as well as crop responses to various mitigation strategies are being recommended. This requires being able to identify the most sensitive and responsive soil physical properties that can limit or enhance crop yield. Identification of the most sensitive indicators will also require identification of new screening tools to ensure cost-effective, meaningful, and efficient monitoring.

Soil physical factors that directly affect crop yield include water, oxygen, temperature, and mechanical resistance (Letey, 1985). The status of these factors can be quantified by using soil physical quality indicators to identify soil compaction and establish crop yield relationships (Arshad et al., 1996; Nortcliff, 2002; Reynolds et al., 2009). These relationships, however, are often influenced by climatic conditions (Letey, 1985; Bölenius et al., 2017), making it difficult to establish direct relationships. As a result, studies have shown that during rainy periods there is often no correlation between soil physical properties and crop yield (Secco et al., 2004; Klein and Camara, 2007; Calonego and Rosolem, 2010; Hakojärvi et al., 2013; Girardello et al., 2014; Cecagno et al., 2016; Calonego et al., 2017).

Tools used to assess causal relationships among soil properties or between selected indicators and crop yield include Pearson's correlation (Shukla et al., 2004; Montanari et al., 2010; Silva et al., 2017), multivariate analysis (Shukla et al., 2004; Santi et al., 2012; Bölenius et al., 2017), and simple as well as multiple linear regression (Flowers and Lal, 1998; Busscher et al., 2001; Montanari et al., 2010; Bölenius et al., 2017). Each method has a variety of strengths and weakness with one of the most limiting being the amount of data needed to accurately measure or model the relationships. Recent advances in computational methods and development of machine learning techniques have greatly enhanced prediction capacity for and modeling of nonlinear relationships in agriculture. The Random Forest algorithm (RFA) (Breiman, 2001) is one method that has been widely applied because of its high accuracy, capacity to identify important co-variables, ability to model complex interactions, flexibility for statistical analysis, and ability to compensate for missing values (Cutler et al., 2007). However, few studies have used RFA to estimate crop yield (Vincenzi et al., 2011; Fukuda et al., 2013; Everingham et al., 2016; Smidt et al., 2016), and only Smidt et al. (2016) included soil physical properties and available water supply as predictor variables.

We hypothesized that a RFA could efficiently identify soil physical properties sensitive to compaction in NT systems, detect short-term alterations in soil structure in response to management practices, and relate those changes to soybean yield in Brazil. Furthermore, by identifying the most sensitive and responsive soil physical property indicators, it will be possible to improve decision-making processes regarding when and how interventions should be made to reduce effects of NT soil compaction. Our objectives were to (i) assess effects of various management strategies for ameliorating compacted soils by measuring soil physical property, soybean growth, and yield responses; and (ii) identify critical soil physical property indicators describing soybean yield response to soil structure changes using RFA, Pearson's linear correlation, and principal component analysis (PCA) as complementary response tools.

MATERIAL AND METHODS

Field Experiment Location and Description

An on-farm field study using commercial equipment was conducted on Santa Helena farm at 21°15′39″ S latitude and 44°31′04″ W longitude within the Campo das Vertentes mesoregion near Nazareno town in the Minas Gerais State of Brazil. The average altitude is 1020 m and the climate, according to Köppen climatic classification, is Cwa with cold/dry winters and hot/rainy summers. Average annual rainfall and temperature are 1300 mm and 19.7°C, respectively (Fig. 1). The soil is classified as Typic Hapludox (Soil Survey Staff, 2014) with clay, silt, and sand contents within the 0- to 0.30-m depth of 530, 250, and 220 g kg^{-1}, respectively.

Five farmer-selected strategies combining physical and chemical manipulations to address NT soil compaction were established in 18 m wide and 80 m long (1440 m^2) strips. Five treatments were studied (Fig. 2):

- T1: NT for 10 yr (control)
- T2: NT with surface application of 3.6 Mg ha^{-1} of agricultural gypsum
- T3: NT with subsoiling plus 1.44 Mg ha^{-1} of highly reactive limestone (relative power of total neutralization = 180%) applied to a depth of 0.60 m between each row
- T4: NT planting following chisel plowing at a depth of 0.26 m
- T5: NT with subsoiling to a depth of 0.60 m plus 1.44 Mg ha^{-1} of surface-applied, highly reactive limestone (relative power of total neutralization = 180%)

The width of each treatment corresponded to two passes with an NT drill. True statistical replication was not feasible, so data were collected from four, 360 m^2 pseudo-replicates within each treatment

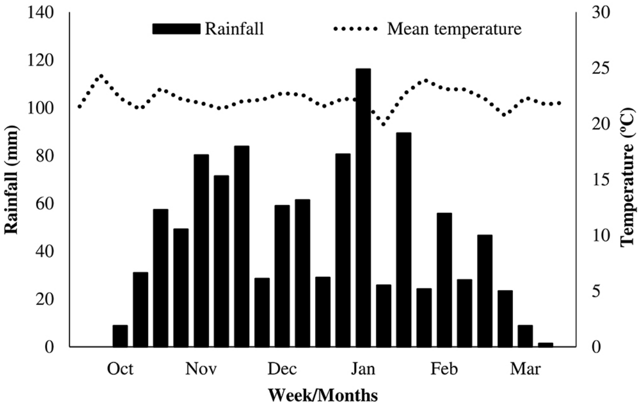

Fig. 1. Weekly average rainfall and temperature for the 2015–2016 summer cultivation.

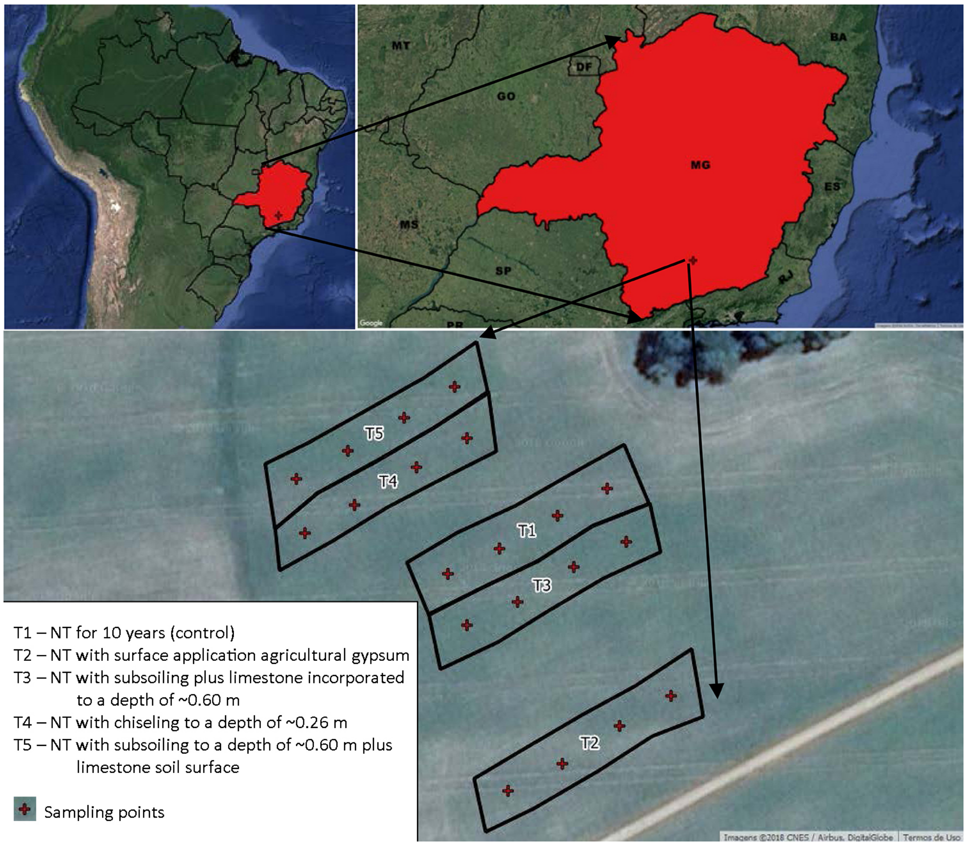

Fig. 2. On-farm experimental layout used to evaluate five mitigation strategies for NT soil compaction in a Brazilian soybean field.

strip. The experimental area has soil homogeneity (Typic Hapludox), similar slope gradient, and equal cropping and management history. A similar statistical approach, using pseudo-replicates, was successfully used in prior studies (Shukla and Lal, 2005; Stavi et al., 2011; Cecagno et al., 2016).

The tillage and chemical amendment treatments were established in September 2015. Soybean (a Syngenta VTOP conventional cultivar) was sown in November 2015 and harvested in March 2016. The crop was fertilized based on soil analyses and considering potential nutrient requirements of the soybean crop (Novais, 1999). At planting, 81 and 120 kg ha^{-1} of P$_2$O$_5$ and K$_2$O fertilizer, respectively, were applied using mono-ammonium phosphate (MAP) and muriate of potash (KCl). Mono-ammonium phosphate was applied in the seed furrow and KCl was broadcast just before planting. Weed, pest, and disease management operations were selected and implemented by our farmer-cooperator. The crop sequence used on the farm consists of a soybean and corn (*Zea mays* L.) rotation during the summer (November–March) followed by wheat (*Triticum aestivum* L.) or dry bean (*Phaseolus vulgaris* L.) during the winter (March–June). When soil moisture conditions favor the plants development, oat (*Avena sativa* L.) was cultivated after the winter crop.

Chemical characteristics for five on-farm treatments following a soybean crop grown from November 2015 through March 2016 are presented in Table 1. The soil compaction status within each NT plot was assessed using a morphological description following 10 yr of no-till planting.

Soil and Plant Sampling and Analysis

Soil samples were analyzed for water pH (soil/water ratio of 1:2.5), soil organic matter (Walkley and Black, 1934), exchangeable Ca^{2+}, Mg^{2+}, and Al^{3+}, and plant-available K and P (Sparks et al., 1996). At harvest, plant height (PHeight) and first pod height (Inser1stpod) were measured from the soil surface to the plant's apex or first pod, respectively, using a ruler on five randomly selected plants from each plot. Seed yield was measured by collecting the beans from five adjacent, 5-m rows spaced 0.6 m apart in each plot (i.e., 15 m^2). Seed weight was corrected to a water content of 130 g kg^{-1} (13%) and converted to Mg ha^{-1}.

Following soybean harvest, soil samples were collected from 0.00- to 0.05-, 0.20- to 0.25-, and 0.30- to 0.35-m depth increments within each plot, using volumetric cylinders (0.025 m height × 0.06 m diam.). Those three depth increments were chosen because soil structure to a depth of 0.60 m is very homogeneous. The samples were saturated and placed on an automated tension table (Ecotech) where they drained to matric potentials of −1, −2, −4, −6, and −10 kPa. They were then placed in a Richards porous plate chamber and drained to matric potentials of −−33, −100, −500, and −1500 kPa (Klute, 1986). The matric potential data and RETC software were used to compute a water retention curve with the Mualen restriction (van Genuchten, 1980).

Porosity of the soil macropore domain (PORp), air capacity (AC), relative field capacity (RFC), and air capacity of soil matrix (ACm) were calculated using the water retention curve as described by Reynolds et al. (2002, 2009). Plant-available water capacity (PAWC) was estimated as the difference between field capacity (−10 kPa) and permanent wilting point (−1500 kPa). Readily available water (RAW) was calculated using field capacity (−10 kPa) as the superior limit and −100 kPa as the inferior limit. Those soil physical properties were also used to estimate field capacity as the soil water content at the inflection point of the water retention curve (PAWCip) and (RAWip) (Silva et al., 2014), and to calculate the S index (Dexter, 2004) and integral energy (IE) based on PAWC (Asgarzadeh et al., 2011) using

Table 1. Chemical characterization of the soil in the experimental area after a summer soybean crop grown from November 2015 through March 2016.†

Treatment	pH	SOM	V	Ca^{2+}	Mg^{2+}	T	Al^{3+}	K	P
		g kg^{-1}	%	——cmol$_c$ dm^{-3}——				——mg dm^{-3}——	
0.00–0.20 m									
T1	5.34	37.2	54.30	2.70	0.55	6.38	0.10	75.50	3.24
T2	5.06	39.2	43.69	2.08	0.55	6.53	0.03	87.00	6.20
T3	5.40	34.5	51.75	2.19	0.61	5.76	0.00	76.00	3.11
T4	5.21	36.1	48.61	2.11	0.53	6.02	0.02	97.25	6.05
T5	4.95	38.8	42.75	1.95	0.56	6.44	0.05	97.00	9.08
0.20–0.40 m									
T1	5.43	33.8	41.43	1.58	0.38	5.06	0.09	59.00	0.91
T2	5.20	35.6	33.10	1.30	0.35	5.58	0.01	73.00	1.13
T3	5.35	33.1	40.40	1.48	0.38	5.05	0.00	54.00	0.99
T4	5.55	33.8	38.39	1.23	0.30	4.31	0.01	55.00	0.85
T5	5.75	34.9	39.03	1.50	0.45	5.13	0.03	60.00	1.66

† SOM, soil organic matter; V, base saturation; T, potential cation exchange capacity; T1, NT for 10 yr (control); T2, NT with surface application of 3.6 Mg ha^{-1} of agricultural gypsum; T3, NT with subsoiling plus 1.44 Mg ha^{-1} of highly reactive limestone (relative power of total neutralization = 180%) applied to a depth of ~0.60 m; T4, NT planting following chisel plowing at a depth of ~0.26 m; and T5, NT with subsoiling to a depth of ~0.60 m plus 1.44 Mg ha^{-1} of surface-applied, highly reactive limestone (relative power of total neutralization = 180%).

the SAWCal software (Asgarzadeh et al., 2014). Bulk density (BD) was determined volumetrically (Grossman and Reinsch, 2002). Total porosity (TP = 1 – BD/PD) was computed using particle density (PD) values obtained by the volumetric flask method (Flint and Flint, 2002). Microporosity (Mic) at –6 kPa, and macroporosity (Mac; Mac = PT – Mic) were also calculated for each sample.

Soil PR was measured before soybean harvest in March 2016 using a dynamic impact penetrometer (model IAA/PLANALSUCARSTOLF) and is reported as a cone index (Stolf, 1991). The PR measurements were replicated three times in each plot, and the mean was determined and represented one replicate per plot. In this way, 12 probings were done in each treatment ($N = 60$). To account for the impact of soil moisture content, PR measurements were made for all treatments within a short period of time at a water content near field capacity.

Statistical Analysis

Descriptive statistics were computed to evaluate variability of soil physical property and plant response date in response to treatments designed to ameliorate NT soil compaction. Using plot data from the non-replicated on-farm study, an analysis of variance (ANOVA) was computed for each sampling depth. The degrees of freedom for each treatment were partitioned to create orthogonal contrasts for NT control vs. NT plus chemical, physical (chiseling or subsoiling), or combined strategies to ameliorate compaction (T1 and T2 vs. T3, T4, and T5); gypsum effects (T1 vs. T2); subsoiling vs. chiseling (T3 and T5 vs. T4); and subsoiling with surface or deep-placement of agricultural limestone (T3 vs. T5). These contrasts were evaluated using the ANOVA residual mean square. Calculations were performed using R software (R Development Core Team, 2017).

Quantification of Plant Response to Soil Physical Properties

To quantify how plants responded to various chemical and physical treatments implemented in an on-farm study to ameliorate NT soil compaction, multivariate analysis (principal component analysis) and linear correlation were applied to the measured and calculated data. The results were then used as input for an RFA to rank the importance of various soil physical property variables with regard to estimating soybean yield response. Details for each phase of the analysis are described below.

Linear Correlation and Principal Component Analysis. Pearson linear correlation ($p < 0.05$) was used to quantify relationships between soil physical properties and soybean response variables. First, however, to avoid redundancy and reduce the number of soil physical properties within each treatment groups, a PCA was performed, which divides the original variables into smaller groups of statistical variables (factors) with minimum loss of information (Hair et al., 2009). For this study our initial 18-variable dataset could be characterized by two new latent variables and viewed within biplots. These analyses were also performed using the R software package FactoMineR (Lê et al., 2008).

Random Forest Algorithm Analysis. The RFA modeling is a non-parametric technique developed by Breiman (2001) as an extension to CART (Classification and Regression Trees). Its purpose is to improve prediction accuracy by combining several "trees" generated from a random vector that is sampled independently, assuming the same distribution for all trees in the "forest." Tree branches are determined based on a subset of covariables chosen randomly from all covariables. The result thus provides a mean representing all trees (Breiman, 2001).

The RFA was generated using the Random Forest software package in R (Liaw and Wiener, 2002). To use an RFA, three parameters must be defined: the number of trees in the forest (ntree), the minimum number of data in each terminal node (nodesize), and the number of variables used in each tree (mtry) (Liaw and Wiener, 2002). For this study ntree = 1000, nodesize = the standard for regression analyses (i.e., five for each terminal node), and mtry = one-third (i.e., 3 of 9) of the total number of predicting variables (Liaw and Wiener, 2002). Yield was predicted using soil physical properties for each depth increment, thus generating four models (i.e., one for each depth increment plus the entire 0.35-m profile). The result is that the increment error percentage in RFA models (%incMSE) demonstrates the importance of each variable with regard to predicting soybean yield.

Finally, the prediction model was validated using an independent dataset. Thus, for each depth increment, data from three plots per treatment were used for calibration and one for validation. Performance of each RFA model was further evaluated by comparing estimated and observed values, proportion of variance explained (Var_{ex}), coefficient of determination (R^2) means, root mean square error (RMSE) and root mean square error relative to the average experimental yield (RRMSE).

RESULTS AND DISCUSSION

Soil Physical Property and Plant Response

Subsoiling (T3 and T5) and chiseling (T4) increased soybean yield and resulted in lower Inser1stpod values than treatments without mechanical intervention (T1 and T2) (Table 2). As expected, the field operations (chiseling or subsoiling) were more effective than either lime (T3 and T5) or gypsum (T2) applications because those treatments did not affect soil chemical properties (Table 1). Other studies have also shown greater soybean yield response to chiseling (Calonego and Rosolem, 2010; Calonego et al., 2017; Cortez et al., 2017) and subsoiling (Botta et al., 2010; Bobade et al., 2016), even in subsequent years. Similar soil property effects were also observed within wheat and corn fields (Klein et al., 2008; Secco et al., 2009), but results still diverge regarding yield improvement (Izumi et al., 2009; Lozano et al., 2016).

This on-farm evaluation indicated both physical and chemical treatments to ameliorate NT compaction were effective at improving soil physical properties, which in turn increased soybean yield, even when rainfall and therefore water supply were sufficient. Studies quantifying subsoiling and chiseling effects in clay soils under NT management have not reached consensus regarding their effect on crop yield, probably because of interactions with available soil water that can significantly influence the severity of soil compaction (Calonego and Rosolem, 2010; Hakojärvi et al., 2013; Girardello et al., 2014; Cecagno et al., 2016; Calonego et al., 2017). Soil water content is also influenced by changes in pore-size distribution, which in granular oxidic soils (Silva et al., 2015) can result in reduced transmission of soil water to plants (Debiasi et al., 2010) and thus expose them to hydric stress in dry years.

Seasonal rainfall of approximately 1000 mm (Fig. 1) at this on-farm site easily met the crop water requirement for maximum yield, which varies between 450 and 800 mm, depending on other climatic conditions, soil management, and plant characteristics (Farias et al., 2007). Of these 1000 mm rainfall, soybean plants were supplied with approximately 7.5 mm of water per day (Fig. 1), during flowering and grain formation, which is therefore considered ideal for those phases (Farias et al., 2007).

Subsoiling was more effective than chiseling with regard to increasing soybean yield (Table 2). This presumably reflected the larger and thicker shanks and breaking of compacted layers deeper within the soil profile than is feasible with chiseling. Subsoiling was confirmed to be more effective for improving soil physical properties (Botta et al., 2006) than chiseling, which often has a residual effect of only 6 to 30 mo, depending on the soil physical properties (Nunes et al., 2014; Drescher et al., 2011). Subsoiling, however, may have a residual effect lasting from 24 to 48 mo for soils where cereal crops are being grown (Busscher et al., 1995) to as long as 120 mo beneath eucalyptus (*Eucalyptus globulus* L.) plants (Curi et al., 2017). Therefore, subsoiling, which does require more energy, may be a more effective practice for alleviating NT compaction when evaluated from economic and environmental perspectives.

There were no statistical differences between the treatments that were subsoiled (T3 and T5); thus, the local (~0.60-m depth) or surface application of limestone had no effect on soybean yield. It was already expected to have little or no effect on soybean yield, because some studies have shown that not even the limestone incorporation has improved the subsequent crop yield in NT consolidated areas (Quincke et al., 2007; Rossato et al., 2009; Fidalski et al., 2015). Similarly, application of gypsum (T2) when compared with the NT control (T1) did not increase soybean yield. These results therefore confirm that increases in soybean yield in this on-farm study occurred due to improvements in soil physical properties.

Table 2. Orthogonal contrasts for soil physical properties and soybean growth and yield variables.†

		Orthogonal contrasts											
		T1 vs. T3, T4, and T5			T1 vs. T2			T3 and T5 vs. T4			T3 vs. T5		
Variable	Depth	×1	×2	*p* value	×1	×2	*p* value	×1	×2	*p* value	×1	×2	*p* value
Yield, Mg ha^{-1}	–	4.02	4.55	**	4.05	3.99	ns‡	4.67	4.30	*	4.75	4.59	ns
Inser1stpod, cm	–	14.65	12.58	***	15.25	14.05	ns	12.47	12.80	ns	12.70	12.25	ns
PHeight, cm	–	88.82	90.57	ns	87.65	90.00	ns	91.22	89.25	ns	90.75	91.70	ns
IE, J kg^{-1}	0.00–0.05	152.88	151.57	ns	150.22	155.55	ns	153.19	148.33	ns	157.36	149.02	ns
	0.20–0.25	157.60	154.56	ns	150.40	164.80	ns	152.89	157.91	ns	149.26	156.51	ns
	0.30–0.35	147.85	138.31	ns	134.15	161.55	*	134.99	144.94	ns	138.26	131.71	ns
	Profile§	152.78	148.15	ns	144.92	160.63	ns	147.02	150.39	ns	148.30	145.75	ns
S	0.00–0.05	0.059	0.088	**	0.069	0.050	ns	0.088	0.086	ns	0.087	0.090	ns
	0.20–0.25	0.050	0.062	*	0.053	0.047	ns	0.067	0.051	*	0.069	0.065	ns
	0.30–0.35	0.058	0.065	ns	0.067	0.049	*	0.068	0.057	ns	0.068	0.069	ns
	Profile	0.056	0.071	**	0.063	0.049	*	0.075	0.065	ns	0.075	0.075	ns
Mic, m^3 m^{-3}	0.00–0.05	0.413	0.372	ns	0.400	0.425	ns	0.371	0.372	ns	0.370	0.373	ns
	0.20–0.25	0.402	0.368	**	0.409	0.396	ns	0.359	0.388	*	0.361	0.356	ns
	0.30–0.35	0.408	0.385	*	0.401	0.415	ns	0.383	0.391	ns	0.378	0.387	ns
	Profile	0.408	0.375	**	0.403	0.412	ns	0.371	0.383	ns	0.370	0.372	ns
Mac, m^3 m^{-3}	0.00–0.05	0.145	0.235	**	0.186	0.105	ns	0.242	0.221	ns	0.254	0.230	ns
	0.20–0.25	0.148	0.191	*	0.150	0.147	ns	0.209	0.155	*	0.211	0.207	ns
	0.30–0.35	0.176	0.189	ns	0.185	0.168	ns	0.196	0.173	ns	0.208	0.185	ns
	Profile	0.157	0.205	**	0.174	0.140	ns	0.216	0.183	ns	0.224	0.207	ns

(continued)

Table 2. Continued.

		Orthogonal contrasts											
		T1 vs. T3, T4, and T5			T1 vs. T2			T3 and T5 vs. T4			T3 vs. T5		
Variable	Depth	×1	×2	*p* value	×1	×2	*p* value	×1	×2	*p* value	×1	×2	*p* value
BD, Mg m^{-3}	0.00–0.05	1.05	0.90	*	1.02	1.01	ns	0.90	0.90	ns	0.90	0.90	ns
	0.20–0.25	1.12	1.04	**	1.12	1.12	ns	1.00	1.10	*	1.01	1.00	ns
	0.30–0.35	1.12	1.01	*	1.09	1.15	ns	1.07	1.11	ns	1.08	1.06	ns
	Profile	1.10	1.01	**	1.08	1.12	ns	0.99	1.04	ns	0.99	0.99	ns
TP, m^3 m^{-3}	0.00–0.05	0.558	0.606	*	0.586	0.530	*	0.613	0.593	ns	0.624	0.603	ns
	0.20–0.25	0.551	0.559	ns	0.559	0.543	ns	0.567	0.543	ns	0.572	0.563	ns
	0.30–0.35	0.585	0.574	ns	0.586	0.583	ns	0.579	0.564	ns	0.586	0.572	ns
	Profile	0.565	0.580	ns	0.577	0.552	ns	0.587	0.567	ns	0.594	0.579	ns
PAWC, m^3 m^{-3}	0.00–0.05	0.159	0.152	ns	0.154	0.164	ns	0.150	0.155	ns	0.140	0.160	ns
	0.20–0.25	0.143	0.129	*	0.145	0.141	ns	0.128	0.132	ns	0.125	0.131	ns
	0.30–0.35	0.139	0.130	ns	0.144	0.135	ns	0.131	0.128	ns	0.125	0.138	ns
	Profile	0.147	0.137	ns	0.148	0.146	ns	0.137	0.138	ns	0.130	0.143	ns
PORp, m^3 m^{-3}	0.00–0.05	0.069	0.128	ns	0.094	0.045	ns	0.136	0.110	ns	0.160	0.113	ns
	0.20–0.25	0.083	0.108	ns	0.081	0.086	ns	0.119	0.084	ns	0.119	0.120	ns
	0.30–0.35	0.094	0.093	ns	0.087	0.100	ns	0.096	0.086	ns	0.111	0.081	ns
	Profile	0.082	0.109	ns	0.087	0.077	ns	0.117	0.094	ns	0.130	0.104	ns
AC, m^3 m^{-3}	0.00–0.05	0.171	0.261	**	0.213	0.129	ns	0.266	0.249	ns	0.275	0.258	ns
	0.20–0.25	0.178	0.220	*	0.182	0.174	ns	0.238	0.183	*	0.239	0.236	ns
	0.30–0.35	0.204	0.216	ns	0.217	0.191	ns	0.225	0.199	ns	0.235	0.215	ns
	Profile	0.184	0.232	**	0.204	0.165	ns	0.243	0.210	ns	0.250	0.236	ns
RFC	0.00–0.05	0.698	0.573	**	0.641	0.755	ns	0.568	0.583	ns	0.562	0.574	ns
	0.20–0.25	0.679	0.610	*	0.677	0.680	ns	0.583	0.664	*	0.584	0.582	ns
	0.30–0.35	0.652	0.625	ns	0.631	0.673	ns	0.613	0.648	ns	0.601	0.625	ns
	Profile	0.676	0.602	**	0.650	0.703	ns	0.588	0.632	ns	0.582	0.593	ns
ACm, m^3 m^{-3}	0.00–0.05	0.102	0.133	ns	0.119	0.084	ns	0.130	0.139	ns	0.115	0.145	ns
	0.20–0.25	0.094	0.112	ns	0.100	0.088	ns	0.119	0.099	ns	0.121	0.116	ns
	0.30–0.35	0.110	0.123	ns	0.129	0.091	ns	0.129	0.112	ns	0.124	0.134	ns
	Profile	0.102	0.123	*	0.116	0.088	*	0.126	0.117	ns	0.120	0.132	ns
RAW, m^3 m^{-3}	0.00–0.05	0.076	0.069	ns	0.075	0.077	ns	0.069	0.070	ns	0.068	0.070	ns
	0.20–0.25	0.067	0.057	**	0.070	0.064	ns	0.056	0.059	ns	0.057	0.054	ns
	0.30–0.35	0.072	0.070	ns	0.078	0.066	*	0.070	0.068	ns	0.068	0.072	ns
	Profile	0.072	0.065	*	0.075	0.069	ns	0.065	0.066	ns	0.064	0.066	ns
PR, MPa	0.00–0.05	1.23	0.77	***	1.09	1.37	*	0.66	0.98	**	0.69	0.64	ns
	0.20–0.25	2.78	1.80	***	2.76	2.81	ns	1.36	2.68	***	1.50	1.21	ns
	0.30–0.35	2.82	2.39	**	2.96	2.68	ns	2.01	3.14	***	1.89	2.14	ns
	Profile	2.28	1.65	***	2.27	2.29	ns	1.34	2.27	***	1.36	1.33	ns
PAWCip, m^3 m^{-3}	0.00–0.05	0.198	0.253	**	0.222	0.175	ns	0.258	0.244	ns	0.261	0.254	ns
	0.20–0.25	0.192	0.210	ns	0.193	0.191	ns	0.220	0.189	*	0.219	0.222	ns
	0.30–0.35	0.205	0.205	ns	0.210	0.201	ns	0.210	0.195	ns	0.213	0.206	ns
	Profile	0.186	0.191	ns	0.202	0.171	ns	0.188	0.197	ns	0.209	0.167	ns
RAWip, m^3 m^{-3}	0.00–0.05	0.107	0.137	**	0.120	0.094	ns	0.139	0.132	ns	0.141	0.137	ns
	0.20–0.25	0.104	0.113	ns	0.104	0.103	ns	0.119	0.102	*	0.118	0.120	ns
	0.30–0.35	0.111	0.111	ns	0.113	0.108	ns	0.113	0.105	ns	0.115	0.111	ns
	Profile	0.101	0.103	ns	0.109	0.096	ns	0.101	0.106	ns	0.113	0.090	ns

* Statistical significance at the 0.05 level.

** Statistical significance at the 0.01 level.

***Statistical significance at the 0.001 level.

† IE, integral energy; Mic, microporosity; Mac, macroporosity; BD, bulk density; TP, total porosity; PAWC, plant-available water capacity; PORp, porosity of soil macropore domain; AC, air capacity; ACm, air capacity of soil matrix; RFC, relative field capacity; RAW, readily available water; PR, penetration resistance; PAWCip, plant-available water capacity using the inflection point as field capacity; RAWip, readily available water using inflection point as field capacity.

‡ Not significant.

§ Represents the mean value calculated for three depths, representing the 0- to 0.35-m profile.

The soil physical properties that were most sensitive to change due to tillage, regardless of depth, were: Mac, Mic, BD, S index, AC, RFC, and PR. On the other hand, IE, TP, PAWC, PAWCip, RAW, RAWip, PORp, and ACm showed significant differences only between the control (T1) and either subsoiling or chiseling (T3, T4, and T5) and/or between subsoiling (T3 and T5) and chiseling (T4) at the 0.20- to 0.25-m depth (Table 2). Among the measured soil physical properties, PR was the most variable within all three depth increments, suggesting it is highly sensitive to chemical and physical manipulations in addition to soil moisture content. The soil physical properties identified in this study as most sensitive to physical, chemical, or combined NT compaction treatments are also those commonly used as soil quality indicators (Arshad et al., 1996; Nortcliff, 2002; Dexter, 2004; Reynolds et al., 2002, 2008).

Relationship between Soil Physical Properties and Soybean Yield

Pearson Correlations

Among the 15 soil physical properties measured at the 0.00- to 0.05-m depth increment, 73, 20, and 7% significantly correlated with soybean yield, Inser1stpod, and PHeight, respectively (Table 3). There was a reduction in significant correlations with depth, presumably because of differences in root distribution for this cultivar and main soil management effect on topsoil, among others. Gregory (1992) found that approximately 80% of soybean root mass is distributed in the top 0.15 m of the soil profile, especially when rainfall is adequate (Fig. 1) and plants do not need to develop a deeper root system.

The greatest variation in soil physical properties was within the top 0.05 m (Table 4), which is the zone most affected by soil and crop management (i.e., wheel traffic, planting, fertilization, harvest, subsoiling, and chiseling practices) and therefore affected by soil compaction (Batey, 2009; Reichert et al., 2009; Drescher et al., 2011; Nunes et al., 2014, 2015). Furthermore, when the entire 0- to 0.35-m soil profile was analyzed, it was the surface layer that was most responsive to management and was therefore a dominant factor driving the whole profile correlation.

At the 0.00- to 0.05-m depth, PR ($r = -0.74$), which is a reliable indicator of soil mechanical resistance, showed the highest correlation with soybean yield. This was followed by properties associated with soil air capacity: Mac ($r = 0.67$), AC ($r = 0.67$), RFC ($r = -0.66$), and S index ($r = 0.64$). Those properties are all related to the capacity of a soil to provide air and water throughout the entire distribution of pores. The least sensitive indicators were those associated with retention capacity and potential water availability PAWCip ($r = 0.63$), RAWip ($r = 0.63$), and Mic ($r = -0.49$).

Penetration resistance at all evaluated depths correlated to soybean yield, which was presumably associated with root cell elongation (Bengough et al., 2001) and its effect on plant shoots (Passioura, 2002) and in agreement with other studies (Busscher et al., 2001; Beutler et al., 2006; Koch et al., 2009; Dalchiavon et al., 2011; Ahmad et al., 2010; Bölenius et al., 2017). This result has an important practical aspect, because it suggests that PR can be used as a fast, low-cost indicator to help with decision-making regarding management practices that should be used to address NT compaction or within pedotransfer functions for evaluating more complex indicators. Bölenius et al. (2017) reported that PR could explain crop yield variation and is therefore a good screening tool for areas with poor soil physical conditions or where chemical or physical treatments were imposed to alter the physical state. However, other reports indicate a lack of correlation with yield under consolidated NT, presumably because of biopores created by previous crops and used by the current crop as a pathway for root growth that are not represented by the penetrometer readings (Stirzaker et al., 1996; Bengough et al., 2011).

Positive and significant correlations between soybean yield and Mac, AC, and S index, as well as a negative correlation with RFC, confirm that disrupting soil compaction alters pore-size distribution, often increasing the relative number of larger pores and thus favoring crop yield because macropores provide most of the soil air porosity.

Table 3. Pearson correlation coefficients of soil physical properties and yield, insertion of the first pod, and soybean plant height at three depths and in the whole soil profile. $N = 20$.†

	0.0–0.05 m			0.20–0.25 m			0.30–0.35 m			Profile 0.0–0.35 m		
Soil property	Yield	Inser1stpod	PHeight	Yield	Inser1stpod	PHeight	Yield	Inser1stpod	PHeight	Yield	Inser1stpod	PHeight
IE	–0.10	0.23	0.37	–0.06	0.10	0.52*	–0.23	0.21	0.19	–0.21	0.27	0.53*
S	0.64**	–0.46**	–0.06	0.43	–0.28	–0.26	0.27	–0.27	–0.16	0.62**	–0.46*	–0.17
Mic	–0.49*	0.25	–0.31	–0.42	0.41	–0.08	–0.39	0.27	0.04	–0.57**	0.39	–0.20
Mac	0.67**	–0.35	0.06	0.45*	–0.24	0.03	0.25	–0.17	–0.03	0.64**	–0.35	0.04
BD	–0.53*	0.32	–0.24	–0.41	0.38	<0.01	–0.43	0.40	0.23	–0.60**	0.44	–0.10
TP	0.58**	–0.31**	–0.18	0.38	0.02	–0.04	–0.07	0.05	<–0.01	0.53*	–0.20	–0.14
PAWC	–0.28	–0.08	–0.42	–0.23	0.24	–0.20	–0.33	0.17	0.02	–0.39	0.09	–0.35
PORp	0.58**	–0.26	0.11	0.37	–0.15	0.17	0.08	<0.01	0.02	0.55*	–0.23	0.15
AC	0.67**	–0.37	0.03	0.44	–0.24	–0.02	0.25	–0.18	–0.07	0.63**	–0.36	–0.01
RFC	–0.66**	0.38**	–0.08	–0.44**	0.30	0.00	–0.29	0.22	0.09	–0.63**	0.39	–0.02
ACm	0.30	–0.26	–0.14	0.29	–0.25	–0.30	0.17	–0.19	–0.10	0.34	–0.32	–0.23
RAW	–0.25	–0.06	–0.51*	–0.22	0.21	–0.54*	–0.04	–0.04	–0.18	–0.24	0.02	–0.59**
PR	–0.74**	0.53*	–0.04	–0.66**	0.46*	–0.24	–0.55*	0.32	–0.12	–0.69**	0.46*	–0.18
PAWCip	0.63**	–0.40	–0.05	0.48*	0.20	0.07	0.06	–0.05	0.03	0.61**	–0.35	<–0.01
RAWip	0.63**	–0.40	–0.05	0.48*	–0.20	0.07	0.06	–0.05	0.03	0.61**	–0.35	<–0.01

* Statistical significance at the 0.05 level.

** Statistical significance at the 0.01 level.

† IE, integral energy; Mic, microporosity; Mac, macroporosity; BD, bulk density; TP, total porosity; PAWC, plant-available water capacity; PORp, porosity of soil macropore domain; AC, air capacity; ACm, air capacity of soil matrix; RFC, relative field capacity; RAW, readily available water; PR, penetration resistance; PAWCip, plant-available water capacity using the inflection point as field capacity; RAWip, readily available water using inflection point as field capacity.

Table 4. Descriptive statistic of soil physical properties, soybean growth, and yield variables. *N* = 20.†

Variable	Depth	Mean	SD	Median	Minimum	Maximum
Yield, Mg ha^{-1}	–	4.34	0.40	4.35	3.59	5.06
Inser1stpod, cm	–	13.41	1.43	13.00	11.20	16.40
PHeight, cm	–	89.87	4.40	90.30	81.40	99.00
IE, J kg^{-1}	0.00–0.05	152.10	16.85	150.68	115.94	188.62
	0.20–0.25	155.78	16.43	156.10	125.55	182.90
	0.30–0.35	142.12	19.33	144.91	103.27	167.60
	Profile‡	150.00	11.62	146.54	135.20	179.71
S	0.00–0.05	0.076	0.024	0.072	0.037	0.113
	0.20–0.25	0.057	0.014	0.055	0.032	0.095
	0.30–0.35	0.062	0.013	0.063	0.042	0.085
	Profile	0.065	0.013	0.065	0.043	0.086
Mic, m^3 m^{-3}	0.00–0.05	0.388	0.042	0.388	0.307	0.465
	0.20–0.25	0.382	0.028	0.380	0.328	0.433
	0.30–0.35	0.394	0.022	0.392	0.351	0.436
	Profile	0.388	0.024	0.388	0.348	0.431
Mac, m^3 m^{-3}	0.00–0.05	0.199	0.073	0.187	0.080	0.337
	0.20–0.25	0.174	0.046	0.172	0.110	0.277
	0.30–0.35	0.184	0.030	0.182	0.141	0.238
	Profile	0.186	0.040	0.184	0.126	0.258
BD, Mg m^{-3}	0.00–0.05	0.961	0.142	0.958	0.657	1.211
	0.20–0.25	1.070	0.076	1.079	0.925	1.229
	0.30–0.35	1.100	0.051	1.092	1.028	1.194
	Profile	1.044	0.072	1.042	0.916	1.167
TP, m^3 m^{-3}	0.00–0.05	0.587	0.048	0.590	0.459	0.663
	0.20–0.25	0.556	0.023	0.550	0.526	0.606
	0.30–0.35	0.578	0.018	0.580	0.544	0.609
	Profile	0.574	0.029	0.573	0.532	0.615
PAWC, m^3 m^{-3}	0.00–0.05	0.154	0.025	0.161	0.098	0.194
	0.20–0.25	0.135	0.013	0.134	0.110	0.163
	0.30–0.35	0.134	0.012	0.133	0.105	0.162
	Profile	0.141	0.012	0.142	0.117	0.160
PORp, m^3 m^{-3}	0.00–0.05	0.104	0.063	0.084	0.027	0.278
	0.20–0.25	0.098	0.036	0.094	0.049	0.187
	0.30–0.35	0.093	0.030	0.096	0.040	0.138
	Profile	0.098	0.032	0.093	0.063	0.167
AC, m^3 m^{-3}	0.00–0.05	0.225	0.072	0.216	0.105	0.348
	0.20–0.25	0.203	0.046	0.199	0.131	0.307
	0.30–0.35	0.211	0.031	0.210	0.164	0.269
	Profile	0.213	0.040	0.213	0.149	0.284
RFC	0.00–0.05	0.623	0.096	0.627	0.460	0.808
	0.20–0.25	0.637	0.068	0.640	0.493	0.751
	0.30–0.35	0.635	0.047	0.639	0.556	0.707
	Profile	0.632	0.057	0.630	0.531	0.728
ACm, m^3 m^{-3}	0.00–0.05	0.120	0.037	0.112	0.046	0.191
	0.20–0.25	0.105	0.024	0.104	0.059	0.153
	0.30–0.35	0.118	0.030	0.115	0.073	0.184
	Profile	0.114	0.022	0.113	0.066	0.142
RAW, m^3 m^{-3}	0.00–0.05	0.072	0.013	0.072	0.042	0.095
	0.20–0.25	0.061	0.008	0.060	0.049	0.078
	0.30–0.35	0.070	0.008	0.069	0.056	0.087
	Profile	0.068	0.007	0.067	0.054	0.082
PR, MPa	0.00–0.05	0.955	0.307	0.981	0.560	1.610
	0.20–0.25	2.192	0.783	2.335	0.837	3.423
	0.30–0.35	2.563	0.541	2.683	1.423	3.303
	Profile	1.903	0.501	2.125	1.031	2.614
PAWCip, m^3 m^{-3}	0.00–0.05	0.231	0.044	0.225	0.151	0.307
	0.20–0.25	0.203	0.023	0.201	0.166	0.249
	0.30–0.35	0.205	0.016	0.205	0.177	0.232
	Profile	0.189	0.050	0.194	0.162	0.247
RAWip, m^3 m^{-3}	0.00–0.05	0.125	0.024	0.121	0.081	0.166
	0.20–0.25	0.110	0.012	0.108	0.090	0.134
	0.30–0.35	0.111	0.009	0.111	0.096	0.125
	Profile	0.102	0.027	0.105	0.088	0.133

† IE, integral energy; Mic, microporosity; Mac, macroporosity; BD, bulk density; TP, total porosity; PAWC, plant-available water capacity; PORp, porosity of soil macropore domain; AC, air capacity; ACm, air capacity of soil matrix; RFC, relative field capacity; RAW, readily available water; PR, penetration resistance; PAWCip, plant-available water capacity using the inflection point as field capacity; RAWip, readily available water using inflection point as field capacity.

‡ Represents the mean value calculated for three depths, representing the 0- to 0.35-cm profile.

Lapen et al. (2004) showed that low air-filled porosity results in low yield and an inefficient plant establishment, thus making it an adequate predictor of biometric properties in agricultural crops. For soybean, lack of soil O_2 may inhibit biological N fixation (Bacanamwo and Purcell, 1999) and the uptake of nutrients. This ultimately decreases root growth and nodulation, most likely, due to the O_2 demand within the biological N fixation process (Amarante and Sodek, 2006).

The treatments with greater soybean yield (T4 and T5) had RFC values of less than 0.6, indicating the crop produced more in the presence of pores responsible for supplying oxygen than water. These results probably reflect the abundant rainfall (Fig. 1) that met crop needs throughout the growing season and especially during flowering and grain formation. There may have even been water excess at some times, which reduced air porosity, since total rainfall was 200 mm greater than the ideal for soybean. Higher RFC values (RFC > 0.7) cause a reduction in N fixation, limiting the plant development due to insufficient aeration (Linn and Doran, 1984; Reynolds et al., 2008).

Regarding indicators of plant water availability, PAWCip and RAWip were more sensitive than conventional PAWC and RAW with regard to soybean yield. The latter indicators did not show a significant correlation. Andrade and Stone (2011) reported that when they used a single independent variable to predict the field capacity, the best correlation occurred with the inflection point, which was also in agreement with studies by Ferreira and Marcos (1983), Mello et al. (2002), and Silva et al. (2014). Those authors suggested soil moisture at the inflection point corresponded to field capacity in tropical soils. The PAWC and RAW determined by classic definition are not considered adequate indicators of soil physical quality, especially in intensive agricultural systems with soil compaction problems. However, there are similar implementations using the superior and inferior limits of PAWC and RAW that do not cause a substantial change in those properties (Reynolds et al., 2008). Therefore, use of the inflection point associated with the water retention curve was useful as an indicator of compaction changes caused by soil management.

Among the soil physical properties measured for the 0.00- to 0.05-m depth increment, PR ($r = 0.53$), S index ($r = -0.46$), RFC ($r = 0.38$), and TP ($r = -0.31$) correlated to Inser1stpod height (Table 3). Penetration resistance also had the highest correlation coefficient at the 0.20- to 0.25-m depth and for the entire soil profile. Plant height was correlated with RAW ($r = -0.51$ and -0.54) to a depth of 0.25 m and with IE ($r = 0.52$) correlated at the 0.20- to 0.25-m depth. The treatments that did not use chiseling or subsoiling to disrupt NT compaction had higher Inser1stpod values when compared with those that were chiseled or subsoiled. Plant height was not influenced by soil management.

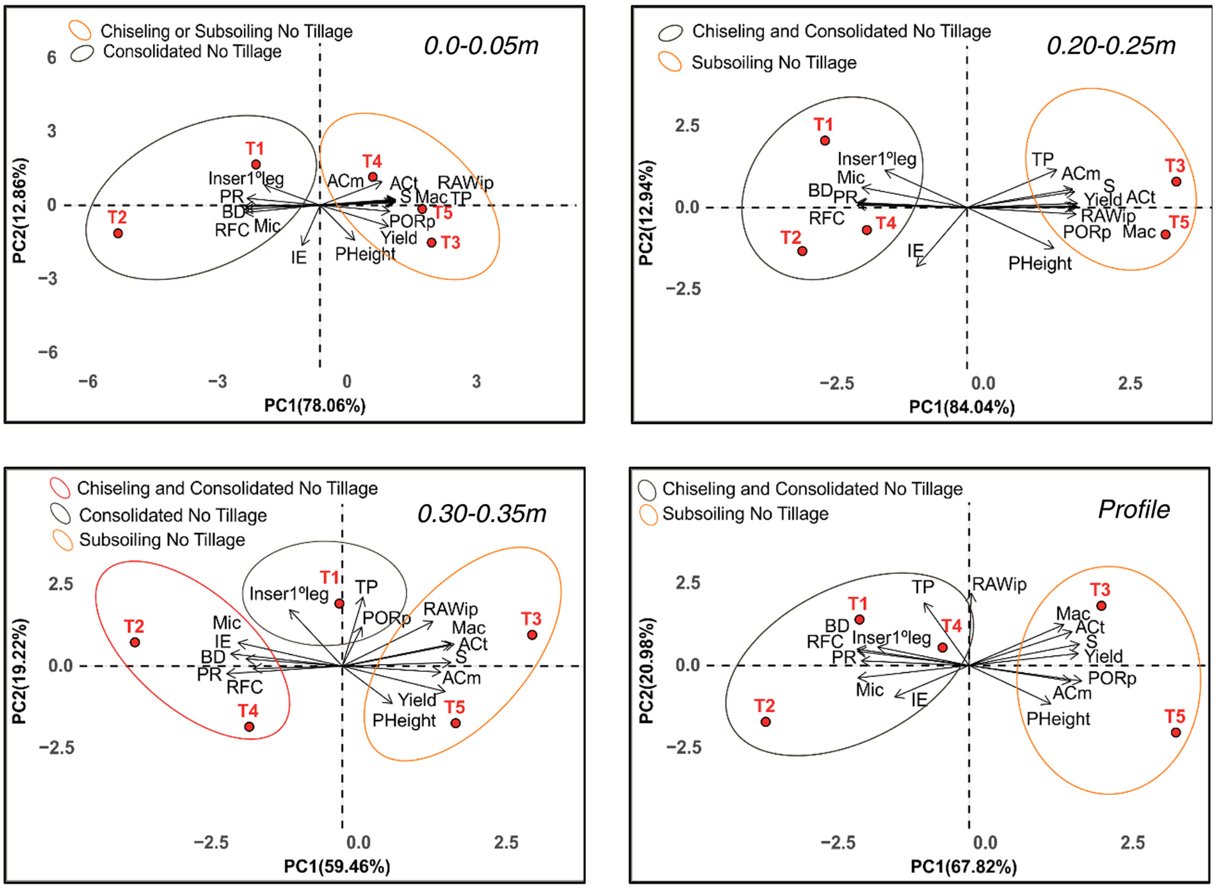

Fig. 3. Principal components analysis of soil physical properties and soybean plant variables in five soil managements. T1, NT for 10 yr (control); T2, NT with surface application of 3.6 Mg ha^{-1} of agricultural gypsum; T3, NT with subsoiling plus 1.44 Mg ha^{-1} of highly reactive limestone (relative power of total neutralization = 180%) applied to a depth of ~0.60 m; T4, NT planting following chisel plowing at a depth of ~0.26 m; and T5, NT with subsoiling to a depth of ~0.60 m plus 1.44 Mg ha^{-1} of surface-applied, highly reactive limestone (relative power of total neutralization = 180%). IE, integral energy; S, S Index; Mic, microporosity; Mac, macroporosity; BD, bulk density; TP, total porosity; PAWC, plant-available water capacity; PORp, porosity of soil macropore domain; AC, air capacity; ACm, air capacity of soil matrix; RFC, relative field capacity; PR, penetration resistance; RAWip, readily available water using inflection point as field capacity; Inser1stpod, height of insertion of the first pod; PHeight, plant height. Ellipses indicate groups of treatments.

Principal Component Analysis

The PCA divided the 18 variables into two groups (PC1 and PC2), making it possible to characterize and quantify the combined importance of variables that were most sensitive to the five on-farm treatments. The quantity of information from the original variables retained by two principal components was 91, 97, 79, and 89% for the 0.00- to 0.05-, 0.20- to 0.25-, and 0.30- to 0.35-m depth increments and the whole soil profile, respectively (Fig. 3). These values are well above the 70% threshold established as adequate PC accuracy (Hair et al., 2009).

Group PC1 explained between 59 and 84% of total variance, whereas PC2 explained between 13 and 21%. Therefore, most variables contributed more with PC1, including soybean yield. For all depth increments, the variables associated with mechanical impediments to root growth (PR and BD) and aeration restrictions (RFC and Mic), which are negatively correlated with soybean yield, were in the left portion of PC1. However, variables related to air and water availability (Mac, ACm, AC, PORp, and RAWip) and soybean yield were more concentrated in the right portion of PC1 (Fig. 3).

For the 0.00- to 0.05-m depth, variables that contributed most to PC1 were Inser1stpod (–0.73), RP (–0.96), Mic (–0.99), BD (–0.98), and RFC (–0.98). Grouping the treatments that did not include chiseling or subsoiling (T1 and T2) are located on the left side of PC1 (negative correlations). On the contrary, ACm (0.80), AC (0.98), RAWpi (0.99), Mac (0.98), TP (0.94), PORp (0.91), and Yield (0.90) associated with chisel (T4) and subsoil treatments (T3 and T5) are located on the right side of PC1 (positive correlations). Within the surface layer (0.00–0.05 m), the control had greater mechanical resistance to root penetration (PR and BD) and water retention (RFC and Mic), decreased pore-size distribution and aeration (AC, S, Mac, PORp, and TP), and lower plant water availability capacity (RAWip). The opposite was observed for treatments that had mechanical disruption of the NT compaction. These results thus show improvement in soil physical conditions for crop yield with mechanical intervention.

At depths greater than 0.20 m and for the entire profile analysis, chiseling was grouped with the treatments that did not disrupt compaction because of the superficial effect of chiseling on soil physical properties. Chiseling simply did not penetrate the entire depth of compaction because it was not effective below 0.26 m. Therefore, considering and confirming the orthogonal contrast results for yield (Table 2), it is possible to affirm that subsoiling treatments (T3 and T5) altered the subsoil physical properties that were important for increasing soybean yield. This is very important for the Cerrado biome because short-term drought is a common occurrence, even during the rainy season.

Variables associated with mechanical resistance to root penetration (i.e., PR), soil aeration (i.e., PORp Mac and RFC), pore size distribution (i.e., S index), and water availability (i.e., RAWip) were highly correlated with soybean yield and therefore formed an acute angle (positive correlation) or angles close to 180° (negative correlation) (Fig. 3). There were no substantial differences in the distribution of variables as a function of soil depth because PCA groups variables as a function of their variance (that is, according to their behavior in the population and that did not change among the sampling depths, despite the decrease in magnitude of correlation coefficients among the variables).

With respect to biometric variables, PHeight was not an effective indicator for a soil management study focused on disrupting NT soil compaction, because there was very little correlation between PHeight and either soil physical properties or soybean yield. Inser1stpod height, however, had a negative correlation with soybean yield, indicating that when the plant delays flowering there is likely a decrease in potential yield. Therefore, Inser1stpod may be a useful indicator to predict the soybean potential yield, making it possible to monitor the soil compaction and make decisions regarding when to use mechanical methods to disrupt soil compaction. For the cultivar used and edaphoclimatic conditions encountered in this study, the greatest yield was associated with Inser1stpod heights between 0.12 and 0.13 m above the soil, whereas the lowest yields had values greater than 0.15 m.

Random Forest Algorithm

The best regression models within this on-farm study were obtained for the 0.00- to 0.05-m depth increment and the whole (0–0.35 m) soil profile as indicated by higher proportion of variance explained (Var_{ex}) values in Table 5. This statistical parameter is an important indicator for comparing the performance of different prediction models (Liaw and Wiener, 2002).

To confirm the results for this on-farm study, a validation model was constructed. Through the R^2 and RMSE it confirmed the best adjustment and the least error, respectively, were associated with the 0.00- to 0.05-m depth increment ($R^2 = 0.80^*$ and 0.295 Mg ha^{-1}; *Significant at 0.05) and for the whole profile ($R^2 = 0.94^{**}$ and 0.31 Mg ha^{-1}; **Significant at 0.01). Furthermore, the RRMSE shows the RFA error for predicting soybean yield was only 7% of the average experimental yield; a level consistent with excellent accuracy (Li et al., 2013). These results thus demonstrate the potential to predict

Table 5. Random Forest model performance and validation for predicting soybean yield based on soil physical properties.†

Predict performance	0.0–0.05 m	0.20–0.25 m	0.30–0.35 m	Profile
	yield, kg ha^{-1}			
Performance indicator				
Var_{ex}, %	23.88	–16.27	–0.78	7.16
Validation parameter				
RMSE, Mg ha^{-1}	0.295	0.354	0.426	0.310
RRMSE, %	6.96	8.20	10.08	7.28
R^2	0.80*	0.76ns‡	0.15ns	0.94**

† Var_{ex}, proportion of variance explained; RMSE, root mean square error; RRMSE, root of the relative mean square error relative to the average yield of the experiment; R^2, coefficient of determination.

* Significant at the 0.05 level of probability.

** Significant at the 0.01 level of probability.

‡ Not significant.

soybean yield in Brazilian NT fields using soil physical property data and an RFA. Other studies that used RFA models to estimate crop yield based on climatic (Everingham et al., 2016), environmental (Vincenzi et al., 2011), and water (Fukuda et al., 2013) variables also found adequate on-farm accuracy in these respective estimations.

Figure 4 shows the percentage of increase in the mean square error (%IncMSE) of the RF prediction model for soybean yield when each of the soil physical properties is removed. Regardless of depth, PR was the most important indicator for predicting soybean yield. Particularly to the models that were significant and validated, the decreasing ranking of importance for the 0.00- to 0.05-m depth is: PR, Mac, S, RFC, AC, TP, PORp, Mic, and BD, and for the whole profile: PR, RFC, Mac, Mic, S, BD, AC, TP, and PORp. There are subtle differences in the importance of various soil physical indicators when the 0.00 to 0.05 and whole profile (0–0.35 m) are compared (Fig. 4), but PR is consistently the most influential variable for predicting soybean yield. Among the nine measured soil physical property indicators, Mac, the S index, RFC, Mic, and BD are also important.

Our results show the Pearson correlation analysis and RFA assessment are in agreement. Regarding the PCA, some properties that were highly related to yield (e.g., PORp and Mic) did not stand out in the RFA model. The PCA was useful for reducing the number of variables and grouping soil physical properties that were responsive to the treatments.

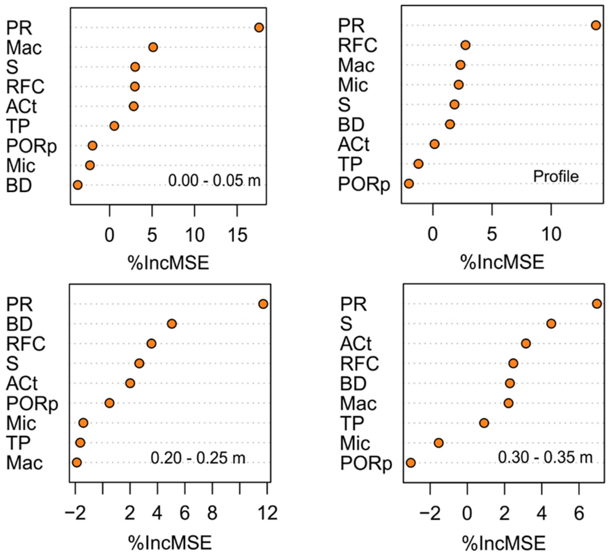

Fig. 4. Importance of soil physical co-variables for predicting soybean yield. S, S Index; Mic, microporosity; Mac, macroporosity; BD, bulk density; TP, total porosity; PORp, porosity of soil macropore domain; AC, air capacity; ACm, air capacity of soil matrix; RFC, relative field capacity; PR, penetration resistance.

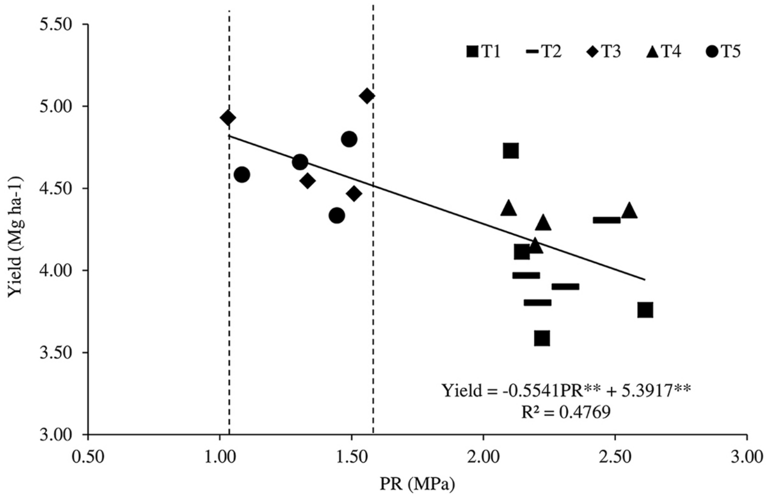

Fig. 5. Regression of yield as a function of penetration resistance (PR), using the profile mean (0.0–0.35 m). Both vertical bars indicate the PR range where soybean yield was at its maximum. **Model parameter statistically significant at the 0.01 level. T1, NT for 10 yr (control); T2, NT with surface application of 3.6 Mg ha^{-1} of agricultural gypsum; T3, NT with subsoiling plus 1.44 Mg ha^{-1} of highly reactive limestone (relative power of total neutralization = 180%) applied to a depth of ~0.60 m; T4, NT planting following chisel plowing at a depth of ~0.26 m; and T5, NT with subsoiling to a depth of ~0.60 m plus 1.44 Mg ha^{-1} of surface-applied, highly reactive limestone (relative power of total neutralization = 180%).

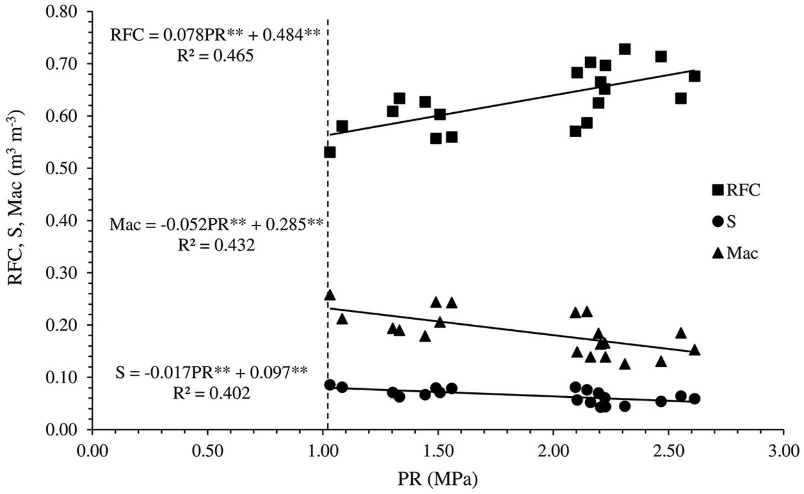

Fig. 6. Regressions of relative field capacity (RFC), S index, and macroporosity (Mac) with penetration resistance (PR), using the profile mean (0.0–0.35 m). Both vertical bars indicate the particle density (PD) optimal range, considering the maximum yield obtained. **Model parameter statistically significant at the 0.01 level.

The most sensitive soil physical properties for detecting changes due to chemical and/or physical treatments (Table 2) were also the most important for predicting soybean yield (Fig. 4). This includes those reflecting mechanical resistance to root penetration (PR), air capacity (AC and Mac), and pore size distribution (RFC and S index). In contrast, water availability indicators were neither sensitive nor did they influence soybean yield. This likely reflects the suitable supply of water by rainfall during the crop period (Fig. 1). Our recommendation, therefore, is to monitor PR, AC, Mac, RFC, and S index to determine if intervention is needed to correct for NT compaction and thus increase soybean yield potential.

Considering PR as a sensitive property to management practices and soybean yield (Tables 2 and 3; Fig. 4), the linear regression of soybean yield as a function of PR was adjusted (Fig. 5), being significant ($p < 0.01$). The optimal range for PR was established as a function of the mean value ± standard deviation of treatments T3 and T5, which had higher yields. Thus, PR between 1.15 and 1.54 MPa was the range related to greater soybean yields (Fig. 5). Penetration resistance above 2MPa, considered critical for most crops, was associated to lesser yields.

Considering the optimal range of PR, the linear regressions were adjusted with PR and RFC, Mac and S index ($p < 0.01$), similarly as proposed by Reynolds et al. (2008), in order to obtain the optimal ranges for these respective soil physical properties (Fig. 6). Thus, the optimal range for RFC was established between 0.573 and 0.604, Mac was between 0.205 and 0.225 $m^3 m^{-3}$, and S Index was between 0.070 and 0.077. These values are more restrictive than the ones presented by Reynolds et al. (2008) and the ones specific to soybean crop (Reichert et al., 2009); however, they were obtained in high-yield conditions.

CONCLUSIONS

Mechanical intervention, specifically subsoiling, after long-term NT (10 yr) improved soil physical properties and increased soybean yield during the first crop cycle within this on-farm Brazilian study. Soybean yield response to chiseling was less than for subsoiling, presumably because the depth of soil property alteration was reduced.

Use of an RFA ranked PR, AC, Mac, RFC, and S index as the most important soil physical property indicators with regard to predicting soybean yield. These soil physical indicators were also sensitive to soil structure changes induced by the various treatments imposed to address NT soil compaction. Therefore, we conclude they should be considered key soil physical properties for monitoring soil compaction and deciding when to correct it. We also point out that if time and fiscal resources are limited, PR is the indicator that should be used to guide on-farm decision-making regarding when and how to address NT soil compaction and its effect on soybean yield.

More studies across different soils types, years of NT, and climates are needed to accurately predict effects of occasional tillage on soil physical quality and crop yield in Brazilian NT systems.

REFERENCES

Ahmad, M., H. Abdullah, M. Iqbal, M. Umair, and M. Ghani. 2010. Effect of deep tillage on soil properties and crop (wheat) yield. Soil Environ. 29:177–180.

Amarante, L., and L. Sodek. 2006. Waterlogging effect on xylem sap glutamine of nodulated soybean. Biol. Plant. 50:405–410. doi:10.1007/s10535-006-0057-6

Andrade, R.S., and L.F. Stone. 2011. Estimativa da umidade na capacidade de campo em solos sob Cerrado. Rev. Bras. Eng. Agric. Ambient. 15:111–116. doi:10.1590/S1415-43662011000200001

Arshad, M.A., B. Lowery, and B. Grossman. 1996. Physical tests for monitoring soil quality. In: J.W. Doran and A.J. Jones, editors, Methods for assessing soil quality. SSSA Spec. Publ. 49. SSSA, Madison, WI. p. 123–141. doi:10.2136/sssaspecpub49.c7

Asgarzadeh, H., M.R. Mosaddeghi, and A.M. Nikbakht. 2014. SAWCal: A user-friendly program for calculating soil available water quantities and physical quality indices. Comput. Electron. Agric. 109:86–93. doi:10.1016/j.compag.2014.09.008

Asgarzadeh, H., M.R. Mosaddeghi, A.A. Mahboubi, A. Nosrati, and A.R. Dexter. 2011. Integral energy of conventional available water, least limiting water range and integral water capacity for better characterization of water availability and soil physical quality. Geoderma 166:34–42. doi:10.1016/j.geoderma.2011.06.009

Bacanamwo, M., and L.C. Purcell. 1999. Soybean dry matter and N accumulation responses to flooding stress, N sources and hypoxia. J. Exp. Bot. 50:689–696. doi:10.1093/jxb/50.334.689

Batey, T. 2009. Soil compaction and soil management: A review. Soil Use Manage. 25:335–345. doi:10.1111/j.1475-2743.2009.00236.x

Bengough, A.G., D.J. Campbell, and M.F. O'Sullivan. 2001. Penetrometer techniques in relation to soil compaction and root growth. In: K.A. Smith and C.E. Mullins, editors, Soil and environmental analysis: Physical methods. 2nd edition. Marcel Dekker, Edinburgh. p. 377–403.

Bengough, A.G., B.M. McKenzie, P.D. Hallett, and T.A. Valentine. 2011. Root elongation, water stress, and mechanical impedance: A review of limiting stresses and beneficial root tip traits. J. Exp. Bot. 62:59–68. doi:10.1093/jxb/erq350

Beutler, A.N., J.F. Centurion, A.P. Silva, and J.C. Barbosa. 2006. Intervalo hídrico ótimo e produtividade de cultivares de soja. Rev. Bras. Eng. Agric. Ambient. 10:639–645. doi:10.1590/S1415-43662006000300015

Bobade, A.B., S.K. Kshirsagar, and M.R. Deshmukh. 2016. The yield performance and economics under different tillage practices of soybean. Adv. Life Sci. 5:2755–2760.

Bölenius, E., B. Stenberg, and J. Arvidsson. 2017. Within field cereal yield variability as affected by soil physical properties and weather variations: A case study in east central Sweden. Geoderma Reg. 11:96–103. doi:10.1016/j.geodrs.2017.11.001

Botta, G.F., D. Jorajuria, R. Balbuena, M. Ressia, C. Ferrero, H. Rosatto, and M. Tourn. 2006. Deep tillage and traffic effects on subsoil compaction and sunflower (*Helianthus annus* L.) yields. Soil Tillage Res. 91:164–172. doi:10.1016/j.still.2005.12.011

Botta, G.F., A. Tolon-Becerra, X. Lastra-Bravo, and M. Tourn. 2010. Tillage and traffic effects (planters and tractors) on soil compaction and soybean (*Glycine max* L.) yields in Argentinean pampas. Soil Tillage Res. 110:167–174. doi:10.1016/j.still.2010.07.001

Breiman, L. 2001. Random forests. Mach. Learn. 45:5–32. doi:10.1023/A:1010933404324

Busscher, W., J. Frederick, and P. Bauer. 2001. Effect of penetration resistance and timing of rain on grain yield of narrow-row corn in a coastal plain loamy sand. Soil Tillage Res. 63:15–24. doi:10.1016/S0167-1987(01)00228-8

Busscher, W.J., J.H. Edwards, M.J. Vepraskas, and D.L. Karlen. 1995. Residual effects of slit tillage and subsoiling in a hardpan soil. Soil Tillage Res. 35:115–123. doi:10.1016/0167-1987(95)00488-2

Caires, E.F., G. Barth, and F.J. Garbuio. 2006. Lime application in the establishment of a no-till system for grain crop production in Southern Brazil. Soil Tillage Res. 89:3–12. doi:10.1016/j.still.2005.06.006

Calonego, J.C., J.P.A. Raphael, J.P.G. Rigon, L. Oliveira Neto, and C.A. Rosolem. 2017. Soil compaction management and soybean yields with cover crops under no-till and occasional chiseling. Eur. J. Agron. 85:31–37. doi:10.1016/j.eja.2017.02.001

Calonego, J.C., and C.A. Rosolem. 2010. Soybean root growth and yield in rotation with cover crops under chiseling and no-till. Eur. J. Agron. 33:242–249. doi:10.1016/j.eja.2010.06.002

Cecagno, D., S.E.V.G.A. Costa, I. Anghinoni, T.R. Kunrath, A.P. Martins, J.M. Reichert, P.I. Gubiani, F. Balerini, J.R. Fink, and P.C.F. Carvalho. 2016. Least limiting water range and soybean yield in a long-term, no-till, integrated crop-livestock system under different grazing intensities. Soil Tillage Res. 156:54–62. doi:10.1016/j.still.2015.10.005

Cortez, J.W., M. Mauad, L.C.F. Souza, M.V. Rufino, and P.H.N. Souza. 2017. Agronomical attributes of soybeans and soil resistance to penetration in no-tillage and chiseled surfaces. Eng. Agric. 37:98–105. doi:10.1590/1809-4430-eng.agric.v37n1p98-105/2017

Curi, N., J.C. Ker, R.F. Novais, P. Vidal-Torrado, and C.E.G.R. Schaefer. 2017. Pedologia: Solos dos Biomas Brasileiros. Sociedade Brasileira de Ciência do Solo, Viçosa.

Cutler, R.D., T.C. Edwards, K.H. Beard, K.T. Cutler, H.J. Gibson, and J.J. Lawler. 2007. Random forests for classification in ecology. Ecology 88:2783–2792. doi:10.1890/07-0539.1

Dalchiavon, F.C., M.P. Carvalho, D.C. Nogueira, D. Romano, F.L. Abrantes, J.T. Assis, and M.S. Oliveira. 2011. Produtividade da soja e resistência mecânica à penetração do solo sob sistema plantio direto no cerrado brasileiro. Agric. Res. Tropics 41:8–19.

Debiasi, H., R. Levien, C.R. Trein, O. Conte, and K.M. Kamimura. 2010. Produtividade de soja e milho após coberturas de inverno e descompactação mecânica do solo. Pesqi. Agropecu. Bras. 45:603–612. doi:10.1590/S0100-204X2010000600010

Derpsch, R., T. Friedrich, A. Kassam, and H.W. Li. 2010. Current status of adoption of no-till farming in the world and some of its main benefits. Int. J. Agric. Biol. Eng. 3:1–25. doi:10.3965/j.issn.1934-6344.2010.01.0-0

Dexter, A.R. 2004. Soil physical quality. Part I. Theory, effects of soil texture, density and organic matter, and effects on root growth. Geoderma 120:201–214. doi:10.1016/j.geoderma.2003.09.004

Drescher, M.S., F.L.F. Eltz, J.E. Denardin, and A. Faganello. 2011. Persistência do efeito de intervenções mecânicas para a descompactação de solos sob plantio direto. Braz. J. Soil Sci. 35:1713–1722. doi:10.1590/S0100-06832011000500026

Everingham, Y., J. Sexton, D. Skocaj, and G. Inman-Bamber. 2016. Accurate prediction of sugarcane yield using a random forest algorithm. Agron. Sustain. Dev. 36:27. doi:10.1007/s13593-016-0364-z

FAO. 2016. AQUASTAT: FAO's Global Information System on Water and Agriculture. Food and Agriculture Organization of the United Nations, Rome. http://www.fao.org/nr/aquastat/ (accessed 4 Feb. 2018).

Farias, J.R.B., A.L. Nepomuceno, and N. Neumaier. 2007. Ecofisiologia da soja. Circular Técnica 48. Embrapa, Londrina.

Ferreira, M.M., and Z.Z. Marcos. 1983. Estimativa da capacidade de campo de Latossolo Roxo distrófico e regossolo através do ponto de inflexão da curva característica de umidade. Ciência e Prática 7:96–101.

Fidalski, J., R. Yagi, and C.A. Tormena. 2015. Revolvimento ocasional e calagem em Latossolo muito argiloso em sistema plantio direto consolidado. Braz. J. Soil Sci. 39:1483–1489. doi:10.1590/01000683rbcs20140428

Flint, A.L., and L.E. Flint. 2002. Particle density. In: J.H. Dane and G.C. Topp, editors, Methods of soil analysis. Part 4. SSSA Book Ser. 5. SSSA, Madison. p. 229–240. doi:10.2136/sssabookser5.4.c10

Flowers, M.D., and R. Lal. 1998. Axle load and tillage effects on soil physical properties and soybean grain yield on a mollic ochraqualf in northwest Ohio. Soil Tillage Res. 48:21–35. doi:10.1016/S0167-1987(98)00095-6

Fukuda, S., W. Spreer, E. Yasunaga, K. Yuge, V. Sardsud, and J. Müller. 2013. Random forests modelling for the estimation of mango (*Mangifera indica* L. cv. Chok Anan) fruit yields under different irrigation regimes. Agric. Water Manage. 116:142–150. doi:10.1016/j.agwat.2012.07.003

Girardello, V.C., T.J.C. Amado, A.L. Santi, M.R. Cherubin, J. Kunz, and T.G. Teixeira. 2014. Resistência à penetração, eficiência de escarificadores mecânicos e produtividade da soja em Latossolo argiloso manejado sob plantio direto de longa duração. Braz. J. Soil Sci. 38:1234–1244. doi:10.1590/S0100-06832014000400020

Grandy, A.S., G.P. Robertson, and K.D. Thelen. 2006. Do productivity and environmental trade-offs justify periodically cultivating no-till cropping systems? Agron. J. 98:1377–1382. doi:10.2134/agronj2006.0137

Gregory, P.J. 1992. Crecimiento y funcionamiento de las raíces. In: A. Wild, editor, Condiciones del suelo y desarrollo de las plantas según Russel. Mundi-Prensa, Madrid. p. 121–175.

Grossman, R.B., and T.G. Reinsch. 2002. Bulk density and linear extensibility. In: J.H. Dane and G.C. Topp, editors, Methods of soil analysis. Part 4. SSSA Book Ser. 5. SSSA, Madison. p. 201–228. doi:10.2136/sssabookser5.4.c9

Hair, J.F., Jr., B. William, B. Babin, and R.E. Anderson. 2009. Multivariate data analysis. 6th edition. Bookman, Porto Alegre.

Hakojärvi, M., M. Hautala, A. Ristolainen, and L. Alakukku. 2013. Yield variation of spring cereals in relation to selected soil physical properties on three clay soil fields. Eur. J. Agron. 49:1–11. doi:10.1016/j.eja.2013.03.003

Hamza, M.A., and W.K. Anderson. 2005. Soil compaction in cropping systems: A review of the nature, causes and possible solutions. Soil Tillage Res. 82:121–145. doi:10.1016/j.still.2004.08.009

Izumi, Y., T. Yoshida, and M. Iijima. 2009. Effects of subsoiling to the non-tilled field of wheat-soybean rotation on the root system development, water uptake, and yield. Plant Prod. Sci. 12:327–335. doi:10.1626/pps.12.327

Klein, V.A., and R.K. Camara. 2007. Rendimento da soja e intervalo hídrico ótimo em Latossolo Vermelho sob plantio direto escarificado. Braz. J. Soil Sci. 31:221–227. doi:10.1590/S0100-06832007000200004

Klein, V.A., M.L. Vieira, F.F. Durigon, J.P. Massing, and F. Fávero. 2008. Porosidade de aeração de um Latossolo Vermelho e rendimento de trigo em plantio direto escarificado. Cienc. Rural 38:365–371. doi:10.1590/S0103-84782008000200011

Klute, A. 1986. Water retention: Laboratory methods. In: A. Klute, editor, Methods of soil analysis. Part 1. SSSA Book Ser. 5.1. SSSA and ASA, Madison, WI. p. 635–662. doi:10.2136/sssabookser5.1.2ed.c26

Koch, H.J., J. Dieckmann, A. Büchse, and B. Märländer. 2009. Yield decrease in sugar beet caused by reduced tillage and direct drilling. Eur. J. Agron. 30:101–109. doi:10.1016/j.eja.2008.08.001

Lal, R., D.C. Reicosky, and J.D. Hanson. 2007. Evolution of the plow over 10,000 years and the rationale for no-till farming. Soil Tillage Res. 93:1–12. doi:10.1016/j.still.2006.11.004

Lapen, D.R., G.C. Topp, E.G. Gregorich, and W.E. Curnoe. 2004. Least limiting water range indicators of soil quality and corn production, eastern Ontario, Canada. Soil Tillage Res. 78:151–170. doi:10.1016/j.still.2004.02.004

Lê, S., J. Josse, and F. Husson. 2008. FactoMineR: An R Package for multivariate analysis. J. Stat. Softw. 25:1–18. doi:10.18637/jss.v025.i01

Letey, J. 1985. Relationship between soil physical properties and crop production. Adv. Soil Sci. 1:277–294. doi:10.1007/978-1-4612-5046-3_8

Li, M.F., X.P. Tang, W. Wu, and H.B. Liu. 2013. General models for estimating daily global solar radiation for different solar radiation zones in mainland China. Energy Convers. Manage. 70:139–148. doi:10.1016/j.enconman.2013.03.004

Liaw, A., and M. Wiener. 2002. Classification and regression by randomForest. R News 2/3:18–22.

Linn, D.M., and J.W. Doran. 1984. Effect of water-filled pore space on carbon dioxide and nitrous oxide production in tilled and nontilled soils. Soil Sci. Soc. Am. J. 48:1267–1272. doi:10.2136/sssaj1984.03615995004800060013x

Lipiec, J., R. Horn, J. Pietrusiewicz, and A. Siczek. 2012. Effects of soil compaction on root elongation and anatomy of different cereal plant species. Soil Tillage Res. 121:74–81. doi:10.1016/j.still.2012.01.013

Lipiec, J., and W. Stepniewski. 1995. Effects of soil compaction and tillage systems on uptake and losses of nutrients. Soil Tillage Res. 35:37–52. doi:10.1016/0167-1987(95)00474-7

Lozano, L.A., C.G. Soracco, R. Villarreal, J.M. Ressia, G.O. Sarli, and R.R. Filgueira. 2016. Soil physical quality and soybean yield as affected by chiseling and subsoiling of a no-till soil. Braz. J. Soil Sci. 40:1–12. doi:10.1590/18069657rbcs20150160

Mello, C.R., G.C. Oliveira, D.V.S. Resck, J.M. Lima, and M.S. Dias Júnior. 2002. Estimativa da capacidade de campo baseada no ponto de inflexão da curva característica. Cienc. Agrotec. 26:835–841.

Montanari, R., M.P. Carvalho, M. Andreotti, F.C. Dalchiavon, L.H. Lovera, and M.A.O. Honorato. 2010. Aspectos da produtividade do feijão correlacionados com atributos físicos do solo sob elevado nível tecnológico de manejo. Braz. J. Soil Sci. 34:1811–1822. doi:10.1590/S0100-06832010000600005

Nortcliff, S. 2002. Standardisation of soil quality attributes. Agric. Ecosyst. Environ. 88:161–168. doi:10.1016/S0167-8809(01)00253-5

Novais, R.F. 1999. Soja. In: A.C. Ribeiro, P.T.G. Guimarães, and V.H. Alvarez, editors, Recomendação para o uso de corretivos e fertilizantes em Minas Gerais. CFSEMG, Viçosa, MG.

Nunes, M.R., J.E. Denardin, E.A. Pauletto, A. Faganello, and L.F.S. Pinto. 2015. Mitigation of clayey soil compaction managed under no-tillage. Soil Tillage Res. 148:119–126. doi:10.1016/j.still.2014.12.007

Nunes, M.R., E.A. Pauletto, J.E. Denardin, A. Faganello, L.F.S. Pinto, and T. Scheunemann. 2014. Persistence of chiseling effects on the compaction of a Nitosol under no-till in a humid subtropical region. Pesqi. Agropecu. Bras. 49:531–539. doi:10.1590/S0100-204X2014000700005

Passioura, J.B. 2002. Soils conditions and plant growth. Plant Cell Environ. 25:311–318. doi:10.1046/j.0016-8025.2001.00802.x

Pittelkow, C.M., B.A. Linquist, M.E. Lundy, X. Liang, K. Jan van Groenigen, J. Lee, N. van Gestel, J. Six, R.T. Venterea, and C. van Kessel. 2015. When does no-till yield more? A global meta-analysis. Field Crops Res. 183:156–168. doi:10.1016/j.fcr.2015.07.020

Quincke, J.A., C.S. Wotmann, M. Mamo, R. Franti, R.A. Drijber, and J.P. Garcia. 2007. One-time tillage of no-till systems: Soil physical properties, phosphorus runoff, and crop yield. Agron. J. 99:1104–1110. doi:10.2134/agronj2006.0321

R Development Core Team. 2017. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.Rproject.org (accessed 2 Feb. 2018).

Reichert, J.M., L.E.A.S. Suzuki, D.J. Reinert, R. Horn, and I. Håkansson. 2009. Reference bulk density and critical degree-of-compactness for no-till crop production in subtropical highly weathered soils. Soil Tillage Res. 102:242–254. doi:10.1016/j.still.2008.07.002

Reynolds, W.D., B.T. Bowman, C.F. Drury, C.S. Tan, and X. Lu. 2002. Indicators of good soil physical quality: Density and storage parameters. Geoderma 110:131–146. doi:10.1016/S0016-7061(02)00228-8

Reynolds, W.D., C.F. Drury, C.S. Tan, C.A. Fox, and X.M. Yang. 2009. Use of indicators and pore volume-function characteristics to quantify soil physical quality. Geoderma 152:252–263. doi:10.1016/j.geoderma.2009.06.009

Reynolds, W.D., C.F. Drury, X.M. Yang, and C.S. Tan. 2008. Optimal soil physical quality inferred through structural regression and parameter interactions. Geoderma 146:466–474. doi:10.1016/j.geoderma.2008.06.017

Rossato, O.B., C.A. Ceretta, L.S. Silva, G. Brunetto, J.C. Adorna, E. Girotto, and C.R. Lourenzi. 2009. Correction of soil acidity in the subsurface of an Oxisol with sandy loam texture under no-tillage. Braz. J. Soil Sci. 33:659–667. doi:10.1590/S0100-06832009000300018

Santi, A.L., T.J.C. Amado, M.R. Cherubin, T.N. Martin, J.L. Pires, L.P.D. Flora, and C.J. Basso. 2012. Análise de componentes principais de atributos químicos e físicos do solo limitantes à produtividade de grãos. Pesqi. Agropecu. Bras. 47:1346–1357. doi:10.1590/S0100-204X2012000900020

Secco, D., D.J. Reinert, J.M. Reichert, and C.O. da Ros. 2004. Produtividade de soja e propriedades físicas de um Latossolo submetido a sistemas de manejo e compactação. Braz. J. Soil Sci. 28:797–804. doi:10.1590/S0100-06832004000500001

Secco, D., D.J. Reinert, J.M. Reichert, and V.R. Silva. 2009. Atributos físicos e rendimento de grãos de trigo, soja e milho em dois Latossolos compactados e escarificados. Cienc. Rural 39:58–64. doi:10.1590/S0103-84782009000100010

Shukla, M.K., and R. Lal. 2005. Erosional effects on soil organic carbon stock in an on-farm study on Alfisols in west central Ohio. Soil Tillage Res. 81:173–181. doi:10.1016/j.still.2004.09.006

Shukla, M.K., R. Lal, and M. Ebinger. 2004. Principal component analysis for predicting corn biomass and grain yields. Soil Sci. 169:215–224. doi:10.1097/01.ss.0000122521.03492.eb

Silva, B.M., G.C. Oliveira, M.E. Serafim, E.A. Silva, M.M. Ferreira, L.D. Norton, and N. Curi. 2015. Critical soil moisture range for a coffee crop in an oxidic latosol as affected by soil management. Soil Tillage Res. 154:103–113. doi:10.1016/j.still.2015.06.013

Silva, B.M., E.A. Silva, G.C. Oliveira, M.M. Ferreira, and M.E. Serafim. 2014. Plant-available soil water capacity: Estimation methods and implications. Braz. J. Soil Sci. 38:464–475. doi:10.1590/S0100-06832014000200011

Silva, M.C.C., M. Andreotti, N.R. Costa, C.G.R. Lima, and C.M. Pariz. 2017. Soil physical attributes and yield of winter common bean crop under a no-till system in the Brazilian Cerrado. Rev. Caatinga 30:155–163. doi:10.1590/1983-21252017v30n117rc

Smidt, E.R., S.P. Conley, J. Zhu, and F.J. Arriaga. 2016. Identifying field attributes that predict soybean yield using random forest analysis. Agron. J. 108:637–646. doi:10.2134/agronj2015.0222

Soane, B.D., B.C. Ball, J. Arvidsson, G. Basch, F. Moreno, and J. Roger-Estrade. 2012. No-till in northern, western and south-western Europe: A review of problems and opportunities for crop production and the environment. Soil Tillage Res. 118:66–87. doi:10.1016/j.still.2011.10.015

Soil Survey Staff. 2014. Keys to soil taxonomy. 12th ed. USDA, Washington, DC.

Sparks, D.L., A.L. Page, P.A. Helmke, and R.H. Loeppert, editors. 1996. Methods of soil analysis. Part 3. SSSA Book Ser. 5.3. SSSA and ASA, Madison, WI.

Stavi, I., R. Lal, and L.B. Owens. 2011. On-farm effects of no-till versus occasional tillage on soil quality and crop yields in eastern Ohio. Agron. Sustain. Dev. 31:475–482. doi:10.1007/s13593-011-0006-4

Stirzaker, R.J., J.B. Passioura, and Y. Wilms. 1996. Soil structure and plant growth: Impact of bulk density and biopores. Plant Soil 185:151–162. doi:10.1007/BF02257571

Stolf, R. 1991. Teoria e teste experimental de fórmulas de transformação dos dados de penetrômetro de impacto em resistência do solo. Braz. J. Soil Sci. 15:229–235.

Tullberg, J.N. 1990. Why control field traffic. In: M.N. Hunter, C.J. Paull, and G.D. Smith, editors, Proceedings of Queensland Department of Primary Industries Soil Compaction Workshop, Toowoomba, Australia. 28, p. 13–25.

van Genuchten, M.T. 1980. A closed form equation for predicting the hydraulic conductivity of unsaturated soils. Soil Sci. Soc. Am. J. 44:892–898. doi:10.2136/sssaj1980.03615995004400050002x

Vincenzi, S., M. Zucchetta, P. Franzoi, M. Pellizzato, F. Pranovi, G.A. De Leo, and P. Torricelli. 2011. Application of a Random Forest algorithm to predict spatial distribution of the potential yield of *Ruditapes philippinarum* in the Venice lagoon, Italy. Ecol. Modell. 222:1471–1478. doi:10.1016/j.ecolmodel.2011.02.007

Walkley, A., and L.A. Black. 1934. An examination of the Degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. Soil Sci. 37:29–38. doi:10.1097/00010694-193401000-00003

Wang, Q., C. Lu, H. Li, J. He, K.K. Sarker, R.G. Rasaily, Z. Liang, X. Qiao, H. Li, and A.D.J. Mchungh. 2014. The effects of no-tillage with subsoiling on soil properties and maize yield: 12-year experiment on alkaline soils of Northeast China. Soil Tillage Res. 137:43–49. doi:10.1016/j.still.2013.11.006

Zhang, Y., R. Wang, S. Wang, H. Wang, Z. Xu, G. Jia, X. Wang, and J. Li. 2017. Effects of different sub-soiling frequencies incorporated into no-tillage systems on soil properties and crop yield in dryland wheat-maize rotation system. Field Crops Res. 209:151–158. doi:10.1016/j.fcr.2017.05.002